Non-mathematics majors studying statistics at universities in Cyprus: factors behind performance

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Abstract

Statistics is increasingly taught as a part of the curriculum programmes of a wide spectrum of disciplines at higher-level institutions. The main goal of this doctoral study is to get an understanding of non-mathematician students' perceptions, challenges and experiences when undertaking a university level introductory statistics course. This research also seeks to investigate affective, motivational and cognitive factors, which may be associated with students' academic performance in statistics.

A mixed-methods research design (that is a combination of quantitative and qualitative data collection methods) was employed. A self-reported questionnaire was administered to a larger sample of students (over five hundred) near the beginning and towards the end of the instruction of a statistics course. A sub-sample of the students was interviewed and thirty of them were selected to act as a source of qualitative evidence to complement the quantitative results.

This study reports on data from a sample of undergraduate majors who attended statistics courses from recognised (both public and private) universities in Cyprus across two academic semesters. Students with a variety of mathematics backgrounds and experiences and from diverse academic departments and degree programmes participated in the study. Quantitative data analyses (including multivariate analyses such as structural equation modelling techniques) and interview data analyses (using thematic analysis) were performed.

The qualitative findings highlight, amongst other things, the importance of the role of the instructor in the statistics education learning process. The key finding of the structural equation modelling techniques, when modelling performance in statistics, is that self-efficacy and resilience in both questionnaire administrations explain and predict statistics performance over and above the other variables (such as liking, interest, value, difficulty and anxiety) included in the model. More specifically, self-efficacy and resilience are found to be directly and positively related to the performance. Self-efficacy has a prominent position in the model since it is also found to be associated with all the variables incorporated into the model.

It is suggested that self-efficacy and resilience, particular in the context of statistics education, are constructs worthy of further investigation from researchers and educators. The potential contribution of the study is to benefit the development of statistics education and offer implications and recommendations for teaching and learning statistics based on the findings.

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Chapter 1 INTRODUCTION

This chapter begins by providing an introductory statement and a brief description of the background of this doctoral research study and continues with sections outlining the focus and the significance of the study. It ends with an outline of the structure of the thesis.

1.1 Introductory Statement and Background of the study

Statistics is the scientific discipline associated with the study of variability and uncertainty, and the attempt to understand this variability and draw inferences under this uncertainty. Statistics encompasses the collection, organisation, analysis, interpretation, presentation and dissemination of data (Dodge, 2006). As stated by many authors (e.g. Moore, 2005; Rossman *et al.*, 2006), it is the science of learning and gaining insight from quantitative data. In 2017, the Italian Statistical Society conference highlighted statistics as the 'grammar of data science' since it arguably gives a 'right' meaning to the data.

Learning statistics has been considered as crucial for problem-solving, logical thinking, critical reading and judgement, and informed decision-making (Derry *et al*., 1995; Kesic, 2011). These are considered as essential skills that individuals need to equip themselves with due to the development of the technology, the abundance of information and the rise of the number and the frequency of numerical data presented (Ben-Zvi and Garfield, 2010). The need to comprehend and critically evaluate statistical information in order to question the quality of the data and the reliability of the reported analysis and draw informed inferences and decisions is deemed as imperative. Embracing statistical knowledge, skills and thinking can enhance personal and professional development.

Underlying the importance of statistics on various facets and aspects of our lives, the incorporation of statistics in the context of education is an important skill. Nowadays, statistics education is ubiquitous at all education levels and across various disciplines (Scheaffer, 2002; Ben-Zvi and Garfield, 2010). Statistics courses have been incorporated into the degree curriculum programmes in higher education institutions from the beginning of the 20th century (Verhoeven, 2009; Emmioğlu, 2011). Usually, a large proportion of university students are required to undertake at least one introductory statistics or statistics-related course as a component of their undergraduate degree programmes. This is a fact not only for mathematics majors but also for students specialising in other disciplines and fields of studies. These fields include, among others, health sciences, pure and applied sciences, social sciences, education, economic and business studies and engineering. For some students, an introductory course in statistics is the only statistics course that they will encounter during their studies at university.

Since non-mathematics university students come from diverse backgrounds and majors, they enter an introductory statistics course with previous learning experiences, acquired knowledge and bring with them a wide range of abilities and skills. Also, they might possess different perceptions and views regarding statistics as a discipline and regarding their own perceived competence to master the subject content and succeed in the course (Garfield and Ben-Zvi, 2007; Chiesi and Primi, 2010; Coetzee *et al.*, 2010). Previous experiences shape students' beliefs about themselves as learners, the subject and the discipline as a whole.

Ben-Zvi and Garfield (2010) advocates that learning statistics might be a challenging process. Many students refer to statistics as being novel and unfamiliar to them at the university level. They contend that statistics requires developing a new way of thinking and learning a new vocabulary (Leavy *et al*., 2013). Kirk (2002) states that there exists a common belief among university students that an elementary statistics course is demanding and needs considerable time and effort, it comprises a lot of mathematics and it is useless and irrelevant to their field of study. Cobb and Moore (1997) talks about the role of context in statistics and from this presence of context in statistical tasks might arise challenges and difficulties especially for beginning learners of statistics (Leavy *et al*., 2013). Sunzuma *et al.* (2012), also, argues that some students find it difficult to see the connection between theory and practice when embarking on a statistics course for the first time. For these reasons, the prospect of undertaking a class in statistics may be intimidating (Carnell, 2008). There is evidence that this academic subject (an introductory statistics as a university course for non-mathematics majors) is usually not popular and considered as a course, which should (only) be passed. A considerable proportion of students view statistics courses as a hindrance to the acquirement of their desired degree (Perney and Ravid, 1990; Vigil-Colet *et al.*, 2008).

According to Garfield *et al.* (2002), the desired goals of an introductory course in statistics can be categorised into three main parts: (a) students' learning (student's statistical literacy, understanding, reasoning, and thinking); (b) the continuation of using and applying statistical knowledge, methods and skills after completing the course; and (c) students' attitudes and beliefs regarding the discipline of statistics and regarding their competence to learn and use statistics. Consonant with above, the appreciation of the value and applications of statistics in students' personal, educational and vocational lives is a crucial goal for an introductory statistics course.

A plethora of researchers and statistics educators direct their attention to and emphasise the importance of improvement of learning outcomes and cognitive issues or aspects such as knowledge and skills that students are expected to acquire and develop during a statistics course. However, non-cognitive factors, the 'other' outcomes of statistics education (Schau, 2003), are also prominent because they may greatly impact statistics education experience and performance in statistics. Such factors can be favourable or adverse in the learning journey to master the subject matter and develop statistical skills. They may also affect the students' choice to pursue more advanced statistics courses in the future and play a key role in the subsequent use of statistics in their professional career and in real-world applications outside the classroom (Gal and Ginsburg, 1994; Gal *et al*., 1997). Nevertheless, non-cognitive and cognitive factors are not independent and cannot be isolated from one another when investigating learning process, potentials, outcomes and achievement (Chiesi and Primi, 2010).

As many researchers have argued (e.g. Gal and Ginsburg, 1994; Baloğlu, 2003), students often experience difficulties and setbacks in statistics courses that may not only be attributed to insufficient aptitudes and lack of knowledge, but also may be reflections of affective and motivational factors such as attitudes and beliefs, feelings of anxiety, confidence, genuine interest and motivations related to statistics.

1.2 Purpose and Focus of the study

Determinants of students' achievement in statistics courses have been the subject of ongoing debate among researchers, instructors and other statistics stakeholders. This study represents an effort to integrate several affective, motivational and cognitive factors, uncover and explore the nature, the linkage and the interaction of them with each other, and subsequently their effects on students' performance in an introductory statistics course.

The primary objective of the present investigation is to capture and get an insight and understanding into non-mathematics students' perceptions, motivations, endeavours, challenges and experiences when undertaking a statistics course offered at the university level. An additional objective driving my research study was the conceptualisation and the operationalisation of the notion of resilience (specifically the construct of resilience in the context of statistics education). As far as I know, the concept of resilience, as applied to the statistics education context, has not been investigated by other researchers. The relationship between resilience and a set of personal and educational factors along with the potential contribution of resilient characteristics and behaviours to the achievement in statistics courses were explored.

To sum up, the overarching goal of the current study is to gain a better understanding of factors affecting performance in the statistics courses and to probe and document the students' views of their experiences when undertaking a statistics course. The aim is to familiarise, understand and represent the perceptions and experiences of a specific population, provide grounds for comparisons, make recommendations for action under similar learning contexts (e.g. quantitative-based courses) and situations and advance extant knowledge accumulation in this area of study.

1.3 Significance and Contribution of the study

As I mention in the next chapters, studies in this area of investigation focus on exploring a small number of factors that are considered to be associated with the learning process and performance in a statistics course. The significance and contribution of this doctoral study lays in the accumulation and investigation of many factors that have been introduced to other relevant theoretical and empirical studies in one research study. Particularly, this current study adds to the stream of the research literature by simultaneously investigating a broader set of variables that are deemed to be interrelated and subsequently associated with performance in statistics. An examination of many variables together purports to shed more light, extend understanding and provide a better picture of their influences and their abilities in explain and predict statistics achievement. According to Harvey *et al.* (1985, p.4), it is important to examine "a variety of both cognitive and affective variables" because "neither component should be isolated when attempting to predict performance or when developing remediation programs". The findings of the study contribute to the general understanding of the structure of statistics performance, especially at the university level.

This research work aims to contribute to the literature of my country (Cyprus). To the best of my knowledge, this is the first attempt concerning students' learning experiences and exploring factors (including affective responses, motivational orientations and cognitive engagement) associated with their performance in a university-level introductory statistics course in Cypriot settings. While stimulated by the desire, the interest and the need to explore the undocumented perceptions and perspectives of students in Cypriot universities on their experiences when undertaking a statistics course, this research project may also encourage researchers and statistics educators to be interested in, carry out and publish additional research investigations in Cypriot settings.

It is hoped that the current study will: add further insights into the constructs under investigation; gain a greater understanding of how some constructs (e.g. self-efficacy) operate in specific cultural settings; advance research on academic (and mathematical resilience); and provide the foundation for further studies to explore the phenomenon of resilience in the statistics education context. More specifically, it is hoped that the research design and methodology, the data analysis techniques and findings of this doctoral study will inform and add evidence to the empirical and theoretical research base on the underlying affective, motivational and cognitive factors contributing to performance outcomes and learning. Since the research objectives (see §§1.2 and 3.2) are mainly focused on students, my study attempts to give voice to the students about their perceptions and experiences and get an insight into how this population 'respond' to an introductory statistics course.

Lastly, it is believed that research of this nature (exploratory and interpretative) could also support and contribute to instructional and classroom practices and might be of interest to practitioners, statistics educators and instructors as they design these statistics courses. The potential impacts include curriculum structure, content and pedagogy. The major findings, the conclusions and the recommendations of this research work may constitute a helpful tool for the stakeholders of statistics education in Cyprus (and beyond) in an effort to develop and improve the efficacy of a statistics education experience.

1.4 Organisation and structure of the thesis document

This research study is organised into seven chapters. This first chapter provides introductory information including the background information, the purpose of the study and the significance and potential contribution. The remaining part of this document has the following structure. The second chapter gives a review of the related literature organised around the main constructs under investigation and lays out the theoretical foundation and background. The third chapter focus on the research design, methodology and the research methods employed in this study. Chapter 4 provides the analyses of the quantitative investigation (i.e. questionnaire responses) and is organised by the main statistical methods used. Chapter 5 presents the findings of the qualitative investigation (i.e. responses to the interviews) focusing on the main themes emerging from the qualitative analysis. The sixth chapter begins by addressing the research questions and priorities of this research study and proceeds by summarising the main findings, highlighting emergent findings and providing recommendations and implications for practice. The final chapter (Chapter 7) provides a summary and a concluding remark of the current study, outlines the main limitations and offers suggestions for future research work.

Chapter 2 REVIEW OF THE LITERATURE

2.1 Introduction

In this chapter, a condensed overview of the most salient ideas and constructs under investigation along with some theoretical propositions and key findings and conclusions from empirical studies are provided. Before the review is presented, an explanation of the process that was adopted for the literature review search and reporting is mentioned. The review of the literature had started when I was trying to refine my research interests and choose a topic for my doctoral proposal. I was looking for studies (both theoretical and empirical) related to the constructs under investigation, more 'general' and then more 'specific' related to mathematics/statistics, and how previous authors and researchers conceptualised, operationalised and investigated these constructs. I classified and grouped into categories (major topics/areas) a number of factors that were deemed to influence performance in a statistics course and I was interested in exploring them. This classification facilitated the organisation of the literature review chapter, the design of the quantitative (i.e. questionnaire) and the qualitative (i.e. interview plan) tools, the data analysis procedures and the reporting and discussion of the main findings emerged from this research study. I tried to make a review regarding the theory and methodology related to the proposed research topic, report the most influential, relevant and recent empirical and theoretical studies related to each construct under investigation and incorporate international perspectives and references from the literature. The literature was used to support and provide a rationale for the proposed research study, relate the proposed research study to prior research especially in statistics and mathematics, and provide supporting evidence for the arguments and conclusions emerged from the study.

The literature review chapter is organised as follows. Nine sections of this chapter are devoted to different topic areas (namely: Statistics Versus Mathematics; Influence of previous mathematics background and performance; Attitudes towards statistics; Interest towards statistics; Anxiety towards statistics; Self-efficacy regarding statistics; Resilience; Motivational and cognitive engagement-related constructs; Demographic and educational-related characteristics). Moreover, findings from research studies, which were recruited university level students in Cypriot and Greek educational settings are presented. This chapter ends by providing a brief description of the theories and theoretical framework related to this research study along with a brief introduction to the theoretical-conceptual model that was designed, developed and tested in the study.

2.2 Statistics Versus Mathematics

Increasingly, statistics tends to be regarded as a distinct discipline rather than a subdomain of mathematics (Moore, 2005; Groth, 2007; Ben-Zvi and Garfield, 2010). A detailed explanation of how statistics is different from mathematics is outlined in some studies (e.g. Gal and Garfield, 1997; Rossman *et al*., 2006; Ben-Zvi and Garfield, 2010). Many researchers assert that the disciplines of mathematics and statistics involve distinct types of reasoning, thinking and understanding and encompass or require different types of cognitive processes and intellectual abilities (Cruise *et al*, 1985; Baloğlu, 2004; Rossman *et al.*, 2006; delMas, 2004, 2011; Ben-Zvi and Garfield, 2010; Hannigan *et al*. 2013). Cobb and Moore (1997) supports this contention by maintaining that statistical thinking relies more on context and variability of data. Bakker *et al*. (2017) states that the role of context is different in statistics from in mathematics; mathematics typically intends to be decontextualized, whereas statistics typically focus on context and the contextual interpretation is deemed as crucial. According to Hannigan (2014), the (powerful) way of statistical thinking gives more emphasis on the role of checking for assumptions and conditions to be met, understanding and interpretation of the statistical output (outcomes), description of results, conclusions to be drawn, supported or data-based inferences and critical judgements. In this regard, many researchers recommends viewing statistics as a mathematical science, or in other words, as a "bridge between mathematics and science" (Ben-Zvi and Garfield, 2010, p.355).

Schau (2003) states that many students who attend a statistics course at university level hold the perception that statistics is mathematics, especially before their enrolment to the course and/or at the beginning of it. Also, they hold the preconceptions that statistics involves a lot of mathematics and someone should be good at mathematics or have an innate talent or ability to attempt statistics. They expect that mastering statistics requires a good knowledge of mathematics. This may have its roots in the fact that the statistics is often taught as a part of the mathematics course curriculum in high school. Thus, it is argued that these students tend to transfer and reproduce their beliefs, attitudes and past experiences related to the subject of mathematics in statistics classes (Gal *et al.*, 1997; Zimprich, 2012).

2.3 Influence of prior mathematics background and performance

Students enter an introductory statistics course with different academic backgrounds and variations in their mathematics background and previous learning experiences with mathematics and statistics. This section reports the findings of several research studies that have investigated the role of mathematics background and prior learning mathematics experiences in affective responses, motivational orientations and cognitive behaviours, and especially in students' performance in statistics courses.

According to Tremblay *et al.* (2000), when dealing with the prior mathematics background and mathematical aptitude, a crucial consideration is the measures selected to assess them. Different researchers have employed various indicators in their attempt to evaluate students' previous mathematics achievements, learning experiences, acquired or perceived mathematical knowledge and abilities. Many studies refer to the mathematics background and achievement as the number and the type of previous mathematics/statistics courses completed at the university or secondary level and grades obtained in these courses (e.g. Sorge and Schau, 2002; Onwuegbuzie, 2003; Nasser, 2004; Väisänen *et al.*, 2004; Carmona *et al*., 2005; Emmioğlu, 2011; Lai *et al*., 2011; Dupuis *et al*., 2012; Gladys *et al.*, 2013). Other studies distribute short-scale tests which purport to evaluate basic mathematics skills (e.g. Lalonde and Gardner, 1993; Schutz *et al.*, 1998; Harlow *et al.*, 2002; Johnson and Kuennen, 2006; Lunsfold and Poplin, 2011; Fonteyne *et al.*, 2015). Both high school performance and current mathematical ability (as measured by students' basic mathematics test scores) were used by Chiesi and Primi (2010) and Galli *et al.* (2011). Many researchers (e.g. Dempster and McCorry, 2009; Sese, 2015) incorporate questions asking students to indicate their prior experiences with mathematics and statistics and to rate their self-perceived mathematical abilities and competencies.

A substantial body of literature reports evidence that previous mathematics and statistics background (along with prior achievement) and mathematical ability are important contributors to and predictors of achievement in statistics courses (see for example Elmore *et al.*, 1993; Lalonde and Gardner, 1993; Schutz, *et al.*, 1998; Tremblay *et al.*, 2000; Sorge, and Schau, 2002; Harlow *et al.*, 2002; Nasser, 2004; Verhoven, 2011; Dupius *et al.*, 2012; Hood *et al.*, 2012; Johnson and Kuennen, 2006; Galli *et al.*, 2008; Lunsfold and Poplin, 2011; Wisenbaker *et al.*, 2000; Chiesi and Primi, 2010; Fonteyne *et al.*, 2015). These research studies support the argument that a stronger mathematical background and a higher mathematical aptitude may benefit students who are enrolled in an introductory statistics course. However, there is no consensus that a strong mathematics background necessarily leads to high performance in statistics courses. For example, Woodward and Galagedera (2006) demonstrates that prior mathematical knowledge does not contribute to success in an elementary statistics course.

Prior exposure to mathematics classes in high school or university level and previous experiences in mathematics might be a possible source of forming certain opinions regarding the field of statistics, even before students enter an introductory statistics course (Gal *et al.*, 1997; Carmona *et al.*, 2005). Recruiting a sample of 827 undergraduate students from two universities in Spain, Carmona *et al.* (2005) finds evidence that students with higher mathematics scores and more mathematically oriented secondary education demonstrated more positive attitudes and dispositions towards statistics. However, this pattern is not found to be consistent among the various scales and dimensions of the attitude assessment instruments. In brief, strong positive relationships between mathematical background, and cognitive competence and affective responses to statistics and weak positive relationships between mathematics background, and value and difficulty ascribed to the statistics subject are detected. Carmichael *et al*. (2009) and Zimprich (2012) corroborate Carmona *et al*.'s (2005) finding by demonstrating that students' prior mathematics experiences had a prominent role in shaping their attitudes towards statistics. Empirical evidence (e.g. Perney and Ravid, 1990; Miils, 2004) supports the view that students who have more experiences in mathematics possess more positive attitudes regarding statistics than students with less experience. Moreover, Nasser (2004) reports that a stronger mathematical aptitude and a lower level of mathematics anxiety are found to be associated with students' more positive attitudes regarding statistics.

Negative previous experiences with mathematics, underachievement in mathematics classes and low levels of perceived mathematics self-efficacy are also found to be correlated with statistics anxiety (see, for example, Zeidner, 1991; Onwuegbuzie *et al.*, 2003; Baloğlu, 2011). Sese (2015), utilising Structure Equation Modelling techniques, demonstrates that students' adequate prior mathematics background has a direct positive effect on their attitudes regarding statistics and a direct negative effect on their statistics anxiety. Moreover, Wisenbaker *et al.* (2000), using a sample of Arabic and English speaking students from colleges in Israel and in the U.S. and by employing path analysis techniques, indicates that more positive attitudes towards mathematics and lower levels of mathematics anxiety are related to greater levels of students' self-efficacy to master and acquire statistical knowledge and skills.

As often argued by researchers (e.g. Murtonen, 2005), many students may struggle and encounter difficulties in the process of learning statistics owing to their prior inadequate mathematics background and preparedness. Lane *et al.* (2002) asserts that students' low self-confidence to master knowledge and succeed in a statistics course might to some extent related to their poor mathematics background and former negative experiences with mathematics-related subjects.

However, there are some empirical studies which did not find strong evidence of the role of the earlier mathematics achievement in several constructs associated with statistics. For example, Birenbaum and Eylath (1994) and Murtonen and Titterton (2004) report that high school mathematics performance is found to be weakly related to negative attitudes, anxiety and difficulties encountered by students in statistics-related courses at university level.

Galagedera *et al.* (2000) examines the effect of students' perceived mathematics abilities in their learning process and ultimately in their performance in an elementary statistics course. An overwhelming majority (about 95%) of the participants reported that they think that mathematical knowledge is a necessary prerequisite to master statistics. Students' perceptions of their mathematics ability are found to affect their interest in statistics, their motivation to do well in the statistics course and their expectations of success in the course. However, no association is detected between students' perceived mathematical competence and the effort that they put forth in statistics.

2.4 Attitudes towards statistics

In his influential paper, McLeod (1992) identifies and distinguishes three concepts related to the affective domain in mathematics education, namely: emotions or emotional feelings; attitudes, orientations or predispositions; and beliefs or ideas. These three concepts are distinguished based on their intensity and stability where emotions are characterised as the most intense and less stable, beliefs as least intense and most stable and attitudes stand between them as being moderately intense and reasonably stable over time. Later on, DeBellis and Goldin (2006) adds a fourth component, namely values. For these researchers, affective representations "is not auxiliary to cognition; it is centrally intertwined with it" (Hannula, *et al*. 2004; p.110). The body of investigation concerning affective concepts in mathematics education can be incorporated into the statistics education context as suggested by Gal *et al.* (1997).

From the three affective-related concepts mentioned above, attitudes construct has been primarily and widely explored in educational and psychological research areas including mathematics and statistics education research. A plethora of research studies have been devoted to the conceptualisation, measurement and variety of topics and constructs that are related to it. In the context of statistics education, the construct of attitudes towards statistics is broadly described as multi-dimensional and multi-layered (in nature). It can be defined as favourable or unfavourable dispositions regarding objects, situations, events, experiences or people related to statistics learning (Schau, 2003; Ajzen, 2005; Chiesi and Primi, 2009). Attitudes can be regarded as something personal. They are often shaped and developed based on the individual's experiences and exposure to related events and tasks and how they perceive such experiences (Olivo-Delgado and Bonilla-Rodríguez, 2009; Arumugam, 2014). It can also be argued that attitudes towards statistics are likely to be influenced by a host of factors instead of by a single one (Gal and Garfield, 1997). Some possible sources of these attitudes might be prior learning experiences and exposure to statistics or mathematics; preconceptions for statistics based on students' out-of-classroom experiences and everyday life; and opinions towards statistics transferred to them by social agents such as family members, friends and so on (Gal *et al.*, 1997). Previous studies provide evidence that attitudes towards statistics are related to prior experiences with mathematics and mathematical background (Onwuegbuzie, 2000; Schau, 2003; Carmona *et al*. 2005; Carmichael *et al*., 2009).

The importance of attitudes in the context of statistics education and especially within an introductory statistics course has been extensively commented in the literature (Gal *et al.*, 1997; Garfield *et al.*, 2002; Leong, 2007). Several researchers (e.g. Gal and Ginsburg, 1994; García-Santillán, 2012) assert that attitudes towards statistics are an essential constituent of the teaching-learning process. These attitudes may have an impact on students' effort, persistence, and ultimately on their achievement outcomes (Schau, 2003b; Hilton, 2004; Ramírez *et al.*, 2012). Hannula *et al*. (2004) emphasises the role of the affective factors in the individual learning process and suggests that they can serve as indicators of learning outcomes and predictors of immediate and future success. As argued by Emmioğlu (2011) and Ramírez *et al.* (2012), individuals may forget what they do not use for a long time, but attitudes and beliefs 'stick'.

Over the past decades, many researchers have used various approaches aiming at capturing and exploring attitudes towards statistics. Traditionally, they have employed survey designs and self-reported measures, such as Likert-type questionnaires (Bond *et al.*, 2012). A systematic review of validity and reliability evidence regarding several instruments that have been developed and adopted to assess attitudes towards statistics is provided by Nolan *et al.* (2012). Nonetheless, there have been inconsistencies in the instruments employed by research studies for measuring attitudes regarding statistics in terms of their structures and their components (e.g. including items related to anxiety concept) which made it difficult to compare and contrast them.

A number of survey instruments have been developed in an attempt to measure and better understand specifically students' attitudes towards statistics exist in the literature. The most commonly mentioned and employed are: the Statistics Attitudes Survey (SAS) by Roberts and Bilderback (1980); the Attitudes toward Statistics- ATS by Wise (1985); and the Survey of Attitudes towards Statistics (SATS) by Schau *et al.* (1995). The Survey of Attitudes towards Statistics (SATS) is the most widely used survey instrument in assessing students' attitudes towards statistics. The evaluation and the validation procedures of the SATS instrument indicated four related, but distinguishable, components of statistics attitudes namely Affect (positive and negative feelings regarding statistics); Cognitive Competence (students' beliefs about their knowledge and abilities when engaged with statistics); Value (students' attitudes regarding the worth, usefulness and relevance of statistics in their personal and professional life); and Difficulty (attitudes concerning the difficulty of statistics as a subject) (Schau, 2003). In 2003, the SATS instrument was expanded to bolster its congruence with the Eccle's *et al*. (1983) Expectancy-Value model by incorporating two additional components, namely effort and interest. The robust psychometric properties of SATS are supported by a number of studies (e.g. Hilton, 2004; Mills, 2004; Cashin and Elmore, 2005; Tempelaar *et al.*, 2007, 2011; Chiesi and Primi, 2009; Verhoeven, 2009; Coetzee *et al.*, 2010; Bechrakis, 2011; Vedramini, 2011; Zimprich, 2012; Hommik and Luik, 2017) which have recruited students coming from diverse educational level, background, majors, ethnicity and so on.

Data gathered from many studies which have been conducted internationally (for example (Netherlands (Tempelaar *et al.*, 2007), the United States (Mills, 2004; Carnell, 2008; Carlson and Winquist, 2011; Griffith *et al*. 2012, South Africa (Coetzee *et al.*, 2010), Turkey (Emmioğlu, 2011), Middle East (Sulieman, 2015), Malaysia (Ashaari, *et al.*, 2011; Ghulami *et al*., 2015), Saudi Arabia (Jahan *et al*., 2016)) reveal that students generally hold neutral or positive attitudes toward statistics after completing a statistics course. This evidence is contrary to the findings of other research studies; for instance, Fullerton and Umphrey (1991) (using a sample of undergraduate advertising students studying in US universities) and Onwuegbuzie (2004) (using a sample consisting of graduate students in educational sciences) which demonstrate that students' negative attitudes regarding statistics outweigh the positive ones.

An extensive body of theoretical and empirical studies has been dedicated to the investigation of the relationship between students' attitudes towards statistics and performance in statistics (see among others Elmore *et al.*, 1993; Sorge and Schau, 2002; Vanhoof *et al.*, 2006; Kim, 2006; Dempster and McCorry, 2009; Ashaari *et al.*, 2011; Zientek *et al*., 2011; Emmioğlu, 2011; Arumugam, 2014; Nguyen *et al.*, 2014; Satake, 2015). Studies that concentrate on this relationship have employed a range of statistical techniques (including correlational analyses, regression analyses and so on). More recently, several studies have explored the role of attitudes towards statistics in explaining performance in statistics courses using Path Analysis or Structural Equation Modelling techniques (e.g. Nasser, 2004; Kim, 2006; Tempelaar, *et al*., 2007; Ismail *et al*., 2008; Chiesi and Primi, 2010; Satake, 2015; Ncube, 2016; Paul and Cunnington, 2017). For example, Chiesi and Primi (2010), by estimating a structural equation model using a sample of undergraduate psychology students in Italy, reports evidence of significant direct effect of attitudes towards statistics on statistics achievement. Regardless of the diversity of the sample populations, the research designs and the instruments employed, an association between attitudes regarding statistics and statistics course outcomes has been consistently detected. A statistically significant and positive relationship between some attitude components and students' performance in statistics is corroborated by many researchers (e.g. Sutarso, 1992; Rhoads and Hubere, 2000; Schau, 2003; Cashin and Elmore, 2005; Evans, 2007; Chiesi and Primi, 2009, 2010; Dempster and McCorry, 2009; Pimenta, 2010; Zhang *et al.*, 2012; Adetona, 2017). This evidence supports the argument that students with more positive attitudes towards statistics are more likely to perform better in a statistics course. According to many authors (e.g. Omwuegbuzi, 2003; Nolan *et al*., 2012), the assessment of students' attitudes regarding statistics is an important tool for predicting course outcomes and academic achievement.

In a meta-analysis study exploring attitudes and achievement in statistics, Emmioğlu and Çapa-Aydin (2012) reviews 14 research studies that have explored post-secondary students' attitudes towards statistics. The majority of these studies utilised the SATS instrument. The authors carried out four separate meta-analyses to examine the association between statistics achievement with the four attitudes components described above. They found that affect and perceived cognitive competence regarding statistics have a medium sized statistically significant positive relationship with statistics achievement; whereas the value and the difficulty students attributed to statistics as a subject have a small but statistically significant association with statistics achievement.

A considerable number of studies have also monitored and evaluated changes in attitudes towards statistics over the duration of a statistics course using a pre-test and post-test study design. However, there is not much consistency among the research findings suggesting perhaps that statistics course context matters. For example, many studies indicate that at least some components of attitudes towards statistics become more favourable over the duration of a statistics course (e.g. Perney and Ravid, 1990; Waters, 1988; Harlow *et al.*, 2002; Limpscomb *et al*, 2002) while other studies find that students' attitudes do not change (Roads and Hubele, 2000; Evans, 2007). On the other hand, some empirical studies report evidence that, on average, students' attitudes towards statistics tend to decline during a statistics course (Verhoeven, 2009; Tempelaar *et al.*, 2011; Zhang *et al.*, 2012).

In the present study, attitudes towards statistics as a construct is defined as an amalgamation of the students' attitudes towards statistics as a discipline/subject and towards the specific statistics course they were attended. Initially, this construct was hypothesised to include students' liking of statistics, their perceived value of statistics, their perceived difficulty of the course and their perceptions towards the nature of the course (such as perceived involvement of mathematics).

2.5 Interest towards statistics

Academic interest is described by many researchers as a domain-specific intrinsic motivational orientation (Schiefele *et al.*, 1992; Köller, 2001). As advocated by Deci and Ryan (1985), people naturally approach activities and engage with tasks that stimulate interest to them. Research on academic interest has consistently argued that the individual's interest can have an impact on learning process and quality of learning as well as on academic achievement. Students with higher levels of interest are more likely to invest more time and effort in learning (Macher *et al*. 2012) and adopt deeper and more elaborated learning strategies (Schiefele, 1991; Hannigan, 2004).

Several other researchers propose that interest encompasses positive affective traits (individual factors) which are associated with learning about ideas, tasks and procedures in a specific domain or subject matter area (Bergin, 1999; Lawless and Kulikowich, 2006). In turn, the interest for a given subject area or topic may grow within the classroom (a situational interest) when students have the opportunity to engage with this topic (Hidi and

Renninger, 2006; Sproesser *et al.*, 2016). In the domain of statistics, Hay *et al.* (2015) have investigated the impact of statistical interest and self-efficacy on academic achievement in a statistical lesson using a quantitative path model. This work suggests that students' interest play an indirect role in students' learning and performance via self-efficacy and demonstrates the crucial role of the classroom experience in students' level of interest.

In this study, within the context of statistics, individual interest refers to students' interest in statistics as a discipline\subject, their enjoyment when learning statistics (for example, when engaging with statistical-related tasks) and their willingness to acquire more statistical knowledge and skills in the future (for example, by undertaking further statistics courses in the university).

2.6 Anxiety towards statistics

In this section, the construct of anxiety, especially in the context of statistics education, is discussed. Statistics anxiety has been defined as "the feelings of anxiety encountered when taking a statistics course or doing statistical analyses; that is, gathering, processing, and interpret[ing]" (Cruise, Cash, & Bolton, 1985, p. 92). It has been identified as one of the prevailing attitudinal issues related to statistics and statistics courses (Onwuegbuzie, 2004; Vahedi *et al*., 2011).

Statistics anxiety can be regarded as a feeling more intense than a negative attitude or a dislike towards statistics. It encompasses emotional reactions and feelings of worry, nervousness, tension, apprehension, fear, panic all associated with statistics. Some researchers (for example, Earp, 2007; Lalonde and Gardner, 2003) posit that attitudes and anxiety about statistics might be interrelated affective components involved in the statistics learning process. This relationship can be seen in earlier empirical investigations (e.g. DeVaney, 2010; Sesé *et al*., 2015; Chiesi and Primi, 2010; Rosli, 2017). In many studies, it is apparent a little or none distinction between them (Nasser, 2004; Papousek *et al.*, 2012). Nevertheless, Chew and Dillon (2014) contends that even though attitudes and anxiety towards statistics are related, they are still two separate constructs.

Many researchers (for example, Perney and Ravid, 1990; Zeidner, 1991; Rodarte-Luna and Sherry, 2008) argue that statistics anxiety may have its origin in students' prior experience and exposure to mathematics, and it is associated with mathematics anxiety. In the pertinent literature, there are studies, which find evidence of a strong positive correlation between mathematics and statistics anxiety (Birenbaum and Eylath, 1994; Paechter, 2017). Nevertheless, although statistics anxiety and mathematics anxiety appear to be highly related (as postulated by Benson, 1989; Zeidner, 1991; Baloğlu *et al.*, 2007), they are two distinct constructs (separate phenomena) and they should be not equated (as initially advocated by Cruise, *et al.*, 1985 and then by Benson, 1989; Baloğlu, 2002; Ruggeri *et al.*, 2008; Zientek *et al.*, 2011; Papousek *et al.*, 2012; Chew and Dillon, 2014). Baloğlu (2004) documents some of the differences and similarities between mathematics and statistics anxiety in terms of definitions, nature, antecedents or sources, effects, assessment measures (instruments) and interventions used. Moreover, although statistics anxiety has been found to be linked with other forms of anxieties experienced in academic settings such as general test anxiety (Benson,1989), it has been established to be a better predictor of statistics performance than general anxiety measures (Finney and Schraw, 2003; Vigil-Colet *et al.*, 2008).

Statistics anxiety is commonly considered to be a situation-specific and a domain- or content-oriented anxiety (Zeidner, 1991; Baloğlu, 2002, 2004; Earp, 2007). It can be raised at a specific time and in a particular situation, especially when students are enrolled in statistics courses or are exposed to statistics in formal educational settings (Onwuegbuzie, 1999; Vahedi *et al.*, 2011). Pan and Tang (2005) points out that statistics anxiety may occur not only because of the lack of training or insufficient knowledge and abilities, but also due to misconceptions about statistics and negative experiences in previous statistics classes.

In the literature, statistics anxiety has been extensively investigated putting emphasis on two main areas: the sources and factors related or contributing to statistics anxiety; and the measurement of statistics anxiety (Pan and Tang, 2005). The possible antecedents of statistics anxiety are broad, and they have been classified into three main categories, namely dispositional (such as individuals personality characteristics such as attitudes, perceptions, self-confidence and perceptions of abilities); situational (such as prior knowledge and learning experiences in statistics, mathematics or research courses, and current statistics course-related factors such as status/type of the course being compulsory or elective, subject content, instructional and evaluation methods); and environmental (such as individuals' socio-demographic and academic characteristics such as gender, age, country of origin, educational level and major of study) (Onwuegbuzie *et al*., 1997; Bell, 1998; Onwuegbuzie and Wilson, 2003; Papanastastiou and Zembylas, 2008; Slootmaeckers, 2012; Zientek *et al.*, 2011; Chew and Dillon, 2014).

Several measures have been developed and administered to assess the students' types and levels of statistics anxiety including the Statistics Anxiety Rating Scale (STARS; *Cruise et al*., 1985); the Statistics Anxiety Inventory (STAI; Zeidner, 1991); the Statistics Anxiety Scale (SAS; Pretorius and Norman, 1992); the Statistics Anxiety Measure (Earp, 2007) and the Statistical Anxiety Scale (STAS; Vigil-Colet *et al.*, 2008); The Statistical Anxiety Rating Scale (STARS), designed by Cruise *et al.* (1985), is currently the most widely and comprehensive distributed instrument for evaluating statistics anxiety (Onwuegbuzie and Wilson, 2003). It is a 5-point Likert-type instrument which consists of six components/subscales (namely worth of statistics, test and class anxiety, interpretation anxiety, computational self-concept, fear of asking for help, and fear of statistics instructors) aiming at capturing the multi-dimensional nature of the statistics anxiety construct (Onwuegbuzie, 2004). The STARS instrument has been utilized by many researchers in different locations (e.g. in the USA by Baloğlu (2002), Onwuegbuzie (2004) and Teman (2013); in the UK by Walsh and Ugumba-Agwunobi (2002) and Hanna *et al.* (2008); in Italy by Chiesi *et al.* (2010); in Taiwan by Hsiao (2010); in China by Liu *et al.* (2011); in Austria by Papousek *et al.* (2012); in Russia by Khavenson *et al.* (2012); in Malaysia by Hamid *et al*, (2014); in Greece by Frangos *et al.* (2013)). Even though these research studies have employed different sample sizes and methods and the participants were from various academic levels and degree programmes, STARS is demonstrated as a suitable instrument (based on its satisfactory reliability and validity evidence) for measuring statistics anxiety.

Empirical findings show that a large proportion of students experienced high levels of anxiety about their statistics course at some point (e.g. Perney and Ravid, 1990; Zeidner,1991; Schau *et al*, 1993,1995; Zanakis and Vanezi, 1997; Baloğlu, 2003; McGrath, 2014; Onwuegbuzie *et al*, 2000,2003; Perepiczka *et al*., 2011; Lalayants, 2012; Hamid and Sulaima, 2014). Statistics courses and especially examinations in these courses are seemed to evoke a high degree of anxiety in students (Macher *et al*., 2013). In her phenomenological study, Malik (2005) elicits undergraduate students' perceptions of statistics anxiety in an introductory statistics course, examines the situations and underlying factors that trigger anxiety and cause negative experiences in statistics (including the inability to decode terminology and symbols, feelings of inadequacy, physiological symptoms and giving up) and proposes factors and strategies that can reduce anxiety.

Several studies have also examined the relationship between statistics anxiety and a number of personality characteristics such as perfectionism, procrastination and trait anxiety (Baloglu, 2002; Walsh and Ugumba-Agwunobi, 2002; Rodarte-Luna *et al*., 2008). Onwuegbuzie and his colleagues have carried out a series of investigations and have found relations between statistics anxiety and a number of factors such as level of perfectionism, level of academic locus of control, and study habits and learning strategies (Onwuegbuzie and Daley, 1999; Onwuegbuzie, 1999; Onwuegbuzie and Wilson, 2003; Onwuegbuzie, 2004).

A growing body of research has perused the potential role of anxiety towards statistics in performance and specifically the relation between statistics anxiety and performance in statistics. Empirical studies, which have focused on this investigation, mostly resulted in negative relationships between statistics anxiety and students' performance in statistics courses (see for example Elmore *et al*, 1993; Zanakis and Valenzi, 1997; Onwuegbuzie, 2003, 2004; Tremblay *et al.*, 2000; Zare *et al.*, 2011; Ali and Iqbal (2012), Macher *et al.*, 2013; Griffith *et al.*, 2014; Malik, 2015). A negative relationship means that lower levels of anxiety towards statistics might result in achieving better grades in the course. This association is also noted in a review of the statistics anxiety literature reported by Chew and Dillon (2004). Previous research studies do not only indicate statistics anxiety as a significant predictor of students' performance in a statistics course (Lalonde and Gardner, 1993; Owneugbuzie and Seaman, 1995; Chiesi and Primi, 2010) but also demonstrate a reciprocal association (bi-directional relationship) between statistics anxiety and course performance (Owneugbuzie, 2000). On the other hand, there are studies which have failed to find a relationship between statistics anxiety and performance. For example, Birenbaum, and Eylath (1994), in a sample of first- and second-year female students in the Department of Educational Sciences attended statistics-related courses, explains the lack of the relationship between grades in statistics and statistics anxiety on the basis of Eysenck's (1982) proposition that anxiety might not affect the product (e.g. course outcome) as much as it affects the efficiency and effectiveness of the learning process.

Many researchers (e.g. Zeidner, 1991; Griffith *et al.*, 2012) advocate that statistics anxiety can hinder the learning process and course performance. Some other researchers (e.g. Owwuegbuzie and Wilson,2003; Macher *et al.*,2013; Slootmakers, 2012) contest the claim and argue that a certain amount of anxiety regarding statistics can have a facilitative effect, meaning that it may motivate learners to work harder, exert more effort, persist longer and eventually perform better in exams. Keeley *et al.* (2008) proposes that curvilinear models are better predictors of test performance in a statistics course than linear models. More specifically, academic performance is found to be poorer when students experienced high or low levels of statistics anxiety, whereas medium levels of anxiety towards statistics result to higher performance. These authors claim that “some anxiety is acceptable” (p.13).

Regarding changes in students’ anxiety, Keeley *et al*. (2008) and Davis (2004) find that statistics anxiety decreased throughout the course. Many researchers have investigated and applied instructional methods and interventions that they presumed that might reduce statistics anxiety. By utilising a pre-test and post-test design, a significant decrease in statistics anxiety levels is reported by many researchers (e.g. D’Andrea and Waters, 2002; Pan and Tang, 2004).

In the current study, anxiety towards statistics as a construct is defined as an affective response (trait or state) of students within the context of statistics education learning experience and especially when students’ undertake a statistics course and dealing with statistics-related situations and tasks.

2.7 Self-efficacy regarding statistics

The psychologist Albert Bandura is a pioneer in research and investigation of the concept of ‘self-efficacy’, which is grounded in self-efficacy theory (Bandura, 1997). He defined perceived self-efficacy as “people's beliefs in their capabilities to produce given attainments" (2006, p. 307). Bandura (1977, 1997) claims that self-efficacy beliefs are manifested from four primary sources, namely: (a) mastery experiences (personal accomplishments); (b) vicarious (observational) learning experiences; (c) social (verbal) persuasions; and (d) emotional arousal.

Self-efficacy is considered to be a multidimensional construct rather than a single, general construct which is domain-, context- and task-specific (Pajares and Miller, 1994; Finney and Schraw, 2003; Larwin, 2014). It is often claimed that self-efficacy is distinct from other self-perception constructs (e.g. self-concept, self-confidence, self-esteem) and compared to them, self-efficacy is the most context-specific evaluation, varies across different dimensions (such as generality, level, strength) and diversifies across individuals, social environment and times (Lent *et al*., 1997; Zimmerman, 2000; Pintrich and Schunk, 2002; Linnenbrink and Pintrich, 2002; Bong and Skaalvik, 2003); Bjiker *et al*., 2006; Zimmerman and Cleary, 2008; Kung, 2009).

The construct of self-efficacy has been investigated in a broad range of contexts, location settings and populations. In educational research, as reported by Pampaka and Williams, (2010), perceived self-efficacy beliefs have been examined in relation to university major and career choices, with respect to affective and motivational constructs and regarding their effect on academic performance and success.

Within the context of mathematics education, self-efficacy regarding mathematics is described as the personal judgements of competence to successfully perform particular mathematical problems or tasks and succeed in courses related to mathematics (Hackett and

Benz, 1989; Pajares and Miller, 1994). Self-efficacy beliefs might transfer to some extent from one domain to another. This is more likely to happen when students believe that the two domains share basic knowledge and skills, as in the case of mathematics and statistics (Bandura 1997, Schneider, 2011). However, in a similar argument with the distinction between mathematics anxiety and statistics anxiety, statistics self-efficacy is related to, yet distinct from, mathematics self-efficacy and it is more prudent to regard and evaluate them as two separate constructs (Finney and Schraw, 2003; Larwin, 2014).

According to Bandura's (1977) social cognitive theoretical framework, where self-efficacy keeps a prominent position, individuals' self-efficacy beliefs may to some extent determine how they behave. Self-efficacy has emerged as an efficient predictor of students' motivation and learning process (Zimmerman, 2000). Especially, self-efficacy can influence students' motivations, learning cognitive engagement and future enrolment in domain-related courses (Pajares, 2006; Schunk, 2003; Choi, 2005; Lou and Choy, 2013). Students who possess higher levels of self-efficacy are more likely to set higher achievement goals, put more effort and persist longer at difficult or challenging tasks compared to students with lower levels of self-efficacy (Pajares and Miller, 1994; Bandura, 1997; Wolters and Rosenthal, 2000; Awang-Hashim *et al.*, 2002; Lent *et al.*, 2002; Usher and Pajares, 2009; Valle *et al*., 2009). In particular, students who have a stronger sense of self-efficacy are motivated to continue in the face of challenge or adverse situation and in turn they become academically resilient (Martin and Marsh, 2002, 2006; Borman and Overman, 2004). From the opposite standpoint, there are researchers (e.g. Schunk, 1991, 1994) arguing that students who had low academic self-efficacy might put more effort and adopt effective learning strategies to compensate for their perceived lack of competence.

In accordance with Bandura's social cognitive theory and Eccles' (1983) Expectancy-Value theory, self-efficacy is assumed to be one of the most important factors that influence academic performance and achievement**.** Findings from empirical studies in the research literature regarding statistics education (see, for example, Mousoulides and Philippou, 2005; Abd-El-Fattah, 2005; Mwamwenda, 2009; Arumugam, 2014) have also demonstrated the relationship between statistics self-efficacy and academic performance. The reciprocal relationship between statistics self-efficacy and performance of sport sciences students undertaking a statistics course is demonstrated by Lane *et al*. (2004).

Pajares (1996) and Gore (2006) posit that academic self-efficacy can be a strong predictor of academic performance, but academic self-efficacy measures should be specifically related to the particular course or subject course content. Several empirical findings support this argument. For instance, some studies, which have employed general self-efficacy measures or even mathematics self-efficacy measures to gauge students' self-efficacy regarding statistics, fail to find an association between their self-efficacy regarding statistics and their performance in statistics (Benson, 1989; Bandalos *et al.*, 1995; Award-Hashim *et al.*, 2002). This evidence, and their main assertion that statistics self-efficacy is task-specific, have prompted Finney and Schraw (2003) to develop two self-report instruments; the Current Statistics Self-efficacy scale (CSSE) and the Self-Efficacy to Learn Statistics scale (SELS). CSSE measures students' self-efficacy in their current abilities to complete statistics-related tasks, whereas SELS measures students' self-efficacy beliefs about their capabilities to execute statistics tasks in the future (Finney and Schraw, 2003).

Questionnaires were administered to undergraduate students majoring in educational psychology. The researchers report evidence that supports the validity and internal consistency of the two statistics self-efficacy scales. A positive correlation between CSSE and SLES scores, a positive relationship between statistics self-efficacy and performance in statistics as well as a rise in students' level of self-efficacy to learn statistics over the duration of an introductory statistics class, are confirmed in this research investigation.

Recently, researches (e.g. Abd-El-Fattah, 2005; Schneider, 2011; Zare *et al.*, 2011; Chiesi *et al.*, 2012; Hii *et al*., 2013; Larwin, 2014; Lindsey, 2017) have employed the CSSE or/and the SELS measure to examine students' current and future self-efficacy to learn statistics respectively. For example, Perepiczka *et al.* (2011), by distributing the SELS scale in a sample of 250 graduate education majors, finds a positive correlation between positive attitudes towards statistics and higher levels of self-efficacy to learn statistics. A negative correlation between students' self-efficacy and their anxiety towards statistics is also demonstrated which means that students with the lowest levels of perceived abilities in statistics had the highest levels of anxiety towards statistics. The latter finding is in line with the findings reported by Perney and Ravid (1991) and Onwuegbuzie (2000).

In the current study, following other researchers' conceptualisation about academic self-efficacy (see for example Bandura, 1997; Eccles and Wigfield, 2002; Schunk and Pajares, 2002), self-efficacy towards statistics as a construct is further defined as individual's confidence and affective and cognitive evaluations of themselves that can successfully perform statistical-related tasks, master statistical-related topics or attain specific goals within the context of a university statistics course.

2.8 Resilience

According to Masten *et al.* (1990, p.426), "resilience is the process of, or a capacity for, or the outcome of successful adaptation despite challenging or difficult situations". Luthar (2006) has traced the development of resilience across five decades and has pointed out that resilience is a construct, which comprises two separate dimensions – the experience of a setback and the positive adaptation following this adversity. In addition, Luthar *et al.* (2000) describes resilience as a dynamic, developmental and malleable process, which involves the complex interaction between personal, environmental and educational-related factors. In the same vein, Goodall and Johnston-Wilder (2015) proposes that resilience is not, or need not be, an inherent aspect of personality instead it can be learned, enhanced and supported so that students become more able to cope with and overcome difficult situations and obstacles.

As is common with many psychological-related constructs - for example, the self-efficacy construct - it has been widely suggested in the literature to consider and measure resilience as context-specific (Chow *et al*., 2018). Resilient behaviours may be context- and time-dependent and change from individual to individual (Santos, 2002). Meichenbaum (2006) also lend support to the claim that resilience is domain-specific and context-specific (e.g. academic, social) explaining that people might show resilient characteristics in one domain in their lives and not in other domains.

Over the past few decades, the resilience construct has raised the interest of researchers from various fields, including among others psychiatry, psychology, sociology and education. In educational and learning context, the term ‘academic resilience’ can be considered as the ability, the strength or the determination of students to cope with difficulties and stressful situations they might encounter in their studies and remain educationally engaged and effective (Borman and Overman, 2004; Sosa and Gomez, 2012). This can take many forms, including avoidance of drop out of courses or university completion; educational success; and achievement of academic goals. Resilience is found to have a marked effect on learning experience, academic competence, academic performance, course completion and, in future, professional practice (Chow *et al.*, 2018).

The phenomenon of academic resilience concerns all the students because at some time throughout their studies, they might experience poor performance (e.g. failure), under-expectation achievement, difficulties, study pressures and stressful situations (Martin and March 2003; Zonnefeld, 2015). Although these unpleasant experiences or times of difficulty might be an inevitable and irreversible part in the mastery learning process, their negative effects can be tackled, lessened or even eliminated by developing resilient learning abilities and behaviours (Hutauruk and Priatna, 2017). More specifically, Hutauruk and Priatna (2017) describes resilience with relation to students’ affective ability to deal with and be able to adapt and overcome challenges, obstacles and stressful, negative or unpleasant situations, turning those into situations that might help and support them towards the acquirement of the desired learning outcomes. Many research articles have also reported a significant relationship between self-efficacy and academic resilience (Borman and Overman, 2004; Martin and Marsh, 2006; Hudson, 2007; Keye and Pidgeon, 2013; Sagone and De Caroli, 2013; He, 2014). It is found that students with higher levels of resilience were more likely to possess higher levels of self-efficacy than students with low levels of self-efficacy. Moreover, Zonnefeld (2015) argues that resilience allows students to put effort to achieve mastery.

A considerable, but not extensive, body of literature has investigated resilience in the context of education (e.g. Wayman, 2002; Waxman *et al.*, 2003; Morales, 2008; Perez *et al.*, 2009; Fong, 2011; Sandoval-Hernandez and Cortes, 2012; Hartley, 2013; Khalaf, 2014). An in-depth investigation of the construct of educational or academic resilience is provided in many research papers (e.g. Waxman *et al*., 2003; Morisson and Allen, 2007). In the field of mathematics, the notion of resilience is an emergent area of research (see, for example, Johnston-Wilder and Lee, 2008, 2010, 2013, 2015; Thornton *et al.*, 2012; Yeager and Dweck, 2012; Kooken *et al.*, 2013; Goodall and Johnston-Wilder, 2015; Peatfield, *et al*. 2015; Hutauruk and Priatna, 2017).

Johnston-Wilder and Lee (2008, 2013) propose and explain the concept of ‘mathematical resilience’ as a positive adaptive approach to mathematics such that allows individuals to continue learning despite barriers and difficulties presented when engaging in mathematics. Johnston-Wilder and Lee (2011) argues that all types of learning and engagement in any educational area require resilience. However, the resilience that is needed for learning and embracing mathematics can be considered as a particular type of resilience and thus it should be viewed as a special concept. The authors (Johnston-Wilder and Lee, 2010, 2011) base their assertion on various factors, including: the teaching methods employed (Nardi and Steward, 2003); the nature of mathematics as a discipline (Jaworski, 2010); and the prevalent beliefs that the mathematical capability is ‘fixed’ and in some way inherent (Dweck, 2000).

In an attempt to assess mathematical resilience, Kooken *et al.* (2013) have created the Mathematical Resilience Scale (MRS), that consists of four mathematical resilience related factors, namely: (a) value, which refers to the students’ belief that studying mathematics is valuable for their current educational goals and future aspirations; (b) struggle, which refers to the students’ perceptions that the challenges and difficulties encountered is an inevitable part of learning mathematics even for people who have high levels of mathematical abilities or skills; (c) growth, which refers to the conviction that the level of mathematical knowledge and ability is not fixed but is malleable and can grow; and (d) resilience, which refers to the orientation to show a positive response when learning mathematics despite difficulties or negative situations (Johnston-Wilder and Lee, 2008, 2010).

In summary, drawing on the literature associated with the concept of resilience, it has emerged that research on resilience, especially in the domain of education, is limited and quite inconsistent (Santos, 2012; He, 2014). There is a degree of diversity in the definitional and background issues of the proposed terminology and in the measures that have been proposed to capture and measure resilient behaviours. Since the attempt to predict and control for resilient responses and behaviours is complex, more precise definitions and stronger theoretical and conceptual frameworks underpinning resilience, as well as appropriate measures and various approaches, are needed to bolster the knowledge and understanding of this phenomenon.

Following Kooken *et al*. (2013), in order to talk about resilience, the students have to face some (type of) adversity, difficulty or challenge which can take various forms such as poor or under expectation performance, failure, stressful situations, struggle or boredom. Negative or unpleasant prior learning experiences with statistics or/and mathematics are also considered as setbacks in the current study. What follows is an effort for a positive outcome or a positive adaptation despite the setbacks. In a step further, resilience can be regarded as, not only the ability or the behaviour to adapt and overcome these unpleasant and challenging experiences, but also to progress and succeed.

In the present study, resilience is initially considered as a broad concept within the educational and learning context (including mathematics). The focus was then to refine this notion to be investigated explicitly to statistics by proposing the term ‘statistical resilience’. For the purposes of this study, statistical resilience is conceptualised as attributes, skills and strategies that allow students to continue learning and engaging with statistics (and the statistics course) despite a set of adverse situations (e.g. failures, difficulties) that may encounter in the statistics learning and mastering process. To this end, this study seeks to explore examples of subject-, course- and/or content-specific resilient (i.e. affective, cognitive and behavioural) responses to any type of academic adversity.

2.9 Motivational and cognitive engagement-related constructs

In the subsections that follow, various constructs related to students' motivational orientations and cognitive engagement including intrinsic and extrinsic motivations; achievement goal orientations (mastery and performance goals); outcome expectations; control beliefs; effort (expenditure); learning strategies and approaches to learning are presented.

Many of these constructs described in this section are considered to be inter-connected and thus often employed and discussed together in the pertinent literature. Nevertheless, Attard (2012) provides differences between the concepts of motivation and engagement especially in the context of mathematics education, and he proposes that when an individual is engaged with mathematics, he or she may have been influenced by motivation; however, on its own, motivation is not enough to preserve high levels of student engagement. Moreover, cognitive engagement might be an indicator of the levels and/or kinds of students' motivations and amount and quality of the effort they exert (Corno and Mandinach, 1983; Joo *et al.*, 2014). In the current study, they are regarded as quite distinct concepts since engagement is more related to students' behaviours, actions and approaches to learning whereas motivations are more associated with beliefs and orientations towards learning (Attard, 2012).

2.9.1 Motivations

Within the motivation-related literature, motivation is a widely used concept and multi-faceted structure, which has been defined from many angles and measured in various ways incorporating several components and constructs, such as self-efficacy, goal orientations, strategies use, control beliefs and so forth (Pintrich *et al*., 1991, 1993). As many authors argue, these studies do not often explicitly explain whether these constructs are part of motivation or are solely associated with motivation (Murphy and Alexander, 2000; Bude *et al.*, 2007).

Nevertheless, motivation can be regarded as an inner driving force that stimulates, directs and sustains students' behaviours and actions towards the accomplishment of certain goals (Glynn *et al.*, 2007; Chowdhury and Shahabuddin, 2007). Bijker *et al.* (2006) states that motivational orientations are multi-dimensional dynamic processes, which encompass an interplay between individuals and context (environment). In addition, drawing from the literature on the motivational domain, the authors endorse that motivations and attitudes are different psychological concepts, where motivations are more cognitively or consciously controlled and regulated by individuals compared to attitudes.

The research on motivation in educational settings usually reports at least two dimensions of academic motivation, namely intrinsic motivation and extrinsic motivation (e.g. Vallerand *et al.*, 1992). According to Pintrich *et al*. (1991), intrinsic motivation concerns the degree to which the students participate in an academic task for reasons such as mastery, challenge, curiosity and personal satisfaction. Regarding extrinsic motivation, conforming to Pintrich *et al.* (1991), it concerns the degree to which the students engage in a task for external reasons such as high grades, rewards, performance, appraisal by others, and competition. Pintrich and Schunk (2002) also support the view that intrinsic and extrinsic motivations are context- and time-dependent.

In the context of education, Pintrich and Schunk (2002) argues that motivation and motivational-related constructs influence the learning process as well as the academic performance of students. In a recent meta-analysis conducted by Özen (2017), 205 research studies are compiled and the results show that motivation had a low-level positive effect on students' achievement.

2.9.2 Achievement goal orientations

Achievement goal orientation refers to the reasons behind students' involvement in learning or participating in specific academic tasks (Dweck and Leggett, 1988; Ames and Archer, 1988; Braten and Stramso, 2004; Zare *et al.*, 2011). At least two types of achievement goals have been often reported and investigated in the literature, namely mastery-development goals and performance (performance-approach and performance-avoidance) goals (e.g. Midgley *et al.*, 2001; Harackiewicz *et al.*, 2002; Shim and Ryan, 2005; Chouinard *et al.*, 2007; Zare *et al*., 2011; Ng, 2012). According to many researchers (e.g. Pintrich, 2000; Eccles and Wigfield, 2002), the adoption of various achievement goals have an impact and is related to affective, motivational, cognitive, behaviour and achievement outcomes.

Achievement goal orientations are supposed to be crucial cognitive processes that have an impact on motivational patterns (Schunk, 1991). According to Linnenbrink and Pintrich (2002) and Glynn *et al.* (2007), students who have mastery (learning) goals tend to be intrinsically motivated, want to attain a broad knowledge and an in-depth understanding of the subject material and focus on acquiring capabilities. Their goal is the self-improvement, development of their personal competence and they tend to compare their current performance with their prior performance (Kaplan and Maehr, 2007; Yough, 2009). On the other hand, students with performance-approach goals tend to be extrinsically motivated, and they endeavour to earn high grades without giving much emphasis on learning for understanding and to demonstrate competence (Kaplan and Maehr, 2007; Yough, 2009).

Two dominant and influential theories in the literature concerning achievement goal and motivation in academic settings are Achievement Goal Theory (Dweck and Legget, 1988; Nicholls, 1989) and Expectancy-Value theory (Eccles *et al.*, 1983; Wigfield and Eccles, 2000). Both theories are based on the social cognitive approaches to motivation.

Many empirical studies have highlighted the relationship between achievement goal settings and academic motivation. For example, Lavasani *et al.* (2014) employs a census sampling technique to recruit undergraduate students majoring in education and psychology sciences in Tehran. By means of path analysis techniques, mastery goals and performance-approach goals are found to have direct positive effects on intrinsic motivation and extrinsic motivation respectively. The findings also indicate that students' goal orientations and academic motivations have a significant effect on the anxiety levels towards statistics.

A number of research studies explore the role of achievement goals in many different academic content fields and stress the close link between them and achievement-related behaviours such as performance. However, results from empirical studies, which have been conducted regarding this link, are often mixed or inconclusive.

In the current doctoral study, students' motivations and achievement goals are combined and investigated together. Aligned with many authors (e.g. Glynn *et al.*, 2007 and Hannula, 2006), motivation to learn statistics is conceptualised as having both cognitive and affective aspects and influences. In addition, the focus is placed on two categories of motivational orientation and achievement goals, namely intrinsic motivation or mastery-development and extrinsic motivation or performance-approach goals. The motivational and achievement goal orientations are then confined to orientations within the specific statistics course.

2.9.3 Outcome expectations

Outcome expectations can be regarded as peoples' expectations of obtaining a particular outcome as a result of performing certain behaviours or engaging with specific tasks (Schunk, 1991). Expectations of success represent the individuals' belief that they will succeed in a task (Pintrich and Schunk 2002). According to Pintrich and De Groot (1990), in academic settings, students' expectations often refer to their performance expectations. Ownuegbuzie (2003) states that outcome expectations are manifestations of self-efficacy beliefs; thus they can be deemed as important indicators of students' perceived levels of self-efficacy. Expectations of success are found to be associated with students' motivation to do well in the statistics course that they are enrolled in (Galagadera *et al.*, 2000). Expectations have also demonstrated to predict achievement in statistics (Ownuegbuzie, 2003; Bandalos *et al.*, 2003). For example, Ownuegbuzie *et al.* (2000) reports evidence that students' outcome expectations along with their anxiety towards statistics are the best predictors of their achievement in a research methodology course. However, as argued by Schunk (1991, p.3), "outcome expectations influence, but do not guarantee, motivation and success".

In the current study, outcome expectations are conceptualised as students' expectations of their performance in the specific statistics course. Unlike the concept of self-efficacy which is considered to be related to the students' perceived abilities and confidence (current or future), expectations concept is oriented to outcomes (e.g. performance) in future within the statistics education context.

2.9.4 Control (over outcomes) beliefs

Control beliefs can be viewed as the individuals' anticipations that they can attain desired outcomes (Eccles and Wigfield, 2002). Schunk *et al*. (1991, 2008, 2012) also define perceived control as a motivational concept which refers to individuals' beliefs that outcomes may occur independently and not being entirely contingent on their own actions or behaviours (external control), or are highly contingent on their behaviours or personal attributes and characteristics (internal control). Rotter (1966) argues that perceived control over outcomes is of crucial significance in understanding the learning process (such as acquisition and performance of skills and knowledge) in various learning situations.

Students' perceived locus of control is assumed to be related with the amount of effort and time that they are willing to invest and the types of learning approaches they use (Pintrich *et al*., 1991; Shah and Gardner, 2008). That is, if students believe that they have control over the results of their learning, for example the grades that they will earn, they are more likely to be mastery motivated, exert more effort, persist longer and use more effective strategies to achieve their goals (Pintrich *et al*., 1991; Martin, 2002). On the other hand, if they feel that their performance is chiefly determined by their instructors, the teaching styles and methods and the easiness or difficulty of the exams tasks, they will minimise their effort because they believe that they will waste their time. Lee and Johnston-Wilder (2008) argues that students' perceived control over learning contributes to the development of academic resilient behaviours.

The body of literature on control beliefs has also documented empirical links between perceived control and many other constructs. Bandura (1986) claims that when people do not perceive that they have control over situations and outcomes, they feel anxious and are not confident with them. Ng (2012) argues that, based on the empirical findings of his study, control beliefs are critical in learning since a strong sense of control beliefs can foster the positive effect of master-development goals and performance-approach goals. Related to this, an argument put forward by Hattie (2011) is that the impact of control beliefs is somewhat greater on motivation outcomes than on subsequent students learning and performance.

In this study, perceived control over learning and performance refers to the students' beliefs about whether statistics-course related outcomes (e.g. performance) are determined by their endeavours (internal control) and are minimally related to external factors (such as instructors and instructional methods).

2.9.5 Cognitive engagement

Following Miller (1996), students' cognitive engagement in activities can be captured and measured by investigating three main components, namely: learning strategies and approaches; effort; and persistence in learning. In the section that follows, each of these statistics course engagement-related constructs are presented in turn.

2.9.5.1 Learning strategies and approaches

Cognitive engagement with academic tasks is often related to learning strategies, approaches, preferences and study strategies used. Biggs (1987) develops a theoretical model of student learning and categorises at least three types of learning strategies, namely deep, surface (shallow) and achieving learning approaches. Students who apply deep approaches focus on strategies geared to master and understand in-depth the subject material. Students who adopt surface approaches rely on rote memorisation of rules and methods and tend to reproduce knowledge mainly for assessment purposes. Lastly, students who use achieving learning approaches aim to succeed through the effective time management and careful study plan.

Different researchers indicate that specific learning strategies or the way students make use of them is related to their academic achievements and can enhance their success (e.g. Schutz *et al*., 1998; Hwang and Vrongistinos, 2002; Gow *et a*l., 2004). Biggs (1987) and Liem *et al.* (2007) argue that deep learning approaches are more desirable strategies in learning and result in higher academic performance, whereas surface learning approaches are regarded to be less desirable cognitive engagements in tasks that lead to lower academic achievement. Onwuegbuzie *et al.* (2000, 2003), also, reports that study skills habits have been consistently found by many researchers to be related to academic performance. For example, Lopez *et al*. (2013), by employing the Approaches and Study Skills Inventory for Students (ASSIST) questionnaire developed by Tait *et al.* (1998), finds evidence that statistics performance was directly positively related to students' adopted strategic (such as organised studying and time management) and deep learning approaches (such as seeking meaning, relating ideas and using of evidence) and negatively related to surface learning approaches (such as lack of purpose, unrelated memorising, syllabus-boundness).

Several researchers (e.g. Dweck and Legget, 1988; Ames, 1992; Elliot *et al.*, 1999; Bessant, 2010; Liem *et al.*, 2008; Coutinho and Neuman, 2008; Verhoeven, 2010) report empirical evidence supporting the association between mastery and performance goals, and learning strategies adopted by students in educational settings. For example, Elliot *et al.* (1999) finds evidence that mastery goals are positive predictors of deep learning approaches, persistence and effort; and performance-approach goals are positive predictors of surface approaches, persistence, effort and performance in examinations. In addition, Liem *et al.* (2008) detects positive relationships between mastery- and performance-approach goals, and deep learning strategies. Furthermore, some researchers (e.g. Bessant, 2000; Biggs, 2003; Verhoeven, 2010) argue that deep-oriented approaches are closely linked with intrinsic interest and motivation, whereas surface-oriented approaches are more associated with extrinsic motivation and minimal effort applied to academic tasks. In a sample that is composed of students confronted with an introductory statistics course, Bandalos *et al.* (2003) reports evidence that students' academic or learning goals are positively correlated with deep-oriented learning strategies and self-efficacy beliefs, and negatively correlated with test anxiety. Pimenta (2010) also demonstrates that deep-processing strategies diminish the level of health science students' anxiety towards the statistics subject and enhance the degree of interest and value placed on it.

In a recent study, Ng (2012), using hierarchically ordered regression techniques in a sample of distance learners, finds that mastery-oriented goals predict in a negative way the adoption of surface strategies and this association is more evident when students' control beliefs are strong. He also reports that self-efficacy and control beliefs are significant predictors of learning strategies applied by students.

Following Hattie (2009), which proposes that it is necessary to combine the learning strategies with the content, learning and study strategies and approaches to learning statistics in the statistics course were investigated.

2.9.5.2 Effort

Effort can be regarded as the "energy students expended on a task (whether that effort is general and typical, or specific to the task)" (McInerney, 2013, p.222). The effort construct in educational-related contexts was mainly explored in relation to students' motivational orientations and cognitive engagement. For example, Valle *et al*. (2009) explores the relationship between students' self-efficacy for their performance and learning and their effort regulation in a sample of university level students and finds evidence that students who hold stronger self-efficacy beliefs were more likely to expend more effort to their academic studies. In the context of statistics, Ashaari (2011), by administering the Statistics Attitude towards statistics (SATS) instrument in first-year university students, provides quantifiable evidence that although students perceive statistics as difficult, they have applied great effort to learn the subject material. Also, in a sample of French-speaking high school students, Chuinard et *al.* (2007) remarks on the significant effect of mastery goal orientations on students' effort expenditure in learning mathematics.

After reviewing the existing literature, Li (2012) contends that there is no general agreement concerning the relationship between effort and academic success. In her study, by employing a sample of Applied Social Sciences students, finds a positive correlation between effort and statistics achievement. The positive relationship between effort and statistics outcomes is also confirmed by Arumugam (2014). In addition, he argues that when students are interested in and enjoyed the statistics course, they valued statistics more and they expend more effort in learning the subject.

According to many researchers (see for example, Dweck, 2000; Tempelaar *et al*., 2011; Yeager and Dweck 2012), some students view effort as a way to develop their competencies and as an essential component of success, whereas some other students hold the belief that effort is an indicator of low capability, incompetence and lack of natural talent. The latter perception influences in a negative way students' appraisal of effort, study habits, and eventually their achievement (Zonnefeld, 2015).

In this doctoral research investigation, effort construct mainly refers to the amount of effort and time that students expend in the specific statistics course.

2.9.5.3 Persistence

Students who persist during studying statistics are students, for example, who continuously invest in learning, do not quit their endeavours easily for mastering the material when they face difficult or dull tasks, and consult their instructor or their classmates when they encounter difficulties (Bude *et al.*, 2007; Liem *et al*. 2008). As claimed by Syed (2013), students who show persistence when faced with failure regard failure as progress towards mastering the subject matter.

Persistence can be considered as an essential ability for students to hold and a contributing factor to academic performance. For example, Pintrich and DeGroot (1990) indicates that cognitive and metacognitive learning strategies along with persistence have a strong impact on mathematics achievement. In addition, Mohsenpour (2008) reports findings showing a significant direct effect of persistence and learning strategies (which were regarded as cognitive variables) on mathematics performance of high school students.

Martin and Marsh (2003; 2006) have developed an academic resilience scale and report that persistence (commitment) is among the five factors (along with self-efficacy, control, planning and low anxiety) which determines and predicts resilience. Johnston-Wilder and Lee (2000) and Kooken *et al.* (2013, p.28) claim that students who have a positive responsive stance towards mathematics and they are resilient learners, "they are not just persisting; they are persisting while experiencing substantial challenges". Guided by these propositions that resilience is something more than just persistence, in the current study, persistence is regarded as a part of being resilient in the statistics course. Thus, this concept is not measured and investigated in isolation.

Several survey instruments have been developed intending to assess students' motivational orientations in academic settings. The Motivated Strategies for Learning Questionnaire (MSLQ) is a self-reported inventory, which has been set up by Pintrich *et al.* (1991) to evaluate students' motivational orientations, test anxiety, learning strategies and study habits. This version of MSLQ was administered by the pioneers to a sample of 380 university students majoring in fourteen different subject areas and five disciplines (natural sciences, computer science, social sciences, humanities and foreign languages). In a subsequent study, Pintrich *et al.* (1993), by administering the MSLQ instrument, find that mastery achievement goals are positive predictors of students' effort and persistence. In turn, effort and persistence have a positive impact on achievement-related outcomes. Later, Bude *et al.* (2007) have constructed the Motivation toward Statistics Questionnaire, which comprises six subscales (namely, affect, stable explanation, outcome expectation, control, effort, and persistence) all related to statistics. The researchers argue that health sciences students' perceived lack of control over performance outcomes might lead to a decline of expectations for success in the statistics course. Limited self-reported engagement with the subject (specifically effort and persistence) is found to be correlated with negative attitudes, which results in poor performance.

2.10 Demographic and educational-related characteristics

Many empirical studies have investigated the effect of several demographic and educational characteristics of students in their affective responses, motivational and cognitive orientations and ultimately in their academic performance within the statistics education context. These investigations have yielded mixed results.

The existing literature is quite inconsistent regarding gender differences in students' attitudes and levels of anxiety towards statistics. Several published studies find that female students display more negative attitudes towards statistics and exhibit slightly higher levels of statistics anxiety than male students (e.g. Benson, 1989; Onwuegbuzie, 2003; Mills, 2004; Tempelaar *et al.*, 2007; DeCesare, 2007; Rodarte-Luna and Sherry, 2008; Mahmud and Zainol, 2008; Perepiczka *et al.*, 2011; Vahedi, 2011; Bechrakis *et al.*, 2011; Paul and Cunnington, 2017; van Es and Weaver, 2018). Nevertheless, the reported gender differences were usually small with effect sizes ranging from mostly small to moderate. Koh and Zawi (2014), employing a sample of 141 postgraduate students registered for a Research

Statistics course at the Faculty of Education at a University in Malaysia, detects the opposite phenomenon; males are found to harbour higher levels of statistics anxiety in comparison with their female counterparts. Zeidner (1991) and Onwuegbuzie (2003) argue that these gender differences might be attributed to different levels of perceived cognitive competence and confidence regarding statistics. Many empirical studies (e.g. Pintrich and De Groot, 1990; Mills, 2004; Mahmud, 2009) also demonstrate that female students report lower levels of self-efficacy compared to males. Chiesi and Primi (2015), by exploring gender differences in attitudes towards statistics, provides evidence that females do not differ in their abilities in statistics, but they exhibited less confidence and more negative attitudes compared to male students. Other research studies demonstrate that gender does not significantly influence attitudes towards statistics (e.g. Waters, 1988; Sutarso, 1992; Dauphinee *et al.*, 1997; Aksu and Bikos, 2002; Davis, 2004; Cashin and Elmore, 2005; Carnell, 2008; Mohanty *et al.*, 2011; Judi *et al*., 2011; Lalayants, 2012). In accord with the above findings, several research papers report no gender differences in anxiety levels experienced by male and female participants (e.g. Baloğlu, 2003; Onwuegbuzie, 2004; Hsiao and Chiang, 2011; Zhang *et al.*, 2012). Regarding effort regulations, many research studies (e.g. Awang-Hashim, 2002; Tempelaar *et al*., 2007, 2011; Hommik and Luik, 2017) show that female students were more willing to apply effort and invest time in learning and studying statistics than male students. Furthermore, Lopez *et al.* (2013), investigating university students' learning approaches in Argentina, finds that females employed a more strategic approach in statistics than males. In a recent study conducted by van Es and Weaver (2018), female students who enrolled in an introductory statistics course in the School of Applied Economics and Management reported expecting lower average final course grades than males. Nevertheless, when investigating gender differences in introductory business statistics performance, Johnson *et al.* (2006) evidences that females were more likely to earn higher grades than males. Many other researchers (e.g. Rhoads and Hubele, 2000; Davis, 2004; Cashin and Elmore, 2005; Bechrakis *et al.*, 2011) find no statistically significant differences in statistics course outcomes between the two sexes.

With respect to the age (or age group) factor, Baloğlu (2003) indicates that older students are more anxious than younger students when they engage in statistics. However, older students seem to appraise more the value and usefulness of statistics compared to their younger counterparts. In a similar manner, Zhang *et al.* (2012) demonstrates that older postgraduate students held more negative attitudes, exhibited higher levels of anxiety and had more difficulties in mastering the material presented in statistics courses than younger students. In addition, Hannigan (2014) finds evidence that older students scored lower than younger ones on all the attitudes components (affect, value, difficulty, cognitive competence, effort) of the SATS questionnaire except the interest component. In contrast, Mahmud and Zainol (2008), in a sample of 43 postgraduate research students, finds no relationships between students' overall attitudes towards statistics and students' profile (such as age and mode of study being full-time or part-time).

With regard to educational-related factors, Aksu and Bikos (2002), in a sample of graduate students at a University in Turkey, demonstrates that academic Department (in their case Languages, Applied Sciences, Physical Sciences and Educational Sciences Department) is the only significant predictor of students' attitudes towards statistics. In the same line, Larwin (2014) finds that students' academic Department (in their case Education, Psychology, Geography, Business, Biological Science and Communication Department) and expected course grade have a significant impact on students' perceived capability to do statistics-related tasks. Conversely, Mohanty *et al.* (2011) reports no statistically significant associations between students' attitudes towards statistics and their demographic and academic characteristics (namely age group, gender, specialisation and type of the course).

The effect of gender and age variables on academic resilience is not agreed upon in the literature. Martin and Marsh (2006) and Kapikiran (2012) report no correlation between gender and academic resilience. On the contrary, Khalaf (2004) finds evidence supporting a statistically significant difference between males and females regarding academic resilience. They demonstrate that males show more academic resilient characteristics compared to females in contrast with Morales (2008) who reports the opposite phenomenon. Moreover, Khalaf (2004) does not find a significant correlation between age and academic resilience.

A considerable amount of research has also investigated racial, ethnic and cultural differences in students' affective, motivational and cognitive orientations in statistics as well as in their statistics achievement (Onwuegbuzie, 1999; Awang *et al.*, 2002; Baloğlu *et al.*, 2011; Mohamed *et al*., 2012; Koh, and Zawi, 2014; Verhoeven, and Tempelaar, 2014; van Es and Weaver, 2018). However, there appears little or no agreement among researchers about the influence of these groups on the investigated factors.

Considering the evidence presented in this section, it seems that the research literature concerning the association between demographic and educational characteristics and a host of other factors is not consistent. The findings and conclusions need to be interpreted with caution due to the different locations, sample populations, research methods employed and the incorporation (and controlling) of other variables in the analysis.

In the current study, students' demographic and academic characteristics are assessed using among others, gender, age group, province, major (degree programme) and academic year of study.

2.11 Findings from Cypriot or Greek population research studies

In this section, research studies, which have recruited university level students in Cypriot and Greek educational settings attending a statistics or a mathematics course as a part of their degree programme and have investigated the variables of interest, are presented.

Anastasiadou (2010, 2011) employ the Students Attitudes toward Statistics and Technology Scale (SASTSc) aiming to measure students' attitudes towards learning statistics with technology and determine the reliability and the validity of this scale. This instrument was administered to Greek students from the Department of Educational and Social Policy of the University of Macedonia. However, even though her studies provide evidence supporting good psychometric properties (e.g. reliability and validity) of the scale, they are hampered by data sets with (arguably small) sample sizes equal to 154 and 123 respectively.

Bechrakis *et al.* (2011) examines the construct validity of the Survey of Attitudes Toward Statistics (SATS) measure by exploring the factorial structure of the scale and its structural invariance across gender. The SATS scale (which was translated into the Greek language) was administered to 1073 undergraduate students from the Departments of Social and Political Sciences of the University of Athens in Greece who enrolled in statistics courses. The results provide evidence supporting good psychometric properties for both the overall scale and its subscales and confirm male and female structural equivalence. Male and female students' attitudes regarding statistics are found to differ slightly in the affective and cognitive competence components, but not in the value component. Also, no differences between males and females in their expected performance in the statistics course were detected.

Chadjipadelis and Andreadis (2006), by employing the SATS questionaire, demonstrates that students who were in a project-based elementary statistics course at the Department of Political Sciences of the Aristotle University of Thessaloniki had significantly higher attitudes scores than those students were taught the introductory statistics course with conventional methods except for the difficulty component. More specifically, students in the project-based group tended to have more positive feelings concerning statistics, believe more in the value of statistics, show greater interest in statistics, exhibit higher cognitive competence beliefs and try harder to learn statistics.

Kiekkas *et al.* (2015) have employed a sample of undergraduate nursing students who attended a biostatistics course in the Department of the Technological Educational Institute of South-western Greece and have implemented a one-group quasi-experimental pre-test and post-course design. Higher post-test scores than pre-test scores on the Greek version of the SATS instrument indicate that generally the course is followed by more positive attitudes towards statistics. Also, significant, although weak, correlations are found between the overall SATS scale score and the examination performance in statistics.

Frangos *et al*. (2013), with the aim to explore the components of statistics anxiety in Greece, adapted the Statistics Anxiety Rating Scale (STARS) questionnaire for the Greek population and examine the factorial structure and psychometric properties using, among others, exploratory and confirmatory factor analysis techniques. The sample was randomly selected and composed of students who had graduated from at least high school (e.g. undergraduate and postgraduate students). The reported results are consistent to the original version of STARS (as tested by Cruise *et al*., 1995) and subsequent psychometric research studies (e.g. Hanna *et al*., 2008; Papousek *et al*., 2012).

Mousoulides and Philippou (2005) have developed a model involving connections and causal relationships among cognitive and affective variables such as motivational beliefs (e.g. self-efficacy beliefs, task value beliefs and goal orientation), self-regulation strategies use and mathematics achievement using a sample of 194 Cypriot pre-service teachers. The data is found to fit the theoretical model well with self-efficacy being a strong predictor of students' mathematics performance. Also, students with higher self-efficacy beliefs, task value beliefs and mastery goal orientations tended to use cognitive and metacognitive strategies more vigorously while also being more able to regulate their own motivational beliefs. These findings are in line with propositions of other researchers (Bandura, 1986; Pintrich, 1999).

To sum up, there is an extensive body of international research concerning the area of investigation of this doctoral study. However, to the best of the researchers' knowledge, there has been little research evidence derived from Cypriot or Greek populations.

2.12 Theories and theoretical frameworks

In this section, a further theoretical grounding and background for the research study is provided. A theoretical background and framework is required to support the proposed research study and justify its importance and significance. In the literature, a variety of theories and models have been proposed and various theoretical/conceptual frameworks and foundations have been employed, in an attempt to explicate and understand the complex relationships among a number of constructs (including affect, self-efficacy, value, effort, motivation) that are deemed to be related to academic performance. In their article paper, Eccles and Wigfield (2002) have provided a comprehensive review of a variety of theories and models that can be found in the educational and psychological literature base and concern individuals' motivations, beliefs, values, interests and goals. In this chapter, in the relevant sections and descriptions of the constructs, some key theories and theoretical frameworks that underpin the research studies in the respective area of investigation, for example, Bandura's (1997) Social-cognitive learning theory, Bandura's (1977, 1986), Self-efficacy theory, Eccles *et al.* (1983), Expectancy-Value theory, are cited. The above-mentioned theories, along with their pioneer(s) and the researchers who have adopted and have used them as a theoretical groundwork for their research studies in the context of statistics education, are reported in **Error! Reference source not found.**. I chose those theories to beneath my research work because they are more relevant to my research purposes and they are the most influential and dominant theories that have used by similar empirical investigations in this area of inquiry.

Here, I briefly mention and explain three theories that supported this research. To start with, Bandura (1977,1986) propose the psychological theory of self-efficacy. This theory states that confidence in one's ability is dynamic – perceived success in the execution of tasks improves expectations for completion of future tasks in that domain. The social cognitive theory (1997) is also based on the research of Bandura and includes the idea of self-efficacy. This theory posits the social context and its emphasis on learning through the dynamic and reciprocal interactions among personal, behavioural and social/environmental factors (LaMorte, 2016). Within the context of statistics education, some studies (e.g. see Table 2.1), which have investigated the construct of self-efficacy, including among others, what it is, how it is associated with similar constructs, how it can be improved and how it affects peoples' learning and performance, mention the above theories.

Regarding Eccles' Expectancy-Value theory, it has been employed to explain the link between expectancy-related and task values-related beliefs with achievement performance, choices, effort and persistence across a wide range of academic domains, subjects and contents (Wigfield and Eccles, 2000; Wigfield and Cambria, 2010). The expectancy component incorporates individuals' beliefs about efficacy, competence, expectations for success and control over outcomes and the perceived value component involves individual's motivations and reasons for engaging in activities and tasks. A large body of research have considered the Eccles' Expectancy-Value Theory, have used it as a theoretical framework and have applied it in the context of statistics education. For instance, Ramirez *et al.* (2010) provides evidence about the congruence between the Expectancy-Value Model and the Survey of Attitudes Toward Statistics (SATS). These authors stress the importance of Expectancy-Value theory and model along with the attitudes towards statistics within the context of statistics education in explaining and understanding students' academic behaviours and achievement in statistics. Moreover, Emmioğlu (2011) examines the structural relationships among mathematics achievement, statistics attitudes and statistics outcomes by estimating a structural equation model, which is labelled Statistics Attitudes-Outcomes Model and is based on Eccle's model and Statistics Attitudes-Achievement Structural Model (Sorge and Schau, 2002). The Statistics Attitudes-Achievement Structural Model, which was developed and tested by Sorge and Schau (2002), has been used to test the directional impacts among four endogenous attitudes and expectancy-value related latent constructs e.g. affect, cognitive competence, value, difficulty), one exogenous variable (e.g. previous success) and the outcome latent variable (e.g. achievement).

Some ideas behind the theories mentioned above have been adopted and adapted to statistics learning experiences, have been combined and used as a theoretical base of and a guide for both the quantitative and qualitative strands of this research work. For example, within the proposed theories, there are constructs. Thus, existing theories and theoretical underpinning of the structure of each construct under investigation are consulted.

In brief, this research work draws together a number of theoretical perspectives and the data have been approached using different theoretical lenses. The theoretical grounding has informed and supported the quantitative and qualitative collection tools along with the data interpretation and explanation and the arguments and suggestions offered.

2.13 Theoretical-conceptual model

Bearing in mind existent theoretical propositions and models, and findings from empirical studies, a theoretical (hypothesised) model was designed and developed. This model informed, and was informed by, the quantitative strand of my research study. Then, a statistical model was developed to represent and test the theoretical or conceptual model. The primary consideration was to encapsulate the main constructs/factors under consideration, which were deemed as having an impact on statistics performance, in a parsimonious structural model, and to test this model empirically using data generated from the population of interest. A path representation (visual diagram), which depicts connections and anticipated paths (indirect and direct effects) among the variables of interest, is presented in the Quantitative Results chapter (refer to §4.10).

Table 2.1 Theories and models from the pertinent literature

THEORIES AND MODELS	**PIONEER (S)**	**RESEARCH STUDIES**
Social-cognitive learning theory	Bandura (1997)	Lee *et al.* (2002); Finney and Schraw (2003); Hall and Vance (2010). Schneider (2011)
Self-efficacy theory	Bandura(1977, 1986)	Schunk (1991); Awang-Hashim *et al.* (2002); Emmioğlu (2011); Zare (2011); Li (2012); Ramirez (2012)
Expectancy-Value model of achievement motivation	Eccles *et al*(1983)	Schunk (1991); Köller (2001); Sorge and Schau (2002); Chuinard (2007); Verhoeven (2009, 2010); Ramirez *et al.*, (2010); Emmioğlu (2011); Schneider (2011); Tempelaar *et al.* (2011); Hood *et al.* (2012); Arumugam (2014)
Statistics Attitudes-Achievement Model	Sorge and Schau(2002)	Chiesi and Primi (2010); Emmioğlu (2011)

2.14 Conclusion

A review of conceptualisations, operational definitions and measurements that are proposed in the literature and are relevant to this research study along with how the various researchers have employed and explored these concepts in their investigations was carried out. In this chapter, a brief description of them is reported (but not discussed in full) in the relevant sections giving more emphasis to their incorporation and investigation within the context of statistics education and the presumed relationships among them. At the end of each section, a preliminary conceptualisation of the key construct, factor or variable being measured and explored in the present study is provided. The interrelationships among affective and motivational factors, and subsequently their associations with the learning process, were initially concerned through the theoretical and empirical frameworks mentioned in this chapter. Some of those theories concerned the same or similar constructs and the ideas that underpinned them, to some extent, overlapped. As mentioned in §1.3, this study is anticipated to add or contribute to existing literature and fill the potential gaps in knowledge. For example, this research aims to accumulate and investigate a number of factors that are deemed to be related to and predict performance in one research study and provide a comprehensive knowledge of the issue at stake. The gap in the knowledge in the existing literature resides on the background theory, which concerns, for example, the resilience construct within the statistics education context and its relation with other constructs and academic achievement. Gap is also identified in the methodological design employed by other empirical studies in this area of investigation. This issue is addressed in this study by combining a longitudinal quantitative approach and a qualitative approach (refer to the next chapter, Chapter 3).

Chapter 3 RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

In this chapter, an overview of the research design and methodology and the research methods they were employed in this doctoral study are described and discussed. It begins by introducing the research questions (and sub-questions) of the study, proceeds with the research methods employed and then provides an overview of the researcher's position and the research paradigm. Next, the research settings and population, a description of the data and the data collection strategies (such as sampling techniques an sample sizes), the design and the development of the research study tools, a summary of ethical consideration issues, a description of the pilot study and a detailed description of the data collection procedures of the main study are stated. What follows is the data analysis procedures used in this study and the issues and evaluation criteria of the quality of this study. Some practical and methodological challenges and difficulties I faced while organising and conducting the research study and analysing the research findings are discussed. Moreover, the selection of the research design, methodology, methods and sources used entailed the necessity of some judgements and decisions to be taken by the researcher. These were based on the overall research objectives along with the researchers' interests, time availability and financial resources. Throughout the chapter, an effort is made to present the stages during the research procedures and be transparent by reporting, justifying and supporting the rationale and idea behind each key decision was taken. This is deemed as evidence of the overall methodological credibility of the study and an attempt to guide the readers on the journey that had led the researcher to the creation of knowledge and understanding.

3.2 Research Questions and Sub-Questions

Based on the stated purposes and aims (see §1.2), my doctoral research study is centred on the following inquiry:

> "What are the relationships, if any, among several affective, motivational and cognitive factors with performance in introductory statistics courses offered at undergraduate level in tertiary institutions in Cyprus? How do the interviews with students help to explain those relationships?"

A number of related Research Questions (RQ) along with Research Sub-Questions (RSQ) were derived and are stated below. These questions were prioritised into primary over secondary ones. It should be noted that the questions were mainly descriptive and exploratory in nature. The quantitative and qualitative approaches that were employed to address the research questions and sub-questions of this study are presented in §3.11 .

3.2.1 Primary research questions and sub-questions

RQ 1: What are the affective responses and perceptions of students over the course of a semester and how do the students describe them?

RSQ 1.1: What are the students' feelings, attitudes and beliefs regarding statistics, interest in learning statistics, perceptions about the usefulness, the worth and the relevance (for their specialisation) of statistics and perceptions about the difficulty of the current statistics course?

RSQ 1.2: What are the types and levels of anxiety related to statistics that students experience, the sources and the effects of these anxieties?

RSQ 1.3: What are the levels of students' perceived self-efficacy regarding statistics, the main antecedents and sources of them?

RQ 2: Can the concept of resilience be adapted in the context of statistics education so that we can introduce the term 'statistical resilience'? What is the relationship between statistical resilience and other examined variables, and performance?

RSQ 2.1: How can the concept of statistical resilience be conceptualised, what are the students' resilience levels, how does resilience develop over the course and what are the resilient strategies and approaches they apply in statistics?

RSQ 2.2: Is statistical resilience related to other examined affective, motivational and cognitive variables and is it a significant predictor of academic performance in a statistics course?

RQ 3: What is the nature, the interrelationships and the potential influences of examined affective, motivational and cognitive factors on the statistics course performance?

RSQ 3.1: What are the students' achievement goals and motivational orientations, expectations of their performance, perceived control over learning and performance? How much study and effort do students put into statistics and what are the learning strategies and approaches they use?

RSQ 3.2: What, if any, relationships hold between students' attitudes, anxiety and self-efficacy regarding statistics, and other affective, motivational and cognitive factors?

RSQ 3.3: Are the examined affective, motivational and cognitive engagement variables related to statistics performance and which of them can explain and significantly predict the performance?

RSQ 3.4: What is the overall best-fitting model that describes the relationships among selected affective and cognitive variables and performance in statistics?

3.2.2 Secondary research questions and sub-questions

RQ 4: What are the students' opinions about the nature of statistics and mathematics and what is the role of the previous statistics/mathematics learning experiences and background in the current statistics course?

RSQ 4.1: What are the students' perceptions about the nature of statistics, the similarities and the differences between statistics and mathematics and the relation between them?

RSQ 4.2: What are the students' previous mathematics and/or statistics background, performance and learning experiences and are these related to their affective perceptions and performance in the statistics course?

RQ 5: Are there any significant differences in affective, motivational and cognitive orientations related to statistics, and in students' performance, with respect to various socio-demographic characteristics?

RQ 6: What suggestions and ideas do the students propose for improving the statistics education experience at the university level?

3.3 Research methods

3.3.1 Mixed-method design

With the purpose of answering the research questions, I set up this research study in both a qualitative and quantitative manner, applying a mixed-method research design (e.g. Tashakkori and Teddlie, 2003; Creswell and Garrett, 2008; Creswell and Plano, 2011). Following other authors' recommendations, research approaches and methods should be mixed in ways that will provide greater insight into the research study topic and the best opportunities for addressing the research questions and offer answers to them (Tashakkori and Teddlie, 2003; Johnson and Onwuegbuzie, 2004). Moreover, when embarking on an investigation, which concerns humans' affective, motivational and cognitive responses and behaviours, a combination of quantitative and qualitative approaches/elements within one study can aid the researcher to detect, understand and explain their complex dynamics from more than one perspective (Creswell, 2009). As Tashakkori and Teddlie (2003) argues, the complexity of educational issues warrants multifaceted research designs (such as mixed-methods). In social sciences, there are ongoing debates about the relative virtues of combing quantitative and qualitative strategies for research (Hughes, 2012). For example, many authors (e.g. Johnson and Onwuegbuzie, 2004; Bryman, 2006; McEvoy and Richards 2006) identify some potential weaknesses and shortcomings coming along when applying mixed method research, such as different ontological and epistemological paradigms (a paradigm clash), mutually exclusive underlying assumptions and philosophies of these approaches and distinct procedures. In this study, opting for a mixed methods approach is not served as a panacea. The arguments offered here is that a mixed methods approach can reconcile and compensate the methodological strengths, flaws and challenges of using either approach alone; complement, broaden and enrich findings and understanding of potential complex research objectives; maximise the interpretation of the findings; and enhance the reliability and validity, and thus the quality and the significance, of the data collected and the results drawn (Erzberger and Kelle, 2003; Collins *et al*. 2006; Gläser-Zikuda and Järvelä, 2008; Creswell and Plano, 2007, 2011; Andres, 2012). Bryant (2011) investigates the implementation of mixed methods in educational research and provides suggestions to the researchers for presenting their mixed methods' findings. These include the rationale of the identification of the study as a mixed method and the justification of using this design and the identification and reporting of the timing and the design of the data collections in both abstract and methods sections.

With the intention of gathering a good deal of information, searching for general patterns, trends and associations across the population and obtaining a broader picture of the constructs under investigation in the target group, self-reported questionnaires were chosen to be administered to the study participants. Lovelace and Brickman (2013) points out that survey instruments, as means for quantitative data collection, give the potential for an easy and quick accumulation of participants' responses, and attach numerical scores to their opinions and beliefs about the topics under consideration. Creswell (2009), also, argues that quantitative collection strategies can be a valuable tool for investigating issues where many variables are involved, as it is in the case in the current research study.

With the aim to delve into and understand in-depth the nature of the circumstances and the factors that have contributed to and affected the participants' responses, face-to-face interviews (with students who had already completed the questionnaires) were chosen to be conducted. The interview approach intends to: provide explanations; clarify and supplement the interpretations of the students' responses to the questionnaire; go beyond the information extracted from answers to the questionnaire questions; and discuss topics or elicit feelings (magnitude and intensity) that cannot be easily obtained by Likert-type statements. Face-to-face and one-to-one discussions can elicit first-hand accounts of participants' learning experiences from their perspectives and probe what meaning and value they ascribed to these experiences (Bogdan and Biklen, 1998; Gray, 2009; Liamputtong, 2013). Students were encouraged to reflect on their personal experiences, behaviours, perceptions, thoughts, motivations, and challenges that they might encounter when undertaking a statistics course, and describe them in their own words. More specifically, a semi-structured interview approach was selected to be followed (Bryman, 2015). The basic format of the interviews was predetermined, and a set of guiding questions was compiled before the execution of them (Robson, 2002; Gray, 2009). Some specific topics and key questions were flagged as mandatory to be discussed with the students during the interviews. However, there was some flexibility (about the how and when these topics would be raised), giving space for related issues and follow-up questions to be put forward in a reflective environment.

The primary data collection was the distribution of the questionnaires (quantitative data gathering), followed by interviews (qualitative data gathering) to inform, complement and enrich the quantitative results. This research design is deemed as a valuable tool because different data sources were coupled together and triangulated to provide statistical summaries and interpretative stories. "Triangulation entails using more than one method or source of data in the study of a social phenomena" (Bryman and Bell, 2003, p. 291) in "an attempt to map out, or explain more fully, the richness and complexity of human behaviour from more than one standpoint" (Cohen and Manion, 2007, p.141). In the current study, a methodological triangulation - a basic type of triangulation - which involves employing more than one method to gather data was implemented (Denzin, 2006, 2012). More specifically, a sequential explanatory design as described by many authors (e.g. Creswell, 2009, Ivankova *et al.*, 2006) was employed with some modifications (see Appendix A1). Kuckartz (2014) classifies sequentially deepening, where the qualitative part renders the quantitative results more plausible, among one of the simple mixed methods research designs. Separate data collection and analysis (sequential) were used for the strategies (questionnaires and interviews) applied in this study. What followed was the integration of the results from both approaches and the interpretation of them. The integration component is considered among the values of mixed-methods research (McKim, 2017). Nevertheless, as Bryman (2006) advocates, the integration is the fundamental challenge of it and not the research design itself.

As was mentioned above, mixed-methods approach was used to triangulate the findings. Initially, the quantitative and qualitative data were collected and analysed separately. The quantitative method (i.e. questionnaire) produced data that were aggregated and analysed, in order, for example to search for patterns and describe relationships. The qualitative method (i.e. interviews) produced data that were used for analysis of individuals and groups and provide within-case and cross-case comparisons. The qualitative method helped also to probe and explain those relationships, trends or patterns emerged from the quantitative one. At a later stage, the qualitative and quantitative results were considered and compared at the group level. Some of the topical domains (i.e. self-efficacy) that were discussed were similar.

3.3.2 Longitudinal component

Bryman (2016, p. 692) defines "longitudinal research as a research design in which data are collected on a sample of people on at least two occasions". The quantitative strand of the current study has the form of a longitudinal study, meaning that the quantitative data collection was conducted over a period of time (Cohen *et al.*, 2007; Arthur *et al.*, 2012) and specifically at two distinct time periods. The questionnaires were administrated near the beginning (i.e. pre-course) and near the end (i.e. post-course) of the instruction of the various statistics classes. I contend that the longitudinal design affords the opportunity to monitor potential changes in students' affective, motivational and cognitive engagement over a statistics course spanning one academic semester. Since the sample of the students could not be the same from one time period to the other (see e.g. §3.6.2) it was assumed that it was at least comparable.

The face-to-face interviews were performed once with each interviewee at some point during the semester after they had completed at least one version of the questionnaire and had undertaken at least one formal assessment (e.g. examination) in statistics. The explanation of the absence of a longitudinal nature in the qualitative strand of the study is that it was deemed as difficult to recruit the same students to be interviewed at two different times throughout the semester. The researcher's and the students' availability and time constraints were among the main reasons.

3.4 Position of the research and an overview of the Research Paradigm

The selection of the research methodology and the methods employed reflects the researcher positionality (Wellington *et al.*, 2005; Savin-Baden and Howell Major; 2013) and in turn has a potential influence on all aspects and stages of the research process (Foote and Bartell, 2011; Holmes, 2014). Thus, it was deemed as important to 'locate' my position and paradigmatic view or conceptual perspective as a researcher. Particular paradigms might be related to certain methodologies (Chilisa and Kawulich, 2012). For instance, a positivism paradigm is more associated with a quantitative methodology whereas a constructivist or interpretative paradigm is more associated with a qualitative methodology. There are also authors who propose mixed research methods as a third research paradigm (Tashakkori and Teddie, 2003; Johnson and Onwuegbuzie, 2004; Gunasekare, 2015). In this research study, a mixed methods approach (that is a combination of quantitative and qualitative research data collection and analysis methods) was employed. McEvoy and Richards (2006) and Zachariadis *et al.* (2010) consider the critical realism philosophical approach as the most suitable for a mixed-methods research design. Critical realism encourages a holistic exploration of phenomena premised on multiple research questions, which use multiple research methods and approaches (Walsh and Evans, 2014). According to Maxwell and Mittapalli (2010), critical realism is compatible with both qualitative and quantitative research, regards both approaches as equally valid and useful and promotes integration and cooperation between them. An important characteristic of critical realism approach is that it fundamentally concerns, contains and urges for ontological assumptions (McEvoy and Richards, 2006). Critical realism offers an ontology that can conceptualise reality and guide empirical work (Given, 2008). Being realist about ontology entails acknowledging that things exist beyond human experience, knowledge and beliefs of those things (Saunders *et al*., 2009; Bhaskar, 2013; Archer *et al*., 2016). Ontological considerations and assumptions are deemed as important for this research study as many different underpinning concepts were assessed. Conceptualising, clarifying and investigating them within a (Cypriot) statistics education context was an important consideration. For example, one of the main concepts that were investigated is students' self-efficacy. Critical realism is pursued because, in terms of ontology, it justifies that this concept can exist and a sense of meaning of it is needed to be established (for example, refer to §2.7 where self-efficacy is defined and conceptualised both generally in the academic context and more specifically with relation to statistics education context). Then, the focus was placed on exploring and understanding its social existence via quantitative methods and qualitative methods. Briefly, the chosen research methodology was informed by critical realist perspectives which are less concerned about objectivity and neutrality and focus more on research impact and positive 'change' or 'improvement' at practical (and theoretical) level. Emphasis was given on critical awareness by examining or re-examining assumptions along with the conditions (or circumstances) that might give rise to them and addressing a corresponding variety of issues using a combination of research methods.

3.5 Research Settings and Population

3.5.1 Location Settings

The location of the study is my country of origin, Cyprus. The research work was carried out with the intention of eliciting perceptions, opinions and experiences related to statistics education offered at the university level in Cyprus. Cyprus is a developing country that has adopted and adapted educational ideas, teaching, learning and assessment methods from several countries' educational systems, including the US, the UK and Greece (Papanastasiou and Zembylas, 2002). Cyprus is among the leading countries in the EU regarding the percentage of citizens who possess a degree from an institution of higher education, by all of the working population (www.greekodom.com). Currently, recognised public (state-funded) and private universities operate in Cyprus. The current study was carried out in both types of universities.

3.5.2 Target population and sample

The target population (i.e. the population of interest) is undergraduate non-mathematics majors who are registered for an in-class introductory statistics course in universities located in Cyprus. It is important to state that these introductory statistics courses are taught mainly by mathematics/statistics instructors. To give an example, in the case of a public university, the statistics courses are service courses, which are offered by the Department of Mathematics and Statistics to other Departments and Faculties, they are not open to Mathematics majors, but they are only accessible from students who are majoring in other academic disciplines.

For the purposes of this doctoral study, I collected data from six universities – two public universities and four private. Overall, I visited thirty-four statistics classes (twenty-one statistics classes) taught by fifteen different instructors in the academic year 2015-2016 spanning two semesters, Fall Semester 2015 and Spring Semester 2016. Consequently, a broad spectrum of academic disciplines, degree programmes and majors are represented among the study participants. The study was limited to the Greek-speaking students attending these statistics classes and the reasons are described later in this chapter. Non-Greek speaking students attend only private universities (due to the language of instruction and evaluation issues) and their number was very limited or none in the classes I had collected data. More information about the data sample is provided later (see, for example, §3.6 and Appendix A4).

3.5.3 Background, context and statistics courses description

In this subsection, background information along with the context in which the study took place are described. With the term context, I refer, among others, to the instructors (course or/and tutorial classes instructors), instructional methods and approaches, materials and tools used (e.g. lecture notes, textbooks, technology), statistics course content, the physical locations (e.g. lecture theatres, classrooms, laboratories), university environment and the educational system. All these collectively are believed that establish the statistics education course experience for both students and their instructors. Even though in the present study, the emphasis is given on individual students' perceptions, it is acknowledged that students are not 'individuals'; are a part of a group. The context within which the students formulated their opinions (individual perceptions) and their experiences could have additional (and possibly notable) impact and meaning on them. In addition, it is postulated that they help in developing my understanding of their 'world' and 'reality'.

At this point, a brief description of the students' prior educational background before entering the higher education is provided. During their studies in upper secondary education (Lyceum) in Cyprus, students have the potential to study mathematics in two different directions or levels, namely core mathematics and advanced mathematics. These mathematics directions share common subject content material (mathematics topics covered); however, they differ in the depth that it is placed in each topic. At the end of the secondary school, in order to enter a public university in Cyprus (and in Greece), students have to undertake a national entrance examination in their chosen subjects. Mathematics (either core or advanced) is one of the compulsory examination courses. Then, the overall matriculation examination grades are used for access to public tertiary universities. By contrast, an essential prerequisite for admission to undergraduate degree programs at the private universities is the successful completion of the secondary education (e.g. a lyceum, a vocational and technical school or a recognised private secondary school) including students' secondary school grades and, sometimes, the sufficient knowledge of the English language. It is generally considered more competitive for students to enter into a public university than a private university. Also, it is worth mentioning that all Greek Cypriot males (except for some special cases) were required to spend maximum two years in the national military service after the end of the high school and before entering into the university.

At the university level, it is common for at least one statistics course to constitute a part of the curriculum of many undergraduate degree programmes. Most of the students have to undertake an introductory course in statistics as a compulsory (required) course. However, it can also be taken by students as an elective. In some cases, an introductory course is followed later on their degree program by more advanced statistics courses or other statistical-oriented courses. The statistics course, in some undergraduate degree curriculums, is a part of the general education courses - as addition and support to the core and specialisation courses - or as a part of the basic required science courses. It should be noted that at public universities the students have to follow the curriculum. That means that they undertake the statistics course (for the first time) the year that is offered by their degree programme. At private universities, the students either they undertake the statistics course in a specific semester or they can attend it in the semester they want (depending on the credits they need to complete for this semester).

Concerning the language policy in higher education, Greek is the language of instruction in all the public universities in Cyprus. Thus, the statistics classes are taught in the Greek language. Nevertheless, the language of instruction (and evaluation) in some introductory statistics courses, which are provided by the private universities, is English. Among the reasons are the university regulations or the design of each class and the admission of students whose first language is not Greek. In the current study, there were ten statistics classes that were offered in the English language.

Regarding the frequency and the timing of the statistics classes, it was found that they varied across different universities and departments. In all the statistics classes of the public universities, students needed to attend each week two lecture classes (with duration of one hour and a half each). In some classes offered by the private universities, students needed to one lecture class (with duration of three hours) or one lecture class (with duration of two hours). Some lecture classes, mostly in public universities, were accompanied by tutorial (or laboratory) classes, which lasted one hour each week (and on a different day than the lecture class). The lecture classes at public universities were taught in large lecture theatres or classrooms and the tutorial sessions in smaller classroom classes, whereas at private universities in small classroom classes or if a technology component was incorporated, the students were in computer labs. The statistics instructor taught the lecture session, whereas the tutorial sessions were taught by the same instructor, by a doctoral student (tutor) or were co-taught by the instructor and the tutor. The tutorials focused mainly on solving practical exercises and applying the statistical theory and methods to exercises and examples.

At the beginning of the instruction of most statistics courses, the instructors provided to the students the course syllabus which commonly included the course description and content; the objectives of the course; the learning outcomes; the teaching methodology; the assessment methods (and the assessment weights); the schedule of lectures and assessment; the required and recommended textbooks/readings and; maybe, some other information.

The statistics courses are one semester-long introductory courses. According to the universities undergraduate handbooks and the information the instructors (or the students) provided to the researcher, these courses were designed to introduce, familiarise and equip students with basic and core concepts, ideas, methods and applications of statistics. Most commonly, they provide students with knowledge and skills of descriptive and inferential statistics. They focus, among others, on elementary probability theory, descriptive statistics (e.g. frequency distributions and tables, graphical representation of data, measures of central tendency and dispersion, measures of association) and inferential statistics (e.g. basic concepts in inferential statistics, point estimates, confidence intervals, t-tests of group means, chi-square tests, one-way analysis of variance, hypothesis testing). The curriculum also covers topics related to random variables, discrete (e.g. binomial) and continuous probability distributions (e.g. normal) and simple linear regressions. Although the title of the courses and its syllabus might vary in some extent in each university and each department within it, the courses are deemed as sharing similar and (probably) comparable curriculum content.

Lecture-based method and written lecture notes on the board were the methods typically employed by the statistics instructors at public universities. In some classes of the private universities, the lectures were delivered using the boards, PowerPoint presentations or a combination of it. Some instructors, who presented the course with power-point presentations imported slides to the Blackboard system of the university before the lecture class or after the lecture class. No technology component or technological support and tools (IT) were involved in some introductory statistics courses (mainly at public universities). For example, in these classes, the students were not exposed to any computer software program for data analysis and statistical applications. However, in some other classes, the course content included the exposure and the learning of a statistical program (such as SPSS and R). Some students had the opportunity to practice in computers and received the help of their instructor or tutor (during the lecture or/and tutorial classes), whereas other students had to complete an assignment using a statistical program, but without having the opportunity to do practice on a classroom environment. Regarding the evaluation criteria, the statistics course grade was largely determined by examinations. More specifically, in all the classes, the final statistical examination took the largest percentage of the final grade. The remaining percentage was allocated to midterm examinations, quizzes, group and individual assignments, projects and/or class attendance and participation.

Even though the curriculum of the course was pre-determined, after informal discussions with some of the instructors, I was informed that they had a relative freedom and autonomy in presenting the subject material and producing their lecture notes based on the assigned learning goals as long as they act within the legislation and constraints, which regulate each tertiary institution. In some cases, the instructional approaches, activities and/or materials were decided collaboratively by the instructors who taught the same course within universities. Also, as the instructors stated, the availability of the resources and supporting equipment influenced the delivery of information to the students. Regarding the students' assessment, instructors were responsible for constructing and grading the evaluation methods (e.g. examinations) and assigning a final statistics grade to each student. It is acknowledged that different individual instructors in different universities (and types of universities) might have diverse instructional styles and philosophies. Moreover, it should be kept in mind that instructors (even the same instructors) might deliver the same content differently in different departments and degree programmes by taking into account departmental features, needs and/or demands. For example, they might give emphasis to particular aspects, examples and exercises; they might use different ways of delivering the information and diverse methods of assessment and type of examination questions; and the lecture notes or the textbooks used might be distinct. In addition, the instructors might set the difficulty at different levels taking into account the students' current degree programme and previous background.

The brief background information mentioned above was intended to give an idea to the reader about the particular context within which this research study was conducted. What follows in the next section is a detailed description of the data and data collection strategies.

3.6 Data and Data collection strategies

3.6.1 Sampling techniques

This subsection deals with the issue of sampling techniques. Without a doubt, the selection of the sample is critical considering that it should be representative of the population of interest. Since it was impossible to have a list and access to all the students enrolled in all the statistics classes offered at all the recognised universities in Cyprus so that a group of students could be randomly selected to complete the questionnaire and a subsample to give an interview, non-probability sampling techniques were employed to select samples from the target population. This means that the samples (from both the quantitative and qualitative data collection procedures) were not selected randomly. The criteria for selecting the sample for the quantitative data collection purposes were different from the criteria for selecting students for the qualitative information-gathering purposes. Nevertheless, the participants of both components of the study were chosen on a voluntary basis.

The quantitative data gathering was performed using a convenience sampling technique. The universities and statistics classes chosen for the present investigation were based on the location, time and availability constraints and permission and co-operation from the pertinent authority (e.g. head of the department, principal of the university). More specifically, the statistics classes included in the study were determined by the instructor's willingness and co-operation to enter into his/her class and distribute the questionnaires. The population sample might be regarded as a convenience sample owing to the familiarity with the location of the study and the universities' conditions, regulations and language of instruction (at least with the public ones). As advocated by Andres (2012), surveys of someone's country can be considered to be examples of convenience samples. The convenience sampling technique was also employed in many educational studies in this area of investigation (e.g. Carmona *et al.*, 2005; Bude *et al.,* 2007; Tempelaar *et al.*, 2007; Verehoven, 2009; Li, 2012; Sunzuma *et al.*, 2013; Larwin, 2014). Also, the entire population is divided naturally into different (non-overlapping) subgroups (e.g. types of universities, universities, statistics courses/classes). The aim was to have an adequate representation of all the subgroups of the population of interest (Farmer *et al*., 1996).

For the qualitative data collection, a purposeful (purposive) sampling technique was employed (Cohen *et al.*, 2007; Creswell, 2009). The primary objective was to select the participants that were more likely to provide research-relevant information and make valuable contributions to the research objectives and questions that have been posed (Patton, 2002; Tashakkori and Teddlie, 2003). After the initial consent and eagerness of the students to participate in a face-to-face interview, the selection of those to be eventually interviewed was based on several factors such as the availability of both the researcher and the students and the convenience of the place and date.

3.6.2 Sample sizes

This subsection looks at the issue of the sample size of both components of the research study. The size of the sample can be informed chiefly by the research topic, the research objectives, and, then, by the study population (and its variability and accessibility) and the research design and methodology adopted (Morse, 2000; Davies *et al.*, 2004; Onwuegbuzie and Collins, 2007; Cohen *et al*., 2007, 2011). Also, a critical issue in determining the sample size is the number of resources and the amount of time the researcher has available (Brunt *et al*., 2017). In this study, the precise number of the participants could not be predicted in advance of conducting the study. When the research study is voluntary, as it was the case in the present study, researchers are at the mercy of students' eagerness and co-operation to take part in either part of it (quantitative or/and qualitative). The number of variables (constructs) under consideration as well as the methods of statistical analysis informed my desired expectations about the sample size of the quantitative data collection (Cohen *et al*., 2011). Regarding the Structural Equation Modelling (SEM), which is considered as the most advanced statistical method used in this study, some researchers propose a minimum sample size for conducting SEM equal to 200 (e.g. Kline, 2005). Also, other researchers recommend as a rule of thumb to have 10 cases per indicator variable as an adequate sample size (Nunnally, 1978). Generally, the more data and the amount of information the researcher has, that is, the larger the tested sample size is, the less the chance of error such as systematic error, or bias, (Fraenkel and Wallen, 2013) and the better the precision of the sample estimates of the parameters under consideration (Biau, 2008). Regarding the qualitative component, the a priori determination of the sample size and sampling adequacy of interview sessions is considered as difficult (Guest *et al.,* 2006; Mason, 2010). Moreover, as Baker *et al.* (2012) proposes, there are no fixed rules or rule of thumbs of how many interviews should be conducted for a research study. The goal in this study was to recruit as a large sample as possible (especially for the quantitative data-gathering) and as representative of the target population as possible (Cohen *et al.*, 2007; Bell, 2014).

As previously stated, the questionnaires were intended to be distributed to the students in classroom settings. Officially, the students are not required to attend the classes at the university level. However, a few instructors included class attendance or/and participation as a part of the cumulative percentage which composed the final statistics grades. This might have an effect on students' motivations for attending the statistics classes. Also, from my personal experience as a student at a public university, students tend to attend classes regularly although attendance is not compulsory or constitute a part of the course grade.

The final sample size of the main study was mainly determined by the willingness and co-operation of the universities, instructors and students, availability, time constraints and financial costs (e.g. printing questionnaires, travel expenses). The full dataset of the quantitative component included a total of 995 questionnaires in the fall semester and 534 questionnaires in the spring semester. The number of students who completed the pre-course version in both semesters were 855 and the number of students who completed the post-course version of the questionnaire were 674. The number of students who completed both the pre-course and post-course questionnaire versions were 496. As expected, the number of the students who completed the post-course version of the questionnaire was less than the number of the students who completed the pre-course version (in the pre-course administration). The smaller sample size (that is the students' lower response rate) during the post-course administration of the questionnaire might be attributed to several reasons including students' withdrawing from the course either formally or informally by not attending the course; non-attendance at the lecture on the day of the questionnaire distribution; or reluctance to complete the post-course version of the questionnaire. Also, it might be the case that students towards the end of the semester tended not to attend all the lecture classes. Nevertheless, the sample size for both administrations was considered adequate for performing the intended statistical analyses. Initially, one class (and, more specifically, 31 pre-course questionnaires and 25 post-course questionnaires) was excluded from the subsequent analyses because the syllabus of the course covered topics more related to an advanced statistics course. A number of questionnaires were also eliminated from further analyses for many reasons such as extensive missing or incomplete data[1]. For the qualitative data collection, I met personally with sixty-five students and performed sixty-three interviews throughout the two academic semesters. More specifically, sixty-one individual and two pair interviews were carried out. It should be noted that not all the interviews were transcribed and included in the subsequent qualitative analyses and the reasons are explained in §3.11.2.

Overall, it is claimed that a high participation rate was achieved since almost all of the students who were present in the classrooms completed the questionnaires. In addition, the number of the students who were willing to participate in the interviews, as well the number of the students who were eventually being interviewed, were higher than expected.

[1] Students with large numbers of missing responses (more than 10% of missing data), students who appeared to be systematically not consistent to their responses, or/and students who failed to fill out the questionnaire accurately (e.g. they selected more than one response to some questions) were excluded.

3.7 Design and development of the research study tools

The following two subsections focus on the design and the development of the research study tools (i.e. survey instrument and interview sample plan) which were used during the data collection process.

3.7.1 Design and Development of the Survey Instrument

This subsection gives an overview of the questionnaire design and development process for the quantitative data collection purposes. In the literature, there is a plethora of survey instruments that have been proposed and developed to measure cognitive and non-cognitive factors associated with the learning process and academic performance. Rather than borrowing and translating an existing published questionnaire, I decided to construct a questionnaire specifically for the purposes of this study with the intention to be more pertinent to the curriculum and conditions applied in Cypriot universities. Nevertheless, some statements were culled from existing survey instruments, reworded, modified or combined with the addition of some new ones and customised to the context of statistics subject. Since, to the best of my knowledge, there are no relevant survey instruments, which measure simultaneously the constructs (variables) under investigation, a questionnaire to assess all these variables was devised. Administrating a (new) questionnaire which was not pre-tested and validated entails some challenges which are discussed in §7.2.

Following the recommendations and strategies offered by many researchers (e.g. Chang, 1996; DeVaus, 2002; DeVellis, 2003; Oppenheim, 2003; Colton and Covert, 2007; Earp, 2007; Gillham, 2010; Rudestam and Rae, 2007), the following steps were utilized during the questionnaire development procedure, which is deemed as a core stage of the research project:

- Reading relevant literature and reviewing existing (established and validated) scales and questionnaires, especially in the context of statistics;
- Brainstorming and generating a bank of items that were candidates to be included in the questionnaire;
- Designing, constructing and developing the layout of the new questionnaire;
- Pre-testing the questionnaire (in the pilot study) and subsequent revision of the questions and statements/items;
- Preliminary analysis and quantitative evaluation of reliability and validity issues;
- Configuration of the final form of the questionnaire

As was mentioned in the introduction of the literature review chapter (see §2.1), in order to facilitate the development of the questionnaire and for purposes of reporting, I classified and grouped into categories (major topic areas) the theoretical constructs and variables under investigation. Here, the categories are put under auxiliary and concise headings and constitute the main domains (group of questions) included in the questionnaire, as follows:

- <u>Dispositions and attitudes domain:</u>

Dispositions and attitudes towards statistics as a discipline and towards the particular statistics course that students were enrolled in (e.g. liking of statistics, opinions about the worth, the usefulness and the relevance of statistics for students' personal, academic and future professional lives, perceptions about the difficulty of statistics, perceptions of gender stereotypes).

- Anxiety domain:

Anxiety towards statistics (e.g. statistics class anxiety; statistical content anxiety; statistical tasks anxiety, including, interpretation and inference anxiety; test and examination anxiety; performance anxiety).

- Self-efficacy domain:

Self-efficacy regarding statistics (i.e. students' self-confidence in their abilities to perform well, execute statistical-related tasks, master basic statistical concepts, acquire statistical knowledge and skills)

- Motivation and Cognitive Engagement domain:

Motivational orientations and cognitive engagement in statistics (e.g. achievement goals, motivations, interest, expectations of performance, control over performance beliefs, effort, and learning strategies and study habits).

- Resilience domain:

Resilient characteristics in general and in statistics (i.e. students' perceived ability to deal with challenges and stressful situations of university the life, perceived ability to overcome setbacks and difficulties faced in the statistics course, strategies applied when they encounter unfamiliar or difficult statistical-related tasks or concepts).

- Mathematics domain:

Background in mathematics (e.g. type of mathematics classes attended in high school, number and type of mathematics courses completed in university); prior performance in mathematics (e.g. university-entry level matriculation scores, grades obtained in previous mathematics courses in university); prior learning experiences with mathematics; attitudes, anxiety and self-efficacy regarding mathematics).

The questionnaire questions (i.e. items) were generated from the above general key domains or topics. Multiple items (indicators) on the same broad topic were produced, in an attempt to capture and reflect each topic, which was assumed to represent a latent construct (Liem *et al.*, 2008; Bell, 2014). The assumption was that by employing this set of various items, the relevant construct (and its level) could be adequately measured (Causapin, 2012; DeVellis, 2013). Thus, each construct (factor) was treated as a latent variable that could not be observed directly and its respective items were handled as their observable manifestations and they were used as observed variables (Byrne, 1998; Emmioğlu *et al*., 2011). As Rose and Sullivan (1996) states, when the unobservable theoretical concepts linked with observable indicators, operationalisations are produced. It has to be mentioned that each construct was measured using a number of items. The number of items was not necessarily the same across the constructs. It was recognised that the domains mentioned above might, to some extent, overlap, but as Earp (2007) asserts, the extent of their overlap is an empirical matter which is examined in later chapters (see Chapters 4 and 5).

It is important to highlight that the majority of the items incorporated the term 'statistics' aiming at emphasising that the questions were targeted at the subject of statistics. For instance, although students might have stable learning strategies and study habits across different subject areas, domain- and course-specific learning strategies applied in statistics courses were requested. Also, in addition to the questions and items related to the topics stated above, the questionnaire included items asking students' opinions and perceptions concerning issues pertaining to the statistics course (for example, students' attitudes, anxiety and self-confidence in terms of using and learning computer software packages related to statistics (e.g. SPSS) and preferred methods of assessment in a statistics course).

When developing the questionnaire for the purposes of this research study, several decisions concerning the type of the questions, the organisation and the sequence of the questions, the choice of wording, the length of the questionnaire and other issues had to be taken. The questionnaire comprised of two parts. The first part consisted of open-ended and closed-ended questions soliciting relevant demographic and personal information (e.g. gender, age group, province, parents' highest educational level) along with information about students' educational background (e.g. major, academic year of study). In order to assess students' background and performance in high school mathematics, students were asked to report what type of mathematics course they completed in the last year of the high school (i.e. core or advanced course) along with the grade they achieved in the mathematics course at the matriculation exams (if they remembered it). Then, in seeking to gauge any students' background and performance in mathematics courses at university, the students were asked to report the number of mathematics courses they have completed and the grades they obtained in these courses. The demographic and educational information was requested with the aim to obtain a representation and description of the sample and draw the demographic and educational profile of the participants of the study as well as to perform some analyses and comparisons among the different groups of students.

The second part was devoted to generating data through Likert-type items and constituted the main part of the questionnaire. Likert-type scales, originally devised by Likert (1932), are widely used in educational survey research designs. In the current study, the participants had to indicate the level of their agreement or disagreement with the statements on a 5-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). A neutral or undecided point that is a 'neither agree nor disagree' option was added, in order not to force the participants to lead to one side or the other (Johnson and Christensen, 2004). Also, in an attempt to minimise response acquiescence or agreement bias (i.e. the tendency of respondents to agree with the statements), some items were negatively stated (DeVellis, 2003). Some shortcomings of administrating questionnaires in a Likert-type format are presented in §7.2. An open-ended question was also included requesting students' comments that they would like to share about statistics and the statistics course they were currently attended.

Due to the longitudinal nature of the study, a pre-course and a post-course version of the questionnaire were prepared and administered to the participants of the research study. The purpose of this action was the questionnaire to be more relevant to the extent of exposure and engagement that students had with statistics over the duration of a statistics course. There were some minor modifications and wording (or phrasing) differences in the two versions taking into account the different times of administration. For example, the pre-test questionnaire items included phrases such as 'I plan to' or 'I will', whereas the post-test questionnaire items included phrases such as 'I did'. In addition, some topics were not included in both versions of the questionnaire, for example, the students' preferences of the assessment methods, which were requested only in the pre-course administration.

The questionnaire was initially written in the English language for the purposes of discussing with my supervisors and reporting in the transfer and final document. Then, it was translated by the researcher in the Greek language with the help of a native English teacher. Finally, it was administered to the students in the Greek language. The rationale behind this action was to facilitate participants' understanding of questionnaire questions and avoid misconceptions due to language issues. Greek is regarded as the participants' first language and it is the language of instruction in public (national) universities and in some courses in private universities. For this reason, only Greek-speaking students participated in the current research study. The English translation of the pre-course version is provided in Appendix A2; the original questionnaire versions in Greek are available upon request. Example items of the second part of the questionnaire are presented in Table 3.1. Based on the content, the items were classified into topic areas (domains).

Table 3.1 Example pre-course questionnaire items

TOPIC AREA (DOMAIN)	EXAMPLE QUESTIONNAIRE ITEM	NUMBER OF ITEMS
LIKING	I like statistics as a discipline.	3
NATURE OF STATISTICS	Statistics involves a lot of mathematics	5
DIFFICULTY	I find it difficult to understand many of the statistical concepts.	4
VALUE	Statistics is a useful subject.	6
INTEREST	Statistics is an interesting subject.	3
ANXIETY	Statistics course makes me feel anxious.	6
SELF-EFFICACY	I believe that I have the abilities to perform well in this statistics course.	7
MOTIVATIONS AND ACHIEVEMENT GOALS	I want to get a goof grade in the statistics course in order to maintain or improve my current academic grade average.	5
EXPECTATIONS OF PERFORMANCE	I expect that I will perform well in this statistics course.	2
CONTROL OVER PERFOMANCE	The performance in the statistics course would be determined by my effort and amount of studying.	2
EFFORT	I plan to do my best in this statistics course	3
LEARNING STRATEGIES	I take well-organised notes in this statistics course.	3
RESILIENCE	If I get stuck on completing a statistical task or exercise on my first try, I will quit.	7
TECHNOLOGY	The use of technology (e.g. statistical software programs) in the class would make the learning of statistics more enjoyable.	3
PREFFERED METHODS OF ASSESSMENT	I prefer mid-term and final examinations as methods of assessment in the statistics course.	3
MATHEMATICS	Mathematics is one of my favourite subjects.	8

3.7.2 Design and development of the Interview Plan

As was previously stated in §0, the interviews were intended to be semi-structured in nature (Newton, 2010). Thus, an interview plan guided the interviews, which were conducted with the students. The qualitative data-gathering instrument (i.e. the sample interview plan) was

devised after a thorough review of the theoretical and empirical investigations related to this area of research. For each major topic area and domain under consideration, a set of main (or guiding) interview questions accompanied by supplementary (and more detailed) questions to be asked were generated and prepared in advanced. Some flexibility and potential alterations in the questions (mainly in the supplementary ones) were allowed owing to the semi-structured nature of the interviews. Semi-structured interviews allowed greater scope for probing or follow-up questions to be asked in real time during the interview. In other words, a conversation was developed with each student to seek elaboration and clarification about his or her responses and reflections. Moreover, to account for the variations exist among universities (and among classes) such as instructional and evaluation methods, classroom settings, students' educational background and level, some modifications and adjustments were done in each student's (or group of students) interview sample plan. The interview questions corresponded with specific questionnaire questions (items) since the interviews served as source of qualitative evidence to inform, explain and compliment the data obtained from the questionnaires. The interview questions to be asked were also based on the individual students' responses to the questionnaire (s). This means that the participants' answers to the questionnaire (s) drove and guided - to a great extent - the interview process (for example, the nature and the order of the questions, the emphasis and the depth given on each topic). Also, depending on the time during the semester that each interview took place, some modifications in the questions were made bearing in mind the extent of experience and engagement with the statistics course that students might had. Thus, a general interview plan (i.e. protocol) for the interviews was prepared along with one individual interview plan for each participant. It should be mentioned that, as I was a junior researcher with no previous experience of designing interview plans or conducting interview , during the qualitative data collection process, I was reviewing and refining, when necessary, the interview questions based on my ongoing reflections and experiences. The English translation of a sample interview plan is provided in Appendix A3. Example questions are provided in
Table 3.2.

Table 3.2 Example questions from the interview plan

TOPIC AREA	MAIN QUESTIONS
FEELINGS, ATTITUDES AND BELIEFS	• Overall, can you say that you have positive or negative attitudes towards statistics? • What are the reasons behind your current attitudes towards statistics?
INTEREST	• Overall, do you enjoy this statistics course?
USEFULNESS, WORTH AND RELEVANCE	• How useful do you think is statistics for your personal, academic and future life?
PERCEIVED DIFFUCULTY	• Overall, do you find this statistics course difficult or easy?
ANXIETY	• Overall, how would you characterise yourself with regards to anxiety feelings related to the statistics course that you are enrolled in?
SELF-EFFICACY	• Overall, how would you describe your levels of confidence regarding this statistics course?

STATISTICS VERSUS MATHEMATICS	• What are your perceptions about the nature of statistics as a discipline/subject? • Do you believe that statistics is the same thing with mathematics?
PRIOR MATHEMATICS/ STATISTICS BACKROUND, AND EXPERIENCES, ATTITUDES, ANXIETY AND SELF-EFFICACY REGARDING MATHEMATICS	• What are your prior mathematics/ statistics background and performance? • Can you recall any learning experiences with maths and statistics that you want to share with me? • Did any prior maths and/or statistics experiences play some role in your attitudes, levels of self-confidence and anxiety towards statistics?
MOTIVATIONS AND ACHIEVEMENT GOALS	• What factors do they motive you to study and learn statistics? • What are your achievement goals in this statistics course?
EXPECTATIONS OF PERFORMANCE	• What are your expectations of performance in this statistics course?
CONTROL BELIEFS	• Do you believe that you have the control over your learning and your performance in statistics?
EFFORT	• Do you think that you put a satisfactory amount of effort when you are studying and learning statistics?
LEARNING STRATEGIES AND APPROACHES	• What learning strategies and approaches do you most frequently use when you are studying for this statistics course?
RELATIONSHIP BETWEEN SEVERAL FACTORS AND PERFORMANCE	• What factors do you believe that may affect your performance in this statistics course?
RESILIENCE	• Do you believe that you can deal effectively with higher education challenges, pressures and stressful situations? • Have you experienced any difficulties and setbacks during this statistics course? How did you cope with them?
RECCOMENDATIONS /SUGGESTIONS	• Do you have any general recommendations for improving a statistics educational experience?
EXPERIENCES RELATED TO THE STATISTICS COURSE	• Are there any particular experiences (positive or negative) that you had in this statistics course and you want to share with me?
OPINIONS ABOUT THE STATISTICS COURSE	• What are your opinions of the statistics course that you are currently attending?

3.8 Summary of ethical consideration issues

In this section, a brief description and summary of the consideration of the main ethical issues that arose in this research study are provided. First of all, before the commencement of the data collection procedures for the pilot and the main study, an application to obtain ethical approval to conduct was sought. The research study was approved by the Faculty Research Ethics Committee of the University of Leeds.

Prior to the data collection, I made personal visits to each university I was interested in gathering information. I had personal contact and conversation with many pertinent people (from both administrative and academic cohorts) to obtain their permission. I also had online and personal contact with the instructors of each statistics class and I requested their cooperation and permission to enter their class.

In seeking to obtain informed consent from the research participants, an information sheet and a written consent form which accompanied the questionnaire was handed out to the students (both are available upon request). The information sheet included a concise description of the nature, purposes and importance of the study along with the rights and the responsibilities (obligations) that the researcher and the participants have. Brief ethical details associated with students' involvement in the research study and the subsequent usage and storage of the data were also stated. The participants were informed that they would not be directly benefitted from the study. However, the findings and conclusions of the study would be provided and disseminated to all the interested participants on request.

During the quantitative data collection, each participant received a survey package, which included the information sheet, the written informed consent and the questionnaire. After the completion of the questionnaire, the participants had to return the signed informed consent and placed the completed questionnaire into a collection box (and not directly to the researcher) ensuring anonymity. The participants were advised to identify themselves only by their university ID number and not mention their names (or any other personal information that was not requested) anywhere on the questionnaire. They were notified that by ticking the informed consent form and by giving their ID numbers, they gave their permission to obtain their performance grades for the statistics instructor. Students' self-reported ID numbers were used to match their responses to the questionnaire in both questionnaire administrations as well as with their final statistics course. Once the responses to both questionnaires and students' grades were matched and validated, the ID numbers were eliminated from the dataset to establish further the confidentiality of the student data.

At the end of the written consent form, there was a question asking the students to indicate if they were willing to participate in a future face-to-face interview with the researcher. The participants were instructed that if they wanted to take part in the interview sessions, they had to provide some personal contact information such as their email address or their telephone number. This information was requested to approach the students later on and arrange the details of the interview sessions (e.g. location, date). However, it was emphasised that it would only be used for the purposes of the research study. The students who consented to be interviewed were informed that even though anonymity to the researcher could not be achieved, indicator numbers would be used to replace their names for analysing and reporting the results. Also, they were assured that they would not be identifiable through future reports and presentations of the data. Any words and phrases used by interviewees that could threaten the confidentiality of the interview data were modified or removed from the reporting of the results to maintain confidentiality. Moreover, for purposes of presenting the results, the name of the universities and the instructors taught the courses were replaced by indicator numbers.

3.9 Description of the Pilot Study

A pilot study, which was conducted prior to the commencing of the main study, was executed as a part of my doctoral training and developmental process. It is often considered as a useful and informative preliminary study before the execution of the main and final investigation (van Teijlingen and Hundley, 2001; Breakwell *et al.,* 2006).

As recommended by many researchers (e.g. Breakwell *et al.*, 2006; Gall *et al.*, 2007; Arthur *et al.*, 2012), the pilot study was carried out using students coming from the same target population from which the sample of the main study would be taken. However, the same students should not be used as this might bias their responses and subsequently the results of the main study (Zailinawati *et al.*, 2006). Unlike the main study that was executed in two time periods (at the beginning and at the end of the semester), the pilot study was executed in one time period and specifically in the middle weeks of the 2015 spring academic semester. I collected information from two universities operate in Cyprus; one public and one private. I administered the questionnaires to six statistics classes taught by three different instructors. The data collection process commenced with the distribution of the self-reported questionnaire followed by the execution of individual face-to-face interviews with the consented students.

The implementation of the pilot study helped to address and identify any potential barriers and difficulties that might arise throughout the execution of real-wold study and might be unnoticeable in the phase of theoretical planning of the study. Among the merits of conducting a pilot study were to: (a) gain experience of collecting, handling and organizing real-world data (since it was the first time of doing a fieldwork), (b) get a first insight into the strengths and weaknesses of the research design and methodology, and the statistical and qualitative analysis plan, (c) test the data collection processes (e.g. the location of the study, the ease of the instruments' administration), (d) check the response rate and the willingness of the students to participate in the quantitative and qualitative data collection processes, (e) pre-test the particular research instruments (the questionnaire and the interview plan), (f) receive feedback, comments or even suggestions and recommendations from the recruited cohort of students.

In more details, pilot study aided in checking the survey instruments (e.g. the questions, the questionnaire administration time). For example, the time the students needed to fill out the questionnaire or the time that they were willing to devote to participate in the study was checked. At the end of the questionnaire, the students were requested in an open question to provide any comments they have about the questionnaire (e.g. content, structure). Also, during the interviews the students were asked to provide any comments that they had for the research study (e.g. the questionnaire and interview questions). The feedback that I received were incorporated into the revised research instruments and helped to improve their overall content and structure (e.g. clarity and wording of the questionnaire statements). Pilot study provided experience to data collection, sample recruitment strategies, data management, organisation, analysis and representation of them. For instance, a preliminary statistical preparation and analysis of the collected data was carried out. This included among others the data entry, the coding of the responses, the treatment of the missing data, the practice of the statistical software, the testing about the appropriateness of statistical tests and the interpretation of the output from the statistical analysis. The items included in the final version of the questionnaire were based on the preliminary analysis of the pilot data.

3.10 Description of the Main Study

In the following subsection, the data collection procedures of the main study are described. The timeline of the data collection extended two academic semesters; the fall academic semester 2015, and specifically, the time period spanned from September 2015 to December 2015 and the spring academic semester 2016, the time period spanned from January 2016 to May 2016. The sample was taken across six recognised universities (two public universities and four private universities) and from 34 statistics classes (with 15 different instructors) offered at university-level in Cyprus. Quantitative data was collected from undergraduate students who were currently enrolled in a statistics course, they were present at the class on the days of the distribution of questionnaire and they were willing to complete it voluntarily. Some information about the courses/classes that I entered and collected data during the fall and the spring semester, including the type and the indicator of the universities' name, the name of the course/class, the indicator number of the instructor who taught each particular class, the programmes of study of the participants, the number of the collected questionnaires (in each administration) and the number of the interviews conducted from each statistics class is presented in Appendix A4.

The data collection was conducted in three stages in each semester. The first stage consisted of the administration of the self-reported questionnaires to the students in each statistics class. More specifically, the quantitative data collection process was executed in two (different) time periods: near the beginning and near the end of the instruction of these statistics classes. In the first period, the pre-course version of the questionnaire was administrated during the third or the fourth week after the beginning of the academic semester. The participants had already been informed about the course content and structure, the teaching and the assessment methods, but they had not experienced and obtained a clear picture of the statistics class environment and the subject material yet. In the second period, the post-course version of the questionnaire was distributed to two weeks before the end of the academic semester. It was anticipated that the students, by this time, had sufficient exposure to the statistics course content and instruction, and they had undertaken at least one examination or another form of assessment in the statistics course. The second stage comprised the execution of the face-to-face interviews with students who filled out at least one version of the questionnaire and who consented to be interviewed. The third stage contained the elicitation of participants' overall statistics performance, which was summarised by the final grade obtained in the statistics course. This final grade was subsequently used in the statistical analyses procedures as a measure and an indicator of the students' statistics achievement. This information was requested from the instructor of each class. However, there were instructors who, although they allowed me to administer the questionnaires to the students in their classes and despite the students' consent of having access to their grades (by writing their ID numbers), did not provide me the students' final grades in the respective statistics class. Thus, I had records about students' grades as provided by the consenting instructors.

For the first stage of the data collection, I made personal visits to the universities and I distributed the questionnaires to the participants of the study. The questionnaires were administered in classroom settings before, during (e.g. class break) or after the lecture classes. They were administered in paper-and-pencil form to the students who were present on the specific day of the administration and who consented to participate. A paper-and-pencil format was employed rather than other types of collection, such as online questionnaire since I could not obtain the permission from the pertinent authority to send the questionnaires to the students' university emails. However, as it was anticipated, the distribution of the questionnaires in classroom settings resulted in an adequate number of students who volunteered to take part in the study.

In general, in the most statistics classes, the questionnaire was completed by all the students who attended the lecture class on the day of the questionnaire distribution. However, in a few classes, some of the students did not want to participate in either stage of the study. So, it was a matter conjecture whether the students that were present at the class and/or were willing to participate differed from the absentees (or non-willing students) concerning their opinions and perceptions about statistics. Regarding this issue, some instructors said that they could not provide me with any information (such as demographics or the statistics course grades) about students who did not give their consent to participate in the study.

Before the administration of the questionnaires to the participants, the statistics instructor introduced me to the students. During the initial contact with the instructors, I requested from them to leave the room during the questionnaire distribution. The reason behind this request was that I wanted to make clear to the students that their instructor did not have any engagement with the research study and that he/she was not going to have access to their questionnaire(s) responses. However, this did not happen in all the classes, since in some classes the instructors were present during the data collection and in some others were not.

Prior to the administration of the questionnaires, information, directions and instructions for completing the questionnaire were given both verbally and written to the students. Any explanations and clarifications about the questions (e.g. wording) were provided to the students by the researcher upon request. The participants were requested to complete the questionnaire as completely as possible. They had the potential to answer the questionnaire at their own pace but within the time constraints. Although formal time constraints were not put to the students for completing the questionnaire, some other reasons (such as being in a hurry, having to attend another class or continuing the statistics lecture class) might burden students when completing the questionnaire.

The second stage of the data collection, that is the qualitative component of the research study, involved the execution of interviews with students who had completed at least one version of the questionnaire and who were willing to give me a face-to-face interview. The interviews were scheduled after the participants had undertaken at least one test in statistics. The location, the date and the time were agreed between the researcher and the participant by giving priority to the participants. They took place at on-campus places or convenient places that were chosen by the participants. The desire was to minimise the disturbance and the inconvenience of the participants. The interviews varied in length from approximately 25 minutes to 77 minutes. Two ways were used to record the interviews; an audio device and my personal smartphone. Some written notes were also taken to support the audio recordings. All the interviews were conducted in the participants' native language (Greek).

Even though one-to-one interviews were initially intended to carry out, four students expressed the desire to be interviewed with one classmate (friend of theirs). Thus, two pair interviews were conducted. This kind of interviews revealed vibrant interactions among the students and stimulated the discussion and the exchange of ideas. In some cases, students expressed similar or contrasting opinions related to an issue discussed.

Some auxiliary forms of data collection, including a field diary, course outline (syllabus), instructors' lecture notes and students' notes, personal classroom observation notes and documentary materials were also gathered. Particularly, I attended and observed one to three lectures (or tutorial) classes of all the statistics classes that I had entered and collected data. The aim was to get a general idea of the classroom environment settings and the physical locations in which the courses were taking place, the subject material that was taught the specific days, the instructional methods, tools and materials used, the classroom environment, the interactions between instructors and students and among students and so on. Even though the initial desire was to include some of this information in the thesis document as supporting evidence, due to the already large amount of information that was compiled, these materials are not formally presented. However, they were used and consulted during the analysis and reporting processes to interpret and explain the questionnaire and interview findings and to informally further triangulate them.

At this point, I (re)state some challenges, concerns and issues that were raised and experienced during the data collection procedures. Challenges faced were -among others- gaining access to the statistics classes; obtaining the final grades from instructors; organising the dates and times of the distribution of the questionnaires which sometimes they clashed; arranging the dates and times of the interviews with the students; and talking with students during the interviews about issues that they were not conformable about them or raising up sensitive issues (such as learning difficulties).

3.11 Data Analysis Procedures

This section provides an overview of the approaches to statistical and qualitative analyses that were applied to investigate the data that had been collected from both the quantitative and qualitative data-gathering processes. The data analysis strategies revolved around the research objectives and questions and were informed by the literature review and similar empirical investigations. The analysis of the data was an ongoing and recursive process that commenced at the beginning of the data collection and continued throughout the data collection, analyses and writing procedures. As the data drove the research procedures, the data analysis approaches were reconsidered, revised and adjusted to better meet the research goals. There was an attempt to select suitable approaches to analyse the data and the best ways of presenting the results. A table, which contains the quantitative and qualitative approaches that were employed to address the research questions and sub-questions of this study, is presented (see Table 3.3). It should be noted that not all the statistical analyses that were performed are reported here due to the space restrictions of a thesis document.

Table 3.3 Research questions and sub-questions along with qualitative and quantitative approaches

RESEARCH QUESTION/ SUB-QUESTION	QUANTITATIVE APPROACH	QUALITATIVE APPROACH
Research Question 1		
Research Sub-Question 1.1	Descriptive statistics and paired t-tests	Interviews
Research Sub-Question 1.2	Descriptive statistics and paired t-tests	Interviews
Research Sub-Question 1.3	Descriptive statistics and paired t-tests	Interviews
Research Question 2		
Research Sub-Question 2.1	Descriptive statistics and paired t-tests	Interviews, Interpretation
Research Sub-Question 2.2	Correlations, Regression Analysis, Structural Equation Modelling	Interviews
Research Question 3		
Research Sub-Question 3.1	Descriptive statistics	Interviews
Research Sub-Question 3.2	Correlations	Interviews
Research Sub-Question 3.3	Correlations, Regression Analysis, General Linear Models	Interviews
Research Sub-Question 3.4	Factor Analysis, Structural Equation Modelling	-
Research Question 4		
Research Sub-Question 4.1	Descriptive statistics	Interviews
Research Sub-Question 4.2	Descriptive statistics, correlations, ANOVAs	Interviews
Research Question 5	t-tests, ANOVAs	Interpretation, Interviews
Research Question 6	-	Interviews

3.11.1 Quantitative Data Analysis methods

The following subsection moves on to provide a description and a summary of the core statistical analysis methods employed in this research study. After the quantitative data from the students (i.e. questionnaire responses) and the instructors (i.e. students' statistics course grades) were collected, the analysis of the quantitative information commenced. A variety of statistical methods and techniques were utilised with the ultimate aim to answer the research foci and questions and draw conclusions. Computer office programs such as Excel and statistical software packages, such as SPSS (Version 23) and AMOS 23.0 (Arbuckle, 2014) were used to handle and organise the data gathered and to facilitate the implementation of statistical tests and methods. A logical sequence in the statistical analysis process was performed by firstly employed less complex statistical techniques (such as descriptive statistics, Pearson's correlation coefficients, t-tests, analyses of variance, regression analysis and general linear model analysis) followed by more advanced methods (such as factor analysis and structural equation modelling techniques). The level for statistical significance is set at a p-value of 0.05 or less (for all the statistical tests) and the reported p-values are two-sided. No adjustment (correction) for multiple testing (e.g. Bonferroni) was applied.

Along with the statistical significance of the results (i.e. p-values), the substantive and practical significance (i.e. the strength of the effect sizes) are reported. The effect size is an objective and (usually) standardised measure of the size of an effect (Field, 2013). As Sullivan and Feinn (2012) proposes, the reporting of p-value is not enough since they can inform the reader whether an effect exists, however it does not show the size of this effect, so it should be supplemented by the reporting of the effect size. For the purposes of interpretation, based on benchmarks for the social sciences as proposed by Cohen (1988) and Field (2013), effect sizes are considered as small ($r=0.1$, $d=0.2$), medium or moderate ($r=0.3$, $d=0.5$) and large ($r=0.5$, $d=0.8$) where r is the correlation coefficient effect size based on 'variance explained' and d is the Cohen's d effect size based on differences between means.

It should be noted that the variables/constructs which were included in some statistical analyses (e.g. correlation and regression analyses) were allocated to four groups: the first group included variables pertaining to the students' demographic and educational background; the second group contained variables related to students' previous mathematics background and performance; the third group included the seven main variables of interest (namely liking, interest, value, difficulty, anxiety, self-efficacy and resilience) and the fourth group consisted of variables associated with motivational and cognitive engagement. Specifically, the third group of variables was chosen as the main variables/constructs of interest tailored according to the goals of this study and the interests of the researcher and were subjected to further analyses (e.g. factor analyses and structural equation modelling). The abbreviated names of selected variables and statistical abbreviations, which are more frequently used in Quantitative Results chapter, are provided in Appendix A5.

3.11.1.1 Pooling across Semesters

In the beginning, four data files (one data file for each semester and each questionnaire administration) were created in SPSS. Differences between semesters (Fall Semester 2015 and Spring Semester 2016) were examined using multivariate analysis of variance (one-way MANOVA) on the seven main variables (subscales) of interest. A significant, but with a (very) small effect size, difference in students' responses based on the semester that they completed the questionnaire was detected only in the pre-course data. Thus, in order to facilitate the data organisation and presentation of the findings, it was decided to pool together the data from two semesters and carry out the analyses in two datasets – the pre-course and post-course datasets. The pre-course dataset contains the participants' responses to the pre-course version of the questionnaire and the post-course dataset includes the responses to the post-course version of the questionnaire.

3.11.1.2 Student grade determination

The students' final grade obtained in the statistics course was used as a measure (i.e. indicator) of their overall performance and it was chosen to be the dependent (outcome) variable in the relevant analyses. The grading systems in public and private universities are slightly different. More specifically, the grading system in public universities is numerical and ranges from 0 to 10, with increments of 0.5. In private universities, both numerical grades (ranging from 0 to 100) and letter grades are assigned to the students at the end of the course. For this research study, I obtained three different types of final grades data from the statistics' instructors: (a) numeric grades ranging from 0 to 10; (b) numeric grades ranging from 0 to 100; (c) letter grades (e.g. A+, B+, B). In order to make the final grade data scaling comparable across the courses/classes for the purposes of analyses, all the grades were converted on the continuous scale 0 to 100. A new supplementary (ordinal) variable was also created which took into account the classification of grades. This variable consisted of five categories namely 0-49 (fail); 50-64 (good), 65-74 (satisfactory); 75-84 (very good); and 85-100(excellent).

Then, with the aim to account for potential heterogeneity or differences across universities, courses and instructors (such as differences in the instructional approaches, the structure of examination and grading), a new variable was created. This variable contained the numerical grades that were standardised within each course (taught by the same statistics instructor) to have mean equal to zero and variance equal to one. Preliminary analyses (such as correlation and regression analyses) were conducted using the new standardised final grade variable. Similar conclusions were obtained as with the raw final grades. Thus, it was decided to use the raw final grades obtained in the statistics course (as the dependent variable) in all the subsequent analyses.

3.11.1.3 Data screening procedures and exploratory analyses

The entry and the coding of the quantitative (questionnaire) - based data were conducted using EXCEL and SPSS programs. Before carrying out any statistical methods, exploratory data analyses through data screening, data visualisation (using graphical representations) and numerical and statistical tests were performed (Tukey, 1977; Cohen *et al.*, 2007). The aim was to gain a first insight into the characteristics and patterns of the data collected. Moreover, the objective of the preparatory or preliminary analyses was to explore the assumptions and the prerequisites of the intended statistical methods. Following Kline (2005) and Warner (2008), prior to conducting multivariate analyses, the datasets need to be investigated concerning (parametric) assumptions of normality; linearity; homoscedasticity (homogeneity of variances); and multicollinearity.

To start with, the amount and the distribution of the missing values were examined. Missing data are “an almost inevitable part of research on people, whether it is medical, educational, or social” (Bland, 2015, p. 305). The pattern (reason) of missing data is more crucial than the amount of missing data since missing values, which are non-randomly missing might have an effect on the generalisability and bias of the results (Haworth, 1996; Tabachnick and Fidell, 2013). An inspection of univariate and multivariate outliers was also carried out. An outlier can be considered as a data point or an observation whose value seems to be quite different from the rest of the sample in the particular data set (Hair *et al.*; 2006; Boslaugh, 2012). These scores might have a much higher impact on the results of the analysis than the others (Schmidt and Hunter, 2003). Multivariate outliers, which are cases with an unusual combination of scores on two or more variables (Schinka *et al*., 2013) were identified with the use of Mahalanobis distance. Mahalanobis distance is a measure of the distance in the multidimensional space of each observation from the mean centre of multidimensional centrality (Hair *et al*., 2006).

In social sciences research and particularly when dealing with real datasets, normality assumptions are rarely met (Erceg-Hurn and Mirosevich, 2008). Screening and testing data for non-normality prior any further statistical procedures performed is a crucial step. As many authors advocate (e.g. Nasser, 2004; Tabachnick and Fidell, 2013), a substantial departure from normality can distort the statistical analyses results, especially of multivariate analyses. For these reasons, the assessment of univariate (and then multivariate) normality was carried out on the variables (subscales) included in the subsequent -more complex - statistical analyses. Several methods and criteria were employed in the present study. These included, among others, visual examinations of the distributions' shape and inspections of graphs such as probability plots, Q-Q plots, box plots, frequency distributions (histograms) with a normal distribution overlay as well as formal inferential tests of normality, such as Kolmogorov-Smirnoff (KS) and Shapiro-Wilk tests. Measures of the shape of the distributions such as skewness and kurtosis values were also examined. Since several methods, including the SEM approach, require the data to fulfil the assumption of following a multivariate normal distribution (Kline, 2015), the data were then explored for substantial departures from multivariate normality. The maximum likelihood (which is the default estimation method in AMOS) is based on the assumption that the data follow a multivariate normal distribution. Mardia's (1970) was therefore consulted. Moreover, following many authors (e.g. Kline, 2005; Walker, 2008; Tabachnick and Fidell, 2013), homoscedasticity of variance assumptions and the linearity between variables were inspected using graphical representations (e.g. scatter plots). Furthermore, in order to examine for potential multicollinearity, a set of bivariate correlations were run between the variables under investigation. Multicollinearity occurs when the independent variables in the model are found to be highly correlated with each other (Tabachnick and Fidell, 2013). This might suggest that the two variables are (actually) measures of the same underlying construct (Warner, 2008). Finally, the issues of reliability and validity are pinpointed in §3.12 and are addressed in the Quantitative Results chapter (see Chapter 4).

3.11.1.4 Descriptive statistics

Descriptive and inferential statistics were employed. Univariate, bivariate and multivariate analyses were performed. The categorical data were summarised and presented using graphical representations (e.g. bar charts) and tabulations (i.e. frequency and percentage tables). The continuous data were analysed using cross-tabulations, visual and graphical methods (e.g. box plots) and statistical tests. More specifically, descriptive statistics (e.g. frequencies) were requested to describe demographic characteristics of the participants and provide general patterns and trends of given responses. Some items were reverse coded to align with the interpretation of higher scores as more favourable towards the particular statement. The questionnaire item-level descriptive statistics such as measures of central tendency (e.g. median) were calculated and reported. Selected subscales related to the seven main constructs (e.g. liking, interest, value, difficulty, anxiety, self-efficacy and resilience) were also developed. These were produced by summing the respective item scores of each subscale and then dividing by the total number of items that form the subscale. The final scores ranged from 1 (non-favourable perception) to 5 (favourable perception). Mean and standard deviation along with further information about the shape and properties of the distribution of scores (such as skewness and kurtosis values) were investigated and reported. For the remaining variables, descriptive statistics of a composite measure (e.g. subscale) were not provided. A mean score was calculated and used for the purposes of further analyses (e.g. correlation analyses).

3.11.1.5 Paired t-tests

The mean scores of selected subscales were investigated for potential changes in students' responses between the beginning and the end of their attendance in a statistics course using paired t-tests. Following Schau (2012) and Beemer (2013), when examining pre-course and post-course score differences, only the students who completed both versions of the questionnaire were compared with each other. The students included in the analysis were those I had matched their ID numbers given in the pre- and post-course administration.

3.11.1.6 Correlation analyses

Correlation analyses were conducted to address the research objectives concerning the association (i.e. shared variance) between two constructs (variables) under investigation. More specifically, the correlation analyses were carried out to examine the linear relationships between pairs of variables and to measure the strength and the direction of these relationships. Nevertheless, no inference about the causality of the variables (causal relationships) that is which variable causes the other to change can be made from the correlation coefficients (Field, 2009). The inter-correlation coefficients (Pearson product-moment correlations) were computed for the continuous variables. The chi-squared test was used to determine whether there was an association (or relationship) between two categorical variables. A point–biserial correlation, which is considered as a special case and is calculated as for Pearson's product-moment correlation, between one dichotomous and one continuous variable were also computed when appropriate. In the current study, in order to describe and interpret the strength of the correlation between the variables, the following criterion (recommended by Evans, 1996) was used for the absolute value of the coefficient: (a) 0.00-0.19 very weak; (b) 0.20-0.39 weak; (c) 0.40-0.59 moderate; (d) 0.60-0.79 strong; (e) 0.80-1.0 very strong. According to Hair *et al.* (2006), the higher the correlation coefficient, the stronger the relationship between the variables and hence the greater the predictive accuracy of the independent/predictor variables. Thus, in order to ensure the accuracy of regression analysis methods, a correlation analysis was (usually) performed first. The square of the correlation coefficient (also known as the coefficient of determination) was also used as a measure of how much of the variability in one variable is shared by the other variable (Field, 2009).

3.11.1.7 Independent sample t-tests and Analyses of variance (ANOVAs)

Independent samples t-tests and one-way analyses of variance were employed to investigate whether there were differences in the mean scores of a number of variables based on various groups that the data were assigned to. Some of the demographic and educational information requested were treated as categorical variables; thus, the relationship between these variables and the subscales of the questionnaire were investigated by employing t-tests and ANOVAs. When comparing binary variables (variables that consisted of two groups), t-tests were used. For variables having more than two categories, ANOVAs were performed. When significant effects were revealed (p-values ≤ 0.05), post hoc comparisons were requested using Tukey's method. In addition to the statistical significance of each test, the effect sizes were calculated and reported to help assess the strength and the precision of the differences. More specifically, for the t-tests, the Cohen's d effect size is calculated and for the ANOVAs, the reported effect size measure was based on group mean information (Cohen's f (1988), where 0.1 is considered as small, 0.25 as medium and 0.4 as large effect size). It should be noted that one practical issue in one-way ANOVA is that the number of cases within each subcategory of the variable needed to be somewhat similar since very unequal sample sizes can affect the homogeneity of variance assumption (Grace-Martin, 2013). In order to accommodate for this issue, following Warner (2008), the assumption of the homogeneity of variance was evaluated by the Levene's test for equality of variance. As a rule of thumb, when significance value was greater than 0.05, the assumption of equal variances held. In the case where the significance value was less than 0.05, the Welch's test or unequal variances t-tests (Welch, 1947), which is considered as a more robust test of equality of means, was used and reported. In other words, a t-test or a classic ANOVA was performed whenever it was just an unequal sample size issue and a Welch's test if it was additionally an unequal variance issue.

3.11.1.8 Linear Regressions and General Linear Models

With the aim to ascertain the contribution and the predictive ability of a number of explanatory variables on the outcome (dependent) variable, simple Linear Regressions (LR) and General Linear Model (GLM) analyses were employed. More specifically, LR and GLM procedures were conducted to explore whether and which factors were significantly associated and contributed to the performance in the statistics course. Also, another aim was to evaluate the proportion of the total amount of variance (how much of the explained variance) accounted for by the independent variables under investigation. When categorical variables were included, GLM (with main effects) approach was used instead of the standard linear regression analysis since it allows a combination of quantitative (continuous) and categorical variables to be included in the specification of the model.

As previously mentioned in this section, the variables under investigation were allocated into groups. For the purposes of LR and GLM analyses, in the pre-course administration, the first group of variables included: five socio-demographic (e.g. gender, age group and parents' higher educational level) and educational-related factors (e.g. academic year of study and first time of attending the course); the second group included four variables, both categorical and quantitative, related to previous mathematics background and performance (e.g. type of mathematics course in high school, mathematics grade in high school matriculation exams, number of mathematics/statistics courses in university, average grade in mathematics/statistics courses in university); the third group included the mean scores of the seven main questionnaire subscales (e.g. liking, interest, value, difficulty, anxiety, self-efficacy and resilience); and the fourth group included two categorical variables and the mean scores of six subscales related to motivational and cognitive variables (e.g. effort, learning strategies, expectations of performance, control over performance, intrinsic motivation and extrinsic motivation). In the post-course administration, the first group of variables included: four socio-demographic (e.g. gender and age group) and educational-related factors (e.g. academic year of study and first time of attending the course); the second group included the mean scores of the seven main subscales; and the third group included three categorical variables and the mean scores of two subscales related to motivational and cognitive variables (e.g. effort and learning strategies).

3.11.1.9 Factor Analyses and Structural Equation Modelling techniques

The next statistical methods applied were Factor Analysis (FA) and Structural Equation Modelling (SEM). Both methods are considered useful tools and strategies to define the structure of the collected data. Particularly, FA can be conducted to validate the questionnaire while SEM can be employed to validate the proposed theoretical model. Factor analysis procedures (Gorsuch, 1983) were utilised to explore and understand the structure of a set of variables and them in terms of their common underlying dimensions (factors). SEM was employed in this study to integrate the investigated variables in a single analysis and assess the relative importance of various direct and indirect links (i.e. significant paths and explained variance) between the variables (DeVaus, 2002; Kline, 2005). SEM is also known as path analysis with the incorporation of latent variables (McDonald and Ho, 2002). It is a widely used statistical causal modelling technique which has been employed by many researchers in this area of inquiry (e.g. Sorge and Schau, 2002; Bandalos *et al.*, 2003; Nasser, 2004; Bude *et al.*, 2007; Tempelaar *et al.*, 2007; Ismail, 2008; Chiesi and Primi, 2010; Emmioğlu, 2011; Mata *et al*., 2012; Escalera-Chávez *et al.*, 2014; Sese, 2015). As previously mentioned in this section, these techniques were employed in selected variables (i.e. questionnaire subscales). It is acknowledged that the selection of variables is a key issue when planning and conducting FA (Warner, 2008). The purpose of doing FA, the explanatory factor analysis (EFA) and confirmatory factor analyses (CFA) procedures along with the procedures for applying SEM techniques are explained in the following parts of this subsection.

<u>Need for and purpose of Factor Analysis (FA)</u>

The questionnaire that was administered to the participants has been designed and constructed for the purposes of this doctoral research study. Hence, it was prudent to examine its psychometric properties. In order to evaluate the construct validity - and specifically, its structural validity - that is the extent to which it evaluates the latent constructs was intended for within the participated sample (Glynn *et al.* 2011), FA procedures were employed. FA is a method, which aid to explore and define the (potential) factor structure that might underlie students' responses to a given set of items (variables) (DeVellis, 2016). Also, it is aimed to discover if this set can be explained by a smaller (i.e. more parsimonious) interpretable and representable number of factors from a large number of variables which is capable of explaining the observed variance in the larger number of variables (Chetty and Datt, 2015). The ultimate aim when employing this method was to reach a factor solution that is believed and is supported to be the most optimal to represent the collected data. To this end, EFA and CFA methods were initially conducted. The factors generated quantitatively were re-visited when analysing and interpreting qualitative data.

<u>Explanatory Factor Analysis (EFA)</u>

Explanatory Factor Analysis (EFA) was first employed to carry out an initial data reduction, examine the interrelationships among items, identify a set of factors underlay the items and investigate whether the factors (constructs) that guided the development and the composition of the questionnaire' items coincided with students' responses and interpretations. According to Thompson (2004, p.10):

> Exploratory factor analysis is for "…exploring the relationships among measured variables and trying to determine whether these relationships can be summarized in a smaller number of latent constructs."

Procedures for applying EFA

The EFA procedures included among others the assessment of the adequacy of the sample for factor analysis (such as the sample size and the matrix of correlation among the items), the methods of extraction of the factors, the methods of the rotation of the factors, the examination of the size and importance of factor loadings, the potential elimination or retention of items and the label and interpretation of the extracted factors. Some methodological considerations and decisions were needed to be taken. The steps followed and the decisions made throughout the process are described further in the Quantitative Results chapter (see Chapter 4). Two separate factor analyses were conducted on the students' responses to the pre-course and post-course versions of the questionnaire to identify and compare the pre-course and post-course factor structure. EFA procedures were carried out using the SPSS software program.

As previously noted, due to the relatively large number of items and the desire to focus on specific constructs, it was decided to explore the factor structure of selected items of the questionnaire. The items that were subjected to FA were hypothesized to assess students' liking of statistics; interest and enjoyment of statistics; opinions about the value, applications and relevance of statistics; perceived difficulty of statistics; anxiety related to statistics; perceived abilities (self-efficacy) regarding statistics; and resilient behaviours applied to statistics. The remaining questionnaire items were omitted for the current FA procedures and may be included in future research investigations.

The most crucial (and critical) decision to be taken in EFA is considered as the determination of the optimal number of factors (Hayton *et al.*, 2004) to retain for subsequent statistical analyses. Regarding the factor extraction, three different methods of extraction, namely Principal Component Analysis (PCA), Principal Axis Factoring (PAF) and Maximum Likelihood (ML), were performed. Because each of these methods has its own advantages and disadvantages, the intention was to explore and verify whether they produced similar (comparable) results.

To determine the most appropriate number of factors (components) which underlie the data collected and best characterise the selected items, several criteria were considered, namely: (a) the criterion of eigenvalue-greater-than-one (Kaiser, 1958); (b) the percentage of variance among items explained by each factor; (c) the Cattell's (1966) scree plot test; (d) the Parallel Analysis test using a Monte Carlo simulation technique (Horn, 1965); (e) the interpretability of the factor solution; and (f) the a-priori hypothesised factor structure (grouping of items) and theory. Regarding the Kaiser's criterion, an inspection of the eigenvalues was carried out. Eigenvalues indicate the proportion of variance accounted by the factors and are used to produce factor loadings (Glynn *et al*., 2007). One drawback of this criterion, as stated by Fabrigar *et al*. (1999), is that usually leads to over factorisation. However, as Pallant (2016) recommends, if the sample size exceeds 250 and the average of the communalities is equal or greater than 0.6, then the Kaiser's criterion of retaining factors with eigenvalues greater than 1 can be consulted. Concerning the second criterion, Pett *et al*. (2003) recommends that the total percentage of variance explained by each factor in order to be retained should be above 5%. Regarding the scree plot criterion, Pett *et al.* (2003), using the Cattell's (1966) criterion, suggests drawing a non-horizontal straight line through the point at which the plotted eigenvalues started to flatten down and select the factors that are above that line. According to Field (2013), with a sample of more than 200 participants, the scree plot provides a fairly reliable criterion for determining the number of factors to retain. However, one shortcoming of this criterion is its subjectivity; that is where to indicate the substantial drop of the eigenvalues and draw the scree line (Kahn, 2006). Many authors (e.g. Horn, 1965; Hayton *et al.*, 2004) argue that PA is probably the most effective and accurate method of determining the appropriate number of factors to retain. The eigenvalues obtained through the EFA using SPSS was compared to the randomly generated eigenvalues based on 100 simulations (the number was requested), the same number of variables and the same number of cases (May, 2009; Palacios *et al.* 2014). The factors with eigenvalues produced by EFA, which were higher than the randomly generated eigenvalues were retained. The justification for this is that "a factor that explains more variance than chance is meaningful" (Khan, 2006, p.692). Lastly, according to Hair *et al.* (2006), in order to determine the most suitable number of factors, empirical evidence and theoretical/conceptual foundations have to be taken into account.

What followed the first selection step was the rotation of the factors that were retained. In order to simplify the factor structure, discriminate between the retained factors and facilitate the interpretation of the original factor structure, two of the main- and the most common- approaches to rotation were employed (Abdi, 2013). These are the orthogonal rotation (and specifically, the varimax rotation) and the oblique rotation (and specifically, the direct oblimin rotation). Orthogonal factor solution assumes that the factors are not highly correlated with each other and thus does not account for any correlation among them, whereas in the oblique rotation the factors allowed to correlate with each other (Brown, 2009). The oblique rotation would result in better estimations of factors because it produces factor loadings based on the assumption that they are related to each other (Fabrigar *et al*., 1999). Factor loading is the relationship between a variable and a factor. The aim was to identify significant loadings for each variable. Following the recommendations of several researchers (e.g. Steve, 1992 as reported by Field, 2009; Hair *et al.*, 2006; Tabachnick and Fidell, 2013), a factor loading with an absolute value greater than 0.4 was selected as a cut-off point to consider it as significant. Moreover, the commonality estimates (h^2), which are the squared multiple correlations of each variable (item) with all others (Field, 2009), are consulted. According to Pallant (2006), items with low communalities values (e.g. less than 0.3) might demonstrate that these items do not fit well with the other items in each factor (component). Items with high communality values imply that they contribute greatly to the model and provide sufficient explanation (Hair *et al*., 2006).

Confirmatory Factor Analysis (CFA)

The responses to the pre-course and post-course version of the questionnaire were subsequently subjected to a CFA to examine further its construct validity within the current data sample. CFA is a special form of factor analysis which was most commonly employed in social science research (Kline, 2005). According to Wigfield and Eccles (2000, p.74):

> Confirmatory factor analysis (CFA) is for "..testing theoretically derived hypotheses about the structure of a set of variables and allowing for the explicit comparison of different alternative models."

Comparison between EFA and CFA

EFA, is a data-driven approach, where statistical methods are used to define the structure of the data; that is to identify which survey instrument items characterise each construct or topic (Cherney and Cooney, 2005), the number of factors and the significant loadings, whereas CFA tests a proposed theoretical model by examining whether the underlying factor structures and the factor-loading pattern fit the actual data sample (Hair *et al.* 2006; Bofah and Hannula, 2015). In contrast to EFA, CFA requires the a priori specification of the underlying latent factor structure; that is to specify which and how many indicator variables (questionnaire items) should assign to which latent factors (constructs).

Procedures for applying CFA

CFA method was employed to evaluate the contribution of each indicator (questionnaire item) to the assigned factors and assess the degree of fit and the adequacy of the hypothesised measurement model(s). Thompson (2004) advises comparing the overall fitting of various alternative models to choose the optimal for the data. Thus, the CFA followed the EFA aiming to compare the factor structures extracted by EFA and select the model which better fits and explains the data of this study (for example, by using model fit indices and theory). Before performing the CFA, an imputation method (i.e. Expectation Maximization) was employed to replace the missing values in the two datasets (see §4.2). CFA analyses were carried out in pre-course and post-course samples using AMOS.

At this point, it should be noted that the CFA was conducted on individual items rather than on parcel items. Many empirical research studies have carried out CFA on item parcels; that is the questionnaire items (variables) within each subscale were grouped into parcels (e.g. Schau *et al*., 1995; Dauphinee *et al*., 1997; Awang-Hashim *et al*., 2002; Hilton *et al*., 2004; Tempelaar *et al*., 2007; Chiesi and Primi, 2008; Stanisavljevic *et al*, 2014). Although the item parcelling technique has merits, as stated in the studies mentioned earlier, its use and the several methods of parcelling remains questionable (Kline, 2005). Thus, I decided to carry out the factor analyses on individual questionnaire items.

The first step when conducting CFA is the model specification. The parameters of the specified model(s) were estimated using the maximum likelihood method. An inspection of the possible elimination of some questionnaire items was conducted. For the investigated model(s), following Kline's (2005, 2011) recommendations, among others, the size and the significance of the item factor loadings, the table of standardised residuals and the suggested modification indices were scrutinised. The factor loading value indicates how well an indicator item measures its corresponding factor. According to Hair *et al.* (2006) and Gefen *et al*. (2000), standardized factor loading estimates should be equal to or greater than 0.7 to achieve good convergent validity. The standardized residuals table was also inspected in both data samples to investigate whether there were any relationships between items which were not well reproduced by the proposed model (Fairchild and Finney, 2006). Suggested cut-off values were standardized residual values greater than 3 (Garson, 2008;

Byrne, 2010). Moreover, the squared multiple correlations, which are also known as R^2 values and represent the amount of variance in each factor explained by the indicator items, were inspected. Small R^2 values (usually less than 0.5) indicate that these particular items might contain large amounts of error (unexplained) variance and might not adequately represent the latent factor (construct) for which they assigned as indicators (Fairchild and Finney, 2006).

Several descriptive measures which assess model fit, model comparison and model parsimony were then consulted (Hair *et al.*, 2006; Chew and Dillon, 2014). Generally, models are considered to have a 'good fit' if the observed data fits the hypothesised/theoretical model(s) well. The overall model fit was assessed by taking into account several Goodness Of Fit (GOF) measures to explore how closely and adequately the several models represented the data and which of the proposed model provided a better fit. Regarding the model fit, a non-significant chi-squared test (χ^2) is usually evidence of a good fit of the model. However, it is believed that a significant chi-square value does not necessarily lead to the conclusion that the model has a poor fit (Glynn *et al*., 2011; Escalera-Chávez, 2014). Many authors (e.g. Hu and Bentler, 1999; Schumacker and Lomax, 2004; Brown, 2006; Hooper *et al*., 2008; Byrne, 2010) argue that chi-square test is very sensitive to multivariate non-normality, sample sizes and complexity of the model (e.g. numerous variables and indicators). In order to compensate for the chi-square limitations, the ration of χ^2 to degrees of freedom (χ^2/df) was also used to compare the relative fit of the proposed models. The rule employed was that as the χ^2/df ratio reduced, the model fit is improved (Hoelter, 1983). The Goodness of Fit Index (GFI) was developed to overcome the shortcomings of the sample-size dependent chi-square value test (Jöreskog and Sörbom 1993). This criterion should be greater than 0.9 to signify a good model fit (Hooper *et al.*, 2008). The Root Mean Square Error of Approximation (RMSEA) which is an absolute fit measure to evaluate the model fit was also considered. The closer the obtained RMSEA value is to 0, the better the fit of the tested measurement model is. The recommended cut-off value of accepting a reasonable model fit is close to 0.5 (Browne and Cudeck, 1993); Brown, 2006). However, Browne and Cudeck (1993) also states that an RMSEA value less than 0.8 also indicates a reasonable fit. The comparative fit of the models was evaluated by examining two incremental fit measures; the Comparative Fit Index (CFI) and the Tucker-Lewis index (TLI). These two measures give the improvement in fit achieved by the proposed model relative to the null model. Values of these indices which are greater than 0.9 are indicators of a good model fit and are deemed as acceptable (Hair *et al.,* 2006; Netemeyer *et al*., 2003; Kline, 2005; Byrne, 2010) and equal to 0.95 are deemed as excellent (Brown, 2006). With regards to the Standardized Root Mean Square Residual (SRMR), Hu and Bentler (1999) recommends a value less 0.09. The model parsimony was assessed using Akaike's Information Criterion (AIC) and the sample size adjusted Bayesian Information Criterion (BIC) where the smallest value information of these indices being indicative of model with a better fit to the data and is preferred over the other tested models (Brown, 2006; Schreiber *et al*., 2006).

Some authors recommend that the incorporation of the error covariances in the specific model might improve the model fit (e.g. Byrne, 2010). To this end, the Modification Indices (MIs) for the covariances were also examined and consulted aiming to achieve a better fit of the sample data. This would be based on the assumption that the specific pairs of items shared common sources of error. Byrne (2010) suggested minimum modifications (i.e. changes in the model post-hoc) regarding allowing covariances among items and these should have theoretical explanations. It is recommended not to covary error terms with latent variables, or with other error terms that are not part of the same factor. The most appropriate modification is to covary error terms that are part of the same factor. However, it is acknowledged the problems of allowing correlated errors (such as that the error covariances to be sample-dependent and not substantial); more details can be found in Hermida (2015). As Vanhoof *et al*. (2011) states, clear guidelines and cut-off point values with regard to which modification indices could be deemed as important are not available. In the current study, it was chosen MIs with a threshold value larger than 40 to be considered as useful information. The strategy followed was to address the highest MIs before addressing the more minor ones. Firstly, a covariance between the error terms with the highest modification index was specified and then it was checked whether the inclusion of this correlation led to a substantial improvement in the model fit. This process was continued until no more MIs were shown up or no more substantial improvement in the model fit was observed. Following Byrne (2010), it was kept in mind that the specification of correlations between the error terms should be meaningful and theoretically sensible. For example, there might be a logical reason for the observed systematic relationships, such as some items were included at the end of the questionnaire, were presented consecutively, were similarly worded or/and had overlapping meaning or content.

Alongside the evaluation of the CFA model, measurement invariance across groups, which is a statistical property of measurement and in the context of CFA is often referred as factorial invariance (Widaman *et al*., 2010), was explored. The aim was to test whether the questionnaire measured the same constructs in the same way across some specified groups a (Lamberti and Banet, 2017). In other words, it was intended to test whether people across the groups conceptualise or interpret the constructs under study in the same way regardless of their group. The first step was to evaluate configural invariance. Configural invariance is a test for invariance of the measurement structure (i.e. item to factor structure) across groups (Putnick and Bornstein, 2016) and explores whether the questionnaire items are associated with the same factors in all groups (De Roover, 2014). Then, metric invariance (i.e. item contribution to latent factor), which tests whether the factor loadings of those questionnaire items are equivalent across groups, was assessed (Horn and McArdle, 1992; Vandenberg and Lance, 2000). In the relevant literature, measurement (factorial) invariance of the STARS instrument and SATS instruments across gender was confirmed by Dauphinee *et al.* (1997) and Teman (2013) respectively.

To assess convergent validity in CFA, the Average Variance Extracted (AVE) for each construct, which is the average percentage of variation explained among a set of items representing a latent construct (Hair *et al.*, 2006), was evaluated. AVE was calculated as the sum of each squared item factor loading divided by the number of items of a factor and should be above 0.5 (Fornell and Larcker, 1981). Discriminant validity through the maximum shared variance (MSV) and the Average Shared Variance (AVS) values which have to be lower than AVE values for the latent constructs (Hair *et al.*, 2006) was also tested. The patterns of the latent factors inter-correlations were also inspected. Moreover, composite reliability (CR) which is a measure of the reliability and internal consistency of a latent construct was investigated (Hair *et al.*, 2006). A value of CR greater than 0.6 (and ideally greater than 0.7) is required.[2]

3.11.1.10 Purpose and Procedures for applying Structural Equation Modelling (SEM) techniques

The last step of the statistical analysis methods was the execution of SEM techniques to understand further the underlying relationships between the constructs of interest and the course performance. The advantage of using SEM techniques laid on their potential to assess the multiple and interrelated dependence relationships simultaneously (Gefen *et al*. 2000; Tavakoli, 2012). Thus, a hypothesised theoretical-conceptual model for prediction performance in a statistics course was proposed. Theoretical considerations, previous findings from empirical studies, results from the EFA and CFA procedures of this study and the researcher's hypotheses and experiences were consulted to set up this model. The aim was to investigate whether the obtained empirical evidence, supported the theoretical story that had been built. Two statistical techniques were combined: the path analysis (structural model) and the factor analysis (measurement model of latent constructs). According to Gefen *et al*. (2000), SEM provides fuller information whether the model is supported by the data instead of using purely standard regression techniques. SEM procedures were carried out using AMOS.

It should be noted that due to the longitudinal nature of this study (see §3.3.2), two separate structural equation models – one for the pre-course data sample and one for the post-course data sample - were designed, developed, tested and revised. The hypothesised structure of the models and the relationships posited were the same regardless of the time of measurement for the purposes of comparison and reporting of the findings.

In order to perform SEM techniques, several books and papers were consulted (e.g. Bentler, 1990; Hoyle, 1995; Hu and Bentler, 1999; Byrne, 2001, 2010; Kline, 2005, 2011; Kaplan, 2000; Diamantopoulos, 2010). Overall, this process involved the conceptualisation, operationalisation, estimation and evaluation of the SEM models. The first steps comprise the model conceptualisation and the model specification. The structural equation model consists of the measurement model and the structural model. The measurement model involves the specification of links between each latent variable (constructs) and its respective indicators (measures) which are considered as manifest (observable) variables. The error terms (residuals) of the indicators of the latent variables (which is the residual of the regressions between the indicator and the latent variable) represent the measurement error.

The structural model involves the specification of the expected relationships (paths) which link the latent variables. The hypothesised path diagram (see Figure 3.1) was derived based

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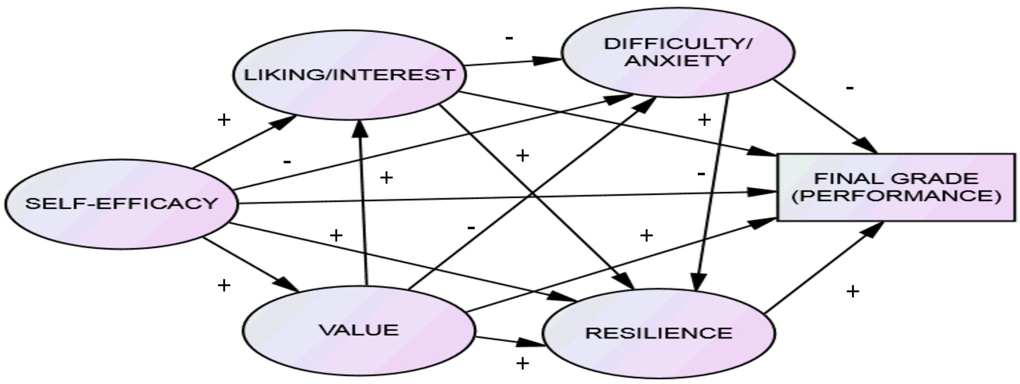
[2] Composite Reliability, which is commonly examined when performing SEM family models, is the measure for internal consistency of reliability that does not assume equal factor loadings for indicators whereas Cronbach Alpha is the measure of internal consistency of reliability that presumes equal indicator loadings and in some cases equal error variances. (Hair *et al*. 2014).

on the latent factors (variables) extracted from the factor analyses. A relationship between two variables is depicted by a one-way straight arrow, which shows which variable is hypothesised to have an effect on the other. Thus, the structural relationships in the model were explained as the effects of one variable incorporated in the model on the other. The proposed model includes interrelations (paths) among independent latent variables and the dependent variable (performance). Statistics performance is considered as the dependent or the outcome variable in the hypothesised model because it was intended to be predicted by all the latent variables included in the model, but itself was not intended to predict any variable inside the model. The latent variables were allowed to have an impact on the dependent variable both directly and indirectly. Appendix A6 presents more information about the model development.

The theoretical-conceptual model (taking into account the results from the EFA and CFA procedures) was specified by positing the following hypothesised relationships (theoretical linkages) among the variables. The self-efficacy construct was hypothesised to have an effect on all the constructs (i.e. liking/interest, value, difficulty/anxiety and resilience) included in the model to highlight the potential impact of students' perceived competence on their affective and cognitive-related reactions and behaviours. More specifically, self-efficacy regarding statistics was speculated to intensify positive attitudes and dispositions towards statistics and positive resilient behaviours and diminish statistics anxiety and perceived difficulties. In essence, self-efficacy was treated as an exogenous latent variable. These hypothesised pathways were based on Bandura's (1994) propositions who argues that self-efficacy beliefs determine how people feel, think, motivate themselves and behave. The link between self-efficacy and anxiety is also discussed by Bandura(1988) which notes that low levels of self-efficacy logically leads to increased anxiety. Furthermore, liking/interest construct was hypothesised to have an effect on difficulty/anxiety and resilience constructs. More specifically, it was conjectured that positive dispositions (liking and interest) could lessen anxieties and perceived difficulties and promote resilient behaviour characteristics in statistics. Moreover, value construct was hypothesised to have an effect on liking/interest, difficulty/anxiety and resilience constructs. In other words, the perceived value of statistics was assumed to increase students' liking and interest towards statistics and positive resilient behaviours and decrease anxieties and perceived difficulties in the course. The hypothesised pathways from liking and value to anxiety were stimulated from the relevant literature (e.g. Chiesi and Primi, 2010) where attitudes (e.g. affect, value) were found to be directly linked to anxiety experienced during the statistics course. In addition, difficulty/anxiety construct was hypothesised to have an effect on resilience construct. Particularly, it was surmised that higher lowers of anxiety and difficulties experienced in the course could enhance resilient behaviours when learning it. The hypothesised pathways between the resilience and the other variables were linked to my own ideas and contentions. Lastly, all the latent variables were initially speculated to be directly related to the final statistics grade, which is considered as the outcome (dependent) variable in the model. The initial model speculated that all the variables were direct predictors of performance with either negative or positive relationships. Previous empirical studies have inspired me for investigating the relationship between the above-mentioned variables and performance (e.g. Sorge and Schau, 2002; Bandalos *et al*., 2003; Chiesi and Primi, 2010). The proposed causal relationships among variables (with the positive and negative signs indicating positive and negative relationships) are illustrated in the following diagram (see Figure 3.1).

Figure 3.1 Hypothesised model of the relationships among the five variables and performance



The next step was to assess the model identification; that is whether there is enough information to estimate the parameters of the hypothesised model that were specified (Diamantopoulos, 2010). This is considered as a property of the model and not a property of the sample data. In order for the model to be estimated, it must be statistically over-identified. This could be achieved when the number of the parameters to be estimated is less than the number of variances and covariances among the observed variables (indicators) which means to have positive degrees of freedom. In other words, the model should have more pieces of information available than the number of parameters which are needed to be estimated.

The last step is the parameter estimation followed by the assessment of the overall model fit. The model fit describes how the theoretical model best represents the data collected. SEM is based on the covariance matrix among the observed variables. The model fit is the comparison between the two covariance matrices - the covariance matrix based on the data (sample covariance matrix) and the covariance matrix which includes the estimated covariances (estimated population covariance matrix). The closer this comparison is, the better the fit of the data. Moreover, the total effects of each variable included in the model, which is the sum of its indirect effects and direct effects (Bollen, 1987) were also consulted. According to Kline (2005), total effects are the amount of effects via any hypothesised paths. In the current study, since final grade variable is the dependent (outcome) variable, the total effects on final grade (performance) are of primary interest.

3.11.1.11 Description of the sample

To give the reader a description of the sample, socio-demographic and academic information for the final sets of participants (after the data screening procedures and exploratory analyses were carried out, see §4.2) are presented below. It should be noted that this information is provided by the students (unless stated) during the completion of the questionnaires.

Gender

The breakdown of gender is presented in Table 3.4. As it can be observed, the samples in both administrations were predominantly female.

Age group

A breakdown by age group (see Table 3.4 revealed that an overwhelming percentage of students who participated in the study in both questionnaire administrations were in the age group of 17-24. This is not surprising since in Cyprus it is common the students to enter the university straight after they finish the high school (and for the males after they finish the military obligations, refer to §3.5.3).

Province

Demographic information that was requested from the students was to indicate the province they came from (see Table 3.4 for more information). It should be noted that data were collected from universities situated in three provinces (namely, Nicosia, Limassol and Paphos). This information was requested to build the demographic profile of the students, but it was not used in subsequent statistical analyses.

Parents' educational level

Students who completed the pre-course questionnaire version were asked to indicate their father's and mother's highest educational level. For the purposes of reporting, a new category variable, namely the parents' educational level variable, was created. This variable was a composite measure of the father's and mother's highest educational level and consisted of three categories namely a low level of education (no education or/and primary education), a medium level of education (secondary or a combination of secondary and university level) and a high level of education (undergraduate and/or postgraduate level). The detailed information is provided in Table 3.4. This information was requested to build the students' demographic profile, but it was not used in further statistical analyses.

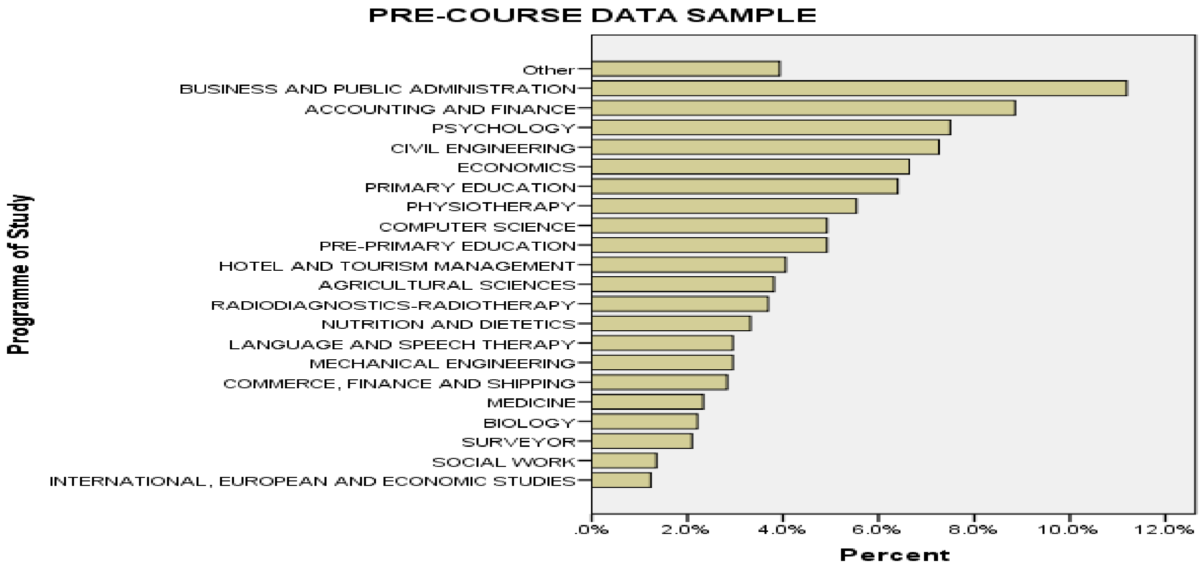
Major (Programme of study) and Faculty Affiliation

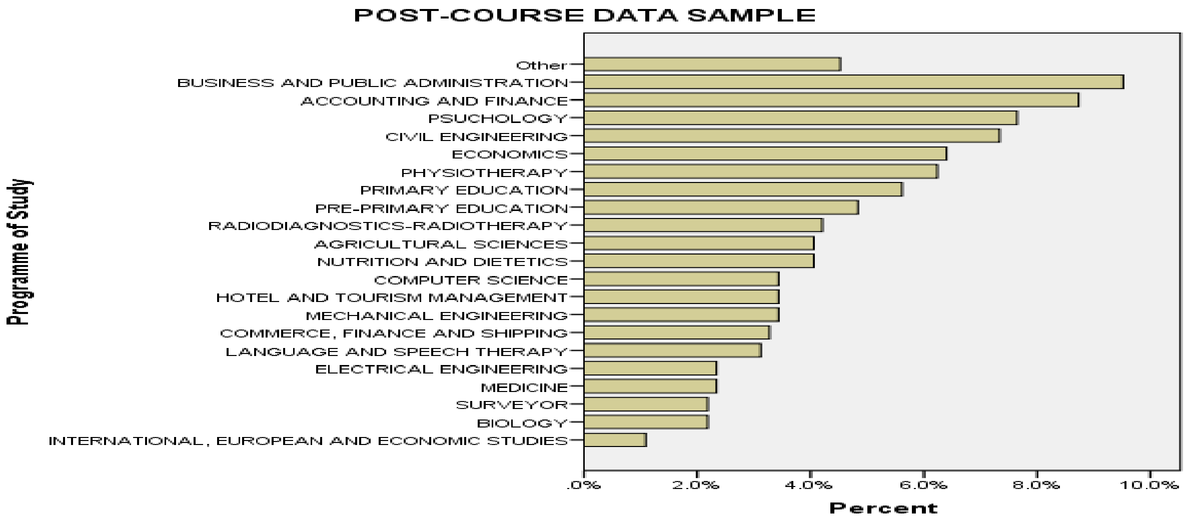
Students were asked to report their degree programme (major) that they were currently enrolled in. Thirty-five different majors were reported. This information is provided graphically in the following bar graphs (see Figure 3.2). The majors who were represented by less than 1% of the respective sample collapsed to the 'other' category. The students' major was then classified into four groups: Education and Social Sciences; Life and Health Sciences; Engineering and Applied sciences; and Economics and Business (see Table 3.5). This information was not requested by the participants. It was created as a categorical variable (which was named 'faculty affiliation') for further analyses purposes.

Table 3.4 Socio-demographic characteristics of the participants for both data sets

Socio-demographic characteristics	**Pre-course (N=815)**	**Post-course (N=641)**
	n (%)	
Gender		
Male	292 (35.8%)	250 (39%)
Female	522 (64%)	391 (61%)
No response	1 (0.1%)	0 (0%)
Age Group		
Between 17-24	782 (96%)	612 (95.5%)
25 and above	32 (3.9%)	29 (4.5%)
No response	1 (0.1%)	0 (0%)
Province		
Nicosia	390 (47.9%)	312 (48.7%)
Limassol	154(18.9%)	118 (18.4%)
Larnaca	137(16.8%)	101 (15.8%)
Famagusta	31 (3.8%)	24 (3.7%)
Paphos	57 (7.0%)	42 (6.6%)
Greece	46 (5.6%)	42 (6.6%)
Parents' educational level		
Low	23 (2.8%)	-
Medium	558 (68.5%)	-
High	187(26.6%)	-

Figure 3.2 Illustration of the majors represented in pre-course and post-course data samples





Academic Year of study

The year of their academic study that they were currently enrolled in was requested from the students. A new variable, which merged the students who were in their third, four or higher year, was created. As can be seen from the Table 3.5, there was a larger representation of students attending their first or second year of studies compared to the students who were in the third or higher years in both questionnaire administrations.

First time of attending a statistics course

The students were requested to indicate whether it was the first time that they were attended a statistics course. As shown in Table 3.5, an overwhelming proportion of students who had completed either questionnaire version circled that it was the first time they attended a statistics course at university level.

Nature of the course

For almost all the students who participated in the pre-course administration, the statistics course was compulsory for their degree programme. This was anticipated since the statistics course was a compulsory course for all the statistics classes I collected data. There was a minimal amount of participants who indicated that the statistics course was not a requirement for their degree programme, but they had chosen to attend one as an elective course (see Table 3.5). This variable was not included in subsequent analyses.

Table 3.5 Educational and Academic characteristics of the participants for both data sets

Educational and Academic Characteristics	**Pre-course (N=815)**	**Post-course (N=641)**
	n (%)	
Faculty Affiliation		
Education and Social Sciences	168 (20.6%)	123 (19.2%)
Life and Health Sciences	150 (18.4%)	134 (20.9%)
Engineering and Applied sciences	199 (24.4%)	157 (24.5%)
Economics and Business	266 (36.3%)	225 (35.1%)
Year of study		
1st year	389 (47.7%)	301 (47.0%)
2nd year	274 (33.6 %)	216 (35.3%)
≥3rd year	149 (18.3%)	114 (17.8%)
First time of attending the course		
Yes	678 (83.2%)	550 (85.8%)
No	135 (16.6 %)	87 (13.6%)
Nature of the course		
Compulsory	804 (98.7%)	-
Elective	10 (1.2%)	-

3.11.2 Qualitative Data Processing, Analysis and Presentation

As Merriam (2009, p.176) proposes: “data analysis is the process of making sense out of data and to make sense out of the data involves consolidating, reducing and interpreting what people have said and what the researcher has seen and read.” To this end, the qualitative data analysis process is regarded as a continuous meaning-making process

(Srivastava and Hopwood, 2009) where the main aim was to identify, understand, develop and communicate the meaning of the students' accounts. It was a systematic, iterative, inductive and interpretive process in order to obtain thorough knowledge and understanding of the data collected from the interviews.

This subsection consists of several parts including the procedures used in the selection of the participants and information about the selected participants; the data analysis procedures (e.g. development, selection, information and presentation of themes); translation issues and reporting approaches; and the inter-coder reliability process. The research challenges encountered and the decisions made throughout the qualitative analysis procedures, which also influenced the reporting of the findings, are presented and explained. These decisions were regarded as essential parts to be integrated into the thesis document, and there was an attempt to convey them as clear and transparent as possible to the readers.

3.11.2.1 Selection and information of the interview participants

In the beginning, due to the large number of interviews (namely sixty-five) that were executed during the qualitative data collection, there was a need to make a selection of those that they would be transcribed and analysed. The selection of a subset of participants over a larger sample of participants who were interviewed constituted a challenge. I confronted the decision of how many students and how to choose those students to be the final cases whose statements would be presented in the Qualitative Results chapter (see Chapter 5). For this purpose, a further purposeful (purposive) sampling technique was employed (Cohen *et al.*, 2007; Creswell, 2009). As Stake (2008) proposes, the particular subset of students should be chosen because it is believed that by understanding them would result to a more comprehensive knowledge and understanding of a still larger collection of students. In addition to this, among the aims was to select enough cases (students) to identify thematic categories (which are explained later in this subsection) and then find representative evidence to fit and support each thematic category.

A few key issues and recommendations from other researchers were considered when selecting the participants to be included in the final qualitative sample. To start with, Bryman (2012) sets forth several factors for selecting participants, including the theoretical underpinnings of the study, the breadth and the scope of the research questions and the heterogeneity of the sample. For the current investigation, participants were primarily selected based on demographic and educational information they provided and more specifically from five subgroups of interest: gender (male or female); semester of attending the statistics course (fall semester or spring semester); type of the university (public or private university); major (degree programme) and number of mathematics classes completed at university level (none, one, two or more). The name of the university, the instructor, the academic year of study and the age group of the participants were also taken into account. The intention was to have a range of attributes of the subgroups of interest represented and to capture the diversity of the universities, statistics courses, classroom environments and instructors. Moreover, Liamputtong (2013) recommends that students can be selected by whether they were able to give valuable contributions to the research goals and foci. More specifically, students who provided rich and detailed information and presented ideas and opinions relevant to the specific topics under investigation were candidates for inclusion in the written document (Patton, 2002; Tashakkori and Teddlie, 2003; Palinkas *et al.*, 2015). As Arthur *et al.* (2012) also states, the selection of the participants should be guided by their potential to provoke insights, understandings, connections and explanations. To this end, I chose the participants whom I believed that were more able to articulate and communicate their opinions and perspectives about specific issues under consideration and overall what they had experienced during the statistics course. The primary focus was on the depth and relevance of information that can be obtained by individual participants (cases) concerning each topic under consideration. As Palinkas *et al.* (2015) suggests, a strategy for purposeful sampling can commence with a broader view giving emphasis on variation or dispersion and proceed to a narrower view emphasising on similarity or central tendencies. Thus, an attempt was made to choose the participants who have proposed different opinions and views regarding a particular topic. and, also, to select those participants who have expressed same or similar ideas regarding this specific topic for the purposes of expanding and explaining each idea more thoroughly. The aim was to be able to compare and contrast across various opinions expressed and corroborate each idea or argument presented with evidence from the interviews.

To give the reader a general description of the selected participants, a table, which provides key demographic and educational information of the final set of the thirty students, is provided in Table 3.6. Each participant was assigned an indicator (e.g. M1-Y1-OGM). This encloses the gender, where M corresponds to males and F to females, the Y, which is the academic year of study and the major (degree programme) of the participants (with abbreviation). Throughout the Qualitative Results chapter (see Chapter 5), the assigned indicator of the students is mentioned. It should be noted that I did not 'invent' or request for the participants to choose a pseudonym for themselves for the purposes of reporting. What followed the selection of a smaller sample of participants from the qualitative data collection was the analysis of the interviews with those participants**.**

3.11.2.2 Development and selection of the codes and themes

With the intention to analyse the qualitative data, I consulted and followed the six phases of the thematic analysis approach as described by Brown and Clarke (2006). These phases (or steps) acted as guidelines for the analysis of the interview data. According to Attride-Stirling (2001), the structure of thematic analysis has significant parallels with basic elements (such as concepts, categories and propositions) of grounded theory approach (Corbin and Strauss, 1990). Braun and Clarke (2006, p. 79) defines thematic analysis as: "a method for identifying, analysing and reporting patterns (themes) within data." Similarly, Attride-Stirling (2001, p.2) describes the merits of conducting a thematic analysis since it "allows a sensitive, insightful and rich exploration of a text's overt structures and underlying patterns". In the current study, thematic analysis strives for' understanding' than 'knowing' the data; focuses on the interpretation of the meaning of participants' accounts; and calls for how the findings are related to and answered the research questions (Braun and Clarke, 2006; King, 2010).

Table 3.6 Key demographic and educational information of the selected participants

Student indicator	**Age group**	**Degree programme/Major**	**Type (indicator of university)**	**Instructor Indicator**
M1-Y1-OGM	25 and over	Oil and Gas Management	Private (U3)	I5
M2-Y2-AFN	17-24	Accounting and Finance	Public (U1)	I1
M3-Y2-ECE	17-24	Electrical and Computer Engineering	Public (U1)	I1
M4-Y2-PHYS	17-24	Physiotherapy	Private (U3)	I7
F5-Y1-AFN	17-24	Accounting and Finance	Private (U3)	I5
F6-Y1-ECON	17-24	Economics	Public (U1)	I2
M7-Y1-PSYC	17-24	Psychology	Private (U3)	I6
F8-Y2-NUTR	25 and over	Nutrition and Dietetics	Private (U3)	I7
F9-Y2-EEN	17-24	Electrical Engineering	Private (U5)	I11
F10-Y1-EDUP	17-24	Pre-Primary Education	Public (U1)	I1
F11-Y1-ABF	17-24	Agricultural, Biotechnology and Food Sciences	Public (U2)	I14
M12-Y2-BPA	17-24	Business and Public Administration	Public (U1)	I2
M13-Y3-BPA	17-24	Business and Public Administration	Private (U3)	I5
F14-Y3-CEN	17-24	Civil Engineering	Public (U2)	I15
F15-Y1-NUTR	17-24	Nutrition and Dietetics	Private (U4)	I9
F16-Y1-PSYC	17-24	Psychology	Public (U1)	I1
M17-Y4-EEN	17-24	Electrical Engineering	Private (U5)	I11
F18-Y1-BPA	17-24	Business and Public Administration	Public (U2)	I2
F19-Y1-PSYC	17-24	Psychology	Public (U1)	I1
F20-Y1-EDU	17-24	Primary Education	Public (U1)	I1
M21-Y6-TOUR	25 and over	Hotel and Tourism Management	Public (U2)	I7
M22-Y1-PSYC	17-24	Psychology	Public (U1)	I1
M23-Y3-MEN	25 and over	Mechanical Engineering	Private (U5)	I11
M24-Y2-AFN	17-24	Accounting and Finance	Public (U1)	I2
M25-Y3-MEN	17-24	Mechanical Engineering	Private (U5)	I11
M26-Y2-COM	17-24	Computer Sciences	Public (U1)	I3
M27-Y1-PSYC	17-24	Psychology	Public (U1)	I1
M28-Y5-RAD	25 and over	Radiology and Radiotherapy	Private (U3)	I7
F29-Y1-IEE	17-24	International, European and Economic Studies	Public (U1)	I2
F30-Y1-CFS	17-24	Commerce, Finance and Shipping	Public (U2)	I7

A combination of manual and electronic tools was employed to organise, manage and analyse the qualitative data. More specifically, the paper-and-pencil method and the NVivo qualitative computer software program were used. By using a computer-assisted data analysis program, it was found to be easier to retrieve information for data analysis and comparison. It should be noted that NVivo assists the researcher to import, organise, manage and categorise the data and overall facilitates the qualitative analysis process. However, the NVivo program does not interpret the data; the making sense out of the data and the interpretation of them is a task of the researcher (Hutchinson *et al*., 2010). Also, as Bazeley (2013, p.18) recommends, “It is important that software is seen as providing tools to support rather than drive analysis”.

The first step, as stated by Braun and Clarke (2006) was the familiarisation of the data. I transcribed by myself the interviews I had executed. This allowed me to develop a greater insight and to familiarise myself with the data collected. Initially, I read a couple of times each transcript I had produced with the aim of developing an overall sense of it and an incremental engagement with the data. Even though the ideal situation is the verbatim transcription as Patton (2002) suggests, this process could be time-consuming and intimidating. There was an attempt to focus on the most pertinent information to the research goals and questions (Yin, 2009). Interview points that seemed to me non-relevant - or less important – to the objectives of the study were removed. This can be considered as a form of ‘data reduction’. It should be noted that throughout the transcription process, I did not embody any descriptions of students’ emotions, feelings, or actions during the interviews.

An intermediate step that was performed, which was not aligned with the phases described by Braun and Clarke (2006), was the organisation and the tabulation of the data before they were manually and electronically open-coded. Miles and Huberman (1994) proposes the use of data matrix approaches which typically organise and tabulate the unit of analysis (e.g. individual participants’ responses) based on key concepts or issues. In the current investigation, since a review of the literature (both theoretical and empirical studies) had been conducted and preliminary quantitative analysis had been executed before the qualitative analyses commenced, a list of possible categories that were anticipated to be found in the interview data was constructed. As Creswell (2009) argues, while the traditional approach is to allow codes to emerge during the qualitative data analysis, it can often be helpful to predefine expected codes and broader categories. Also, due the semi-structured nature of the interviews entailed that some topics were predetermined to be discussed. Although the order and the wording of the questions varied from participant to participant, each main topic comprised a number of main questions. Some probing (follow-up) questions that were asked were placed under the main, and more general, questions. Thus, the interview transcripts were initially sorted into questions (and categories of questions) and tabulated using these categories, which had been devised based on the interview plan. The students’ responses (phrases) were then classified into the most relevant categories of questions. There were instances where students’ responses were designated to multiple categories since some of them seemed to fit into more than one category (conceptual concept). It should be mentioned that the interview tabulation mirrored, to some extent, the subscales (major categories) of the questionnaire with the addition of new ones (for example, the students’ opinions about the instructor and the instructional methods). Following Ryan and Bernard (2003), the analysis of the content and meaning of the data tables resulted in the identification of a candidate set of themes. By the end of this intermediate step, an initial (and tentative) set of major categories, which comprised questions by the researcher and responses by the participants, had been identified.

The second step, as described by Braun and Clarke (2006), included the generation of the initial codes. According to many researchers (e.g. Creswell, 2009; Rossman and Rallis, 2013), coding is the starting point for qualitative data analysis before developing interpretations and bringing meanings to data. As specified by Saldaña (2009, p.3), "a code in qualitative inquiry is most often a word or short phrase that symbolically assigns a summative, salient, essence-capturing, and/or evocative attribute for a portion of language-based data." The open-coding procedure allows to capture the potential detail, variation and intricacy of the data gathered (Breakwell *et al*., 2006). The preliminary open-coding procedure was performed in paper-and-pencil form. Line-by-line coding was conducted to the student's responses to each of the interview questions. I attached preliminary codes with the intention to capture briefly the main idea/content underpin each phrase (or a group of phrases). Some of the phrases had more than one codes applied or they were not coded. I tried to create appropriate, sensible and representative codes that capture and summarise the essences of the interview data. The next step was to perform the coding of the interviews with the assistance of the NVivo software program. During this process, 'memos' or 'annotations' in NVivo were also created to document my broader thoughts and impressions about the codes and the coded data.

At this stage of the qualitative analysis, my supervisor, Professor John Monaghan (hereafter JM), provided helpful guidance. We worked together on a selected interview transcript, which I had translated into the English language. We discussed, exchanged opinions and wrote down provisional codes that were derived inductively from the interview transcript. What followed was to construct and define the initial list of codes having as guidelines the provisional codes we developed together. By the time the preliminary coding was finished, all the codes and their relevant data extracts from all the transcribed interviews were collated. However, the process of fitting the data extracts into categories required continuous and iterative refinement.

The next three steps, as described by Braun and Clarke (2006), involved: (a) the search for the themes and the construction of them; (b) the review of the themes; and (c) the definition and naming of them. As defined by Braun and Clarke (2013, p.4), "a theme is a coherent and meaningful pattern in the data relevant to the research question." During this process, and within the framework of the main codes that emerged from the ongoing analysis process, the students' responses were analysed by the key common ideas and concepts and then gathered under topics. These topics eventually made up the main thematic categories (i.e. themes). As Strauss and Corbin (1990) states, codes can be categorised around concepts and conceptualised based on the similarities and common characteristics to form the broader thematic categories. In the present study, there was a combination of thematic categories that derived from the theory, previous empirical studies and research objectives (theory-driven) and thematic categories, which emerged from the data during the analysis process (data-driven).

The initial set of categories (that is, the candidate categories) which were produced during the data tabulation process (i.e. the intermediate step described before) were carefully reviewed and refined taking into account the thematic categories that were generated from the open-coding procedures. Some of them were modified, collapsed together, separated, or eliminated. At the end of this stage, all the coded data were placed under the relevant thematic category. Each thematic category was considered to constitute and reflect a specific conceptual domain. What followed was the labelling of themes, which should serve as descriptive tools (Holliday, 2007).

After the analysis of the qualitative data following the thematic analysis approach, a ‘codebook’ was developed. This ‘codebook’ (which is available upon request) represents the final outcomes of the coding procedures and is a table comprising a list of the main thematic categories (themes) and the associated codes. A branching arrangement of the codes within the themes was used. It also included some hints (descriptions or special words) -which can be referred as sub-codes- and were highlighted from the students’ responses and were deemed as helpful for identifying these themes (and codes). It should be noted that the ‘codebook’ was based on the careful review and the preliminary coding of twenty transcribed interviews. The remaining ten selected interview transcripts were also reviewed, but no new codes, and subsequently themes, emerged. This gave me the confidence, but not the certainty, that saturation (i.e. when no more codes can be detected in the data) at least on the main themes and codes had been achieved. In total, sixteen thematic categories were identified and labelled (which are deemed to be descriptive) and they are reported below:

1. University/ High school programme
2. Statistics course/module
3. Prior Mathematics/Statistics background, performance and experiences
4. Statistics versus Mathematics
5. Attitudes and opinions (e.g. liking and interest) about statistics
6. Value of statistics
7. Difficulty/Easiness of statistics
8. Anxiety towards statistics
9. Self-efficacy regarding statistics
10. Knowing/Learning in statistics
11. Achievement Goals and Motivational Orientations in statistics
12. Statistics performance
13. Statistics instructor and methods of instruction
14. Software for learning statistics
15. People
16. Suggestions/Recommendations

The next step was to further confine the sixteen thematic categories to a smaller number of combined categories based on their thematic or conceptual similarity (Saldaña, 2015). The pertinent research literature recounts a similar use of reducing codes and categories. For example, as Lichtman (2006) and Creswell (2009) reports, the most qualitative research studies in education can generate 80 to 100 codes that will be organised in 15-20 thematic categories which be eventually synthesised into five to seven major concepts. The eight combined thematic categories along with a short description of the meaning, the concepts and the ideas related to each one are provided below:

1. *Prior Mathematics and/or Statistics background, performance, and experiences*
   In this category, students’ prior mathematics or/and statistics learning experiences and personal histories; perceived knowledge and abilities; and

mathematics/statistics performance in primary school, high school and university are included. The focus was explicitly placed on whether (and in what way) these prior experiences affected their perceptions, behaviours and experiences of the statistics course.

2. *Statistics Versus Mathematics*
   In this category, students' opinions and views about the similarities and/or differences between statistics and mathematics (including, for example, students' opinions about the nature of statistics as a discipline and subject and about statistics and mathematics as disciplines and as subjects/classes that are offered at high school and university level) are incorporated. Moreover, whether and how students' attitudes and opinions, levels of anxieties and perceived abilities regarding statistics were differentiated from mathematics are mentioned.

3. *Students' affective reactions and behaviours*
   This broad thematic category is devoted to the affective reactions and behaviours of the students during the statistics course. The categories which are included concerned students' attitudes, opinions and interest in statistics; usefulness, relevance and applications of statistics; anxiety towards statistics and self-efficacy regarding statistics. These categories constitute separate sections in the Qualitative Results chapter.

4. *Knowing/Learning and Motivational orientations in statistics*
   This broad category includes, among others, students' motivational orientations and achievement goals in statistics; the amount of studying and effort in statistics; learning strategies and approaches to statistics. During the data-driven coding approach, a code/construct, which was not tapped during the quantitative collection and analysis, emerged. The data relevant to this construct were coded as students' perceived understanding of the subject matter. Also, this broad category contains information related to the students' resilient behaviour and characteristics.

5. *Statistics instructor and instructional practices*
   The personality of statistics instructors and their pedagogical strategies constitute another category (and subsequent section in the Qualitative Results chapter). It has to be reminded that the Quantitative Results chapter does not include a similar section since the questionnaire does not contain questions about students' opinions and views regarding the statistics instructor and the methods of instruction. However, throughout the review and the analysis of the interview data, the importance and the influence of the instructors (and their methods/behaviours) on students' affective, cognitive and motivational orientations was flagged.

6. *High school/University programme and Course/Module*
   This category is dedicated to the students' opinions about the statistics course/module and institutional-related information. The responses associated with the students' opinions about contextual variables (such as the language of instruction) and the classroom settings (such as the classroom environment/climate) are presented. Students' experiences of a university-level degree programme and the comparison with the high school programme are included. Students' opinions about

the incorporation and the use of technology (and statistical software programs) along with their affective reactions of using technology are reported. Students' suggestions and recommendations for improving a statistics course are reported and discussed in the Discussion chapter (see Chapter 6).

7. *Statistics Performance*
   This category is composed of topics related to the students' outcome expectations of their performance in the statistics course, perceived control over performance and learning and the current and preferable methods of assessment in the statistics course. Regarding the contribution of several factors to statistics performance, particular attention is placed on the Quantitative Analysis and Results Chapters.

8. *People*
   During the coding procedure, a thematic category named People was constructed. It includes data extracts of students' reference to their family members (e.g. their educational, perceived support and expectations); other students (seniors/classmates); previous statistics/mathematics teachers and self-references (i.e. self-identity). The centre of interest was whether (and how) these social agents influenced individual students' learning and performance in statistics.

3.11.2.3 Inter-Coder Reliability

Once the list of the thematic categories and the codes was developed, tabulated, defined and clearly described, the next step was to explore its reliability. This was done by Inter-Coder Reliability (hereafter ICR). ICR or inter-coder agreement check is deemed as an essential procedure for assessing the reliability of a researcher's coding (Mouter and Vonk Noordegraaf, 2012) and verifying "whether the codes assigned were meaningful, logical and consistent with those that other readers would assign" (Usher, 2009, p.285). A high rate of inter-coder agreement could allow arguing for "an unequivocal, common vision of what the codes mean" (Miles and Huberman, 1994, p. 64). In this process, the extent to which two (or more) different people would apply the same codes to the same interview excerpts was examined. Then, the correspondence between the applications of the codes to the interview data by the two people was calculated. For the current study, a pilot ICR process was firstly conducted with my supervisor (JM), and then the original one with the help of a fellow doctoral student in Mathematics Education whose native language is Greek.

The interview transcription that was used for carrying out both ICR processes (pilot and main) was from the Student 22 (see Appendix A8). He was a first-year psychology male student who attended a compulsory introductory statistics course in Fall Semester 2015. I chose a part of the interview transcription as the training (i.e. practice) part with my supervisor (which I translated it in English). JM and I worked independently and applied themes and codes to the same interview material using as a guide the same coding system (i.e. the 'codebook'). There were in total 22 questions (asked by me) and 22 responses (given by the student). Some responses have been assigned to multiple codes as they contained multiple concepts. Then, we compared our coding. We checked whether we assigned the same themes (and codes) to each response that is if we coded the same interview excerpts the same way. The aim was to examine whether the two codings were similar or if there existed great variations. In total, we had 9 complete agreements (we have assigned the same themes), 11 agreements in retrospective (10 of them were agreements in retrospective from JM and 1 from me) and 2 disagreements. Agreement in retrospective means that initially, we had a discrepancy in the coding, but after discussion, we agreed on using the same themes. We also discussed the reasons for any inconsistencies arose during the pilot ICR process.

Another part of the same interview transcript (comprising 25 questions/responses) was selected to be used in the main ICR process. In the interview part chosen, 13 out of 17 categories (including the 'no code' category) were supposed to be tapped. During the meeting with the fellow PhD student, whose I gave the pseudonym Maria for the purposes of reporting, I introduced to her my 'codebook'. I explained briefly what each theme (and code) represent (i.e. the conceptual definition of them) and the rationale for developing them. I also tried to explain to her what distinguishes each one from the others. Maria worked alone and applied line-by-line coding to each of the responses. What followed was the comparison of the two independent codings (my coding and her coding). The coding cross-check included the counting of the agreements and disagreements between the fellow student (Maria) and the researcher (me). A high degree of agreement (at least on the themes) was reached. In total, we had 21 (out of 25) complete agreements (that is we assigned exactly the same themes) and 4 agreements in retrospective (3 of them were agreements in retrospective from Maria and 1 from me). A table with the results of the main ICR was prepared and is available upon request.

3.11.2.4 Writing and presenting the themes

The last step as described by Braun and Clarke (2006) was the writing up of the themes. Both a within-case analysis (where the interview transcripts of each participant were examined deeply) and a cross-case analysis (where patterns, similarities and differences across interviewees were explored) were carried out. However, for the purposes of reporting, the findings are displayed in a cross-case manner following a theme-by-theme presentation (King and Horrocks, 2010). In other words, rather than presenting individual students' accounts separately, the Qualitative Results chapter was organised into themes and patterns emerged across interview sessions of participants for the sake of making comparisons and reaching conclusions.

As explained earlier, sixteen thematic categories (which were then combined into eight for in order to present, define and explicate them here) were identified. These categories were assumed to capture and describe the main issues, ideas and concepts found in the qualitative data. Due to the space limitations of the thesis document, there was a variation on the length and the specificity of reporting these categories in the Qualitative Results chapter. That does not mean that the importance of each thematic category is not 'valued'. All of the established thematic categories were deemed important; however, those that were of particular interest and relevance to the objectives of the study and the researcher were used to be relied on to tell the story to the readers.

Guba and Lincoln (1981), as mentioned in Merriam (1998), proposes several central criteria for selecting and constructing categories that are comprehensive and illustrative. Firstly, the number of the people noted something and how frequently it was discussed during the interview session have to be considered. The participants might also point out what is important to them and give an indication to the researcher. Moreover, a category (or some categories) might emerge from the data and can be ‘unique’ thus, they are worthy incorporated into the final report. The criteria mentioned above along with other considerations guided the decision of choosing which themes were reported to a greater extent in the current thesis. First of all, I considered the mixed-methods research design of the study. Following a similar manner throughout the quantitative analysis and reporting procedures, I had to select a set of variables/constructs to focus on and perform the advanced statistical analysis. Some of the variables investigated in the quantitative part are also the main thematic categories in the qualitative part. However, new thematic categories were constructed during the qualitative data analysis to accommodate the participants’ responses to the interviews. To give an example, instructors and instructional practices were not topics tapped by the questionnaire items, but they were found to be prominent during the interviews. Secondly, the nature and the frequencies of the phrases or ideas expressed by students regarding each thematic category were taken into account. It should be noted that the frequencies were not precisely calculated; instead, it was only a rough estimate. Thus, how many students discussed a topic, how frequently was mentioned and the ‘importance’ they placed on it were also informed the length of each thematic category. Thirdly, the theoretical and empirical literature in this area of investigation was considered.

In the qualitative analysis chapter, each section (or subsection) is devoted to a thematic category (theme) and the information extracted from the individual cases (students) is cited and dispersed throughout the relevant section (Yin, 2009). This aimed to aid in drawing interpretations and conclusions about the most salient features of a particular theme or construct. Each thematic category is written as a narrative passage to develop and convey a story and contribute to the overall story (Braun and Clarke, 2006).

The sections (and subsections) were further organised into related topics, ideas and meanings as derived from students’ responses. These were supported by data; that is pieces extracted from the interviews (i.e. interview excerpts). The initial draft of the qualitative results chapter included a large number of interview extracts – evidence for claims. Due to the length and world restrictions, a reduction and a selection of the extracts from the interview transcripts to be reported was performed. As Holliday (2007, p.106) argues: “The criteria for determining which fragments of data are selected will always be subjective as all the other aspects of qualitative research.” These fragments can be selected based on their richness of experience and insight and their suitability for description, interpretation and explanation of the particular topics under investigation (Emmel, 2013). At this stage, the main objective was to choose targeted, relevant, rich and vivid quotes which exemplified and adequately reflected the essences of the data and also supported and provided evidence of the comments or claims have been made. The reported excerpts and quotes seemed to my intuition that are representative of selected participants’ statements from each thematic category and illustrative of the experiences shared by them during the interviews. An attempt was made to give a comprehensive picture of the participants’ experiences by incorporating all the range of opinions and points of view regarding a particular topic or issue under consideration. There was an attempt to capture and portray multiple perspectives, detect similar opinions as well as diverging views and perspectives in students' accounts. The intention was various perspectives to be represented without favouring or dismissing any of them.

A selection of quotes from students who shared similar experiences or perceptions about specific issues or topics was also performed. The aim was to carefully select the pieces of the data which are relevant and rich; meaning that they embraced as many of the key elements as possible (Holliday, 2014). In some cases, the number of quotes reported for each topic reflected the frequency and the importance the participants' placed on each topic. However, the generalisability of the findings (for example, more female students have these opinions about a specific issue) and the allocation of the student into a particular category are not among the objectives of the Qualitative Results chapter.

The quotes in the Qualitative Results chapters were reported, to a great extent, as they were expressed by the students using their own words in order to convey and reflect their feelings, thoughts, perceptions and impressions as precisely as possible. As Corden and Sainsbury (2016) argues, the reporting of the participants' actual spoken words offer to the reader a better description, insight and understanding of the data than if the researcher paraphrases all the verbatim quotations. However, punctuation and capital letters were added to enhance the readability of the writing. I concentrated on the words of the respondents without reporting their emotional body language and non-verbal communications (e.g. their facial expressions, their tone of voice) when they were speaking.

Regarding the way of reporting the quotes, an attempt was made to mix the short, long or embedded quotes. The longer ones were separated from the paragraph without including quotation marks around them. There were quotes (usually these with less than two or three lines in length) which were incorporated in the main text and quotation marks were used. Italics were used within the main text when I referred to students' actual words or phrases and single quotation marks when the students said something in a metaphorical sense. Also, some of the participants' statements were paraphrased or summarised and were included in the paragraph without quotation marks. This was done mostly in the cases where several participants pointed out the same issue or shared similar experiences.

At this point, it has to be mentioned the translation process of the quotes and the 'language barriers' during this process. The interview excerpts (i.e. the participants' words) which are presented throughout this thesis were translated into the English language for reporting and disseminating the findings. All the reported quotes were taken and translated from the original transcripts (written in the Greek language). During the translation from Greek to English, I tried to preserve the original content and meaning of the students' words. I am aware that some of the reported extracts do not follow the appropriate English writing and the correct English syntax. The possible reasons are that the face-to-face interviews were conducted in the spoken language, were performed in the Greek language (and especially in the Cypriot dialect which is not a written language) and were audiotaped. Also, since English is my second language, the translation of the students' words might not be so 'accurate'. In order to accommodate for the latter issue, I contacted a British native speaker; I asked her to translate into English some examples of quotes and then I checked both translations. My supervisors' guidance also helped towards this process.

At this stage, it is worth mentioning that the responses gathered from the open-ended question, which was included at the end of both versions of the questionnaire, were not subjected to any qualitative analysis procedure. Instead, they were used to support the interpretation of both quantitative and qualitative findings.

To sum up, the qualitative analysis process included descriptive, exploratory and comparative analysis (Namey *et al.*, 2008). Following the coding, the categorising, the descriptions and the interpretations, the Qualitative Results chapter (see Chapter 5) serves for communicating and presenting the findings using a narrative way.

3.12 Issues of the quality of the research study and evaluation criteria

In this research study, with the aim to determine the issue of quality throughout the data collection and analysis process, an attempt was made to address standards and meet criteria for various types of validity and reliability by providing reasonable evidence. Regarding the quantitative component, reliability and validity are among the most fundamental considerations in the process of designing, developing and evaluating a survey instrument. Regarding the qualitative component, Noble and Smith (2015) proposes alternative terminology for the qualitative research concerning concepts such as reliability and validity which are commonly related to quantitative research and are presented later. For example, throughout this chapter, an effort was made to report, clarify and justify every stage of the research design and methodology. For instance, the processes by which the questionnaire and its items, as well as the design of the interview plan, were constructed and developed were thoroughly described.

To start with, the psychometric properties of the proposed quantitative measurement tool, which is its reliability and validity, when it was applied to the Cypriot sample, were of particular interest and they investigated. The quality of the measurement tool (in this case, the questionnaire) is believed as having a crucial role in the subsequent analysis and interpretation of the data. According to Lovelace and Brickman (2013, p. 611), reliability can be regarded as “the consistency or stability of measure”, that is, “the extent to which an item, scale or test would provide consistent results if it is administered again under similar conditions”. Hence, the internal consistency of selected questionnaire items (i.e. internal coherence of students’ responses) was evaluated using Cronbach’s alpha reliability coefficients (Cronbach, 1951, 1984). Cronbach’s alpha is considered to be one of the most popular and important index of reliability and its value is dependent on the number of items in the scale and the inter-correlations between the items (Nunnally, 1978). As many authors argued (Miler, 1995; Tavakol and Dennick, 2011), the alpha coefficient assumes that unidimensionality exists in a sample of a set of items rather than simply measure it. George and Mallery (2003) reports the following rule of thumb for describing internal consistency using Cronbach’s alpha: 0.9 excellent, > 0.8 good, > 0.7 acceptable, > 0.6 questionable, > 0.5 poor, ≤ 0.5 unacceptable. The alpha coefficients (reliability estimates) for the hypothesised subscales as well as for the subscales extracted from the factors analyses were computed and reported in §§4.2 and 4.8. All the subscales (except the pre-course Difficulty subscale) were reached the 0.7 criterion for acceptable internal consistency as recommended by many authors (e.g. Tabachnick and Fidell, 1996; Hair *et al.*, 2006; Fraenkel and Wallen, 2012).

Except for evidence of the questionnaire's consistency, that is its reliability, it was deemed crucial to also assess its accuracy, that is its validity. The general concept of validity basically refers to the extent to which a test/tool measures what it targets to measure, for example, whether the measurement tool of a construct assess the construct it claims to measure (Brown, 1996; King, 2010; Bryman, 2012). Also, as explained by many researchers (e.g. Messick, 1995; Glynn, 2007), validity is concerned with the degree to which theoretical base and empirical evidence support the use and the interpretation of questionnaire items and scores.

There are different types and forms of validity evidence, with the three major ones to be the construct validity, the content validity and the criterion validity (Brown, 1996). Trochim *et al*. (2015, p.128) reports that construct validity is seen as "the overarching category that contributes (with reliability) to the quality of the measurement, with all of the other measurement validity labels falling beneath it." One of the procedures for establishing construct validity is by means of factor analysis. Factor analysis procedures (EFA and CFA) were carried out separately for the pre-course and the post-course administration of the questionnaire with the aim to provide evidence of construct validity of the selected questionnaire' subscales. These procedures are described in more detailed in §3.11.1 and the results are reported in §§4.8 and 4.9. Further evidence of construct validity was performed during the CFA and involved the assessment of convergent validity and discriminant validity (Hair *et al*., 2006). Useful measures included the Composite Reliabilities (CR), the Average Variance Extracted (AVE) and the Shared Variances (SV) were described in §3.11.1 and evaluated in §4.9. Another approach of the validity of the questionnaire (that is, the criterion validity) was investigated and provided through Pearson product-moment correlation coefficients between the questionnaire subscales and the criterion measure (that is the students' grades in the statistics course). Chapter 4 (e.g. §4.5.3) address this issue and provides further information.

In order to achieve external validity (that is how well the sample generalises to the population) a number of criteria should be considered. For example, a high participation rate is needed and a representative sample is required. The first criterion is claimed to be achieved in this study. However, since the sample was not selected randomly, multiple replications of the study are needed to enhance generalisation of the findings (see §7.2).

Turning now to the qualitative component, in their seminar works, Lincoln and Cuba (1985; 1989) recommend alternative terms or criteria of quantitative research (to) be employed in order to judge qualitative research, which include issues of credibility/trustworthiness, transferability, dependability, and confirmability. To resolve the issues mentioned above a number of strategies related to each one were employed.

The first type of evidence to determine quality is credibility which is related to the internal validity (Lincoln and Cuba, 1985) and whether the qualitative research part examines what it claims to examine and reflect what actually occurred in the field (natural setting) (Cohen *et al.*, 2010). As Burns (1994) suggests, the goals of the research along with the main questions were outlined and the interview questions were oriented and designed to address these research aims. Throughout the data collection, there was an attempt to engage and understand the context and the settings of the study and build trust and rapport with the students. Maxwell (2005, p.80) argues that the semi-structured interview technique enhances the ‘‘internal validity and contextual understanding and is particularly useful in revealing the processes that led to specific outcomes’’. Also, following Noble and Smith’s (2015) recommendations, the application of validity to the qualitative research could be demonstrated with the recognition that multiple realities exist and the clear and accurate presentation of various opinions and perspectives shared by the interviewees. In addition to this, the reporting of the exact quotes, as mentioned by the participants, is believed to support the degree of consistency between the researcher’s interpretations and the ideas shared by the individual interviewees.

The second type of evidence to provide quality is transferability, which is related to the external validity and the extent that the findings of the research study could be transferable or applicable to other (similar) contexts, settings, populations and so forth (Lincoln and Guba, 1985). To this end, there was an attempt to describe the context and the background of the study and provide descriptions regarding all the stages of the research design to familiarise the readers (external persons) and assist them to be able to apply the findings judiciously. As previously stated (see, for example, §7.2), it was not anticipated the results of this study to be generalisable to all settings and populations, but instead to be useful and of some importance to other (similar) populations and groups.

The third type of evidence for quality is dependability, which is paralleled to the reliability (Lincoln and Guba, 1985) and whether the research procedures are clear, the findings are consistent and the study could be repeated. Following Noble and Smith’s (2015) recommendations, the application of reliability to the qualitative research could be established with the reporting and consistency of each process of the study, including the methods and approaches used. Following Ary *et al*.’s (2010) recommendations, an audit trail was created which incorporates rich and detailed descriptions (records) of the processes employed to collect, analyse and interpret the data and could aid the reader to evaluate the dependability of the research by tracking this audit trail.

The fourth type of quality to be discussed is confirmability, which is related to the researcher’s objectivity and neutrality and the extent or degree to which the researcher influences and biases the findings (Pandey and Patnaik, 2014). In enhancing the confirmability of the study, there was an attempt to identify and report any personal and research approaches biases that might have an impact on the findings and provide data and evidence that support the research findings and conclusions.

Another two steps to deal with the issues of rigour and quality of the qualitative component of the study, as it is already mentioned in previous subsections, were the pre-testing of the questions and the inter-coder reliability process. More specifically, the questions included in the interview plan of the main study were initially tested with the participants in the pilot study and then revised accordingly (see §3.9). Moreover, the inter-coding reliability, which was explained in a previous subsection, was evaluated with the assistance of my supervisor and a colleague to warrant the consistency of the coding process.

Overall, regarding the quality in both quantitative and qualitative research, in the current study, there was an attempt to maintain by reporting, explaining and justifying with sufficient detail the data collection methods and the procedures of analysis used (for example, the codes and the thematic categories developed for analysis) along with the research decisions and their potential consequences giving the readers the opportunity to evaluate the evidence and the findings themselves. It is deemed as crucial to show that both components of the study were credible and replicable and the procedures could be reproduced. As Bhatt (2017) during a conference argued, rigour and transparency allow the research study to be more accessible to others (knowledge transfer) and increase the opportunities for partnership (knowledge enhance).

3.13 Conclusion

In this chapter, the overall research design and methodology of this doctoral study are outlined. The two chapters which followed (Chapter 4 and 5) are concerned with presenting the results of the quantitative and qualitative analysis respectively.

Chapter 4 QUANTITATIVE RESULTS

4.1 Introductory statement

In this chapter, the results of the questionnaire data analysis are provided. The specific quantitative methods and approaches that were employed to address the research foci and questions of this research study are illustrated in §3.11. As explained earlier (see §3.11.1), the statistical analyses were conducted on two data sets - the data set which contained the students' responses to the pre-course version of the questionnaire and the data set which contained the responses to the post-course version of the questionnaire. Selected findings of the statistical analyses are presented in tables or graphs in the main document (or in Appendices) and certain highlights of them are reported and discussed in the main text. A significant value of 0.05 (two-tailed) was used for the statistical tests. Information about the strength of relationship (i.e. effect size) for the statistically significant findings was also reported (see §3.11.1. for the guidelines that are followed). The abbreviated names of the variables/constructs and questionnaire items along with abbreviations of statistical terms are presented in Appendices A2 and A5.

4.2 Data screening procedures and exploratory analyses

In this section, preliminary data screening procedures, exploratory data analyses and preliminary reliability assessments are reported and described (some of these results are reported in Appendix B1 or are available on request). Before conducting the analyses that were of primary interest for the current study, a number of procedures and tests were carried out in both data sets to screen, clean and prepare the data for the implementation of the subsequent statistical methods. The aim was to gain a first insight into the data and investigate them visually, graphically, numerically and statistically at univariate and multivariate level. These procedures included, among others: identification and correction of the data entry and data coding errors; evaluation of the amount and distribution (patterns) of missing data and decisions about treating them; detection of influential outliers and decisions about handling them; and assessment of the internal reliability of scores on selected questionnaire' subscales. Some assumptions (such as normality, multicollinearity, linearity and homoscedasticity) needed also to be checked and verified so that inferential statistics could be employed in the following statistical analyses of the data.

4.2.1 Accuracy of the data entry

The questionnaires' responses were entered manually into the SPSS software program. Thus, it was deemed as crucial to examine if the data have been correctly entered into the program and to identify and treat any potential problems. To detect any coding errors in the data files (for example, whether the values of all the variables were within the intended range), frequency distribution tables (descriptive statistics or frequencies) for all the variables (both quantitative and categorical) and graphical inspections were performed.

4.2.2 Amount and distribution of missing data

After the inspection of the data entry accuracy, the amount and the distribution of the missing data values were examined. I found that the variables with the most missing data were those related to students' grades (e.g. expected grade in statistics) followed by those associated with previous mathematics background and performance (e.g. grade achieved in previous courses). For example, the final grade variable contained a large number of missing data (namely 28.6% and 18.9% in the pre-course and post-course dataset respectively). All the other variables (e.g. closed-ended questions requesting demographic and academic information) had less than 5% of missing data. Especially, missing data did not exceed 2% for any Likert-type item included in both versions of the questionnaire. The next step -and the most important consideration when handling missing data- was to investigate the patterns for the missing data. I performed the Little's (1988) Missingness Completely at Random test (MCAR) on selected questionnaire' subscales individually and separately in the two data files. The MCAR tests indicated that the missing data patterns could be considered being completely missing at random since the analyses revealed statistically non-significant results. More information is provided in Appendix B1.

Following Tabachnick and Fidell's (2013) recommendations, since the two data sets could be considered as large enough (refer to §3.6.2), the small amount of missing data (less than 5% in most of the variables) and the random pattern of missing data, any approaches and decisions about how to deal with the missing data were not so critical. As those authors argue, any procedures for managing and dealing with missing values would not lead to dramatic differences in the results.

The subsequent statistical analyses were decided to be conducted without deleting any cases or variables with missing information. In the current study, pairwise deletion technique, where all the available information was included, was employed unless stated. For example, before conducting the CFA and SEM approaches, a single imputation method was used to deal with the missing values (and overcome AMOS software limitations). The missing values for all the independent variables (subscales) were replaced by imputed values using the Expectation-Maximization (EM) technique. However, the missing data for the final grade variable -which is the dependent variable in the model- could not be handled or replaced with any missing data handling strategies. Thus, any analyses involving the final grade variable relied on the reduced sample taking into account only the cases (participants) whose their grade was available to the researcher.

4.2.3 Detection and treatment of outliers

Detection of outliers and decisions made about treating them (i.e. whether it would be removed, transformed or not) were also under investigation. Before running the subsequent statistical analyses, the questionnaire subscales in both data sets, which were used in the multivariate analyses (such as CFA and SEM), were inspected for the presence of both univariate and multivariate outliers using statistical techniques and graphical representations (see Appendix B1). Due to the emphasis on multivariate techniques, univariate outliers were not being taken into account and more attention was placed on the multivariate outliers. In order to detect multivariate outliers, the Mahalanobis distance value for the selected questionnaire subscales was examined. The Mahalanobis distance was evaluated as a chi-square test with degrees of freedom equal to the number of variables included in the regression. A value greater than the critical value suggested by this criterion was flagged as a multivariate outlier. In the pre-course and post-course data sets, twelve and seven cases (students) respectively were identified as multivariate outliers because they exceeded the critical value of χ^2 (7) = 24.322, p<.001 where 7 is the number of variables included in the regression analyses. Thus, I decided to remove them from the data sets. After the dropping of the multivariate outliers, it was observed that the kurtosis parameter value of the variables (subscales) of interest was improved (refer to §4.3.2 for information about kurtosis values).

4.2.4 Tests for normality assumptions

The univariate and multivariate distributional properties of the variables (subscales) included in the more complex statistical analyses (such as SEM) were investigated to determine whether normality assumptions could be acceptable or not. Considering the criteria of assessment and inspection of the univariate distributions of the variables, some deviations from the normal distribution were observed; however, these deviations did not seem to be substantial. In addition, following Verhoeven (2009) and Judi *et al*. (2011), large sample sizes can be treated as they follow the normal distribution. The sample size for both data sets (N=815 and N=641 in the pre-course and post-course respectively) could be considered as sufficiently large to claim that the distribution of the sample means approximately followed the normal distribution, as the Central Limit Theorem states. Regarding the examination of substantial departures from multivariate normality, the Mardia's coefficient gave a significant result indicating that the multivariate distribution of the investigated data was not normal. However, with relatively large samples, it is relatively robust against the violations of normality (Diamantopoulos, 2010). More information is provided in Appendix B1 and upon request.

4.2.5 Homoscedasticity and Linearity

The next step was to assess the homoscedasticity of variance assumptions and the linearity between variables. Homoscedasticity of variance was inspected using bivariate scatter plots of a set of pair of variables (selected subscales). Inspection of the graphs indicated that homogeneity of variable assumption was not substantially violated. Also, graphical methods (e.g. scatterplots) were employed to determine whether the relationship between the independent variables (e.g. self-efficacy) and the dependent variable (i.e. final grade) were linear or not. Since no serious non-linearity was detected, it was assumed linear relationships in the data. More information is provided in Appendix B1 and upon request.

4.2.6 Multicollinearity

Another step of the data screening procedures was to check for multicollinearity. The matrices of correlations between the variables under investigation are reported in the relevant sub-sections. No correlations were found to be 0.9 or higher in absolute value so it could be deduced that there was no evidence of multicollinearity in the data.

4.2.7 Internal Reliability of the constructs

Warner (2008) recommends preliminary examination and reporting of the internal reliabilities of the variables before conducting analyses that use those variables. Thus, before the execution of the following analyses (e.g. FA and SEM), the seven main hypothesised questionnaire' subscales on both datasets underwent an initial analysis of their internal consistency or the reliability of the constructs they measured. The conventions followed for describing internal consistency using Cronbach's alpha are reported in §3.11.1.

Based on the reliability analyses of the pre-course and post-course self-efficacy subscales, the Cronbach's alpha would be improved if the item "Statistics is among the courses that I have the least confidence" (SE6) deleted. Thus, this item was discarded from both subscales and was not included in the subsequent analysis. From the reliability analyses output of the difficulty subscale in both data samples, it was revealed that, higher internal reliability could be achieved if one item, more specifically the item "I find the statistics course demanding" (DIF1), deleted. It was found to be weakly correlated with the other items that composed the difficulty subscale and additionally to have low item-to-total correlations. Moreover, during the interviews, I noticed that the students did not interpret this particular item in a similar way. Based on that observation and the result of the internal reliabilities, this item was omitted from the subscales and not included in further analyses. In addition, it was noted that, if one item related to resilience (RES5) deleted, the reliability of the pre-course resilience subscale would be (marginally) improved. However, this was not in case with the post-course resilience subscale. Thus, it was decided to retain this item for now.

The Cronbach's reliability coefficient values for the seven subscale items of the pre-course version of the questionnaire, after the removal of the two items, ranged from 0.64 to 0.90. The difficulty subscale was found to have the lowest reliability estimate namely 0.64. The Cronbach's reliability coefficient values from the seven subscales of the post-course version of the questionnaire ranged from 0.75 to 0.91, indicating acceptable to excellent internal reliabilities and consistencies. The detailed results are provided in Table 4.1.

The correlations between the individual item scores and the mean subscales' scores were also investigated (see Table 4.1). All the item-total correlations were found to be greater than 0.5 and were significant at 0.05 level. Thus, it can be concluded that most of the items contributed to the particular subscale (construct) that they were supposed to be included. Also, the inter-item correlations from the items from the same construct (results are not reported here) were found to be above 0.3. This is an indication of the internal homogeneity of the items composed each subscale (Coromina, 2014). The Cronbach's reliability coefficient values and the investigation of the item-total correlations were also evaluated for the modified subscales deriving from the subsequent factor analysis procedures (see §4.9).

Table 4.1 Pre-course and Post-course Cronbach's alphas coefficients for selected variables

HYPOTHESISED VARIABLE/ SUBSCALE	Final number of items	Cronbach's alphas		Item-to-total Correlations (Range)	
		Pre-course	**Post-course**	**Pre-course**	**Post-course**
LIKING	3	0.82	0.87	0.85 to 0.88	0.89 to 0.90
INTEREST	3	0.79	0.87	0.81 to 0.86	0.88 to 0.90
VALUE	6	0.87	0.91	0.71 to 0.84	0.74 to 0.89
DIFFICULTY	3	0.64	0.75	0.71 to 0.81	0.78 to 0.85
ANXIETY	6	0.90	0.91	0.74 to 0.86	0.76 to 0.88
SELF-EFFICACY	6	0.87	0.88	0.74 to 0.82	0.74 to 0.84
RESILIENCE	5	0.78	0.84	0.63 to 0.82	0.74 to 0.82

4.3 Descriptive statistics

In this section, the results from the preliminary descriptive analysis, which were conducted separately for the pre- and post- courses versions of the questionnaire, are presented. It should be reminded that information and general description of the sample (such as gender, age group) is provided in the Methodology chapter (refer to §3.11.1). In the following pages, the results of the students' responses on the first part of the questionnaire (including closed-ended questions) and the second part of the questionnaire (including the Likert-type items) are summarised. This section is organised by the hypothesised variables (constructs) investigated. For each variable (construct), the relevant questions (items) included in the questionnaire(s) along with the main findings are reported. More information about the reporting of the quantitative results is provided in §3.11.1.

4.3.1 Responses to the first part of the questionnaire (open and closed-ended questions)

4.3.1.1 Expected statistics course grade

Students were asked to indicate their expected grade in the statistics course given a choice of 5 clusters of grades ranging from 'Fail' to 'Excellent' (1: 0-4.9, 2: 5.00-6.4, 3: 6.5-7.4; 4: 7.5-8.4; 5: 8.5-10). I followed the grades' classification of the public universities. The results are presented in Table 4.2. The students' expected grade at the beginning and at the end of the course and the actual grade (which was transformed as categorical variable with the same number of clusters) that students obtained in the statistics course were then compared. Spearman's correlations were found to be significant (ρ=0.45 and ρ=0.65 for the pre-course and post-course administration respectively).

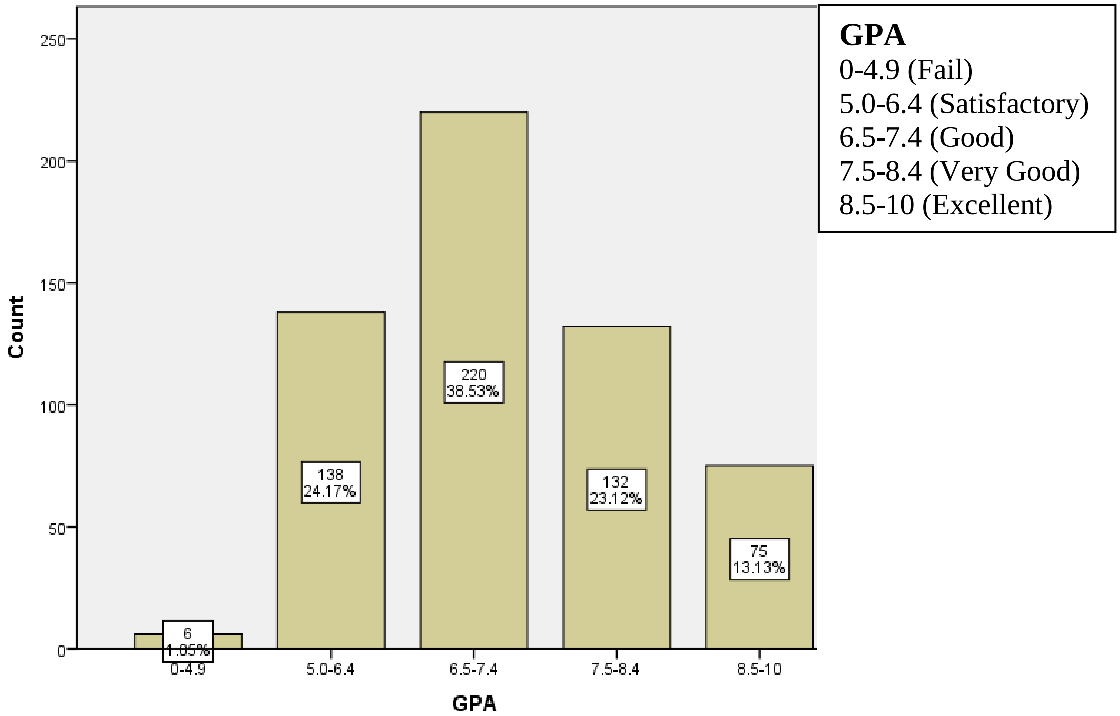
Table 4.2 Frequencies of the Expected Grade in the statistics course

VARIABLE		n	1 (Fail)	2 (Satisfactory)	3 (Good)	4 (Very good)	5 (Excellent)
Expected grade	**Pre-course**	792	13 (1.6%)	182 (22.3%)	220 (27%)	234 (28.7%)	143 (17.5%)
	Post-course	638	14 (2.2%)	161 (25.1%)	142 (22.2%)	169 (26.4%)	152 (23.5%)

4.3.1.2 Grade Point Average (GPA)

Grade Point Average (GPA) was requested from the students in the pre-course administration as an indicator of their general academic performance in the university until the semester they completed the questionnaire. This information was assessed on a 5-point scale ranging from ‘Fail’ to ‘Excellent’ (as described above) where students had to select in which category their current GPA fell. The results are presented in the following bar chart (see Figure 4.1). A high GPA was supposed to indicate a high performer student at his/her degree programme. It was also presumed that a higher grade point average might be associated with a higher performance in statistics. Significant statistical associations were detected between GPA and students’ expected grade in statistics (ρ =0.67) as well as between GPA and the final grade students achieved in statistics (ρ=0.57).

Figure 4.1 Students’ Grade Point Average (GPA) in university



4.3.1.3 Previous Mathematics Background and Performance

The previous mathematics background and performance of students in high school was requested in the pre-course questionnaire version and assessed using two variables, namely the type of the mathematics course completed at the third year of the high school and the grade they achieved in mathematics at the high school matriculation entrance examination. It should be reminded that students who attended public high schools (Lyceums) in Cyprus had the option to study mathematics at two levels - core mathematics or advanced mathematics (see §3.5.3). Of those answered this question, 67% circled that they had completed the advanced mathematics and 32.4% the core mathematics course. Regarding the grade that students obtained in matriculation entrance exams, 92.3% of the students answered this question. The minimum grade reported was 3 and the maximum was 20 with a range of values equals to 17 (out of 20). The mean value of the reported grades was calculated to be equal to 14.39.

Regarding their previous mathematics background and performance at university level, the students were requested to circle the number of courses taken among four options (i.e. none, one, two, more than two), report the name of the courses and the grade they obtained in these courses. Most of the students (43.6%) had not previously completed any mathematics course, 23.9% had completed one course, 24.9% had completed two courses and 7.5% had undertaken more than two courses before the current statistics course. For the purposes of further analyses, the students who completed two or more than two courses were merged in one category. Some of the courses, which were mentioned by the students were, among others, Calculus, (Linear) Algebra, Mathematical Methods, Numerical Methods and Basic concepts of Mathematics in Pre-primary or Primary school.

Concerning the previous mathematics performance, due to the different grading systems between universities (and especially type of universities), this information is presented based on the type of the university. In public universities, this information was made available of 48.8% of the students. The average reported grade obtained in previous mathematics courses was 6.54 (out of 10). In private universities, this information was available for 15.8% of the students. The average grade obtained was 81.56 (out of 100). It should be noted that, in cases where the students reported that they had completed two or more courses, the average grade of the highest self-reported grades was calculated.

4.3.1.4 Choice of the statistics course if it was optional

A closed-ended question with five possible options requested for students to indicate how possible it would be to take a statistics course if they had the choice (i.e. if it was optional for their degree programme).The majority of the students (the mode response to this question was 4) in both administrations claimed that it was somewhat likely to choose a statistics course if it was not compulsory. More details are presented in Table 4.3.

Table 4.3 Frequencies of the possibility of choosing a statistics course if it was optional

VARIABLE		n	**Very Unlikely**	**Somewhat unlikely**	**Neither likely or unlikely**	**Somewhat likely**	**Very Likely**
Choice of the course	**Pre-course**	812	112 (13.7%)	178 (21.8%)	155 (19.0%)	253 (31.0%)	114 (14.0%)
	Post-course	638	91 (14.2%)	126 (19.7%)	119 (18.6%)	202 (31.5%)	100 (15.6%)

4.3.1.5 Time expenditure for studying statistics

In both versions of the questionnaire, the first part was ended by asking a closed-ended question (with three options) related to the amount of studying that students were willing to put (or put) for studying statistics outside of the university class in a typical week (without having a statistics examination) during the academic semester. Also, in the post-course questionnaire version, an additional question was included requesting the average number of hours spent per week for studying when students had statistics test/examinations. From the students' responses, it was revealed that, when an examination was approaching, they tended to devote more time for studying at home. More details are provided in Table 4.4.

Table 4.4 Frequencies of the time expenditure for studying statistics

VARIABLE			n	Less than 3 hours	Between 3 and 6 hours	More than 6 hours
Time Expenditure	Typical week	**Pre-course**	812	613 (75.2%)	191 (23.4%)	8 (1%)
		Post-course	641	496 (77.4%)	130 (20.3%)	15 (2.3%)
	During exams	**Post-course**	638	87 (13.6%)	316 (49.3%)	235 (36.7%)

4.3.2 Responses to the second part of the questionnaire (Liker-type questions)

The following part of this section provides the descriptive statistics and summary information of the students' responses to the individual Likert-type items of the questionnaire. Analyses of the data were carried out separately for the pre-course and post-course version of the questionnaire and thus the descriptive summaries are presented separately. Nevertheless, the investigation of any potential pre-course and post-course differences on selected subscales was reported in a separate section (see §4.4).

4.3.2.1 Liking of statistics

The liking subscale (which composed of three items) was designed to assess students' liking of statistics and the particular statistics course they were currently attended. As can be seen in Table 4.5, the students tended to select the 'agree' option to all the three items in both questionnaire administrations. Most of the students reported that they liked statistics as a discipline (LIK1) by agreeing or strongly agreeing with the statement. An even higher proportion of students agreed or strongly agreed that they liked the subject material of the statistics course (LIK2). Lastly, around 60 percent of students in total in both administrations agreed or strongly agreed that statistics was not among their worst subjects (LIK3). Around one fifth of the students disagreed or strongly disagreed with the three pre-course and post-course items measuring students' liking of statistics.

The liking subscale generated an empirical mean of 3.39 and 3.40 in the pre-course and post-course administration respectively. Also, the distribution of the liking subscale was negatively skewed (coefficient of skewness was -0.63 in both administrations) indicating that the students' mean liking scores tended to be concentrated toward the right-high end of the distribution (more favourable opinions).

Table 4.5 Descriptive statistics of individual items and the subscale related to Liking construct

LIKING CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
LIK1	812	57 (7%)	96 (11.8%)	291(35.7%)	320 (39.3%)	48 (5.9%)	3.00
LIK2	813	47 (5.8%)	129 (15.8%)	229 (28.1%)	352 (43.2%)	56 (6.9%)	4.00
LIK3	812	52 (6.4%)	115 (14.1%)	132 (16.2%)	305 (37.4%)	208 (25.5%)	4.00
Post-course (N=641)							
LIK1	641	32(5%)	102 (15.9%)	195 (30.4%)	265 (41.3%)	47(7.3%)	3.00
LIK2	641	31(4.8%)	104 (16.2%)	147 (22.9%)	307 (47.9%)	52(8.1%)	4.00
LIK3	639	35(5.5%)	97 (15.1%)	132 (20.6%)	259 (40.4%)	116(18.1%)	4.00

LIKING SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	809	3.39	0.91	-0.63	0.09	-0.15	0.17
Post-course	639	3.40	0.93	-0.63	0.10	-0.15	0.19

Note: where SD= strongly disagree, D=disagree, NAD=neither agree or disagree, A agree, SA= strongly agree (and hereafter)

4.3.2.2 Interest towards statistics

The interest subscale consisted of three items in both questionnaire versions. The results are reported in Table 4.6. In both administrations, more than half of the respondents in total were favourable (44.0% agreed and 8.1% strongly agreed in the pre-course administration and 46.0% agreed and 8.9% strongly agreed in the post-course administration) towards the statement that statistics course is an interesting subject (INT1). Similarly, a greater amount of students in total found interesting the studying of statistics (INT3) by agreeing (32.3% and 35.1% in the pre-course and post-course administration respectively) or strongly agreeing (13.9% and 2.7% in the pre-course and post-course administration accordingly) with that statement than the students who disagreed (17.1% and 22.3% disagreed in the pre-course and post-course administration respectively) or strongly disagreed (7.6% and 6.1% with it. Even though most of the students found the statistics course and the studying for statistics interesting, they did not show to be willing and interested in attending more statistics courses in the future. Specifically, 53.5% and 46.8% of the students in the pre-course and post-course administration accordingly displayed unwillingness to attend more statistics courses in the future (INT2) by choosing the ‘disagree’ or ‘strongly disagree’ option.

The empirical mean of the interest subscale was found to be equal to 3.03 in both administrations indicating a moderate level of interest in learning and studying statistics in the aggregate.

Table 4.6 Descriptive statistics of individual items and the subscale related to Interest construct

INTEREST CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
INT1	813	59 (7.2%)	98(12.0%)	231 (28.3%)	359(44.0%)	66(8.1%)	4.00
INT2	814	187(22.9%)	249(30.6%)	221 (27.1%)	129(15.8%)	28(3.4%)	2.00
INT3	814	62(7.6%)	139(17.1%)	237 (29.1%)	263(32.3%)	113(13.9%)	3.00
Post-course (N=641)							
INT1	638	31(4.8%)	86(13.4%)	169 (26.4%)	295(46.0%)	57(8.9%)	4.00
INT2	640	91(14.2%)	209(32.6%)	204 (31.8%)	123(19.2%)	13(2.0%)	3.00
INT3	640	39 (6.1%)	143(22.3%)	216 (33.7%)	225(35.1%)	17(2.7%)	3.00

INTEREST SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	813	3.03	0.92	-0.26	0.09	-0.45	0.17
Post-course	637	3.03	0.88	-0.32	0.10	-0.46	0.19

4.3.2.3 Nature of statistics as a course

The nature of statistics as a course was assessed using five and four items in the pre-course and post-course administration of the questionnaire respectively. The results of the descriptive statistics are presented in Table 4.7. Regarding the students' perceptions about the involvement of the theory and practical applications (exercises) in the statistics course (NAT1), in both administrations, just fewer than fifteen percent of the respondents agreed or strongly agreed that the statistics course involved more theory and around sixty percent of the respondents agreed or strongly agreed that the statistics course involved more practical applications.

With regards to the involvement of mathematics in the statistics course (NAT2), in the pre-course administration, almost the half of the students, namely 35.8% agreed and 13% strongly agreed, and approximately one quarter, namely 22.7% disagreed and 3.2% strongly disagreed, that statistics involved lots of mathematics. In the post-course administration, a slightly lower percentage of students (namely 32.4% agreed and 10.1% strongly agreed) said that the statistics course involved lots of mathematics, whereas approximately one-third of the students, namely 30.9% and 3% disagreed and strongly disagreed respectively with that statement. In the question asking whether someone should be good at mathematics to perform well in statistics (NAT3), in the pre-course administration, 37.3% of the students (more specifically, 31.4% disagreed and 5.9% strongly disagreed) were against this statement. An even larger percentage (44.4% in total, 39.3% disagreed and 5.1% strongly disagreed) was observed in the post-course administration. The total percentage of the students who were in support of this statement was 35.9% and 32% in the pre-course and post-course administration respectively.

Concerning the students' perceived struggle in statistics (NAT4), more than half of the respondents in total believed that even the high performing students could face difficulties in statistics (43.3% and 47.6% agreed and 11.9% and 10.1% strongly agreed in the pre-course and post-course administration accordingly) whereas around a quarter of those who responded to this statement disagreed or strongly disagreed with it. In response to the statement whether male and female can perform equally well in statistics (NAT5), which included only in the pre-course version the questionnaire, most of those surveyed were supporters of it (namely, 36.3% agreed and 27.4% strongly agreed). A minority of participants (namely 5.0% disagreed and 2.2% strongly disagreed) believed that this was not the case and 28.3% were undecided.

Table 4.7 Descriptive statistics of individual items related to the Nature of statistics as a course

NATURE OF STATISTICS AS A COURSE (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
NAT1	813	107(13.1%)	375(46.0%)	211(25.9%)	101(12.4%)	19 (2.3%)	2.00
NAT2	806	26(3.2%)	185(22.7%)	197(24.2%)	292(35.8%)	106 (13.0%)	3.00
NAT3	812	48(5.9%)	256 (31.4%)	215(26.4%)	217(26.6%)	76 (9.3%)	3.00
NAT4	813	21(2.6%)	102 (12.5%)	240(29.4%)	353(43.3%)	97(11.9%)	4.00
NAT5	809	18(2.2%)	41(5.0%)	231(28.3%)	296(36.3%)	223(27.4%)	4.00
Post-course (N=641)							
NAT1	641	76 (11.9%)	344 (53.7%)	128 (20.0%)	78(12.2%)	15(2.3%)	2.00
NAT2	640	19 (3.0%)	198 (30.9%)	150 (23.4%)	208 (32.4%)	65(10.1%)	3.00
NAT3	639	33(5.1%)	252(39.3%)	149 (23.2%)	188 (29.3%)	17(2.7%)	3.00
NAT4	640	12 (1.9%)	97(15.1%)	161 (25.1%)	305 (47.6%)	65(10.1%)	4.00

4.3.2.4 Difficulty of statistics

The difficulty construct was assessed initially using four items in both questionnaire administrations. One item (DIF1) was removed during the reliability analysis procedures (see §4.2) and thus three items composed the final difficulty subscale. As reflected in Table 4.8, around forty percent of the students considered the statistics course that they were enrolled as more difficult than their other academic courses (DIF2) by choosing the 'agree' or the 'strongly agree' option. A slightly lower percentage of students had the opposite opinion and they disagreed or strongly disagreed with this item.

Around one fifth of the students in total reported that they found it difficult to apply statistical methods (DIF3) whereas nearly half of the students disagreed or strongly disagree with that statement in both questionnaire administrations. Regarding the item whether they found it difficult to understand the statistical concepts (DIF4), in the pre-course administration, 33.3% and 4.7% of the students agreed and strongly agreed respectively and 29.6% and 5% disagreed and strongly disagreed accordingly. However, in the post-course administration, a larger percentage of students (namely 40.7% and 5.0% agreed and strongly agreed respectively) found it difficult to understand concepts presented to them and percentages equal to 24.6% and 1.4% expressed their disagreement and strongly disagreement respectively of perceiving it as difficult.

Overall, the students were found to have a moderate level of perception of difficulty of the statistics course as shown by the empirical mean of the Difficulty subscale (2.92 and 3.02 in the pre-course and post-course administration respectively) which was close to the theoretical mean (i.e. 3.00).

Table 4.8 Descriptive statistics of individual items and the subscale related to Difficulty construct

DIFFICULTY CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
DIF2	812	53 (6.5%)	243 (29.8%)	199 (24.4%)	246(30.2%)	73(9.0%)	3.00
DIF3	812	48(5.9%)	344(42.2%)	256 (31.4%)	136(16.7%)	28(3.4%)	3.00
DIF4	813	41(5.0%)	241(29.6%)	222 (27.2%)	271(33.3%)	38(4.7%)	3.00
Post-course (N=641)							
DIF2	641	30 (4.7%)	195(30.4%)	141 (22.0%)	222(34.6%)	53(8.3%)	3.00
DIF3	641	33(5.1%)	267(41.7%)	205 (32.0%)	116(18.1%)	20(3.1%)	3.00
DIF4	640	9(1.4%)	158 (24.6%)	180 (28.1%)	261(40.7%)	32(5.0%)	3.00

DIFFICULTY SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	811	2.93	0.78	0.15	0.09	-0.43	0.17
Post-course	640	3.02	0.80	0.02	0.10	-0.66	0.19

4.3.2.5 Value of statistics

The value sub-scale (which composed of six items) was developed to assess the value, usefulness and relevance that students placed on statistics for their personal, educational and professional life. The results are summarised in Table 4.9. At the beginning of the course, nearly 70% of the students were in favour (strongly agreed or agreed) towards the question posing the statistics is a useful subject (VAL1). At the end of the course, about two-thirds of the students namely 52.9% were agreed and 13.6% strongly agreed with this statement. Around sixty percent of the students in both administrations reported appreciating the value of the statistical knowledge for their everyday life (VAL3) by selecting the ‘agree’ or the ‘strongly agree’ option. In both administrations, more than half of the students agreed or strongly agreed that they would use what they have taught in this statistics course in the future (VAL4) and they believed that statistics would be useful in their future professional career (VAL5). Also, a high proportion of students (over sixty percent in total) reported that statistics is related and has applications in their field of study (VAL6) by selecting the ‘agree’ or the ‘strongly agree’ option in both administrations. The percentage of the students who were against (i.e. they selected the ‘disagree’ or ‘strongly disagree’ option) with the above-mentioned questionnaires’ items related to the value of statistics were 20% and below. Nonetheless, in the both administrations, a larger percentage of students were against than in favour of the question stating that statistics should be taught to all the students regardless of their major of study (VAL2).

The empirical mean score of the items composed the value subscale was 3.47 and 3.41 in the pre-course and post-course administration respectively which indicated that overall students tended to recognise the value of statistics for their personal and future professional life. In addition, the distribution of the mean subscale score was negatively skewed in both administrations showing that the students’ scores tended to be concentrated toward the right-high end of the distribution (more favourable opinions towards the value of statistics).

Table 4.9 Descriptive statistics of individual items and the subscale related to Value construct

VALUE CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
VAL1	811	27(3.3%)	47(5.8%)	169 (20.7%)	427 (52.4%)	141(17.3%)	4.00
VAL2	812	129(15.8%)	196(24.0%)	222 (27.2%)	199 (24.4%)	66(8.1%)	3.00
VAL3	814	39(4.8%)	104(12.8%)	176 (21.6%)	383 (47.0%)	112(13.7%)	4.00
VAL4	814	59 (7.2%)	104(12.8%)	191 (23.4%)	320 (39.3%)	140(17.2%)	4.00
VAL5	814	53 (6.5%)	91(11.2%)	223 (27.4%)	329 (40.4%)	118(14.5%)	4.00
VAL6	814	40(4.9%)	66(8.1%)	165 (20.2%)	323 (39.6%)	220(27.0%)	4.00
Post-course (N=641)							
VAL1	639	23 (3.6%)	37 (5.8%)	153 (23.9%)	339 (52.9%)	87(13.6%)	4.00
VAL2	641	61(9.5%)	179(27.9%)	176 (27.5%)	185(28.9%)	40(6.2%)	3.00
VAL3	641	27(4.2%)	78(12.2%)	135 (21.1%)	335 (52.3%)	66(10.3%)	4.00
VAL4	641	27(4.2%)	103(16.1%)	172 (26.8%)	272 (42.4%)	67(10.5%)	4.00
VAL5	641	31(4.8%)	83(12.9%)	183 (28.5%)	281 (43.8%)	63(9.8%)	4.00
VAL6	641	32 (5.0%)	75(11.7%)	127 (19.8%)	339(52.9%)	68(10.6%)	4.00

VALUE SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	809	3.47	0.83	-0.56	0.09	-0.02	0.17
Post-course	639	3.41	0.83	-0.78	0.10	0.47	0.19

4.3.2.6 Anxiety towards statistics

The anxiety construct was evaluated using six items in both versions of the questionnaire. As it can be observed from the Table 4.10, around forty percent of the respondents were in favour (agreed or strongly agreed) that statistics course made them feel anxious (ANX1) whereas around thirty-four percent of the respondents were against (disagreed or strongly disagreed) with that statement in both administrations.

Regarding the causes of statistics anxiety, 11.6% (7.4% agreed and 4.2% strongly agreed) and 13.7% (10.1% agreed and 3.6% strongly agreed) felt anxious when attending a statistics lecture class (ANX2), 25.8% (20.4% agreed and 5.4% strongly agreed) and 23.4% (19% agreed and 4.4% strongly agreed) indicated anxiety towards completing assignments in statistics (ANX3), 25.6% (19.5% agreed and 6.1% strongly agreed) and 30.4% (25.1% agreed and 5.3% strongly agreed) were more anxious when studying for statistics compared to the other courses (ANX4) and 37.4% (26.7% agreed and 10.7% strongly agreed) and 35.1% (27.1% agreed and 8% strongly agreed) felt anxious when thinking of an upcoming examination in statistics (ANX5) in the pre-course and post-course administration respectively. Also, 53% (40.2% agreed and 12.8% strongly agreed) and 43.7% (34.5% agreed and 9.2% strongly agreed) of the students in the pre-course and post-course administration respectively worried that they would not perform as well as they want to the statistics course (ANX6).

The empirical mean of the anxiety subscale was 2.78 and 2.72 in the pre-course and post-course administration respectively, which showed that overall, the students who participated in the study did not exhibit or experience high levels of anxiety in statistics.

Table 4.10 Descriptive statistics of individual items and the subscale related to Anxiety construct

ANXIETY CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
ANX1	814	70 (8.6%)	212(26.0%)	207 (25.4%)	243(29.8%)	82(10.1%)	3.00
ANX2	812	234(28.7%)	353(43.3%)	131 (16.1%)	60(7.4%)	34(4.2%)	2.00
ANX3	810	135(16.6%)	290(35.6%)	175 (21.5%)	166(20.4%)	44(5.4%)	2.00
ANX4	813	138(16.9%)	312(38.3%)	154 (18.9%)	159(19.5%)	50(6.1%)	2.00
ANX5	813	104(12.8%)	238(29.2%)	166 (20.4)	218(26.7%)	87(10.7%)	3.00
ANX6	814	58(7.1%)	164(20.1%)	160 (19.6%)	328(40.2%)	104(12.8%)	4.00
Post-course (N=641)							
ANX1	636	50 (7.8%)	167(26.1%)	167 (26.1%)	194(30.3%)	58(9.0%)	3.00
ANX2	640	182(28.4%)	291(45.4%)	79 (12.3%)	65(10.1%)	23(3.6%)	2.00
ANX3	636	131(20.4%)	256(39.9%)	99 (15.4%)	122(19.0%)	28(4.4%)	2.00
ANX4	640	98(15.3%)	233(16.3%)	114 (17.8%)	161(25.1%)	34(5.3%)	2.00
ANX5	637	66(10.3%)	233(36.3%)	113 (17.6%)	174(27.1%)	51(8.0%)	3.00
ANX6	640	48 (7.5%)	186(29.0%)	126 (19.7%)	221(34.5%)	59(9.2%)	3.00

ANXIETY SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	806	2.78	0.93	0.24	0.09	-0.40	0.17
Post-course	631	2.72	0.93	0.313	0.97	-0.54	0.19

4.3.2.7 Self-efficacy regarding statistics

The self-efficacy construct was initially evaluated using seven items aiming to assess students' self-efficacy levels regarding statistics. The final self-efficacy subscale was composed of six items after the elimination of one item (SE6) during the initial internal reliability analyses (see §4.2). The descriptive statistics are set out in Table 4.11. A high percentage of those surveyed (over seventy percent in both administrations) reported confidence (i.e. they chose the 'agree' or 'strongly agree' option) in their ability to perform well in the statistics course (SE1). Also, over sixty percent of students in both administrations were confident (i.e. they chose the 'agree' or 'strongly agree' option) in understanding the theoretical part of statistics (SE2), applying statistical methods (SE3) and understanding the basic ways of solving exercises (SE5). Around of fifty percent of the respondents agreed or strongly agreed that they had confidence in explaining and writing conclusions after statistical analyses (SE4). Lastly, in the pre-course administration, 29.1% and 5.8% of the students agreed and strongly agreed respectively that they were confident in mastering even the most difficult parts of the statistics course (SE7). In the post-course administration, 37.9% and 4.4% reported agreeing and strongly agreeing accordingly with that statement.

The empirical mean of the self-efficacy subscale was calculated as 3.61 and 3.59 in the pre- and post-course administration respectively. Also, the mode response for all the items (except SE7) was 4 which shows that the students tended to reflect an 'agree' perspective regarding their self-efficacy beliefs.

Table 4.11 Descriptive statistics of individual items and the subscale related to Self-efficacy construct

SELF-EFFICACY CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
SE1	813	13(1.6%)	38(4.7%)	159(19.5%)	456(56.0%)	147(18.0%)	4.00
SE2	814	12(1.5%)	58(7.1%)	166 (20.4%)	468(57.4%)	110(13.5%)	4.00
SE3	814	15(1.8%)	58(7.1%)	212 (26.0%)	458(56.2%)	71(8.7%)	4.00
SE4	814	16(2.0%)	86(10.6%)	281 (34.5%)	369(45.3%)	62(7.6%)	4.00
SE5	814	9(1.1%)	36(4.4%)	135 (16.6%)	536(65.8%)	98(12.0%)	4.00
SE7	814	45(5.5%)	128(15.7%)	357 (43.8%)	237(29.1%)	47(5.8%)	3.00
Post-course (N=641)							
SE1	641	6 (0.9%)	29(4.5%)	143 (22.3%)	366(57.1%)	97(15.1%)	4.00
SE2	641	7(1.1%)	51(8.0%)	177 (27.6%)	373(58.2%)	33(5.1%)	4.00
SE3	641	8 (1.2%)	36 (5.6%)	162 (25.3%)	379(59.1%)	56(8.7%)	4.00
SE4	640	9(1.4%)	66(10.3%)	228 (35.6%)	294(45.9%)	43(6.7%)	4.00
SE5	641	6 (0.9%)	38(5.9%)	101 (15.8%)	438(68.3%)	58(9.0%)	4.00
SE7	638	23(3.6%)	130(20.3%)	214 (33.4%)	243(37.9%)	28(4.4%)	3.00

SELF-EFFICACY SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	813	3.61	0.65	-0.68	0.09	1.47	0.17
Post-course	637	3.59	0.63	-0.69	0.10	1.18	0.19

4.3.2.8 Resilience

The students' general academic reliance and their resilience regarding statistics were evaluated using two and five items respectively in both versions of the questionnaire. As shown in Table 4.12, the mode value for all the items related to the resilience construct was 4 indicating that respondents tended to choose the 'agree' perspective.

The majority of the students (around sixty percent) reported that they could deal effectively with the challenges and pressures of a university degree (RES1) by selecting the 'agree' or 'strongly agree' option. Also, around sixty percent of the students in both administrations reported that they would not or did not let a failure (e.g. a bad grade in an exam) to affect their confidence (RES2). Regarding the items, which referred specifically to the statistical resilience, in the pre-course administration, a large percentage of students (specifically 64.4% circled 'agree' and 16.1% circled 'strongly agree') stated they will keep trying in statistics even if their studying and effort do not have the desired results (RES7). In the post-course administration, 59.9% of the students agreed and 8.6% strongly agreed with this statement. Over seventy percent of the students continued engaging when trying to solve an exercise (RES3) or to understand a concept (RES4) in the statistics course as revealed by their selection of the 'agree' or 'strongly agree' option. More than sixty percent of those surveyed in both questionnaire administrations agreed or strongly agreed that, when they faced difficulties in statistics, they searched for alternative strategies (RES5). In addition, more than half of the students in both administrations reported continuing to work on a statistical task until they finish it even if they would not find it interesting (RES6).

The empirical mean of the statistical resilience (hereafter resilience) subscale, which composed of five items, was 3.74 and 3.63 in the pre-course and post-course administration respectively. Also, the distribution of the subscale was negatively skewed in both administrations which means that the statistical resilience subscale mean scores tended to cluster at the right-high end of the distribution (more favourable responses).

Table 4.12 Descriptive statistics of individual items and the subscale related to Resilience construct

RESILIENCE CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
RES1	813	14(1.7%)	81(9.9%)	245 (30.1%)	401(49.2%)	72(8.8%)	4.00
RES2	812	19(2.3%)	100(12.3%)	183 (22.5%)	385(47.2%)	125(15.3%)	4.00
RES3	812	9(1.1%)	79 (9.7%)	142 (17.4%)	422(51.8%)	160(19.6%)	4.00
RES4	813	7 (0.9%)	41 (5.0%)	127 (15.6%)	499(61.2%)	139(17.1%)	4.00
RES5	813	10 (1.2%)	85 (10.4%)	191 (23.4%)	443(54.4%)	84(10.3%)	4.00
RES6	811	13(1.6%)	89(10.9%)	243 (29.8%)	398(48.8%)	68(8.3%)	4.00
RES7	812	9(1.1%)	29 (3.6%)	118 (14.5%)	525(64.4%)	131(16.1%)	4.00
Post-course (N=641)							
RES1	640	9(1.4%)	62(9.7%)	156 (24.3%)	370(57.7%)	43(6.7%)	4.00
RES2	640	17(2.7%)	101(15.8%)	141 (22.0%)	297(46.3%)	84(13.1%)	4.00
RES3	641	1 (0.2%)	66 (10.3%)	135 (21.1%)	355(55.4%)	84(13.1%)	4.00
RES4	639	2 (0.3%)	48 (7.5%)	122(19.0%)	392(61.2%)	75(11.7%)	4.00
RES5	641	5 (0.8%)	72 (11.2%)	176 (27.5%)	348(54.3%)	40(6.2%)	4.00
RES6	641	5 (0.8%)	108(16.8%)	167 (26.1%)	309(48.2%)	52(8.1%)	4.00
RES7	641	6 (0.9%)	50 (7.8%)	146 (22.8%)	384(59.9%)	55(8.6%)	4.00

RESILIENCE SUBSCALE (MEAN SCORE)							
	n	M	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Pre-course	809	3.74	0.60	-0.81	0.09	1.46	0.17
Post-course	639	3.63	0.64	-0.66	0.10	0.56	0.19

4.3.2.9 Motivations and Achievement Goals in statistics

The students' motivational orientations and achievement goals in the statistics course were requested by including five items in the pre-course questionnaire administration. For further analyses purposes (e.g. correlations), this construct was sub-divided into two components and two subscales were created namely the extrinsic motivation subscale (composed of the MOT1 and MOT3 items) and the intrinsic motivation subscale (composed of the MOT4 and MOT5 items). The item-level descriptive statistics are displayed in Table 4.13.

For almost ninety percent of students (44.3% and 45.4% circled the 'agree' and 'strongly agree' option respectively) getting a good grade to maintain their overall GPA (MOT1) was among their motivation goals (the median value is equal to 4). 10.2% of the students agreed and 3.3% strongly agreed that they want only to pass this statistics course (MOT2) (the median value is equal to 2). Displaying their abilities to others such as family and classmates (MOT3) had a median score equal to 3 with the half of the students disagreed or strongly disagreed with this statement. Just over sixty percent of the students in total reported agreement or strong agreement with the items assessing the goal to obtain as many knowledge and skills as they could in the statistics course (MOT4) and the personal satisfaction when mastering statistics (MOT5).

Table 4.13 Descriptive statistics of individual items related to Motivations and Achievement Goals construct

MOTIVATIONS AND ACHIEVEMENT GOALS CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
MOT1	813	11(1.3%)	13 (1.6%)	58(7.1%)	361(44.3%)	370(45.4%)	4.00
MOT2	811	251(30.8%)	286(35.1%)	164 (20.1%)	83(10.2%)	27(3.3%)	2.00
MOT3	814	186(22.8%)	220(27.0%)	207 (25.4%)	144(17.7%)	57(7.0%)	3.00
MOT4	813	22 (2.7%)	67 (8.2%)	217 (26.6%)	394(48.3%)	113(13.9%)	4.00
MOT5	813	23(2.8%)	93 (11.4%)	198 (24.3%)	386(47.4%)	113(13.9%)	4.00

4.3.2.10 Expectations of performance in statistics

The pre-course version of the questionnaire included two questions to gauge students' expectations of their performance in the statistics. The results are shown in Table 4.14. The central tendency for the students' expectation of performing well in the course (EXP1) was located in the range of agreement. More specifically, over sixty percent of the students reported expecting to perform well in the course by choosing the 'agree' or 'strongly agree' option. Responding on the question whether they expected to perform as well as or better than their classmates in the statistics course (EXP2), almost fifty percent of the students neither agreed or disagreed, about twenty-five percent agreed, about five percent strongly agreed, around sixteen percent disagreed and around fifty percent strongly disagreed.

Table 4.14 Descriptive statistics of individual items related to Expectations of performance construct

EXPECTATIONS OF PERFORMANCE CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
EXP1	814	11(1.3%)	48 (5.9%)	250 (30.7%)	413(50.7%)	92(11.3%)	4.00
EXP2	814	42(5.2%)	134(16.4%)	395 (48.5%)	203(24.9%)	40(4.9%)	3.00

4.3.2.11 Control over performance in statistics

Students' perceptions of their control over performance were requested using two items in the pre-course version of the questionnaire. The descriptive statistics are displayed in Table 4.15. Students mainly had an internal locus of control as revealed by the questionnaire responses. More specifically, an overwhelming percentage of the students 51.0% agreed and 28.7% strongly agreed) were in favour of the statement that their performance in statistics would be determined by their studying and effort (CON1) whereas only a minimal percentage (5.0% disagreed and 1.3% strongly disagreed) were against it. Moreover, 20.7% of the students agreed and 10.6% strongly agreed on the statement that their performance would be mainly determined by their instructor (and instructional methods) than their personal effort than their personal effort (CON2), 32.1% stayed undecided or neutral, 29.7% disagreed and 6.6% strongly disagreed.

Table 4.15 Descriptive statistics of individual items related to Control over performance construct

CONTROL OVER PERFORMANCE (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
CON1	812	11(1.3%)	41(5.0%)	110 (13.5%)	416(51.0%)	234(28.7%)	4.00
CON2	813	54(6.6%)	242(29.7%)	262 (32.1%)	169(20.7%)	96(10.6%)	3.00

4.3.2.12 Effort in statistics

The amount of effort students planned to exert or exerted in the statistics course was assessed though three items which included in both versions of the questionnaire. As shown in Table 4.16, students gave a favourable response towards all the statements related to the effort construct. Over eighty percent of the students in both questionnaire administrations agreed or strongly agreed that they planned to attend or attended the statistics lecture classes (EFF1). Also, over ninety percent of the students in the pre-course administration (43.8% agreed and 49.0% strongly agreed) that they planned to do their best in statistics (EFF2). In the post-course administration, 49% and 25.4% of the students agreed and strongly agreed respectively that they did their best in statistics. More than half of the students (41% agreed and 16.8% strongly agreed) planned to study for statistics during the semester (EFF3) as they indicted in the pre-course administration. In the post-course administration, a percentage of 46.2% (33.9% agreed and 12.3% disagreed) reported studying throughout the semester and not only when they had an examination whereas a percentage of 31.8% (26.8% disagreed and 5.0% strongly disagreed) reported studying only when an examination was approaching.

Table 4.16 Descriptive statistics of individual items related to Effort construct

EFFORT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
EFF1	811	21(2.6%)	38 (4.7%)	52 (6.4%)	312(38.3%)	388(47.6%)	4.00
EFF2	811	5 (0.6%)	10 (1.2%)	40 (4.9%)	357(43.8%)	399(49.0%)	4.00
EFF3	814	42(5.2%)	142(17.4%)	159 (19.5%)	334(41.0%)	137(16.8%)	4.00
Post-course (N=641)							
EFF1	639	9(1.4%)	30(4.7%)	34 (5.3%)	240(37.4%)	326(50.9%)	4.00
EFF2	636	5(0.8%)	35(5.5%)	119 (18.6%)	314(49.0%)	163(25.4%)	4.00
EFF3	640	32 (5.0%)	172(26.8%)	140 (21.8%)	217(33.9%)	79(12.3%)	3.00

4.3.2.13 Learning strategies in statistics

Four items were included in both versions of the questionnaire to assess students' learning strategies and approaches in the statistics course. As can be seen from the data presented in Table 4.17, over seventy percent of the students in both administrations reported taking well-organised notes (LES1) by selecting the 'agree' or 'strongly agree' option. Around forty percent of the students agreed or strongly agreed that when studying for statistics, they put together information from different sources such as lectures and tutorial notes (LES2). However, a larger percentage of students disagreed or strongly disagreed than agreed or strongly agreed with the statement that apart from reading the course notes, they looked for extra information related to the statistics course (LES3). Lastly, over two-thirds of the students in both administrations were in favour of trying to understand the course content instead of memorising it (LES4) as indicated by agreeing or strongly agreeing with that statement.

Table 4.17 Descriptive statistics of individual items related to Learning strategies construct

LEARNING STRATEGIES CONSTRUCT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
LES1	812	14 (1.7%)	69 (8.5%)	130(16.0%)	447(54.8%)	152(18.7%)	4.00
LES2	812	62(7.6%)	211(25.9%)	188(23.1%)	281(34.5%)	70(8.6%)	3.00
LES3	812	63(7.7%)	259(31.8%)	198(24.3%)	235 (28.8%)	57(7.0%)	3.00
LES4	811	16(2.0%)	103(12.6%)	145(17.8%)	354(43.4%)	193(23.7%)	4.00
Post-course (N=641)							
LES1	638	10(1.6%)	46 (7.2%)	88 (13.7%)	313 (48.8%)	181(28.2%)	4.00
LES2	639	74(11.5%)	210(32.8%)	113(17.6%)	184(28.7%)	58(9.0%)	3.00
LES3	638	90(14.0%)	268(41.8%)	99 (15.4%)	135(21.1%)	46(7.2%)	2.00
LES4	641	13(2.0%)	93 (14.5%)	110(17.2%)	328(51.2%)	97(15.1%)	4.00

4.3.2.14 Learning of statistical software programs

The students' opinions and attitudes about the incorporation of learning statistical software programs in the statistics course were assessed using three items in both versions of the questionnaire. The results are displayed in Table 4.18. Overall, the students seemed to be in favour of learning to use technology in the statistics course. This deduced from the finding that 68.2% and 60.7% of the students agreed or strongly agreed that the incorporation of technology (e.g. a statistics statistical program) could make the learning of statistics more enjoyable (TEC1) in both administrations. Only a small percentage (8.2% and 11.5% of the respondents in the pre-course and post-course administration respectively) strongly disagreed or disagreed with it. Also, in the pre-course administration, over sixty percent of the students (51.4% agreed and 12.1% strongly agreed) reported that they believed that they have the abilities to learning using a statistical software program (TEC2) whereas only around ten percent (9.0% circled 'disagree' and 1.8% circled 'strongly agree') were non-confident of the prospectus of using statistical programs. In the post-course administration, almost half of the respondents (43.8% agreed and 5.8% strongly agreed) seemed to be confident as statistical learners using a statistical program whereas around twenty percent (15.6% disagreed and 3.3% strongly disagreed) indicated not being confident. About one-fifth of the students in both administrations felt anxious about learning to use statistical programs by agreeing or strongly agreeing with that statement whereas almost the half of them reported that incorporation of technology in statistics courses did not evoke anxiety to them (TEC3) by disagreeing or strongly disagreeing with that statement).

Table 4.18 Descriptive statistics of individual items related to Learning statistical software programs

LEARNING STATISTICAL SOFTWARE PROGRAMS (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
TEC1	814	12(1.5%)	6.7(23.4%)	191 (23.4%)	411(50.4%)	145(17.8%)	4.00
TEC2	814	15(1.8%)	73(9.0%)	208 (25.5%)	419(51.4%)	99(12.1%)	4.00
TEC3	814	96(11.8%)	306(37.5%)	253 (31.0%)	140(17.2%)	19(2.3%)	3.00
Post-course (N=641)							
TEC1	641	18 (2.8%)	56 (8.7%)	178 (27.8%)	309(48.2%)	80(12.5%)	4.00
TEC2	640	21 (3.3%)	100(15.6%)	201 (31.4%)	281(43.8%)	37(5.8%)	3.00
TEC3	641	65(10.1%)	255(39.8%)	188 (29.3%)	114(17.8%)	19(3.0%)	3.00

4.3.2.15 Preferred methods of assessment in statistics

The responses to three items included in the pre-course questionnaire version were used to evaluate how students would like to be evaluated in the statistics course. The results are presented in Table 4.19. Almost forty-five percent of the students agreed or strongly agreed that they preferred examinations as a method of assessment whereas nineteen percent disagreed or strongly disagreed (ASS1). Thirty-six percent of the students reported being undecided or neutral by choosing the ‘neither agree nor disagree’ option. A large proportion of the students (namely 40.9% circled ‘agree’ and 20% circled ‘strongly agree’) reported preferring to undertake examinations with open books (ASS2). Also, 24.2% and 12.0% of the students agreed and strongly agreed respectively that they would like to be evaluated by assignments rather than examinations in statistics (ASS3). A further 38.5% responded in a negative manner (29.2% disagreed and 9.3% strongly disagreed) to this statement leaving 25% being not sure.

Table 4.19 Descriptive statistics of individual items related to Preferred methods of assessment

PREFERRED METHODS OF ASSESSMENT (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
ASS1	812	35(4.3%)	120(14.7%)	293 (36.0%)	315 (44.7%)	49(6.0%)	3.00
ASS2	813	19(2.3%)	96(11.8%)	202 (24.8%)	333(40.9%)	163(20%)	4.00
ASS3	813	76(9.3%)	238(29.2%)	204 (25.0%)	197 (24.2%)	98(12.0%)	3.00

4.3.2.16 Opinions and attitudes regarding Mathematics

Seven items in the pre-course version of the questionnaire were employed to assess students’ opinions and attitudes about the subject of mathematics. The results identified in these responses are shown in Table 4.20. Most of the students showed positive attitudes towards mathematics in terms of their liking and interest in mathematics as revealed by their answers to the questions whether mathematics is among their favourite subjects (MAT1) and whether they have always enjoyed the learning of mathematics (MAT2). Also, an overwhelming percentage of students, namely 55.1% agreed and 20.5% strongly agreed that mathematics is a useful subject to learn (MAT3). Almost forty percent of the students perceived the mathematical thinking difficult for them (MAT4), whereas almost half of the students reported that mathematics did not make them feel anxious (MAT5) by selecting the 'agree' or 'strongly agree' option to these statements. Moreover, most of the students (namely 45.9% and 53.4% respectively) reported having confidence in their mathematical abilities (MAT6) and perceiving mathematics among the subjects that they are strong (MAT7). Finally, approximately half of the students (38.3% circled 'agree' and 12.6% circled 'strongly agree') admitted that previous experiences with mathematics have influenced (positively or negatively) their attitudes towards statistics (MAT8).

Table 4.20 Descriptive statistics of individual items related to Opinions regarding Mathematics

OPINIONS REGARDING MATHEMATICS (INDIVIDUAL ITEMS)							
	n	SD	D	NAD	A	SA	Median
Pre-course (N=815)							
MAT1	813	126(15.5%)	148(18.2%)	183(22.5%)	243(29.8%)	113(18.9%)	3.00
MAT2	811	76 (9.3%)	141(17.3%)	183(22.5%)	311(38.2%)	100(12.3%)	4.00
MAT3	812	16 (2.0%)	40(4.9%)	140(17.2%)	449(55.1%)	167(20.5%)	4.00
MAT4	809	60 (7.4%)	195(23.9%)	239(29.3%)	252(30.9%)	63(7.7%)	3.00
MAT5	810	61(7.5%)	139(17.1%)	148(18.2%)	182(22.3%)	86(10.6%)	3.00
MAT6	802	40(4.9%)	125(12.3%)	269(33.0%)	293(36.0%)	75(9.2%)	3.00
MAT7	812	70(8.6%)	158(19.4%)	149(18.3%)	299(36.7%)	136(16.7%)	3.00
MAT8	813	41(5.0%)	136(16.7%)	221(27.1%)	312(38.3%)	103(12.6%)	4.00

4.4 Comparing pre- and post-course scores using paired sample t-tests

In order to investigate potential changes in students' responses over the semester, pre-course and post-course scores were examined (refer to Table 4.21). For the purposes of these analyses, only students who had both pre-course and post-course subscale mean scores were included (n=496). Paired (dependent) sample t-tests using pre-course and post-course subscales (e.g. liking, interest, value, difficulty, anxiety, self-efficacy, resilience, and effort) were performed. The results indicated that by the end of the statistics course, subscale mean scores pertaining to the value of statistics, difficulty of statistics, effort in statistics and resilience in statistics showed a statistically significant decline and the subscale mean scores pertaining to the difficulty of statistics showed a significant increase. The statistically significant differences are considered to be of relatively small effect size.

Table 4.21 Changes of selected variables between pre- and post- course (n=496)

VARIABLE/ SUBSCALE	**n**	**Pre-course**	**Post-course**	**Paired Difference**	**t -value (paired)**	**p-value**	**Cohen's d**
		M(SD)	M(SD)	M(SD)			
LIKING	491	3.42(0.87)	3.39(0.92)	-0.02(0.66)	-0.77	0.44	-
INTEREST	494	3.07(0.91)	3.02(0.88)	-0.05(0.67)	-1.79	0.07	-
VALUE	493	3.46(0.82)	3.37(0.84)	-0.09 (0.61)	-3.19	<0.05	0.11
DIFFICULTY	494	2.93(0.76)	3.07(0.78)	0.14 (0.74)	-4.15	<0.05	0.18
ANXIETY	485	2.74(0.89)	2.72(0.92)	-0.01(0.73)	-0.45	0.65	-
SELF-EFFICACY	492	3.64(0.60)	3.59(0.63)	-0.04(0.58)	-1.64	0.10	-
RESILIENCE	490	3.80(0.59)	3.67(0.63)	-0.13 (0.58)	-4.91	<0.05	0.21
EFFORT	490	4.07(0.68)	3.83(0.73)	-0.24 (0.99)	-6.20	<0.05	0.24

4.5 Correlations between the variables

Bivariate inter-correlations were carried out to inspect correlation patterns and estimate direction and strength of the linear relationships between several variables. Pearson's product-moment correlation method was employed unless stated. The criteria of evaluating the size of the observed effects, using the correlation coefficient values, are presented in §3.11.1. Correlational analyses were conducted on both datasets - the students' responses to the pre-course and the post-course questionnaire version. The correlation matrices which are tables displaying the correlations among the variables are provided.

4.5.1 Correlations between the seven main variables (subscales)

Inter-correlation analyses between the mean scores of the seven main variables (subscales) of interest were conducted and the results are displayed in Table 4.22. The analyses using information from students' responses to the pre-course administration showed that the liking subscale had the lowest correlation with the resilience subscale (r=0.41) and the highest correlation with the interest subscale (r=0.82). The high correlation raised the issue whether the items composed these two subscales might measure the same construct. This was investigated further by conducting factor analysis procedures (refer to §4.8). Moderate correlations were detected between the liking subscale and the subscales of value, difficulty, anxiety, self-efficacy and resilience (ranging from 0.55 to 0.60 in absolute value) and all were in expected direction. Also, interest subscale was strongly related to the liking subscale (r=0.82) and the value subscale (r=0.62) and was moderately related to the other subscales (difficulty, anxiety, self-efficacy and resilience). Students' scores in value subscale correlated positively, though moderately and weakly, with their scores in the self-efficacy and resilience subscales respectively and negatively, though weakly, with their scores in the difficulty and anxiety subscales.

Moreover, there was significant evidence of weak to moderate relationships between difficulty subscale and all the other subscales except the anxiety subscale. The weakest correlation was found between difficulty and resilience subscales (r=-0.26) and the strongest between difficulty and anxiety subscales (r=0.64). Factor analyses suggested that these two variables (constructs) could constitute a single variable (see §4.8). With regards to the inter-correlations among anxiety subscale and the other subscales, these were found to be negative and weak to moderately correlated (ranging from -0.26 to -0.58) except the correlation between anxiety and difficulty.

In addition, moderate linear relationships (ranging from 0.42 to 0.56 in absolute value) between self-efficacy subscale and all the other subscales were detected. Weak and moderate, but significant, correlations were also observed between resilience subscale and the all the subscales under consideration (ranging from 0.26 to 0.56 in absolute value) with the strongest correlation be found between resilience and self-efficacy subscales (r=0.56).

A similar pattern of correlations emerged with respect to the students' responses to the post-course version of the questionnaire. More specifically, the liking subscale was found to be very strongly related to the interest subscale (r=0.87), strongly related to the value subscale (r=0.63) and moderately related to the anxiety, difficulty, self-efficacy and resilience subscales (correlations ranged from 0.40 to 0.59 in absolute value). Pearson's correlation coefficients demonstrated that there were strong relationships between interest subscale and liking and value subscales (r=0.87 and r=0.67 respectively) and moderate relationships between Interest subscale and difficulty, anxiety, self-efficacy and resilience subscales (ranging from 0.42 to 0.56 in absolute value). Weak and moderate associations were also detected between the value subscale and difficulty, anxiety, self-efficacy and resilience subscales (ranging from 0.31 to 0.45). Difficulty subscale was positively and strongly related to anxiety subscale (r=0.65) and negatively related to the other subscales (with correlations ranging from -0.37 to -0.59). Also, correlation analyses showed that the anxiety subscale was moderately correlated with the self-efficacy sub-scale (r=0.53) and weakly correlated with the resilience subscale (r=-0.37). The associations between self-efficacy subscale and all the other subscales were moderate (correlation coefficients ranged from 0.45 to 0.59 in absolute value) with the strongest correlation emerged between elf-efficacy and resilience subscales (r=0.62). Resilience subscale showed weak to moderate correlations with all the investigated subscales except self-efficacy subscale.

Overall, all the seven subscales were significantly correlated with each other at the 0.01 level and in the expected direction. The pairwise subscale inter-correlations did not reveal to be extremely high (that is above 0.9) resulting to multicollinearity (as described in §4.2). The effect sizes of all the correlations, except the ones between the pre-course subscales of Difficulty and Resilience and Anxiety and Resilience, ranged from medium to large.

Table 4.22 Pre-course and post-course Correlation Matrices of the seven main variables

PRE-COURSE CORRELATION MATRIX							
VARIABLE/ SUBSCALE	**VARIABLE/SUBSCALE**						
	LIK	**INT**	**VAL**	**DIFF**	**ANX**	**SE**	**RES**
LIKING	1	0.82	0.60	-0.55	-0.58	0.56	0.41
INTEREST	0.82	1	0.62	-0.48	-0.51	0.56	0.44
VALUE	0.60	0.82	1	-0.31	-0.34	0.42	0.34
DIFFICULTY	-0.55	-0.48	-0.31	1	0.64	-0.45	-0.26
ANXIETY	-0.58	-0.51	-0.34	0.64	1	-0.52	-0.26
SELF-EFFICACY	0.56	0.56	0.42	-0.45	-0.52	1	0.56
RESILIENCE	0.41	0.44	0.34	-0.26	-0.26	0.56	1

POST-COURSE CORRELATION MATRIX							
VARIABLE/ SUBSCALE	**VARIABLE/SUBSCALE**						
	LIK	**INT**	**VAL**	**DIF**	**ANX**	**SE**	**RES**
LIKING	1	0.87	0.63	-0.59	-0.53	0.59	0.40
INTEREST	0.87	1	0.67	-0.55	-0.46	0.56	0.42
VALUE	0.63	0.67	1	-0.39	-0.32	0.45	0.31
DIFFICULTY	-0.59	-0.55	-0.39	1	0.65	-0.56	-0.32
ANXIETY	-0.53	-0.46	-0.32	0.65	1	-0.53	-0.27
SELF-EFFICACY	0.59	0.56	0.45	-0.56	-0.53	1	0.62
RESILIENCE	0.40	0.42	0.31	-0.32	-0.27	0.62	1

Note: All the reported correlation coefficients are significant at the 0.01 level.

4.5.2 Correlations between affective, motivational and cognitive engagement variables

Bivariate correlations between several variables (namely, liking, interest, value, difficulty, anxiety, self-efficacy, resilience, effort, learning strategies, expectations of performance, control over performance, intrinsic and extrinsic motivation) when this information was available in the pre-course and post-course data sets were calculated to inspect their associations with each other. The correlation analyses results are displayed in Table 4.23.

In both administrations, an examination of the correlation coefficients between the effort subscale and all the other subscales revealed very weak to moderate correlations. The strongest relationships were found between the effort and learning strategies subscales (r=0.45 and 0.51 in the pre-course and post-course administration respectively) and the effort and resilience subscales (r=0.46 and 0.50 in the pre-course and post-course administration accordingly). A similar pattern of associations was observed between the pre-course and post-course learning strategies subscale and the all other subscales with the strongest ones to be found between the learning strategies subscale and the subscales of effort and resilience. Furthermore, in the pre-course data set, Pearson's correlation coefficient reflected that there were weak to moderate, but significant, correlations between the expectations of performance subscale and all the other subscales with the highest correlation to be found between the expectations of performance subscale and the self-efficacy subscale (r=0.65). Also, the correlational investigation revealed very weak to weak, but significant, correlations between the control over performance subscale and all the other subscales. The strongest correlation was found between the control and self-efficacy subscales (r=0.31). Moreover, in the pre-course administration, intrinsic motivation subscale was moderately correlated with the liking, interest, value, self-efficacy, resilience and learning strategies subscales. The correlations between the intrinsic motivation subscale and the other subscales were very weak to weak, but all significant and in the expected direction. Between the extrinsic motivation subscale and all the other subscales, the largest correlation coefficients values, although weak, were found between the extrinsic motivation and intrinsic motivation subscales (r=0.30) and the extrinsic motivation and expectations of performance subscales (r=0.23). No statistically significant correlations existed between the extrinsic motivation subscale and the subscales of anxiety and difficulty.

Table 4.23 Pre-course and post-course Correlation Matrices of several affective, motivational and cognitive engagement variables

PRE-COURSE CORRELATION MATRIX							
VARIABLE	VARIABLE						
	LIK	INT	VAL	DIF	ANX	SE	RES
EFFORT	0.29*	0.32*	0.26*	-0.07*	-0.10*	0.27*	0.46*
LEARNING STRATEGIES	0.31*	0.33*	0.28*	-0.11*	-0.09*	0.31*	0.49*
EXPECTATIONS	0.50*	0.50*	0.31*	-0.45*	-0.52*	0.65*	0.44*
CONTROL	0.24*	0.24*	0.25*	-0.10*	-0.21*	0.31*	0.21*
INTRINSIC MOTIVATION	0.53*	0.57*	0.54*	-0.23*	-0.19*	0.44*	0.51*
EXTRINSIC MOTIVATION	0.20*	0.21*	0.11*	-0.07	0.03	0.22*	0.21*

PRE-COURSE CORRELATION MATRIX						
VARIABLE	**VARIABLE**					
	EFF	**LS**	**EXP**	**CON**	**IM**	**EM**
EFFORT	1	0.45*	0.28*	0.22*	0.38*	0.21*
LEARNING STRATEGIES	0.45*	1	0.26*	0.18*	0.42*	0.22*
EXPECTATIONS	0.28*	0.26*	1	0.24*	0.35*	0.23*
CONTROR	0.22*	0.18*	0.24*	1	0.25*	0.13*
INTRINSIC MOTIVATION	0.38*	0.42*	0.35*	0.25*	1	0.30*
EXTRINSIC MOTIVATION	0.21*	0.22*	0.23*	0.13*	0.30*	1

POST-COURSE CORRELATION MATRIX							
VARIABLE	**VARIABLE**						
	LIK	**INT**	**VAL**	**DIF**	**ANX**	**SE**	**RES**
EFFORT	0.19*	0.19*	0.17*	-0.12*	-0.11*	0.35*	0.50*
LEARNING STRATEGIES	0.25*	0.29*	0.28*	-0.14*	-0.11*	0.39*	0.45*

POST-COURSE CORRELATION MATRIX		
VARIABLE	**VARIABLE**	
	EFFORT	**LEARNING STRATEGIES**
EFFORT	1	0.51*
LEARNING STRATEGIES	0.51*	1

Note: * indicates that correlation is significant at the 0.05 level

4.5.3 Correlations between investigated variables and statistics performance

The correlation matrices depicting the relationships between the outcome variable (students' final grade in the statistics course) and those variables investigated in the study and considered as independent are presented in Table 4.24. Regarding the correlations between the final grade variable and the variables of the pre-course questionnaire version, all the subscales except value, anxiety and control over performance, were found to be significantly correlated with the final grade in statistics. All the significant correlations were found to be very weak to weak in magnitude and in the expected direction. The highest correlation was found between the final grade variable and the expectations of performance subscale (r=0.30) followed by the correlations between the final grade variable and the self-efficacy, resilience and learning strategies subscales (all r=0.23). Slightly higher correlation coefficients were obtained between the final grade variable and the subscales of the post-course version of the questionnaire (e.g. seven main subscales, effort and learning strategies subscales). All resulting correlations were found to be statistically significant at the level of 0.05, but very weak to moderate, and in the expected direction, with self-efficacy and resilience subscales showing the strongest correlations (r=0.41 and r=0.35 respectively).

Regarding the square of the correlation coefficient (R^2), in the pre-course administration, self-efficacy and resilience showed weak correlations explaining both 5% of the variance in statistics performance. In the post-course administration, 17% and 12% of the variation in the statistics performance can be explained by the self-efficacy and resilience respectively.

Table 4.24 Inter-correlations between the outcome and the independent variables (pre-course and post-course)

PRE-COURSE	
Outcome Variable	**FINAL GRADE**
Independent Variable	
LIKING	0.11*
INTEREST	0.12*
VALUE	0.05
DIFFICULTY	-0.09*
ANXIETY	-0.09
SELF-EFFICACY	0.23*
RESILIENCE	0.23*
EFFORT	0.18*
LEARNING STRATEGIES	0.23*
EXPECTATIONS	0.30*
CONTROL	0.07
INTRINSIC MOTIVATION	0.12*
EXTRINSIC MOTIVATION	0.12*

POST-COURSE	
Outcome Variable	**FINAL GRADE**
Independent Variable	
LIKING	0.22*
INTEREST	0.19*
VALUE	0.14*
DIFFICULTY	-0.27*
ANXIETY	-0.31*
SELF-EFFICACY	0.41*
RESILIENCE	0.35*
EFFORT	0.34*
LEARNING STRATEGIES	0.22*

Note: * indicates that the correlation is significant at the 0.05 level.

4.5.4 Correlations between items related to statistics and mathematics

The correlations between the pre-course subscales related to statistics and the individual items related to mathematics were investigated. A significant, but almost moderate, correlation ($r = 0.39$) was found between the liking of statistics subscale and the item which assessed liking of mathematics (MAT1). Also, weak to moderate correlations were found between interest, value, difficulty, anxiety, self-efficacy and resilience subscales related to statistics and the item which related to the liking of mathematics. A moderate relation ($r=0.41$) was detected between interest in statistics subscale and the item which measured interest in mathematics (MAT2). All the other correlations between the item, which assessed interest in mathematics and the statistics-related subscales, were found to be very weak to weak. A positive, but weak, relationship (r=0.35) was also noted between the value of statistics subscale and the item which evaluated students' perceived value of mathematics (MAT3). Weak to moderate correlations were observed between the item, which assessed students' opinions about the value of mathematics and all the other subscales associated statistics. Moreover, a significant, but weak, correlation (r=0.25) was found between the difficulty of statistics subscale and the item which was related to the difficulty of mathematics (MAT4). All the other correlations between this item and the subscales related to statistics were found to be very weak to weak. A moderation correlation (r=0.55) was found between anxiety towards statistics subscale and the item which was related to anxiety towards mathematics (MAT5). This item was moderately associated with all the other subscales which measured constructs related to statistics. Furthermore, self-efficacy regarding statistics subscale and the item which was related to the confidence in mathematical abilities (MAT6) were detected to be moderately correlated (r=0.43). Also, a weak and negative association (r=-0.26) was inspected between self-efficacy regarding statistics subscale and the item which was related to the students perceptions whether mathematics is among the subjects they are strong (MAT7). Very weak to weak associations were identified between the two items, which purported to assess students' perceived mathematics self-efficacy and all the other subscales related to statistics. Lastly, very weak to weak significant associations between all the items related to mathematics constructs (with one exception) and the final grade variable was revealed. More specifically, final grade obtained in statistics was not significantly correlated with the interest in learning mathematics.

Significant, but very weak to weak relationships, were detected between all the investigated subscales related to statistics and the variables related to high school entrance matriculation grade in mathematics and the average grade obtained in previous mathematics courses. In addition to this, a weak (r=0.29) and a strong (r=0.63) correlation was found between the final grade in statistics and the entrance matriculation mathematics grade and the average university mathematics courses' grade respectively.

Point–biserial correlations were conducted between the type of high school mathematics course (e.g. core or advanced mathematics) and the investigated subscales related to statistics. With one exception (the relationship between this variable and the resilience sub-scale), those relationships were found to be significant ($p < 0.05$), but of small magnitude.

4.6 Variations by demographic and educational characteristics using independent sample T-tests and ANOVA tests

The next step was to conduct multiple bivariate comparisons (independent sample t-tests) and multivariate comparisons (ANOVA) to investigate whether there were any statistically significant differences on students' responses in selected subscales in terms of different demographic and educational factors/characteristics. Demographic and educational variables considered in these analyses were gender, age group, first time of attending the course and number of mathematics courses completed. The results are provided in the following tables. The effect sizes (Cohen's d for t-tests and Cohen's f for ANOVAs) for the statistically significant results are also reported.

4.6.1 Analyses of Gender differences

In order to evaluate whether there were differences in mean scores of the questionnaire subscales between males and females, independent sample t-tests were conducted (refer to Table 4.25). The results of the t-tests showed that, in both administrations, there were no differences between the two genders in the six main subscales (liking, interest, value, difficulty, self-efficacy and resilience). A significant gender difference existed in the mean score of the anxiety subscale. More specifically, female students reported experiencing significantly higher levels of anxiety than male students. Moreover, in the pre-course dataset, significant differences were revealed between males and females with respect to the effort, learning strategies, intrinsic motivation, extrinsic motivation and expectations of performance variables except the control over performance variable. Female students were found to be more intrinsically and extrinsically motivated, put forward greater effort and use more the investigated learning strategies. However, male students found to have higher expectations of their performance in statistics than their female counterparts. Also, in the post-course data set, a significant effect of gender showed that women were more likely than men to exert effort and apply the investigated learning strategies in the statistics course. Finally, in both data administrations, there was not a significant gender difference in the mean score of the final grades achieved in statistics. The effect sizes were ranged from small to medium.

Table 4.25 T-test results of 'Gender' Differences in several variables

VARIABLE/ SUBSCALE	Gender	n	M	SD	Test statistic	df	p-value (effect size)
PRE-COURSE LIKING	Male	288	3.36	0.93	-0.65	806	p=0.52
	Female	520	3.41	0.90			
POST-COURSE LIKING	Male	249	3.42	0.88	0.39	637	p=0.69
	Female	390	3.39	0.96			
PRE-COURSE INTEREST	Male	291	3.00	0.93	-0.60	810	p=0.55
	Female	521	3.04	0.91			
POST-COURSE INTEREST	Male	248	3.06	0.88	0.68	635	p=0.50
	Female	389	3.01	0.88			
PRE-COURSE VALUE	Male	289	3.46	0.86	-0.20	806	p=0.84
	Female	519	3.47	0.82			
POST-COURSE VALUE	Male	248	3.41	0.81	-0.11	637	p=0.92
	Female	391	3.41	0.84			
PRE-COURSE DIFFICULTY	Male	291	2.92	0.73	-0.21	808	p=0.84
	Female	519	2.93	0.80			
POST-COURSE DIFFICULTY	Male	250	2.98	0.78	-1.22	638	p=0.22
	Female	390	3.05	0.81			
PRE-COURSE ANXIETY	Male	288	2.65	0.88	-2.98*	636.4	p<0.05 (0.22)
	Female	517	2.85	0.85			
POST-COURSE ANXIETY	Male	246	2.60	0.88	-2.50	629	p<0.05 (0.22)
	Female	385	2.80	0.96			
PRE-COURSE SELF-EFFICACY	Male	292	3.62	0.66	0.35	810	p=0.73
	Female	520	3.60	0.65			

POST-COURSE SELF-EFFICACY	Male	248	3.59	0.58	0.21	635	p=0.84
	Female	389	3.58	0.65			
PRE-COURSE RESILIENCE	Male	289	3.68	0.59	-0.94	805	p=0.35
	Female	518	3.71	0.53			
POST-COURSE RESILIENCE	Male	249	3.59	0.54	-1.79	635	p=0.08
	Female	388	3.64	0.59			
PRE-COURSE EFFORT	Male	288	3.90	0.76	-4.04*	530.0	p<0.05 (0.30)
	Female	519	4.11	0.66			
POST-COURSE EFFORT	Male	248	3.68	0.75	-4.03	633	p<0.05 (0.33)
	Female	387	3.92	0.69			
PRE-COURSE LEARNING STRATEGIES	Male	287	3.24	0.65	-5.37	803	p<0.05 (0.39)
	Female	518	3.49	0.62			
POST-COURSE LEARNING STRATEGIES	Male	248	3.15	0.63	-4.25	634	p<0.05 (0.34)
	Female	388	3.37	0.67			
PRE-COURSE INTRINSIC MOTIVATION	Male	291	3.43	0.88	-4.35*	536.6	p<0.05 (0.33)
	Female	520	3.70	0.77			
PRE-COURSE EXTRINSIC MOTIVATION	Male	291	3.31	0.76	-4.03	810	p<0.05 (0.30)
	Female	521	3.53	0.72			
PRE-COURSE CONTROL	Male	290	3.72	0.70	-0.07	808	p=0.94
	Female	520	3.73	0.69			
PRE-COURSE EXPECTATIONS	Male	292	3.45	0.73	2.27	811	p=0.02 (0.17)
	Female	521	3.32	0.79			
PRE-COURSE FINAL GRADE	Male	203	64.50	20.50	-0.90	579	p=0.37
	Female	378	66.08	20.00			
POST-COURSE FINAL GRADE	Male	203	68.27	19.89	-1.72	518	p=0.09
	Female	317	71.18	18.09			

*Equal variance not assumed; Welch statistic (Robust test of equality of means) was used

4.6.2 Analyses of Age Group differences

As previously reported when examining the demographics of participants (see §3.11.1), both data sample sets consisted of predominately traditional students (i.e. students in the age group 17-24). A series of t-tests were carried out to check whether there were differences between the two age groups (i.e. the group of participants between 17 and 24 and the group of participants age 25 or older) on the mean scores of the questionnaire' subscales (refer to Table 4.26). These analyses in the pre-course and post-course data yielded non-significant results for the comparisons indicating similar distributions of students' responses on the seven main questionnaire subscales. However, in the pre-course data the results indicated that there were significant differences in the extrinsic motivation scores between the two age groups where the students in the age group 17-24 found to be more extrinsically motivated than students who were older (the effect size was considered as medium). In addition, in both data sets, students did not significantly differ in the grade they achieved in the statistics course in terms of their age group.

Table 4.26 T-test results of 'Age Group' differences in several variables

VARIABLE/ SUBSCALE	Age Group	n	M	SD	Test statistic	df	p-value (effect size)
PRE-COURSE LIKING	17-24	776	3.39	0.91	0.50	806	p=0.62
	25 and over	32	3.31	0.92			
POST-COURSE LIKING	17-24	610	3.37	0.93	-0.10	637	p=0.92
	25 and over	26	3.41	0.81			
PRE-COURSE INTEREST	17-24	781	3.02	0.91	-0.50	810	p=0.62
	25 and over	31	3.11	1.11			
POST-COURSE INTEREST	17-24	608	3.03	0.88	0.54	635	p=0.59
	25 and over	29	2.94	0.85			
PRE-COURSE VALUE	17-24	777	3.46	0.83	-1.21	806	p=0.23
	25 and over	31	3.65	0.79			
POST-COURSE VALUE	17-24	610	3.41	0.83	-0.21	637	p=0.83
	25 and over	29	3.44	0.82			
PRE-COURSE DIFFICULTY	17-24	778	2.92	0.77	0.88	808	p=0.38
	25 and over	32	3.04	0.83			
POST-COURSE DIFFICULTY	17-24	611	3.01	0.80	-1.82	638	p=0.07
	25 and over	29	3.29	0.76			
PRE-COURSE ANXIETY	17-24	773	2.77	0.93	-1.30	803	p=0.20
	25 and over	32	2.98	0.91			
POST-COURSE ANXIETY	17-24	602	2.70	0.94	-1.38	629	p=0.17
	25 and over	29	2.95	0.74			
PRE-COURSE SELF-EFFICACY	17-24	780	3.61	0.64	0.18	810	p=0.86
	25 and over	32	3.59	0.89			
POST-COURSE SELF-EFFICACY	17-24	608	3.60	0.63	0.97	635	p=0.33
	25 and over	29	3.48	0.48			
PRE-COURSE RESILIENCE	17-24	775	3.70	0.54	-0.61*	32.4	p=0.55
	25 and over	32	3.78	0.74			
POST-COURSE RESILIENCE	17-24	608	3.61	0.58	0.42	635	p=0.68
	25 and over	29	3.57	0.53			
PRE-COURSE EFFORT	17-24	776	4.04	0.71	-0.38	805	p=0.73
	25 and over	31	4.09	0.59			
POST-COURSE EFFORT	17-24	607	3.84	0.72	1.90	633	p=0.06
	25 and over	28	3.57	0.75			
PRE-COURSE LEARNING STRATEGIES	17-24	773	3.40	0.64	0.12	803	p=0.90
	25 and over	32	3.39	0.59			
POST-COURSE LEARNING STRATEGIES	17-24	607	3.29	0.66	0.01	634	p=0.99
	25 and over	29	3.28	0.65			
PRE-COURSE INTRINSIC MOTIVATION	17-24	780	3.60	0.81	-1.06	809	p=0.29
	25 and over	31	3.78	0.94			
PRE-COURSE EXTRINSIC MOTIVATION	17-24	780	3.46	0.73	3.05*	32.3	p<0.05 (0.36)
	25 and over	32	3.14	1.03			
PRE-COURSE CONTROL	17-24	780	3.73	0.69	0.73	808	p=0.47
	25 and over	30	3.63	0.79			
PRE-COURSE EXPECTATIONS	17-24	781	3.36	0.76	-1.38	811	p=0.17
	25 and over	32	3.57	0.96			
PRE-COURSE FINAL GRADE	17-24	553	65.70	19.80	0.65	579	p=0.51
	25 and over	28	63.14	26.75			

POST-COURSE FINAL GRADE	17-24	496	70.18	18.44	0.55*	24.1	p=0.59
	25 and over	24	67.21	26.17			

*Equal variance not assumed; Welch statistic (Robust test of equality of means) was used

4.6.3 Analyses of First Time of Attending differences

As previously reported in §3.11.1, an overwhelming percentage of students attended the current statistics course for the first time. In order to explore whether the students' responses to the questionnaire subscales were associated with this factor, t-tests were conducted (see Table 4.27). The results in the pre-course data set indicated that, among the seven main subscales, there were significant differences only in the interest subscale in according to whether it was the first time or not for attending a statistics course. Students who attended statistics for the first time were more likely to be interested in statistics than the students who had attended a statistics course before. Among the motivation and cognitive engagement-related variables, the t-tests revealed three variables (namely effort, intrinsic motivation and extrinsic motivation) for which the students attending the course for the first time or not differed significantly. More specifically, students who attended the course for the first time had higher intrinsic and extrinsic motivations and were willing to put more effort compared to the students who had previously attended a statistics course.

Similar patterns of significant differences were revealed when conducting sample t-tests at the post-course data set with the addition of the significant difference on the resilient liking and resilience subscales. More specifically, liking in statistics, interest towards statistics, resilience behaviours and effort in statistics were rated higher by the students who attended first time the course than those who had completed a statistics course before. In both data sets (pre-course and post-course), statistically significant differences were obtained in the final grade variable. More specifically, students who attended the course for the first time obtained higher grades on average than students who had attended a statistics course before. All the effect sizes (Cohen's d) of the significant differences were considered to be small except the effect sizes for the final grade differences which were considered to be large.

Table 4.27 ANOVA results of 'First Time of Attending' differences in several variables

VARIABLE/ SUBSCALE	**First Time**	**n**	**M**	**SD**	**Test statistic**	**df**	**p-value (effect size)**
PRE-COURSE LIKING	Yes	674	3.42	0.88	1.85*	172.88	p=0.07
	No	133	3.25	1.03			
POST-COURSE LIKING	Yes	548	3.42	0.92	3.00	631	p<0.05 (0.24)
	No	85	3.20	0.97			
PRE-COURSE INTEREST	Yes	676	3.07	0.91	8.87*	190.02	p<0.05 (0.28)
	No	135	2.81	0.92			
POST-COURSE INTEREST	Yes	546	3.05	0.87	2.05	621	p<0.05 (0.22)
	No	87	2.85	0.93			
PRE-COURSE VALUE	Yes	673	3.48	0.82	0.24*	179.05	p=0.80
	No	134	3.46	0.90			
POST-COURSE VALUE	Yes	548	3.42	0.91	0.94	631	p=0.35
	No	85	3.33	0.95			

PRE-COURSE DIFFICULTY	Yes	675	2.91	0.76	-0.64*	177.63	p=0.52
	No	134	2.97	0.85			
POST-COURSE DIFFICULTY	Yes	550	3.00	0.80	-1.58	632	p=0.12
	No	84	3.15	0.82			
PRE-COURSE ANXIETY	Yes	671	2.76	0.92	-0.97	802	p=0.33
	No	133	2.85	0.98			
POST-COURSE ANXIETY	Yes	542	2.69	0.94	-1.84	623	p=0.07
	No	83	2.89	0.93			
PRE-COURSE SELF-EFFICACY	Yes	676	3.61	0.65	0.28	809	p=0.78
	No	135	3.60	0.68			
POST-COURSE SELF-EFFICACY	Yes	548	3.59	0.64	0.78	629	p=0.44
	No	83	3.53	0.55			
PRE-COURSE RESILIENCE	Yes	673	3.71	0.55	1.12	804	p=0.27
	No	133	3.65	0.54			
POST-COURSE RESILIENCE	Yes	549	3.65	0.63	2.18	633	p<0.05 (0.24)
	No	86	3.49	0.68			
PRE-COURSE EFFORT	Yes	671	4.07	0.69	2.74	804	p<0.05 (0.25)
	No	135	3.89	0.73			
POST-COURSE EFFORT	Yes	545	3.85	0.72	2.19	629	p<0.05 (0.24)
	No	86	3.67	0.78			
PRE-COURSE LEARNING STRATEGIES	Yes	672	3.42	0.64	1.48	802	p=0.14
	No	132	3.33	0.65			
POST-COURSE LEARNING STRATEGIES	Yes	546	3.29	0.65	0.86	630	p=0.39
	No	86	3.23	0.72			
PRE-COURSE INTRINSIC MOTIVATION	Yes	674	3.64	0.80	2.90	808	p<0.05 (0.26)
	No	134	3.42	0.89			
PRE-COURSE EXTRINSIC MOTIVATION	Yes	676	3.48	0.73	2.69	809	p<0.05 (0.25)
	No	135	3.29	0.81			
PRE-COURSE CONTROL	Yes	674	3.75	0.69	2.39	807	p=0.17
	No	135	3.60	0.70			
PRE-COURSE EXPECTATIONS	Yes	677	3.37	0.78	0.20	810	p=0.84
	No	135	3.35	0.74			
PRE-COURSE FINAL GRADE	Yes	486	66.66	20.45	12.19*	146.13	p<0.05 (0.60)
	No	94	59.55	17.58			
POST-COURSE FINAL GRADE	Yes	457	71.15	18.48	3.62	515	p<0.05 (0.48)
	No	60	61.87	19.98			

*Equal variance not assumed; Welch statistic (Robust test of equality of means) was used

4.6.4 Analyses of Number of mathematics courses completed differences

One-way ANOVAs showed that there were differences in students' attitudes (e.g. liking, interest value), anxiety and self-efficacy regarding statistics based on the number of mathematics courses (e.g. none, one, two or more) completed at the university level (see Table 4.28). More specifically, results indicated that students who had completed two mathematics courses had more favourable attitudes in terms of their liking, interest and value regarding statistics than those who had completed none or one mathematics course before. Also, students who had completed one mathematics course before reported experiencing more anxieties, perceiving the course more difficult, possessing lower levels of self-efficacy and exhibiting less positive resilient behaviours compared to the students who had not attended any course or had attended two courses. Regarding differences in the final grade, students who had completed one course obtained lower grades than students in the other groups did.

Table 4.28 ANOVA Results of 'Number of mathematics courses' differences in several variables

VARIABLE/ SUBSCALE	# OF MATHS COURSES	n	M	SD	Test statistic	df	p-value (effect size)
PRE-COURSE LIKING	0	353	3.39	0.98	15.23*	480.4	p<0.05 (0.18)
	1	193	3.14	0.88			
	≥2	262	3.58	0.79			
PRE-COURSE INTEREST	0	355	3.00	1.01	12.48*	494.4	p<0.05 (0.16)
	1	194	2.82	0.82			
	≥2	263	3.21	0.83			
PRE-COURSE VALUE	0	355	3.44	0.91	15.33*	475.8	p<0.05 (0.19)
	1	192	3.26	0.82			
	≥2	261	3.66	0.69			
PRE-COURSE DIFFICULTY	0	355	2.91	0.82	12.66*	486.2	p<0.05 (0.17)
	1	193	3.14	0.72			
	≥2	262	2.79	0.73			
PRE-COURSE ANXIETY	0	351	2.79	0.93	6.92	802	p<0.05 (0.23)
	1	191	2.96	0.89			
	≥2	263	2.64	0.94			
PRE-COURSE SELF-EFFICACY	0	355	3.61	0.69	4.89	809	p=0.01 (0.11)
	1	193	3.50	0.63			
	≥2	264	3.69	0.61			
PRE-COURSE RESILIENCE	0	353	3.78	0.60	4.29	805	p=0.01 (0.10)
	1	193	3.64	0.62			
	≥2	262	3.79	0.58			
PRE-COURSE FINAL GRADE	0	222	68.37	18.70	12.53	578	p<0.05 (0.21)
	1	109	57.14	19.70			
	≥2	250	66.70	20.73			

*Equal variance not assumed; Welch statistic (Robust test of equality of means) was used

4.7 Predicting grade performance using Linear Regression and General Linear Model analyses

With the aim to ascertain the contribution and the predictive ability of a number of explanatory variables on the outcome (dependent) variable, simple Linear Regressions (LR) and General Linear Model (GLM) analyses were employed. Separate analyses were performed on both datasets (pre-course and post-course responses to the questionnaire) on the dependent variable (final grade in the statistics course).

Given the large number of independent (predictor) variables that were of interest, it was decided to carry out a set of LRs and GLMs. In addition, based on the observed correlation patterns, it was decided to include all the independent variables and classified them into a group of variables which are reported in §3.11.1. Then, each potential predictor variable in the group was regressed individual on the dependent variable by running several initial regressions. The variables that were found to be significant when entered into the model as the only predictors were retained and included in the final model of each group of variables. The results of the final LRs using the seven main subscales are presented in Table 4.29 and the final results of the GLMs which were run for each of the other group variables are reported in Table 4.30.

To start with, in the pre-course dataset, the three GLMs having as gender, age group and parents' high educational level as single predictors and the final grade as the dependent variable did not reveal to be significant (i.e. p-values greater than 0.05). Students' academic year of study and whether it was the first time of attending the course were found to make a significant contribution to the students' final grade in statistics alone. However, when combined, only whether it was the first time of attending the course turned to be significant ($F(1,574)=8.23$). This corresponded to small effect size.

GLMs were performed and showed that the four variables assessing previous high school and university mathematics background and performance individually and significantly predicted students' performance. When combined, three out of four variables (except for the type of mathematics course students attended in high school) were found to be significant predictors (with p-values less than 0.05) and explained 18% of the variability of statistics performance. The effects of these variables were considered to be large.

The predictive power of each of the seven pre-course subscales in the students' final grades was examined using LRs. Each of the subscales, except the value subscale, was found to be significant determinants of the final grade. The most important predictors, when added individually to the model, were resilience variable accounting for 5.6% followed by the self-efficacy variable accounting for 4.6% of the total variance of performance outcomes. When the final grade was regressed on the six subscales simultaneously, 6% of the total variation was explained with the self-efficacy (Beta=0.19, p-value < 0.05) and the resilience (Beta=0.14, p-value < 0.05) variables to be the only significant predictors (see Table 4.30).

In order to predict performance, among the variables associated with motivational and cognitive engagement, GLMs were employed since some variables related to the expectations of performance and effort constructs were categorical. All the variables when entered individually to the model, except the control over performance variable, were found to be significant predictors of performance. When the final GLM model was run, after deleting the variable that lacked significance, the findings suggested that among this group of variables, only the expected grade categorical variable ($F(4,502)=22.78$) and the learning strategies subscale ($F(14,502)=2.04$) remained significant contributors and predictors explaining 23% of the total variation in statistics performance. The effects of these variables were considered to be medium to large.

With respect to the post-course data, none of the two demographic factors alone (gender and age group) found to be significant predictors of performance. When another two GLMs were run using the academic year of study and variables, significant results were obtained. Each of the two educational-related variables (namely academic year of study and first time of attending the statistics course) made an individual and collaborative statistically significant contribution to the explanation of variance in statistics performance ($F(2, 513) = 4.90$ and $F(1,513)=14.38$, $p < 0.05$). These corresponded to small effect sizes.

Next, the seven main subscales were regressed individually on the final grade variable. All of them were found to be significant explanatory predictors of performance. Self-efficacy and resilience variables explained alone the largest amount of the variability in performance (17% and 12% respectively). When the seven variables were entered into the final regression model, only the three of them (namely anxiety, self-efficacy and resilience) remained significant predictors of the grade (Beta = -0.15, 0.25, 0.19 respectively, p-values < 0.05) with self-efficacy variable followed by the resilience variable being the strongest predictors (see Table 4.30). Together these variables were found to explain 20% (R^2 value) of the total variability in performance.

The expected grade (categorical variable), the effort subscale along with the two categorical variables assessing the hours spent for studying statistics (in a typical week and during exams) and the learning strategies subscale were found to significantly predict performance when univariate GLMs were conducted on motivational and cognitive engagement-related variables. When the final grade variable was regressed on all these variables simultaneously, 47% of the total variation was explained with the learning strategies subscale, the effort subscale along with the hours spent during a typical week and the expected grade variable turned to be significant key predictors of performance (with p-values less than 0.05). The effect sizes were considered to be medium to large.

Table 4.29 General Linear Models predicting final grades (pre-course and post-course)

PRE-COURSE					
Tests of Between-Subjects Effects					
Source	**Type III SS**	**df**	**Mean Square**	**F**	**p-value**
Corrected Model	5635.72	3	118.57	4.69	<0.05
Intercept	1225646.49	1	1225646.49	3062.04	<0.05
First Time of Attending	3295.65	1	3295.65	8.23	<0.05
Year of study	1549.24	2	774.62	1.94	0.15
Error	229755.44	574	400.27		
Total	2716138.25	578			
Corrected Total	235391.15	577			

*R^2=0.02, Adjusted R^2=0.02

PRE-COURSE					
Tests of Between-Subjects Effects					
Source	**Type III SS**	**df**	**Mean Square**	**F**	**p-value**
Corrected Model	79731.51	118	675.69	3.68	<0.05
Intercept	1225646.49	1	125263.37	381.55	<0.05
Number of Maths Courses at university	3886.68	2	1943.34	10.57	<0.05
Average grade of Maths courses at university	35295.81	43	820.83	4.47	<0.05
Type of Maths at high school	234.68	1	234.68	1.28	0.26
Mathematics grade at high school	19921.31	71	280.58	1.53	<0.05
Error	229755.44	574	400.27		
Total	2716138.25	578			
Corrected Total	235391.15	577			

*R^2=0.80, Adjusted R^2=0.58

PRE-COURSE					
Tests of Between-Subjects Effects					
Source	**Type III SS**	**df**	**Mean Square**	**F**	**p-value**
Corrected Model	69560.15	54	1288.15	4.18	<0.05
Intercept	59283.45	1	59283.45	192.39	<0.05
Hours of studying (in a typical week)	447.56	2	223.78	0.73	0.48
Expected Grade	28077.09	4	7019.27	22.78	<0.05
Effort	3816.52	10	381.65	1.24	0.26
Learning Strategies	8799.11	14	628.51	2.04	<0.05
Expectations	1398.75	8	174.84	0.57	0.81
Intrinsic Motivation	3320.74	8	415.09	1.35	0.22
Extrinsic Motivation	1500.79	8	187.60	0.61	0.77
Error	154691.31	502	308.15		
Total	2622968.25	557			
Corrected Total	224251.45	556			

*R^2=0.31,Adjusted R^2=0.24

POST-COURSE					
Tests of Between-Subjects Effects					
Source	**Type III SS**	**df**	**Mean Square**	**F**	**p-value**
Corrected Model	7926.77	3	2642.26	7.70	<0.05
Intercept	928721.76	1	928721.76	2707.49	<0.05
First Time of Attending	4932.63	1	4932.63	14.38	<0.05
Year of study	3359.39	2	1679.70	4.90	<0.05
Error	175968.72	513	343.02		
Total	2722238.00	517			
Corrected Total	183895.49	516			

*R^2=0.04, Adjusted R^2=0.04

POST-COURSE					
Tests of Between-Subjects Effects					
Source	**Type III SS**	**df**	**Mean Square**	**F**	**p-value**
Corrected Model	83125.59	35	2375.02	11.97	<0.05
Intercept	1194414.33	1	119414.33	601.62	<0.05
Hours of studying (in a typical week)	1229.09	2	614.55	3.10	<0.05
Hours of studying (during exams)	136.81	2	68.40	0.35	0.71
Expected Grade	47056.07	4	11765.02	59.27	<0.05
Effort	6420.61	11	583.69	2.94	<0.05
Learning Strategies	5761.62	16	360.10	1.81	<0.05
Error	93884.96	473	198.49		
Total	2694686.00	509			
Corrected Total	177010.55	508			

*R^2=0.47, Adjusted R^2=0.43

Table 4.30 Linear Regressions predicting final grades (pre-course and post-course)

PRE-COURSE			
PREDICTOR VARIABLE	**Beta (Standardised Coefficient)**	**t-test**	**p-value**
LIKING	-0.04	-0.51	p=0.61
INTEREST	0.04	0.54	p=0.59
VALUE	-0.03	-0.66	p=0.51
DIFFICULTY	-0.04	-0.74	p=0.46
ANXIETY	0.07	0.07	p=0.59
SELF-EFFICACY	0.18	2.92	p< 0.05
RESILIENCE	0.14	2.60	p < 0.05

*R=0.27, R^2=0.07, Adjusted R^2 = 0.06

POST-COURSE			
PREDICTOR VARIABLE	**Beta (Standardised Coefficient)**	**t-test**	**p-value**
LIKING	0.002	0.02	p=0.99
INTEREST	-0.08	-0.94	p=0.35
VALUE	-0.01	-0.20	p=0.84
DIFFICULTY	-0.04	-0.71	p=0.48
ANXIETY	-0.12	-2.17	p< 0.05
SELF-EFFICACY	0.25	3.74	p < 0.05
RESILIENCE	0.19	3.41	p< 0.05

*R=0.45, R^2=0.20, Adjusted R^2 = 0.19

4.8 Exploring the factor structure using Exploratory Factor Analysis (EFA)

4.8.1 Aim of EFA

To determine, explore and gain a better understanding of the underlying factor structure of the seven main questionnaire subscales, EFA method was employed. The aim was to extract the factor structure of each variable/construct, verify or not the conceptual and pre-determined grouping of the items, eliminate - if it was necessary - problematic (or weak) items (i.e. indicators) and better understand the interrelationships among the items and variables. EFA was carried out separately for the pre-course and post-course data samples.

4.8.2 Adequacy of the sample data

Before conducting FA, both data samples were checked whether they were suitable for this analysis. Tabachnick and Fidell (2013) suggests having at least 300 cases for FA. The sample sizes of 815 and 641 for the pre-course and post-course administrations respectively were considered being adequate sample sizes. Initially, 32 items of the questionnaire were subjected to FA instead of all the questionnaire items (the reasons are mentioned in 3.11.1). FA was deemed appropriate because the ratio of cases (participants) to variables exceeded 10 to 1 (Tabachnick and Fidell, 2013). It should be noted that the results of the final factor analyses (after removing the problematic items) are reported. The factorability and the adequacy of the correlation matrices of items were checked (Pallant, 2016).The inspection of the correlation matrix tables revealed that all the items were correlated 0.3 or above with at least one item indicating factorability (Neill, 2008). Also, Kaiser-Meyer-Olkin (Kaiser, 1970; 1974) Measure of Sampling Adequacy (KMO) gave values of 0.95 in both samples which was above from 0.6 and close to 0.9 which are indicated as the recommended and the perfect minimum values respectively (Field, 2009); the Bartlett's Test of Sphericity (Bartlett, 1954) values were statistically significant (χ^2 (496) = 13945.94, $p < .05$ and χ^2 (528) = 13981.01, $p < .05$), the determinant of the correlation matrices were not zero and the diagonals of the anti-image correlation matrix for both samples were higher than 0.8. Considering these overall indicators of sampling adequacy, the data for both samples fulfilled the assumptions and considered to be appropriate for carrying out EFA (Pett *et al*., 2003).

4.8.3 Identification of the factors

4.8.3.1 Extraction of the factors

Concerning the factor extraction methods, Principal Component Analysis (PCA), Principal Axis Factoring (PAF) and Maximum Likelihood (ML) methods were performed. Because ML method requires the data to meet the multivariate normality condition (Kahn, 2006), which both samples did not satisfy (refer to §4.2), the results from ML are not reported. Nevertheless, similar factorisations and patterns of item loadings onto their respective factors were observed when comparing the result outputs using PCA, PAF and ML methods thus the factor solution can be regarded as method-invariant (Roesken *et al*., 2011).

The Kaiser's criterion (i.e. factors with eigenvalues greater than 1) was the first criterion that was employed to determine the number of factors to retain. Regardless of the extraction method, the same number of factors - specifically, five - was extracted suggesting a five-factor solution in both samples. This means that five factors met the criterion of having eigenvalue greater than 1. It should be noted that the eigenvalues of the fourth and the fifth factors were only slightly larger than 1.0 (<1.4).[3]

Initial eigenvalues showed that the total amount of variance explained by this factor structure using PCA was 60.90% and 66.08% in the pre-course and post-course sample respectively. According to Hair *et al.* (2006), in the social sciences, a factor solution that accounts for 60% of the total variance (and sometimes less than this percentage) can be considered as satisfactory. Regarding the pre-course sample, the first three factors explained relatively large amounts of variance, namely a total of 53.05% of the variance, with the remaining two factors explained smaller amounts of variance (less than 5.0%). Similarly, in the post-course sample, the first three factors accounted for a total of 58.21% of the variance. The first factor can be clearly regarded as the most important factor since it accounted for over of thirty percent of the total variance in both samples. The eigenvalues associated with each factor and the variance contribution of each of the latent factors (total, percentage and cumulative) to the five-factor model are represented in Table 4.31.

Another approach to determine the number of factors to extract is the total percentage of variance explained by them. As it can be seen in Table 4.31, three factors met the 5% criterion with percentages of explained variance ranging from 8.02% to 35.77% and from 8.88% to 39.04% in the pre-course and post-course samples respectively.

Table 4.31 Variance contribution for the five-factor model (pre-course and post-course)

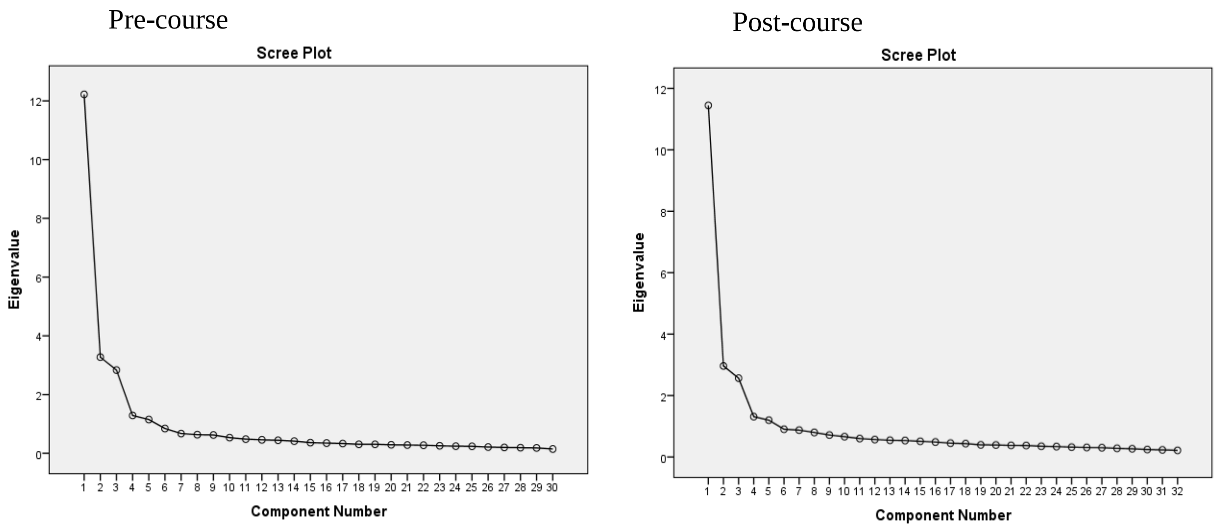
PRE-COURSE			
Total Variance Explained			
	Initial eigenvalues		
Factor/Component	**Total**	**% of variance**	**Cumulative %**
Factor 1	11.45	35.77	35.77
Factor 2	2.96	9.26	45.03
Factor 3	2.57	8.02	53.05
Factor 4	1.31	4.11	57.16
Factor 5	1.20	3.75	60.90

POST-COURSE			
Total Variance Explained			
	Initial eigenvalues		
Factor/Component	**Total**	**% of variance**	**Cumulative %**
Factor 1	12.49	39.04	39.04
Factor 2	3.30	10.30	49.34
Factor 3	2.84	8.88	58.21
Factor 4	1.33	4.16	62.38
Factor 5	1.19	3.71	66.08

[3] EFA showed that items related to general resilience and items related to resilience in statistics loaded onto two separate factors. Thus, general resilience items were not used in subsequent FA.

The examination of the scree plot, which represents the eigenvalues for factors in descending order, was another criterion used for selecting the number of factors to retain. The scree test produced the following graphs in SPSS (see Figure 4.2). Three factors were retained by consulting the scree plot line in both samples as described in §3.11.1.

Figure 4.2 Scree plot (pre-course and post-course)



Following the steps provided by Pallant (2016), parallel analyses (PA) were also conducted using the program Monte Carlo PCA (see §3.11.1 for more information). The results from PA recommended retaining only three factors (components) in both data samples.

Cumulatively, by taking into account the above recommendations from several criteria and by perceiving that it was better to retain more factors than too few, it was decided to select both the three- and the five-factor solutions for further investigation. A combination of conceptual foundation (for example, the number of factors that was expected in the structure) and empirical evidence (for example, the number of factors that can be reasonably supported by the data) were considered.

4.8.3.2 Rotation of the factors

Once the factors and their loadings were obtained, in order to facilitate the interpretation of the factor structure, factor rotation was applied. Following the recommendations of Pallant (2016), the analyses were initially run using both orthogonal (varimax) and oblique (oblimin) rotation approaches. However, due to the nature of the constructs under investigation and taking into account prior theoretical and empirical research studies, the factor (subscales) of the questionnaire were presumed to be correlated. By looking at the component correlation matrices, it was reasonable to assume that the three factors and the five factors were interrelated to some degree in both samples. It was also observed that oblimin rotation produced a better-defined factor structure of the data. Thus, only the results from direct oblique rotation are reported.[4]

[4] The varimax rotation produced similar results with the oblimin solutions; that is the same questionnaire items loaded on the same factors (constructs).

An inspection to eliminate potential problematic items based on EFA results was then carried out. The rotated component matrix was inspected to examine the factor loadings of each variable (item). Individual items, which did not load on any factor or loaded less than 0.4 on their main factor, were not included in the factor structure and they are suppressed in relevant reported tables (e.g. Table 4.32). As anticipated, due to the nature of some constructs under investigation, some items were loaded onto more the one factor (i.e. cross-loadings). Two- reverse-coded items (namely, “Statistics is among my worst subjects” and “I find it easy to apply statistics formulas and methods”) were the ones which either cross-loaded (e.g. loaded onto more than one factor) or did not have significant loading onto any factor. These two items were eliminated before the final factor analyses were carried out.

The next step was to assess the communalities of the variables. Therefore, the communalities tables were consulted. In both samples, for the three- and five-factor structures, all the final commonalities estimates were greater than 0.3.

4.8.4 Presentation of the factor structures

For the last stage, factor analysis procedures were conducted on the remaining 30 items in both samples. The EFA results presented were produced using Principal Component Analysis (PCA) to obtain the underlying factors (components) and direct oblimin rotation (the delta value is set at zero) to obtain the rotated factor loadings. The three factors in the three-factor solution explained 53.50% and 58.24% in the pre-course and post-course data sample accordingly. The five factors in the five-factor solution explained 61.65% and 66.40% of the variance in the pre-course and post-course data sample respectively.

For the five-factor model, Table 4.32 presents the factor groupings, the questionnaire items (index numbers), their standardized factor pattern coefficients (final factor loadings) along with their final communalities after extraction for the pre-course and post-course data sample. Similar information was tabulated for the three-factor model and these tables are provided upon request. The tables show how many and which questionnaire items have significant structure/pattern coefficients on their respective factor [5]. Within the two data samples, it can be postulated that it was relatively clear how the items loaded onto their respective main factors for both factor structures. It should be noted that the items which had relatively low communality values (below 0.5), but significant loadings on their respective factor (above 0.4), were retained to the EFA analyses and they were placed under scrutiny in the subsequent CFA procedures (see §4.9). Since each indicator (item) loaded significantly on its corresponding factor and the standardised factor loadings were greater than 0.5, the convergent validity, which is a subtype of construct validity, was supported.

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[5] The pattern and structure coefficient matrices generated similar factor loadings of the measured variables and therefore similar interpretations. Thus, for clarity and simplicity reasons, only the pattern coefficients are presented here.

Table 4.32 Five-factor 30-item structure of the EFA for the pre-course and post-course samples

PRE-COURSE						
	Factor Pattern Coefficients					Communalities (h^2)
ITEM	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
LIKING1	0.62					0.67
LIKING2	0.68					0.71
VALUE1					-0.66	0.63
VALUE2					-0.61	0.46
VALUE3					-0.68	0.56
VALUE4					-0.84	0.73
VALUE5					-0.82	0.74
VALUE6					-0.82	0.64
DIFFICULTY2		0.62				0.50
DIFFICULTY4		0.59				0.37
INTEREST1	0.65					0.74
INTEREST2	0.58					0.59
INTEREST3	0.53					0.65
ANXIETY1		0.83				0.76
ANXIETY2		0.63				0.51
ANXIETY3		0.76				0.65
ANXIETY4		0.77				0.70
ANXIETY5		0.81				0.69
ANXIETY6		0.71				0.57
SELF-EFFICACY1				0.77		0.66
SELF-EFFICACY2				0.78		0.58
SELF-EFFICACY3				0.76		0.68
SELF-EFFICACY4				0.77		0.66
SELF-EFFICACY5				0.80		0.67
SELF-EFFICACY7				0.55		0.52
RESILIENCE3			0.69			0.60
RESILIENCE4			0.85			0.74
RESILIENCE5			0.54			0.37
RESILIENCE6			0.72			0.56
RESILIENCE7			0.70			0.61
Eigenvalue	10.60	2.92	2.54	1.29	1.16	
Percentage of Common Variance Explained	35.32%	9.73%	8.45%	4.30%	3.85%	

POST-COURSE						
	Factor Pattern Coefficients					Communalities (h^2)
ITEM	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
LIKING1	0.74					0.67
LIKING2	0.74					0.71
VALUE1				0.78		0.63
VALUE2				0.59		0.46
VALUE3				0.69		0.56
VALUE4				0.85		0.73
VALUE5				0.87		0.74
VALUE6				0.89		0.64
DIFFICULTY2		0.58				0.50
DIFFICULTY4		0.51				0.37

INTEREST1	0.70					0.74
INTEREST2	0.70					0.59
INTEREST3	0.68					0.65
ANXIETY1		0.85				0.76
ANXIETY2		0.77				0.51
ANXIETY3		0.87				0.65
ANXIETY4		0.80				0.70
ANXIETY5		0.83				0.69
ANXIETY6		0.69				0.57
SELF-EFFICACY1					0.64	0.66
SELF-EFFICACY2					0.45	0.58
SELF-EFFICACY3					0.90	0.68
SELF-EFFICACY4					0.73	0.66
SELF-EFFICACY5					0.82	0.67
SELF-EFFICACY7					0.43	0.52
RESILIENCE3			0.63			0.60
RESILIENCE4			0.81			0.74
RESILIENCE5			0.83			0.37
RESILIENCE6			0.82			0.56
RESILIENCE7			0.73			0.61
Eigenvalue	11.39	3.28	2.81	1.33	1.19	
Percentage of Common Variance Explained	37.95%	10.92%	9.37%	4.25%	3.91%	

Notes: 1. Extraction method: principal component analysis; rotation method: oblimin rotation
2. Only items with pattern coefficients of 0.4 or greater and no cross-loadings are displayed.
3. All factor loadings were significant (p-value < 0.05).

4.8.5 Determination of the number of factors and correlations between them

Thus far, the results of the EFA provided initial evidence and support of the three and five underlying factor structures for both samples. More specifically, one criterion suggested that a five-factor solution underlined the selected questionnaire items, whereas three criteria proposed a three-factor solution. However, because of the relatively large number of items composed each factor if three factors were retained, and taking into account the interpretability of them, both factor solutions (that is the three- and the five-factor solution) were selected and investigated further on CFA.

Afterwards, an inspection of the component correlation matrix for the two factor structures in both data sets was conducted. The inter-correlations among the five factors were found to be weak to moderate ranging from 0.25 to 0.49 in absolute value. The inter-correlations among the three factors in both samples were ranged from 0.30 to 0.42 in absolute value. This provided evidence of homogeneity within and distinctiveness between the factors (which composed the subscales of the questionnaire) in both factor structures and enhanced the discriminant validity (Kline, 2011; Ghiselli *et al*., 1981).

4.8.6 Label and interpretation of the factors and summary information

Each extracted factor was labelled and broadly interpreted taking into account the constructs explained by the items that loaded onto the relative factor**.** When a three-factor solution was selected, the first factor put together two items related to students’ liking of statistics, three items related to enjoyment and interest in statistics and six items related to the value, worth and importance students' placed on statistics. Thus, the first factor was labelled 'dispositions and attitudes'. The second factor was called 'anxiety and difficulty' and included two items which were related to the perceived difficulties experienced in the statistics course and six items which were associated with anxieties towards statistics. The third factor was named 'self-efficacy and resilience'. This factor contained six and five items from the hypothesised self-efficacy resilience subscale respectively. It reflected students' perceived abilities and resilient behaviour characteristics related to statistics.

When a five-factor solution was selected, the five items related to liking and interest constructs were combined to form a single factor – the first factor. Within the five-factor structure, items related to students' anxiety towards statistics and perceived difficulty of statistics were still composed one factor (the second factor) which consisted of eight items. Self-efficacy and resilience were considered as separate factors in the five-factor structure (the third and the fourth factor), whereas these two comprised one factor in the three-factor solution. Moreover, contrary to the three-factor structure, the six items associated with the value of statistics loaded onto a separate factor - the fifth factor.

The results suggested that the items related to liking and interest in statistics to load on the same factor and thus they could be considered empirically as the same construct. Even though initially it was hypothesised that they were different constructs, it could be supported to load to on the same factor since they seemed to share close content meaning and represent general dispositions towards statistics. Also, contrary to the initial hypothesis that difficulty and anxiety formed separate components, the EFA suggested that these two constructs composed one factor both in three- and five-factor solutions. Moreover, the three-factor solution grouped self-efficacy and resilience as one factor. Taken as a whole, it is postulated that the interpretability of the final factor structures was meaningful. The possible explanations of these factor structures are further examined and discussed in the Qualitative Results (see Chapter 5) and Discussion (see Chapter 6) chapters.

The following table (see Table 4.33) provide the factor score means, standard deviations and Cronbach's alpha coefficients of the five-factor solution for the pre-course and post-course data samples. The corresponding tables for the three-factor solution are available upon request All the factors produced reliability with Cronbach's alpha score greater than 0.7. This value should be the minimum for a factor to be retained for subsequent use in other multivariate analysis and decision-making based on the rule of thumb as reported by Field (2009).

Table 4.33 Mean, Standard Deviation and Cronbach's Alpha values of the five-factor solution (pre-course and post-course)

FACTOR	# of Items	M		SD		Cronbach's alpha	
		Pre-course	**Post-course**	**Pre-course**	**Post-course**	**Pre-course**	**Post-course**
LIKING/ INTEREST	5	3.13	3.15	0.86	0.86	0.86	0.92
VALUE	6	3.47	3.41	0.83	0.83	0.87	0.91
DIFFICULTY/ ANXIETY	8	2.84	2.83	0.85	0.85	0.90	0.90
SELF-EFFICACY	6	3.61	3.59	0.65	0.63	0.87	0.88
RESILIENCE	5	3.74	3.63	0.60	0.64	0.78	0.84

4.9 Testing the models using Confirmatory Factor Analysis (CFA)

4.9.1 Aim of CFA

The next step was to conduct CFA approach which specifies causal relationships between factors/constructs rather than only correlations. It is also considered to be the measurement model of SEM which tests relationships between latent variables and their observed indicators.

4.9.2 Model specification and parameter estimates

The CFA models with three and five latent constructs, representing the three and five factors extracted by the EFA respectively, were specified and tested. The aim was to explore the fit of the two different models and ascertain the best-fitting model. The three factors were: dispositions and attitudes factor (which included liking, interest and value); difficulty and anxiety factor; and self-efficacy and resilience factor. The five factors were: liking and interest factor; value factor; difficulty and anxiety factor; self-efficacy factor and resilience factor. The two measurement models consisted of three and five factors respectively (which were considered as the unobserved variables) with 30 observed variables and 30 residuals (unobserved errors). The 30 questionnaire items retained according to the results of the EFA were the 30 observed variables in CFA. All the factors included in the models were allowed to covary with each other. The initial assumptions made were that each item (observed variable) loaded onto a single factor and the error terms were not correlated (Kline, 2005).

First of all, an overall assessment of the model quality was conducted. For the three-factor and five-factor models, in both samples, all the unstandardized regression weights (i.e. paths between variables) were statistically significant at the 0.05 level. In the three-factor model, the magnitudes of standardized regression weights (factor loadings) ranged from 0.39 to 0.85 and from 0.56 to 0.86 in the pre-course and post-course sample respectively. In the five-factor model, all the items had moderate to high factor loadings on their hypothesised factor ranging from 0.47 to 0.85 and from 0.57 to 0.89 in the pre-course and post-course sample accordingly. An acceptable threshold value for the factor loadings can be considered a significant value greater than 0.5 (Hair *et al.*, 2006). The results of the three-factor model (in the pre-course sample) showed that there were two items associated with the resilience construct which had regression weights to their respective factor which were below 0.5 (namely 0.39 and 0.49). This might be an indication of relatively low convergent validity, which means the items might have information about other factors rather than the corresponding factor alone. One of the concerns was that the items, which had low standardized regression weights might cause problems in the model fit. It was also noticed that the set of items, which had the lowest factor loadings in EFA, also showed the lowest factor loadings in CFA. The standardized factor loadings (parameter) estimates for the five-factor model for both samples are reported later in Table 4.35. The equivalent information for the three-factor models is available upon request.

Moreover, the standardized residuals table was inspected in both data samples. It was observed that one item related to resilience construct (RES5) had a few pairwise residual values slightly above 3 for both samples. Given that this particular item had among the lowest regression weights in EFA and CFA and it was suggested by the preliminary reliability analyses (see §4.2) to improve the reliability of the pre-course resilience subscale if deleted, it was decided to be eliminated from the models in both data sets.

The squared multiple correlations for the three-and five-factor solution were also inspected. In the five-factor solution, the squared multiple correlations ranged from 0.22 to 0.65 and from 0.32 to 0.80 in absolute value in the pre-course and post-course samples respectively. In both factor solutions (three and five factor), the lowest values were found for the resilience- and difficulty-related items indicating that they contributed less than the other items to the explanation of the variation in their corresponding factor. In this case, even though EFA grouped together difficulty- and anxiety-related items, CFA recommended that the two items related to difficulty might not address issues specifically related to students' anxieties towards statistics. However, these items were not removed from the model as they were the only ones which intended to assess the students' perceived difficulty of the statistics course and they were not found to stand as a single factor (in EFA).

4.9.3 Model fit indices

The next step was to evaluate the adjustment and the model fit of alternative models based on multiple criteria and common rules of thumb suggested in the literature (see §3.11.1). The results of the final goodness-of-fit indices for each model are presented in Table 4.34. Regarding the model fit, a significant chi-square (χ^2) test was found for all the models under investigation. The χ^2/df was considerably greater than 3 for the three-factor model in both samples indicating not a very good model fit, whereas it was less than 3 for the five-factor model demonstrating a good fit for the data in both samples. Concerning the GFI measure, in both samples, the three-factor model did not reach the recommended values. The five-factor model for the pre-course sample reached the literature's cut-off values concerning this model fit whereas the post-course sample did not exceed the value of 0.9. The RMSEA values were questionable for the three-factor solution, whereas for the five-factor solution in both samples were acceptable since the recommended cut-off value of accepting a reasonable model fit is close to 0.5. Regarding the comparative fit of the models, the CFI and the TLI values were inspected. In both samples, the three-factor model did not reach the recommendable values, whereas the five-factor model was closed to the excellent value for the two comparative fit indices. Moreover, in the three- and five-factor models, in both data samples, the SRMR values were less than 0.09 indicating acceptable model fit. With respect to the model parsimony, the results revealed that, although considering the model complexity, five-factor model was still preferred in both samples since there was a decrease in the AIC and BIC values.

According to the various criteria delineated above, a five-factor model appeared to fit the data for both samples acceptably. Results yielded that the five-factor model provided a better explanation and fit of the data than the three-factor model (and other alternative models). For example, the four-factor model (as forced by EFA) was also constructed and tested for both samples (results are not reported in this thesis document). Thus, the five-factor measurement model was pursued and explored further to be improved aiming to gain a better fit of the sample data via modification.

4.9.4 Modification Process

Although the five-factor model reached the acceptable values of the GOF measures (except for the GFI in the post-course sample) indicating an acceptable model fit for both samples, there might be some room for improvement. Within the current data sets, the Modification Indices (MIs) part of the AMOS output suggested allowing correlations between some error terms which were part of the same factor. [6] The rationale behind the modifications done was firstly the error terms to be correlated only on the items that load on the same factor and secondly the specified error covariances to be among items that they had similar (or overlapping) content meaning. The strategy followed was to address the highest MIs before addressing the more minor ones. For both data samples, the error covariance with the highest MIs was between two items related to the anxiety construct and more specifically the item assessed students' anxiety when attending a lecture class in statistics (ANX2) and the item assessed anxiety when having to do assignments in statistics (ANX3). Instead of incorporating an error covariance between these two items, the item, which had the lower standardised factor loading, was eliminated in both models. Then, the models were re-run. In the five-factor model, an improvement in the model fit was observed with the model fit indices reached the required levels for an acceptable model fit except (again) for the GFI value (0.89) which approached, but not reached the minimum required value (i.e. 0.9).

The MIs output was then re-examined. In the pre-course data, one error covariance was suggested and included in the model (that is, the error covariance between two items composed the value factor). The similarity in the content meaning could justify the addition of the covariance between this pair of error terms. In the post-course data, it was suggested the incorporation of one path between the residuals of the two items associated with the difficulty factor. There appeared to be a unique association between each of these pairs of items, which was not accounted by the factor (construct) that they were assigned to. After the inclusions of these error covariances, it was observed that the ratio of the chi-square to

[6] It is acknowledged that the modification indices are a diagnosis of the AMOS program of how the model fit can be improved from a statistical point of view and for the specific sample which is used to carry out the analyses.

degrees of freedom was reduced as well as the GFI, CFI and RMSE came even closer to the desired values for the acceptable model fit. The modified five-factor model yielded a better fit and description of the sample data compared to the original five-factor model. This is illustrated in Table 4.34. After the modified models were re-run, no more MIs above the threshold of 40 were detected. To sum up, the examination of the MIs resulted in the elimination of one item and the inclusion of one pairwise error covariance in each model (pre-course and post-course) which were deemed as meaningful and theoretical sensible.

Table 4.34 Fit Indices for three CFA measurement pre-course and post-course models

PRE-COURSE MODEL		**3-FACTOR (original)**	**5-FACTOR (original)**	**5-FACTOR (modified)**
Model Fit	χ^2	2470.8	1302.2	1058.5
	df	402	395	392
	Sig.	0.00	0.00	0.00
	χ^2**/df**	6.15	3.30	2.70
	RMSEA	0.08	0.05	0.046
Model Comparison	**CFI**	0.84	0.93	0.95
	TLI	0.83	0.92	0.94
Model Parsimony	**GFI**	0.80	0.90	0.92
	AIC	2596.79	1442.24	1204.53
	BIC	2893.09	1771.46	1547.86
	SRMR	0.07	0.05	0.05

POST-COURSE MODEL		**3-FACTOR (original)**	**5-FACTOR (original)**	**5-FACTOR (modified)**
Model Fit	χ^2	2725.55	1340.46	1025.25
	df	402	395	339
	Sig.	0.00	0.00	0.00
	χ^2**/df**	6.78	3.40	3.02
	RMSEA	0.09	0.06	0.05
Model Comparison	**CFI**	0.81	0.92	0.94
	TLI	0.80	0.92	0.94
Model Parsimony	**GFI**	0.72	0.82	0.90
	AIC	2851.55	1480.46	1159.26
	BIC	3132.72	1792.32	1165.62
	SRMR	0.07	0.05	0.05

Note: where χ^2= chi-square; df= degrees of freedom; Sig. = statistical significance; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; GFI = Goodness of Fit Index; AIC= Akaike's Information Criterion; BIC = sample size adjusted Bayesian Information Criterion; SRMR = Standardized root mean square residual

Table 4.35 Item Factor Loadings (Unstandardized and Standardized Coefficients) from the modified 5-factor CFA (measurement models) and squared multiple correlations

PRE-COURSE MODEL						
FACTOR/ LATENT CONSTRUCT	**Item/ Observed variable**	**Unstandardized Coefficients**	**SE**	**p-value**	**Standardized Coefficients**	R^2
LIKING/ INTEREST	LIK1	0.88	0.03	<0.05	0.78	0.61
	LIK2	0.91	0.04	<0.05	0.79	0.62
	INT1	1.00		<0.05	0.84	0.71
	INT2	0.87	0.04	<0.05	0.68	0.46

	INT3	0.99	0.04	<0.05	0.76	0.58
VALUE	VAL1	0.86	0.05	<0.05	0.72	0.52
	VAL2	0.84	0.06	<0.05	0.55	0.30
	VAL3	0.87	0.05	<0.05	0.65	0.42
	VAL4	1.22	0.06	<0.05	0.83	0.69
	VAL5	1.17	0.05	<0.05	0.84	0.71
	VAL6	1.00			0.71	0.51
DIFFICLUTY/ ANXIETY	DIFF2	0.84	0.05	<0.05	0.62	0.39
	DIFF4	0.84	0.05	<0.05	0.53	0.69
	ANX1	1.18	0.05	<0.05	0.85	0.72
	ANX3	1.03	0.05	<0.05	0.74	0.54
	ANX4	1.14	0.05	<0.05	0.80	0.64
	ANX5	1.22	0.06	<0.05	0.82	0.67
	ANX6	1.00			0.72	0.51
SE	SE1	0.99	0.05	<0.05	0.76	0.58
	SE2	0.86	0.05	<0.05	0.66	0.44
	SE3	1.01	0.05	<0.05	0.79	0.63
	SE4	1.03	0.05	<0.05	0.77	0.59
	SE5	0.88	0.05	<0.05	0.76	0.58
	SE7	1.00			0.68	0.46
RES	RES3	1.26	0.07	<0.05	0.70	0.49
	RES4	1.26	0.07	<0.05	0.82	0.67
	RES6	1.06	0.07	<0.05	0.62	0.39
	RES7	1.00			0.68	0.47

POST-COURSE MODEL						
FACTOR/ LATENT CONSTRUCT	**Item/ Observed variable**	**Unstandardized Coefficients**	**SE**	**p-value**	**Standardized Coefficients**	**R^2**
LIK/INT	LIK1	0.98	0.03	<0.05	0.86	0.73
	LIK2	0.98	0.04	<0.05	0.84	0.71
	INT1	1.00			0.87	0.76
	INT2	0.91	0.04	<0.05	0.77	0.60
	INT3	0.93	0.03	<0.05	0.83	0.69
VAL	VAL1	0.86	0.05	<0.05	0.84	0.70
	VAL2	0.84	0.06	<0.05	0.64	0.40
	VAL3	0.87	0.05	<0.05	0.73	0.53
	VAL4	1.22	0.06	<0.05	0.87	0.76
	VAL5	1.17	0.05	<0.05	0.89	0.80
	VAL6	1.00			0.81	0.65
DIF/ANX	DIF2	1.30	0.09	<0.05	0.62	0.38
	DIF4	1.00			0.55	0.31
	ANX1	1.88	0.13	<0.05	0.87	0.75
	ANX3	1.64	0.12	<0.05	0.74	0.54
	ANX4	1.91	0.13	<0.05	0.84	0.76
	ANX5	1.81	0.13	<0.05	0.80	0.80
	ANX6	1.61	0.12	<0.05	0.73	0.65
SE	SE1	0.87	0.04	<0.05	0.78	0.60
	SE2	0.73	0.04	<0.05	0.68	0.46
	SE3	0.81	0.04	<0.05	0.74	0.55
	SE4	0.90	0.05	<0.05	0.76	0.58
	SE5	0.76	0.04	<0.05	0.73	0.53
	SE7	1.00			0.75	0.56

RES	RES3	1.00			0.73	0.53
	RES4	1.06	0.06	<0.05	0.83	0.69
	RES6	1.08	0.06	<0.05	0.73	0.53
	RES7	0.84	0.06	<0.05	0.65	0.42

Notes: 1. Maximum likelihood method was used (whole sample)
2. SE: Standard Error, R^2 :Squared Multiple Correlations

4.9.5 Examination of the reliability and validity of the measurement model

Before moving on testing a casual structural model, it was deemed as necessary to assess the reliability and the validity of the measurement model that is to examine whether factors demonstrate adequate validity and reliability. The inter-factor correlations of the five-factor model in both data samples are presented in Appendix B3. Weak to strong coefficients of correlation (ranging from 0.33 to 0.71 and 0.33 to 0.73 in absolute value) were found in the pre-course and post-course administration respectively. The fact that each factor was not very highly correlated with each other (that is the bivariate correlation to exceed 0.9) supported adequate discriminant validity evidence of the examined latent factors where the five factors are related but still distinct constructs (Kline, 2005). Moreover, the construct validity was established since the model fit indices met the required levels as described in previous subsections. To assess convergent validity in CFA, the Average Variance Extracted (AVE) for each construct was evaluated. The AVE estimates were found to be greater than 0.5 for all the latent constructs which shows that the majority of the variance of the indicators to be attributed to the construct. Discriminant validity was also confirmed since the maximum shared variance (MSV) and the Average Shared Variance (AVS) values were both lower than AVE values for all the latent constructs. The discriminant validity was also confirmed since the square root of the AVE of each construct was higher than the inter-construct correlations (correlations between the constructs). Also, all Composite Reliability (CR) scores were found to be (well) above the thresholds values described in §3.11.1.

4.9.6 Measurement model invariance

What followed was to examine the measurement model invariance of the best-fitting model (in this case the five-factor model) with respect to gender. The aim was to assess whether the measurement model for the two groups (e.g. males and females) were equivalent representations of the same construct. The first step was to evaluate configural invariance. The hypothesised factor structure represented in the CFA of the two groups (i.e. male and female) achieved an adequate fit based on the fit indices. Once configural invariance was obtained, the next step was to assess for metric invariance. The chi-square difference test (that is the chi-square for unconstrained and constrained models) on the two groups gave a non-significant p-value value at 0.05 level resulted in a factor structure which was equivalent across males and females.

4.9.7 Brief summary of EFA and CFA procedures

To sum up, EFA procedures were initially employed in the pre-course and post-course data sets. The Kaiser's eigenvalue criterion proposed the presence of five factors with eigenvalues exceeding 1, whereas scree plot test, the total percentage of variance explained and the parallel analysis criteria proposed to extract three factors. Only individual items with factor loadings greater than 0.4 were retained in the factor structures. The resulted set of items was subsequently subjected to CFA and two measurement models were tested. The goodness of fit indicators showed that the three-factor model did not meet or approach the recommended values indicating that it might not fit the data adequately. Taken together the recommendations of the GOF indicators, it was proposed that the five-factor model represented an adequate description of the data for both samples and it was considered superior to the three-factor model. The five-factor model was further re-specified (after the investigation of the MIs and standardized regression residuals) and an improved, however not substantial, fit of the pre-course and post-course data was achieved. Given the acceptable and adequate fit, the estimation of the parameters was further investigated and reported. For all the factors, their respective items had satisfactory statistically significant parameter estimates (standardized regression weights). It should be noted that FA for both data sets (pre-course and post-course) were identical in terms of the number of factors, the items assigned to each factor/construct and similar regarding the results of the overall fit of the data to the hypothesised factor models.

4.10 Building and testing the statistical model using Structural Equation Modelling (SEM)

What followed was a development of the CFA models (without any modifications) into full SEM with the addition of the final grade variable. For the consideration of multivariate normality and the treatment of missing values refer to the §4.2. Since all the students (cases) whose final grade was not available were removed from the SEM analyses, the data sample sizes were reduced for both samples (n=583 and n=520 in the pre-course and post-course samples respectively).

For the current investigation, five independent variables (the five factors, which were extracted from the FA analyses) and one outcome variable (i.e. final grade) were chosen to be included in the hypothesised model. More specifically, the SEM techniques were used to investigate and explain the relationships among liking/interest, value, difficulty/anxiety, self-efficacy and resilience factors and in turn the relationships of these factors to the overall final grade students obtained in the statistics course.

The initial hypothesised model (Model A) was derived from the results and suggestions of the EFA and CFA analysis procedures. It included five latent variables and twenty-eight manifest variables. The operationalisation of the latent variables by the multiple indicators was done based on the results obtained from FA. Statistically significant correlations were detected among the latent variables with each other and the outcome variable which supported the hypothesised relationships in the model (see e.g. §4.5.3).

The initial theoretical-conceptual model was specified by positing several hypothesised relationships (theoretical linkages) among the variables (refer to Figure 3.1). Based on the results from the analysis, all the measurement coefficients (that is the relationships between the latent variables and their indicators) were found to be statistically significant and in the expected direction. Nevertheless, since the measurement model was examined and its assessment (e.g. squared multiple correlations, the composite reliability, the average variance extracted) for the whole data sample was investigated in previous sections (see §§4.8 and 4.9), selected results of the SEM measurement models are reported later in this section.

With the aim to explore the structure of statistics performance, more attention was placed on the structural component or the path model. The hypothesised directions and strengths of the structural relationships (that is the relationships between the latent variables of interest) were evaluated and the results are presented later in Table 4.37. In both samples, among the hypothesised direct relationships between the variables, two were turned to be insignificant; the relationship from liking/interest to resilience and from value to resilience (p-values were greater than 0.05). Self-efficacy was the variable that found to influence directly (and in the expected direction) all the other variables included in the model with the strongest impact (i.e. larger regression weight estimate) in absolute value found on the resilience variable. Also, it was hypothesised and confirmed by the data that students' dispositions (liking and interest) affected negatively the anxieties and difficulties experienced throughout the course. Moreover, the perceived value of statistics was found to be directly and positively related to students' liking and interest in statistics. In the post-course sample data, value was found to be directly and negatively related to difficulty and anxiety, and difficult and anxiety towards statistics were found to be directly related to students' resilient behaviours.

Regarding the structural relationships between the five independent variables and the outcome variable, significant direct effects of self-efficacy and resilience on final grade were found as revealed from the significant paths between these two variables and performance in both data samples. However, in the post-course sample, an additional significant direct effect was detected, that is a direct effect of difficulty/anxiety variable on final grade variable. The hypothesised direct effects of liking/interest and value on final grade were found to be not statistically significant (with p-values greater than 0.05) in both samples. In the pre-course sample, liking/interest and value variables did not also show any significant indirect relationships with performance. However, in the post-course sample, liking/interest and value were found to have an indirect effect on final grade through difficulty/anxiety variable. Thus, these two variables were turned to be indirectly related to the statistics performance. The theoretical-hypothesised relations that were statistically confirmed and supported by the data along with these that were not confirmed are presented in Table 4.36. These findings are also illustrated in path diagrams (see Figure 4.3).

Next, the structural paths which were not found to be statistically significant (that is, where insignificant structural coefficients were obtained) were removed in both data samples. More specifically, six hypothesised paths (liking/interest to resilience, value to resilience, value to difficulty/anxiety, liking/interest to final grade, value to final grade and anxiety to final grade) were deleted from the model that was developed from the pre-course sample data. When this model was re-rerun, another hypothesised path turn to be insignificant and thus removed from the model (namely the path from difficulty/anxiety to resilience). Four hypothesised paths (liking/interest to resilience, value to resilience, liking/interest to final grade and value to final grade were deleted from the model that was designed from the post-course sample data. Two refined models (pre-course Model B and post-course Model B) were constructed and evaluated. The effects (direct, indirect and total) of the Model B in both data sets are provided in Appendix B4. With respect to the total effects, the value variable did not seem to substantially contribute to the final grade variable. Based on that observation and the lack of significant links between value variable to other variables (e.g. resilience), it was decided to eliminate the value variable and re-rerun the model (Model C) to also potentially further improve the model fit. However, an improvement in the model fit was not observed, thus I decided to keep the value variable in the model. The estimated final structural models (Model B) for both data sets are presented in Table 4.37.

Regarding the explanatory power of the endogenous variables included in the model, this was evaluated by the squared multiple correlations. For the pre-course and post-course variables included in the models, except for the self-efficacy variable since it was treated as exogenous, the R^2 values were found to lay between 0.21 to 0.57 in the pre-course sample and 0.22 to 0.61 in the post-course sample. The R^2 values of the final grade variable showed that 8% and 21% of the variance in the outcome variable (performance) was accounted for by the pre- and post-course latent variables included in each model respectively.

Table 4.36 Hypothesised and confirmed structural relationships (pre-course and post-course)

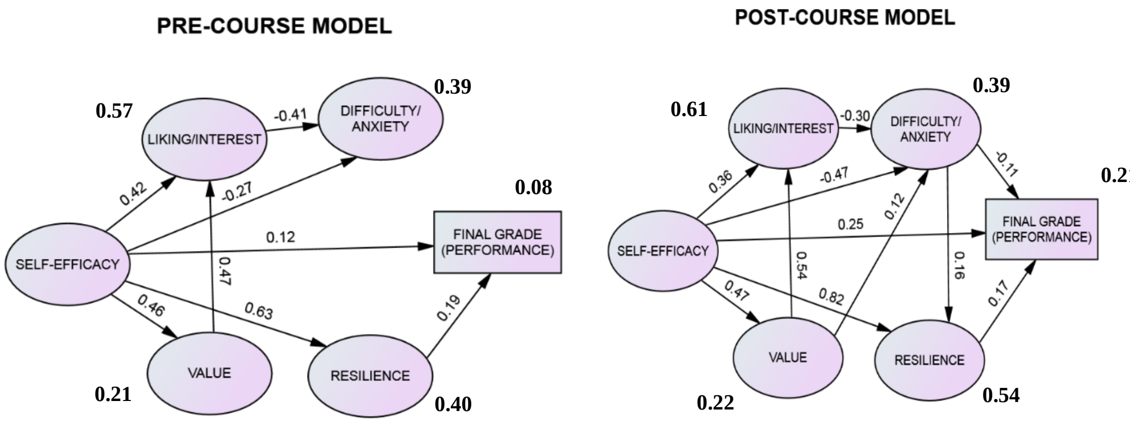
Hypothesised Structural Relationship	**Confirmed Structural Relationship**	
	Pre-course	**Post-course**
SELF-EFFICACY→LIKING/INTEREST	√	√
SELF-EFFICACY →VALUE	√	√
SELF-EFFICACY →DIFFICULTY/ANXIETY	√	√
SELF-EFFICACY →RESILIENCE	√	√
LIKING/INTEREST→DIFFICULTY/ANXIETY	√	√
LIKING/INTEREST → RESILIENCE	×	×
VALUE → LIK/INT	√	√
VALUE→ RESILIENCE	×	×
VALUE→ DIFFICULTY/ANXIETY	×	√
DIFFICULTY/ANXIETY →RESILIENCE	×	√
LIKING/INTEREST →FINAL GRADE	×	×
VALUE→ FINAL GRADE	×	×
DIFFICULTY/ANXIETY → FINAL GRADE	×	√
SELF-EFFICACY→ FINAL GRADE	√	√
RESILIENCE → FINAL GRADE	√	√

Table 4.37 Estimated final Structural Equation Model (Model B) of performance (pre-course and post-course data)

PRE-COURSE MODEL		
Structural Relation	**Unstandardized Regression Weight Estimate (S.E.)**	**Standardized Regression Weight**
SELFEFFICACY→LIKING/INTEREST	0.49 (0.05)	0.42
SELF-EFFICACY →VALUE	0.61 (0.06)	0.46
SELF-EFFICACY →DIFFICULTY/ANXIETY	-0.40(0.08)	-0.27
SELF-EFFICACY →RESILIENCE	0.63(0.06)	0.63
LIKING/INTEREST→DIFFICULTY/ANXIETY	-0.52 (0.07)	-0.41
VALUE→ LIKING/INTEREST	0.41(0.04)	0.47
SELF-EFFICACY→ FINAL GRADE	3.59 (1.83)	0.12
RESILIENCE → FINAL GRADE	6.35(2.12)	0.19

POST-COURSE MODEL		
Structural Relation	**Unstandardized Regression Weight Estimate (S.E.)**	**Standardized Regression Weight**
SELFEFFICACY→LIKING/INTEREST	0.45 (0.05)	0.36
SELF-EFFICACY →VALUE	0.53 (0.06)	0.47
SELF-EFFICACY →DIFFICULTY/ANXIETY	-0.71(0.09)	-0.47
SELF-EFFICACY →RESILIENCE	0.82(0.07)	0.82
LIKING/INTEREST→DIFFICULTY/ANXIETY	-0.36(0.08)	-0.30
VALUE→ LIKING/INTEREST	0.60(0.05)	0.54
VALUE→ DIFFICULTY/ANXIETY	0.17 (0.08)	0.12
DIFFICULTY/ANXIETY →RESILIENCE	0.11(0.03)	0.16
SELF-EFFICACY→FINAL GRADE	7.39 (2.26)	0.25
DIFFICULTY/ANXIETY→FINAL GRADE	-2.16 (1.11)	-0.11
RESILIENCE→FINAL GRADE	4.97(2.16)	0.17

Figure 4.3 Path diagram **(**structural model) of the relationships between five factors and performance (pre-course and post-course)



Notes: 1. All paths reported are significant at the 0.05 or lower.
2. Significant standardized path coefficients (theoretical relations that were confirmed) are shown in normal font.
3. Square multiple correlation coefficients (i.e. explained variance) are given in bold font.

To sum up, three alternative models were tested: the initial hypothesised model (Model A); the hypothesised model after removing the insignificant paths (Model B); and the hypothesised model after removing the insignificant paths and the value variable (Model C). The final model (Model B) yielded an acceptable fit based on the investigated model fit indices (see Appendix B4). I mainly focused on four of them, namely chi-square statistic value, RMSE, CFI, and SRMR, which together gave a consistent good picture of the overall model fit based on the recommendations on acceptable fit indices (e.g. Kline, 2005).

As a final remark, it should be noted that there were some similarities as well as differences in the conclusions that were reached for the SEM analyses with regards the pre-course and post-course data samples. For example, the post-course structural coefficients (i.e. the regression weights) were found to be larger in magnitude than the pre-course ones. Also, the difficulties and anxieties experienced in the statistics course towards the end of the course were found to directly influence performance in statistics whereas such as a relationship was not confirmed using the data collected near the beginning of the course.

4.11 Conclusion

This chapter describes the statistical analyses employed and the primary results obtained. The next chapter focused on the results obtained from the qualitative investigation and analyses (Chapter 5).

Chapter 5 QUALITATIVE RESULTS CHAPTER

5.1 Introductory statement

The qualitative component was employed to address the research questions and sub-questions (as reported in §3.2) and meet the objectives of this study (see for example §1.2). In a previous chapter (refer to §3.11), it is tabulated which specific research questions (and sub-questions) were tackled by qualitative approaches. In this chapter, the main findings obtained from the responses given by the students and through the analysis of the semi-structured interviews conducted with them are presented. It is believed that a good number of students (namely thirty) contributed to the data and, in turn, to the interpretation, commentary and discussion of them. The selected data segments and the relevant examples extracted from the interview transcripts were considered to support and develop the findings of the qualitative analyses and are provided in the following sections. The research decisions made throughout the reporting of the Qualitative Results chapter (started from the analysis process) are provided and explained in the Methodology Chapter (refer to §3.11.2).

The main thematic categories (i.e. themes) emerged from the qualitative analysis process (see §3.11.2) were used to structure the remaining of this chapter. Each main theme constitutes a section, which is divided into subsections. The main headings represent the main themes and the subheadings are, in the most cases, the emergent codes in this chapter. Each section commences with a short introductory statement, which briefly links each theme to the relevant questionnaire questions (if any) and summarises the primary focus of the main questions posed to the participants during the interview. The main body of each section contains the relevant data (quotes from students) and the interpretation of the data (comments or arguments) with the aim of illustrating the findings, adding evidence and providing adequate insight for the readers. Responses from different participants were assembled to enable comparisons and provide similarities and differences in students' perspectives. An attempt was made to present statements from a range of students to give space for different perspectives and voices to be heard. As indicated earlier (see §3.11.2), italics used throughout this section signify exact words shared by the students.

My initial consideration was to delineate the thematic categories and detect how these connected to each other. Nevertheless, some of the thematic categories overlapped and information related to each of them is inevitably mentioned in the other's section. The linkages and interrelationships between them are explored further in the Discussion chapter (see Chapter 6) where the results are initially structured by the research questions and then discussed giving emphasis to the key findings of the study as a whole.

5.2 University/High school programme

The questionnaire did not include any questions regarding students' opinions about the university programme. During the interviews, students were requested to comment about the university programme, compare it with the high school program and then remark on the statistics course programme. These questions were deemed as relevant since almost the half of the students who completed the questionnaires were attending their first year (or even their first semester) in the university (see §3.11.1).

The almost-consensus impression was that the first-year students found the university programme less pressing and demanding than the high school programme. The main reason was the preparation for the entrance matriculation exams that students had to undertake at the end of the high school. For some of the students, their future studies depended on their performance on those exams. They reported feeling less stressed at the university compared to the high school because they were aware of having a second chance (for example, midterm and final exams and assignments) if they failed in one exam (F10-Y1-EDUP; F11-Y1-ABF; F20-Y1-EDU). There were also students who compared their ways of studying in high school and in university (F5-Y1-AFN; F9-Y2-EEN). As one of them reflected:

> F9-Y2-EEN: Now, at university, I study something that I like and I have chosen. I feel that I study calmer, more concentrated and more organised. I perceive that I can plan and manage my studying. Also, I noticed that, with less studying, I understand and grasp some things easier than in high school. In high school, I felt very pressed.

However, there were students who stated that they found the university programme (and curriculum) demanding and intensive. They mentioned the *heavy workload of the semester* (M26-Y2-COM; M-Y1-TOUR); *the need for attending lots of hours of lecture classes and having to study during a day* (F14-Y3-CEN; F20-Y1-EDU); and *the amount of evaluation assessments (such as tests, exams and assignments) and accumulation of them during the same period of time (*M7-Y1-PSYC; F29-Y1-IEE). Other factors (such as job and family commitments) seemed to add to the difficulty of handling the demands of the university degree programme (M1-Y1-OGM; F8-Y2-NUTR). Some students reported that even though they found the university programme demanding, they managed to deal effectively with it with study organisation and time management (M3-Y2-ECE; F16-Y1-PSYC).

After the discussion about the university programme and the comparison with the high school, students were asked to specifically express their opinions about the statistics course programme. Some students mentioned its pressures and demands and shared difficulties in managing their time and studying to cover and digest all the material and information were delivered to them (M7-Y1-PSYC; M26-Y2-COM; F30-Y1-CFS). One of them shared:

> M7-Y1-PSYC: I found the programme of the statistics course pressing and tight. You have to run against the time to learn and absorb as much as you can for the Statistics II course, especially when you know that it would be more difficult than now. I acknowledge that I also do not manage my time for studying statistics well.

Oppositely, some students reported that they did not find the introductory statistics course programme pressing or demanding, but instead manageable (M12-Y2-BPA; F15-Y1-NUTR; M17-Y4-EEN; M25-Y3-MEN).

5.3 Statistics’ Course/Module

During the interviews, students were asked to share their opinions about some contextual variables regarding the statistics course/module they were currently enrolled in. The questionnaire did not include any questions explicitly related to this topic.

5.3.1 Language of instruction (and evaluation)

Information about the language of instruction at public and private universities is stated in §3.5.3. During the interviews, students were asked their opinion about the language of instruction (and evaluation) of the statistics course and what they would prefer if they had the choice.

There were students who mentioned that they do not face (or they do not think they would face) difficulties if the language of instruction in the current statistics course was in English (M12-Y2-BPA; M25-Y3-MEN). However, difficulties with the language of instruction were articulated by a portion of students as the following excerpt exemplifies:

> M23-Y3-MEN: If they were in Greek, they would be more comprehensible to me. It might have been less difficult to understand the theoretical part so I could easier choose which method is needed to solve the exercises. I think everyone would prefer to learn in his language.

There were students who described how the language of instruction and evaluation (being in English) influenced not only their learning process, but also their performance in the statistics course (F5-Y1-AFN). Participants also described the strategies they applied on their own to overcome the language-based difficulties as well as the practices that their instructor used (M1-Y1-OGM; M23-Y3-MEN).

Although some students mentioned the difficulties they experienced, they stated preferring the statistics course to be taught in English because they found the terminology easier (F5-Y1-AFN) and more useful and applicable to their degree programme and their future job (M1-Y1-OGM; M23-Y3-ME). Other students who mentioned their preference towards the language of instruction to be in English supported their opinion by stating the advantages of it (F8-Y2-NUTR; M13-Y3-BPA; M25-Y3-MEN). A representative excerpt is given below:

> M25-Y3-MEN: I think it is better to be taught the course in English because is a global language, the language of the business nowadays and you can extract more information related to the course from the Internet. Also, there is a small adjustment that a student will need to do afterwards if he wants to do a master's degree abroad or search for a job in a broader international market.

5.3.2 Number of statistics courses

During the interviews, students were queried whether they believed that one statistics course is enough or more statistics courses should be offered as a part of their undergraduate degree programme. Divergent views were expressed. The students who argued that one introductory statistics course is enough for their field of study mentioned that *it is good to have a firm, but not advanced, knowledge of statistics* (F11-Y1-ABF; F30-Y1-CFS); *statistics at a more advanced or deeper level is not useful for their major* (M23-Y3-MEN; M27-Y1-PSYC); and *they would have (or had) other mathematics courses (possibly more useful) to attend during their academic studies* (F14-Y3-CEN; M17-Y4-EEN). On the other side, there were participants who were in favour of having more statistics courses as a part of their degree curriculum programme (e.g. F29-Y1-IEE; F18-Y1-BPA). Supporters of this side stated that more statistics courses are necessary in order to *be more specialised and oriented to their particular field of study* (F15-Y1-NUTR; M28-Y5-RAD) and *incorporate the learning and the training in a statistical software program* (F8-Y2-NUTR).

5.3.3 Type of the course (being compulsory or elective)

As was shown in §3.11.1, for almost all the students who took part in this research study, the statistics course was compulsory for their degree programme. Students were asked whether they believed it was good to be a compulsory or it would be better to be offered as an elective course so that they could choose it if they wanted. The interviewees who were in support of the position the statistics course to be compulsory stressed the usefulness of statistics for their everyday life, their further academic studies (e.g. dissertation project) and their future professional lives (e.g. M4-Y2-PHYS; F14-Y3-CEN; F16-Y1-PSYC; F18-Y1-BPA; M24-Y2-AFN; M28-Y5-RAD). Two students commented that it is good that statistics is offered as a compulsory course rather than as an elective otherwise the students would probably not select it and they would not have the opportunity to engage with statistics (M22-Y1-PSYC; M25-Y3-MEN). Also, responding on this question, two students argued that a compulsory statistics course is better to be taught as a part of their degree programme rather than a compulsory mathematics course as they have already known the basics of mathematics from previous school years (F19-Y1-PSYC; F20-Y1-EDU).

On the other hand, for a number of students' points of view, statistics course should be offered as an elective course for their degree programmes and not as a compulsory. Two psychologist students asserted that it is better the students to have the choice if they want to undertake a statistics course depending on their specialisation and the future career they envision themselves, for example, if this would be related to research investigations or experiments (M7-Y1-PSYC; M27-Y1-PSYC). One interviewee, who was pursuing a degree in electrical engineering and was strongly opposed to the compulsory nature of the statistics course, justified his opinion by arguing the absence of usefulness and relation of statistics to their field of study and future career goals (M17-Y4-EEN). Another student, who was majoring in mechanical engineering, claimed that statistics should not be compulsory for the engineering students because there are specialists in statistics who can carry out the statistical investigations that engineers might need so they can consult them (M23-Y3-MEN).

5.3.4 Academic year of study

During the interviews, I asked the students their opinion about the year of their academic studies that they have to complete the statistics course (refer to §3.5.3 about information regarding this). Some students said that statistics is better to be offered earlier in the undergraduate programme that is in their first or second year (F16-Y1-PSYC; F19-Y1-PSYC). One of them justified it by arguing that the subject material of the university statistics course was similar (at least the first chapters) to the statistics they have been taught as a part of the core mathematics class in high school and they would be easier for them to 'follow' the course (F19-Y1-PSYC). Also, many students argued that knowledge and skills in statistics can constitute a basis and they can be helpful, useful and applicable to their upcoming academic courses (F8-Y2-NUTR; F9-Y2-EEN; M22-Y1-PSYC; M25-Y3-MEN). On the other hand, some students argued that statistics course should be taught in later years (e.g. third or fourth year) of their degree programmes. Supporters of this position mentioned the transition from high school to the university and the need to adjust to the university environment and demands before attending a statistics course (F10-Y1-EDUP; F20-Y1-EDU). Other students who preferred the completion of a statistics course in a later year of their studies so that they would be more 'experienced' and able to deal with statistics (M28-Y5-RAD; F30-Y1-CFS); they could appreciate more its value and usefulness (F14-Y3-CEN); and some things would be more 'fresh' to their minds to apply them in other academic courses or their dissertation projects (M7-Y1-PSYC; M28-Y5-RAD).

5.3.5 Course content

During the interviews, the students made some comments about the content of the statistics course. They mentioned that for the requirements of an introductory course and the learning goal outcomes, the content was relatively good (M1-Y1-OGM; M25-Y3-MEN) and provided a good introduction to many statistical concepts and methods (M2-Y2-AFN; M12-Y2-BPA). However, one student said that even though he could say that the course content was very satisfactory to meet their needs, he stated that: *I do not think that students (we) are the 'right' people to judge how good the content of the course is* (M26-Y2-COM).

5.3.6 Tutorial sessions

As previously stated (see §3.5.3), some of the statistics lecture classes (commonly in public universities) were supplemented by weekly tutorial classes taught by the statistics instructor, an assistance instructor (e.g. doctoral student) or co-taught by both of them. Students were requested to give their opinions and feedback about the tutorial sessions.

Some students described how the tutorial sessions were carried out. The majority of them were traditional tutorials, which were taking place in lecture classes. Two students reported that the assistant instructor, before starting to solve the exercises asked the students about their thinking of approaches to solve these exercises (F18-Y1-BPA; M21-Y6-TOUR). On the other hand, there were students who said that the assistant instructor commenced solving the exercises and then he/she just explained to them the steps he/she followed (F19-Y1-PSYC; M22-Y1-PSYC). These students argued that they preferred the assistant to ask them how they could go to solve an exercise before giving them the 'ready solution'. A different way of tutorial sessions was mentioned by one student who described that they were taking place in labs once a week by the instructor of the course and the students had to solve exercises using the SPSS statistical package (F11-Y1-ABF).

Most of the students reported perceiving the existence and the attendance to tutorial sessions helpful and useful for their learning process in statistics. Common reasons stated were that tutorials help students to *reflect, clarify and gain a better understanding of the subject material and exercises covered in the lecture class (*M26-Y2-COM; M3-Y2-ECE; F16-Y1-PSYC); *apply the methods and formulas they have learned in the lecture class* (F10-Y1-EDUP; M26-Y2-COM); *practice in more and various types of exercises* (F10-Y1-

EDUP; F16-Y1-PSYC; F21-Y6-TOUR; M24-Y2-AFN); *crosscheck the exercises if they solved it in advanced* (M3-Y2-ECE; M2-Y2-AFN); and *have time to ask for more questions and explanations than during the lecture class* (F10-Y1-EDUP).
Moreover, there were students who raised the issue of having two different instructors in statistics - one main instructor for the lecture classes and one assistant instructor for the tutorial classes. Some of them argued that they preferred it because they could hear explanations from different persons (F18-Y1-BPA; F21-Y6-TOUR), whereas some others found it *confusing* (F20-Y1-EDU; M22-Y1-PSYC; M27-Y1-PSYC). Also, three students commented about the duration of the tutorials in statistics and they proposed that they would have liked to last longer; for example, two hours rather than just one (F10-Y1-EDUP; F16-Y1-PSYC; F18-Y1-BPA).

5.3.7 Classroom environment/climate

During the interviews, students were requested to comment about their perceptions of the classroom environment and climate in the statistics course and whether could have an impact on their learning process and performance. To start with, two students compared the current classroom environment in statistics with previous statistics classes that they had attended before. They said that the previous statistics classes were big lecture classes with a larger amount of students and they did not like it (M1-Y1-OGM; M23-Y3-MEN). Also, two students described the current classroom environment in the (private) university as being similar to the classroom environment in high school (M1-Y1-OGM; F18-Y1-BPA). They said that it is like a lesson -a seminar session and not a lecture- and they preferred it.

Some students commented about the size of the statistics class. All of them claimed that the fewer the students in the class, the better it is (M13-Y3-BPA; F14-Y3-CEN). They justified it by claiming that in smaller -in size- classes *the students can more easily contact and interact with the instructor and with each other* (M23-Y3-MEN) and *the instructor show personal interest to the students* (M25-Y3-MEN; F29-Y1-IEE). One student (F10-Y1-EDUP) commented on the composition of the class (i.e. pre-education and education majors) and how this affected her participation in the class (for example, not feeling comfortable to ask questions).

A number of students shared that the classroom environment and climate can have an impact on their learning especially in the statistics course (M4-Y2-PHYS; M17-Y4-EEN; M28-Y5-RAD). They claimed the importance of quietness and the absence of fuss, noise or disorder (F20-Y1-EDU; M25-Y3-MEN). These students argued that the classroom environment might affect their concentration in the lecture class (F9-Y2-EEN; F14-Y3-CEN; M28-Y5-RAD). Particularly, one student mentioned that she was often distracted by other students at the class (F30-Y1-CFS).

Many students also advocated that their classmates' performance level could play a role in their learning process. One student perceived the general classroom level as low, which did not give her an incentive to try her best in the statistics course (F15-Y1-NUTR). Other students said that it if the general level of performance is high *it can help you to improve yourself* (M4-Y2-PHYS) and *try your best to reach them* (F16-Y1-PSYC). However, the latter student also added that the high-performance level of the class might be not so good because *you feel that you are not so good like others, or at worst, you feel dump*.

5.4 Previous Mathematics/Statistics background, performance and experiences

During the interviews, students described their previous background, performance and experiences with mathematics and statistics in secondary school (Gymnasium) and in high school (Lyceum). They also reflected on their experiences with mathematics/statistics courses that they attended at university level before entering to this statistics course.

5.4.1 Previous experiences with mathematics/statistics in secondary and high school

Students shared their performance in mathematics-related courses and they tried to explain the reasons for doing or not doing well in mathematics. There were students who ascribed their previous mathematics performance to the lack of studying, effort and satisfactory attention and to their personal characteristics such as not being mature enough (M7-Y1-PSYC; F9-Y2-EEN; M25-Y3-MEN). Other students claimed that their performance in high school mathematics was related to their opinions and interest in mathematics as is shown in the excerpt below:

> M24-Y2-AFN: Generally, I did not like mathematics. I did not have a good relationship with mathematics. Thus, it did not appeal to me to study for it. This is the reason that I did not perform very well in maths in the matriculation exams.

A central role in students' engagement and performance in mathematics had to do with their mathematics teachers in secondary and high school and this arose in their responses (M7-Y1-PSYC; F5-Y1-AFN). The mathematics teachers seemed to also influence students' opinions, attitudes and interest, uncomfortable feelings and perceived confidence in mathematics (M3-Y2-ECE; M13-Y3-BPA; F30-Y1-CFS). As a student described:

> F10-Y1-EDUP: Some mathematics teachers in high school were not very good. Some of them did not have the control of the class; some others did not explain the subject very well. I had teachers who were very strict. There was a teacher who brought us a test every week without notice. In this way, you cannot love mathematics and you cannot perform well on it.

The way of teaching mathematics and the delivering of the new information had an influence on students' learning of mathematics as the following student described:

> F14-Y3-CEN: In the second year of the high school, it was the first time I did advanced mathematics. The teacher did not write anything on the board. Even to show us some graphics or to do an exercise, she used a computer program. I had a very hard time. I did not like this way of teaching because if you do not solve it by yourself to see where you made the mistake, you cannot learn. We had to solve some exercises at home, but it was not the same as trying to solve them during the class and asking questions at the same time.

Two students commented that they had mathematics teachers in school who had the subject knowledge, but they could not transfer it to their students (M4-Y2-PHYS; F5-Y1-AFN). Another student noted that his teacher' way of teaching in high school did not match with his own way of learning (M13-Y3-BPA). He proposed that, especially for mathematics which is a wide subject, a different teacher is needed to teach each sub-component of it because every teacher cannot transmit with success all of the subject material. Also, two students mentioned that teachers' tendency to *promote* some students and *disregard* others had affected their learning in mathematics in high school (F9-Y2-EEN) and had resulted in creating deficiencies in mathematics (F18-Y1-BPA; F30-Y1-CFS).

A student described her previous experiences and performance in mathematics throughout secondary and high school (F15-Y1-NUTR). To summarise, she claimed that her not so good performance in mathematics in high school (compared to the university where she is an excellent student) was due to the improper guidance and the lack of approachability of her teachers; the difficulty of mathematics; and the limited amount of her studying and interest in mathematics.

Problem-solving difficulties in school were stressed by two interviewees (M1-Y1-OGM; M22-Y1-PSYC). As one of them reflected:

> M1-Y1-OGM: I could not study for mathematics in school. I started studying, I found them hard to understand, to figure out how to solve the exercises and I stopped, I gave up.

5.4.2 Previous experiences with mathematics/statistics courses in university

Students' experiences with mathematics/statistics courses they attended at university level prior to entering the current statistics course were requested. There were students who had attended a statistics course in the past (in the same or a different university). For example, one student, who had attended a statistics course in a British university, before described his previous learning experience and concluded that he did not gain anything from completing this course (M17-Y4-EEN). The reasons were that he did not have the basis of the engineering discipline, he could not understand the reason for doing some things, so he could not apply them. Another student, who had completed a statistics course at a public university in Greece, described the lesson and the lecture class and he compared it with the current class as follows:

> M1-Y1-OGM: In my previous university, the lecture class was big (around 100 students) and the statistics instructor proceeded very quickly. We could not follow him. I did not pay too much attention. The subject material was much more than now, was more difficult and complicated and the way of teaching was not helpful.

There were also students who talked about their previous performance in university mathematics courses. One student attributed the achievement of the minimum passing grade in a previous mathematics course (Algebra) to the lack of appropriate attention and effort and the insufficient preparation (M7-Y1-PSYC). The role that mathematics instructors played in their performance was stressed by a number of students. For example, one student had previously attended two mathematics courses (M24-Y2-AFN). He recalled that he performed better in Mathematics II than in Mathematics I course because the instructor of the Mathematics II taught and explained the subject material in the way he liked to learn.

Another student compared her experience with the same mathematics course, but with a different instructor, in two different semesters (F18-Y1-BPA). As she reflected:

> F18-Y1-BPA: Unfortunately, the previous semester we had to take the module “Mathematical Methods”. I like mathematics, but this module was a bit complicated. We had 3 different instructors and this confused us. One of the main instructors, he scared us by stressing that the most students failed this course. I also found the exams exercises very difficult. I was very anxious during the exams. At the end, I failed the course. This semester, I attend again the course. This time the things are better. The instructor is closer to us, she does not make us feel anxious and the examination topics are more achievable.

5.4.3 Perceived mathematical abilities

Interviewees were also asked to share their perceived mathematical abilities. Some students mentioned that they believed they were good or bad at mathematics based on their previous engagement and performance in mathematics as well as on their everyday life (M12-Y2-BPA; F18-Y1-BPA; M28-Y5-RAD; F29-Y1-IEE). As one of the students communicated:

> F18-Y1-BPA: The previous semester was a very bad experience for me. It made me think if I am not good at maths; if I do not have the inclination and the brain to understand it.

There were two students who stated that when they studied, they understood mathematics and they were good at it (F10-Y1-EDUP; F16-Y1-PSYC). Another student said that she had never believed that she was good at mathematics because she did not engage seriously and consistently with it (F5-Y1-AFN). Moreover, some students compared their perceived abilities and performance in mathematics with other subjects (F20-Y1-EDU; M22-Y1-PSYC). For example, a psychologist major stated that he was not good at mathematics and numbers and he concluded that he is not a *maths type of person* (M22-Y1-PSYC).

5.4.4 Recall of statistical pre-knowledge

Students were asked to recall any exposure to statistics-related topics they had and any statistics concepts they remembered that they had been taught before attending this statistics course. A number of interviewees mentioned that some things they were doing in the current statistics course were familiar to them from the high school. The majority of them recalled probabilities and combination chapters from high school mathematics. The chapter of distributions (F6-Y1-ECON) and the measures of central tendency and dispersion, such as the standard deviation (M1-Y1-OGM; F29-Y1-IEE) were also reported.

After an inspection of the mathematics course content in high school, I found that statistics and probabilities are taught to a greater extent to students who chose core mathematics than to those who chose advanced mathematics in the third year of the high school. This issue was also highlighted by three interviewees (M3-Y2-ECE; M26-Y2-COM; F29-Y1-IEE).

As previously mentioned (see § 3.5.3), in Cyprus, after the completion of the high school, it is compulsory for the males to join the military services (for one or two years). One student said that, because of this gap, he just remembered the general idea and some statistical terms (M7-Y1-PSYC). Another student said that he vaguely remembered some things he has done in statistics in high school and they *flashed through his mind* that he had seen them before (M26-Y2-COM). However, one student mentioned that he could not remember anything from the statistics he had done in high school, like a *blackout,* as he described it (M27-Y1-PSYC).

In a similar manner, one interviewee said that he could not recall anything from high school (M25-Y3-MEN). Nevertheless, he recalled a statistical topic (more specifically, the distributions) he had learned in a course at the university and admitted that it helped him a lot in this statistics course that he knew it.

5.4.5 Comparison between statistics in high school and in university

Students were requested to compare the statistics and the statistics course they had done in high school with statistics they currently attended in the university. There were students who reported considering statistics easier in high school compared to the university (F16-Y1-PSYC; M27-Y1-PSYC). The probability chapter was mentioned as being more difficult in university compared to the probability theory they were taught in high school (M27-Y1-PSYC). Two education-related majors mentioned that the subject matter of the university course was related to the high school statistics content (for example, tables, graphical representations, average values), but they were taught to them at a deeper level at the university (F10-Y1-EDUP; F20-Y1-EDU). An engineering major although she claimed that the level of statistics at university was more advanced compared to high school admitted that she found them *more understandable and clear* to her now (F9-Y2-EEN).

One interviewee said that everything he has been taught so far in statistics at university (such as frequencies, random variables and probabilities), he has encountered them before in high school mathematics in Greece (M13-Y3-BPA). Thus, it was like a repetition for him in university. Nevertheless, he mentioned finding the exercises in high school more difficult than the ones he had to deal with in the private university he currently attended. Similarly, another interviewee stated that, because of the preparation she had received from her high school mathematics teacher (for example, by giving to the students university-level exercises), she found the subject matter (such as the probabilities and combinations) easier in the university (F18-Y1-BPA).

Responding to this question, two students said that they found some familiar things, but they noticed differences between high school and university regarding the symbolism and the way of solving the exercises (M27-Y1-PSYC; F16-Y1-PSYC). Nevertheless, the latter student argued that the way of thinking and the logic do not differ a lot. One student added that high school provided foundation knowledge so that he can manage to learn statistics in university (M1-Y1-OGM).

5.4.6 Comparison between mathematics and statistics courses in university

Students were asked to compare the statistics course they attended this semester with mathematics and statistics courses they had already completed in previous academic semesters. The students mostly commented about the course content and the way of instruction, highlighted similarities and differences between the courses and eventually reported their preferences (M2-Y2-AFN; F9-Y2-EEN; M12-Y2-BPA). In general, they found the way of teaching and delivering the subject material quite similar (M3-Y2-ECE; F29-Y1-IEE). Some students placed attention to the involvement of theory and practical applications in those courses and compared them based on that (F11-Y1-ABF; M25-Y3-MEN). A student's description is provided below:

> M7-Y1-PSYC: I believe that there are high relations between the two courses - Statistics and Algebra- regarding the way of teaching and delivering the subject matter. In both courses, there were theories and applications. Everything was clear in Algebra. You need to learn the formulas and apply them. In Statistics, we are introduced to more terms and theoretical assumptions of the methods. I might prefer Algebra because it was more straightforward for me.

5.5 Statistics versus Mathematics

This main thematic category included students' perceptions about the nature of statistics as a discipline and subject; the involvement of mathematics in the statistics course; the involvement of theory and practical applications in the statistics course; the inclination towards mathematics/statistics and the gender differences or stereotypes in statistics. Also, students' comparison between mathematics and statistics, their opinions about mathematics and a comparison between the opinions regarding mathematics and statistics are reported.

5.5.1 Nature of statistics as a discipline/subject

Students' perceived opinions about the (distinctive) nature of statistics as a subject/discipline were requested. To start with, one student characterised statistics as a *language*, which is accompanied by its own rules and concepts (F8-Y2-NUTR). Another student argued that since statistics has to do with probabilities, someone has to *deal with ambiguity and uncertainty in every stage* (M3-Y2-ECE). A similar comment follows:

> M26-Y2-COM: In statistics, you will never say that you are certain about something.

There were students who talked about the logical nature of statistics. They claimed that *everything in statistics is based on logic* (F10-Y1-EDUP) and *statistics is about logic and whether you have* (M3-Y2-ECE) or *understand* (F18-Y1-BPA) *this logic*. Also, some students argued that statistics requires thinking; a *logical thinking/reasoning* (M2-Y2-AFN; M17-Y4-EEN; F29-Y1-IEE) and a *critical thinking* in order to *select the appropriate method/test, the right timing of using it and the way to interpret the results* (F10-Y1-EDUP). Three students even mentioned about its *own thinking* (M4-Y2-PHYS) and *a new or special way of thinking* (F8-Y2-NUTR; F16-Y1-PSYC).

One student also characterised statistics as a *clever subject* (F9-Y2-EEN). In a similar vein, another student contended that *in statistics you need to do that 'click' in your brain, you need to grasp the topic that is transferred to you* (F19-Y1-PSYC).

The hierarchical nature of statistics was also pointed out. Students described the learning of statistics *as a logical pyramid* (M2-Y2-AFN); a *puzzle* (M4-Y2-PHYS); a *tower* (F19-Y1-PSYC) and a *chain* (F10-Y1-EDUP; F19-Y1-PSYC). A common view amongst the students was that in statistics it was necessary to build and add to the existing knowledge. One of the students mentioned:

> F19-Y1-PSYC: Statistics is like a tower. You build the knowledge; there are blocks. If you lose one block, you might lose the whole tower. It is a chain. Thus, whenever you do not understand something, whenever you have a question, it is better to solve it in order to maintain and add up to this chain.

Related to the above comments, a number of students talked about the interconnections between the chapters in statistics. Statistics was described as a highly interconnected discipline (M2-Y2-AFN) and in the statistics course all chapters are connected with each other (F5-Y1-AFN; M17-Y4-EEN). There were students who argued that some chapters were more intertwined with each other, whereas some others were more independent (F8-Y2-NUTR; F10-Y1-EDUP; F19-Y1-PSYC; M23-Y3-MEN). Nevertheless, they agreed on achieving a good understanding of each chapter before moving to the next one. Among the students' justifications was *to have a rounded idea and knowledge of statistics* (F15-Y1-NUTR; F20-Y1-EDUC) and *not create gaps and deficiencies* (F9-Y2-EEN; F30-Y1-CFS). Two students further emphasised that in statistics *you have to develop an understanding of every single concept and idea delivered in the course* (F9-Y2-EEN; F16-Y1-PSYC). The understanding of the ways that the statistical terms or concepts (which might be included in different chapters) are linked to each other was also pointed out by one student (M2-Y2-AFN). In addition, the importance of developing a conceptual understanding and acquiring interpretative skills in statistics was mentioned by a number of students.

Three students described statistics as a *methodological discipline* (M2-Y2-AFN; M24-Y2-AFN; F29-Y1-IEE). Two other students referred to its *procedural nature* and they argued that in statistics *if you follow the procedures you will reach to the solution* (M7-Y1-PSYC; F18-Y1-BPA). There were also students who talked about various and alternative ways and approaches to solving exercises in statistics (F9-Y2-EEN; F10-Y1-EDUP). One of them claimed:

> F9-Y2-EEN: If there is something in statistics that you doubt about it, for example, in a formula, you can prove it by using graphical representations to see it and visually.

Some students also stressed the need for *dedication and sustained level of commitment in statistics* (F19-Y1-PSYC; M26-Y2-COM) and the importance of *concentration* and *focus* both in classroom settings and examination conditions (F19-Y1-PSYC; F30-Y1-CFS). They pointed out the necessity for *practising and solving exercises* (F8-Y2-NUTR; F9-Y2-EEN; F14-Y3-CEN; M26-Y2-COM) and *paying attention to details* (M2-Y2-AFN). Also, another student said that statistics is a subject which students cannot study it on their own, but they require the explanation from an expert, in their case the instructor (F9-Y2-EEN). As a last comment, some students when compared statistics to other subjects mentioned that it involves tasks and exercises that were more cognitively demanding or they were different kind of tasks they had previously encountered (M28-Y5-RAD; F30-Y1-CFS)

5.5.2 Involvement of mathematics in the statistics course

Both versions of the questionnaire included two questions assessing students' perceptions of the involvement of mathematics in the statistics course and the advantage of having a (previous) mathematical background. During the interviews, regarding the perceived involvement and use of mathematics in the statistics course they currently attended, the majority of the students said that the statistics course involved basic mathematical knowledge and required simple or fundamental mathematical operations/calculations. They specifically argued that when doing statistics *you do not need advanced or very specialised mathematics* (F19-Y1-PSYC); *you do not need to have a strong background in mathematics* (F11-Y1-ABF); and *you only need a computational machine* (M1-Y1-OGM; M3-Y2-ECE). Some students said that mathematics is a necessary prerequisite for attempting statistics since it requires some basic mathematical competencies including algebraic concepts such as doing operations with numbers, mastering of equations and inequalities, solving integrals and derivatives and reading and producing graphs and tables. However, one student stated that, from his point of view, statistics involved a lot of mathematics and he contended that *for sure, you could not avoid mathematics in statistics* (M22-Y1-PSYC).

Three students referred to the statistics instructors and their way of teaching, which they believed influenced involvement of mathematics in the statistics course (F14-Y3-CEN; F20-Y1-EDU; F30-Y1-CFS). More specifically, one of them communicated:

> F20-Y1-EDU: As our instructor told us, the statistics course does not need any contact with mathematics, at least not so much. She said that we did not require to have mathematical knowledge because we would have to do standard mathematical-related things in statistics. However, as I can see in the course until now, there is some mathematical knowledge, some mathematical terms that we need to know.

Students were also asked whether they believed that previous experience, background and engagement with mathematics could be an advantage while learning statistics. For some students, the mathematical background can aid in *practising someone's mind* (M28-Y5-RAD) and *shaping or developing mathematical thinking* (F20-Y1-EDU) before attending a statistics course. As one student argued:

> M24-Y2-AFN: Someone might have an advantage of being familiar with dealing with numbers. Someone who does not have so much contact and practice in mathematics might find it difficult to tackle with mathematical procedures. I believe that if someone is good at mathematics, he might do it better in statistics, but this is not absolute.

Some students believed that they had an advantage over those who did not have previous or recent contact with mathematics and/or statistics and they might face difficulties in the statistics course (F18-Y1-BPA; F29-Y1-IEE). Nevertheless, two students argued that the strategy for someone who is not good at mathematics or not have the appropriate mathematical background is studying, practising and appropriate effort (F6-Y1-ECON; F18-Y1-BPA). Lastly, one engineering student, who chose the course as an elective and his classmates were psychology majors, argued that he did not think having an advantage over them because he had completed more mathematics courses at the university (M3-Y2-ECE). The advantage for him was that he had introduced to statistics in a course of his major degree programme. As he concluded:

> M3-Y2-ECE: If someone had pre-existing knowledge and skills in areas relevant to statistics and he had understood statistical topics from before, it is more likely to do it better in this statistics course.

5.5.3 Involvement of theory and practical applications in the statistics course

Students' perceptions about the involvement of theory and practical applications in the statistics course they attended were assessed in both versions of the questionnaire. These perceptions along with their preferences were further investigated during the interviews. To start with, some students mentioned that the statistics course was more practically oriented (F14-Y3-CEN; F18-Y1-BPA; F20-Y1-EDU; M25-Y3-MEN). As one of them described:

> F14-Y3-CEN: The way that our instructor delivers the statistics course is more practical and involves more exercises than theory. When a new chapter starts, she begins with an example to give us the formulas and then she solves the exercises. She only mentions a few definitions and theorems. Also, she does not examine us in theoretical-related topics.

One student said that, in his opinion, the statistics course involved too much theory where it should not (M1-Y1-OGM). He justified it by arguing that for the students is easier to figure out something if the instructor applies it to exercises. A similar comment was made by two more students who claimed that *they can understand the theory in statistics after its application to practice* (M28-Y5-RAD; F30-Y1-CFS).

A number of students considered both theory and practice necessary in learning statistics. They further supported a structure of a statistics lesson, which includes a combination and a balance of them (F5-Y1-AFN; M17-Y4-EEN; F20-Y1-EDU). One of the students argued:

> F11-Y1-ABF: It is important to learn both -you cannot neglect theory- and then link theory and practice to understand statistics better

Nevertheless, the majority of the students mentioned that they preferred the instructors to give emphasis to practical applications of statistics (M3-Y2-ECE; F5-Y1-AFN; F11-Y1-ABF; F19-Y1-PSYC) even some of them considered themselves as more theoretical persons (F16-Y1-PSYC; M21-Y1-TOUR; M22-Y1-PSYC; M27-Y1-PSYC). Also, there were students who contended that for their field of study they need to know and, they are more interested in, the practical applications of statistics (M25-Y3-MEN; M26-Y2-COM).

5.5.4 Inclination towards mathematics/statistics

During the interviews, the students were queried on whether they believed that natural talent (or inclination) is necessary for learning and performing well in statistics. One student argued that generally in natural sciences, an inclination or a talent is important and is an extra advantage (F16-Y1-PSYC). In a similar vein, some students mentioned inclination towards mathematics and innate mathematical ability. There were students who claimed that if *someone's brain is working in mathematics* and he is *mathematically inclined* (F9-Y2-EEN) definitely he will perform better in statistics (M4-Y2-PHYS; F6-Y1-ECON). One student shared: *I believe that statistics is for people who have natural and inherent learning towards mathematics* (F29-Y1-IEE). Particularly, there were students who said that inclination is necessary for doing statistics (M7-Y1-PSYC; M24-Y2-AFN; F30-Y1-CFS)

There were interviewees who connected the level of intelligence with the statistics learning and performance. Two of phrases mentioned were that *someone should be clever to perform well in statistics* (F9-Y2-EEN) and *it would be 'revealed' in statistics if someone is clever*

(F21-Y6-TOUR). One of the students gave as an example the probabilities chapter and he claimed that except studying, probabilities need brain, thinking and logic (F21-Y6-TOUR). There were also students who talked about having a practical mind rather than an inclination or a talent (M3-Y2-ECE; M4-Y2-PHYS; M27-Y1-PSYC).

The importance of a combination of having an inclination and putting forward effort and studying to perform well in statistics was stressed by some students (M2-Y2-AFN; F16-Y1-PSYC; F18-Y1-BPA). One of them said:

> F16-Y1-PSYC: In statistics, you need both - a tendency to learn and a will to study. I think the intelligence and the mind are essential as well as the effort, studying and learning strategies someone uses.

One student talked about talents that *people have on their own and talents that are a matter of learning - if you study, you can learn it-* and he argued that *in statistics, both can happen* (M27-Y1-PSYC). There were also students who pointed out that *everyone has the potential to perform well in statistics if he/she strives for it* (F10-Y1-EDUP). The argument that it is not a matter of talent, but instead of positive attitudes and effort, was also put forward:

> F8-Y2-NUTR: Someone should have positive attitudes towards statistics. I do not think it is a matter of talent. He/she must like to work on statistics because without effort and practice you cannot do it, you cannot be successful.

The relation between inclination and amount of studying and effort in statistics was raised up by many students (M13-Y3-BPA; M17-Y4-EEN). For example, some students reflected on their personal experience and they claimed that if someone *'has' it* - has some inclination or flair for it - it would easier for him/her to understand and he/she can even study less (F10-Y1-EDUCP; M13-Y3-BPA).

Nevertheless, some students conveyed the view that inclination is *not enough* or *absolutely necessary* when engaging with statistics (F20-Y1-EDU; M21-Y1-TOUR; M22-Y1-PSYC; M23-Y3-MEN). One student shared his (personal) journey in the statistics course when justifying the absence of the necessity of having an inclination towards statistics by stating:

> M22-Y1-PSYC: I do not think everyone should have an inclination to achieve in statistics. In my case, I studied very well, I put effort, I performed well in the examination, and I do not have an inclination either in mathematics or in statistics.

5.5.5 Gender differences/stereotypes

The questionnaire included a question requesting from students their opinion whether females and males could perform equally well in the statistics course. During the interviews, students' perceptions regarding gender differences/stereotypes were discussed further. A number of students stated that they believed that the gender does not (really) matter (F6-Y1-ECON). Two students advocated that it does not have to do with gender, but *it is up to the individual person* (M28-Y5-RAD) and *individual's talents, inclinations and way of thinking* (F18-Y1-BPA). Another student said that both male and female could equally perform well if they study and put an effort in statistics (F14-Y3-CEN). A related comment is presented below:

> M13-Y3-BPA: In manual jobs, such as constructors, it is easier, and maybe more productive, for males to work than for females. However, in something that requires

thinking and studying, such as statistics, I believe both have the same brain and the potential to do it well.

However, there were students who alluded that females might perform better than males in statistics. They justified it by arguing that females are *willing to devote more time to studying* (M12-Y2-BPA); are more *hard-working* (M21-Y6-TOUR) and are *more concentrated and attentive to detail* (M7-Y1-PSYC) than males. Oppositely, one female student who supported that males might perform better than females advocated:

> F20-Y1-EDU: Although this might be a bit sexist, men from their nature are superior to women and tend to perform better in practical subjects.

Finally, one student referred to TED talks, which are given by academics in a variety of topics. He recalled a talk he heard about gender differences and cognitive abilities and he explained:

> M25-Y3-MEN: I believe that males probably perform better in practical things and females do it better in things that are more theoretical. In a TED talk that I heard, there were psychologists who talked about the differences in male and female brains. They said that females have a double hippocampus, which is responsible for the memory, than males. They found evidence, which favours females on memory-related tasks. On the other hand, they also found evidence that males have better spatial skills, which are part of mechanical skills and are related to STEM disciplines – including mathematics. Based on that, it should be the case that males and females might have different skills, but I believe that we (males) are somewhat better in more technical and practical disciplines such as engineering and statistics.

5.5.6 Comparison between Mathematics and Statistics

During the interviews, I asked students whether they considered mathematics and statistics as different or the same things and why. Students talked about differences as well as interrelationships between statistics and mathematics they have identified. A group of students pointed out that mathematics and statistics are *different sciences/disciplines, but someone cannot separate them* (F8-Y2-NUTR). They said that they are *not the same thing*, but they are *related* (F14-Y3-CEN; F18-Y1-BPA), *connected* (M2-Y2-AFN; F15-Y1-NUTR; F19-Y1-PSYC) and *based on one another* (F10-Y1-EDUP). One student said that *statistics is joined in mathematics (*M13-Y3-BPA). Another student argued:

> M25-Y3-MEN: They are not the same thing, but they are interrelated because mathematics uses statistical techniques and you can also find mathematics involved in statistics.

There were students who reported that there is a close relationship between statistics and mathematics (M7-Y1-PSYC; M12-Y2-BPA; F20-Y1-EDU). Students seemed to recognise that statistics *contains mathematics* (M4-Y2-PHYS; F8-Y2-NUTR; F18-Y1-BPA) and *'borrows' things from mathematics* (M21-Y1-TOUR). They argued that the most of the concepts and formulas be taught in statistics have a mathematical base. One student said that she did not distinguish them since she believed that statistics seemed to *come from mathematics* and has *its roots in mathematics* (F16-Y1-PSYC). One student contended:

> F20-Y1-EDU: I think that statistics and mathematics go together. This is the reason I believe that statistics consists a component of the mathematics curriculum in high school.

The perceived close relationship between mathematics and statistics was further emphasised by two students who alluded that *they are almost brothers* (M4-Y2-PHYS) and *they are relatives* (M27-Y1-PSYC). Nevertheless, these two students pointed out the distinctive nature of statistics. One of them stated:

> M4-Y2-PHYS: Mathematics and statistics are almost brothers. However, they are distinct. For example, my brother and I have the same blood, but we are different.

A number of students mentioned that statistics is specialised whereas mathematics are broader and more general (F8-Y2-NUTR; F10-Y1-EDUP; M13-Y3-BPA; F16-Y1-PSYC). They considered it as a *branch* (M7-Y1-PSYC; M27-Y1-PSYC), a *subset* (F8-Y2-NUTR; M13-Y3-BPA), a *subfield* (M21-Y1-TOUR; F29-Y1-IEE); and a *part* (M1-Y1-OGM; M7-Y1-NUTR) of mathematics. One student contended that mathematics has various branches - one of them is statistics- and each one is different from the other and has other pre-requisites (F19-Y1-PSYC). Other students asserted that statistics, even though is similar to mathematics, has *other applications and uses* (F15-Y1-NUTR) and *different purposes/aims* (M12-Y2-BPA).

There were also students who considered mathematics and statistics as not (exactly) the same, but as different or separate things because they have distinct subject matter (M3-Y2-ECE; F5-Y1-AFN; F18-Y1-BPA; F21-Y6-TOUR). An excerpt related to this is:

> M3-Y2-ECE: Mathematics uses more types, derivatives and integrals whereas statistics is more about probabilities. Probabilities are a bit different from the mathematics we know; and they are not about calculations, they are about logic.

Related to the above comment, a subset of students compared the logic and the way of thinking and understanding of mathematics and statistics. They argued that statistics has *a distinct kind of thinking* (M4-Y2-PHYS; F9-Y2-EEN; F18-Y1-BPA); a *different way of thinking when solving exercises*; (F11-Y1-ABF); and *a different logic than mathematics* (F9-Y2-EEN; F14-Y3-CEN).

A number of students stated further differences and similarities they have identified between mathematics and statistics such as the ways of approaching and solving exercises (F9-Y2-EEN; F11-Y1-ABF). There were students who argued that mathematics and statistics have different methods and approaches to solve problems and they employ different tools (M25-Y3-MEN; M26-Y2-COM). One of them stated:

> M25-Y3-ME: Mathematics and statistics can be used to model and understand the world around us, but they employ different approaches to achieve that.

There were also students who talked, not only about different procedures and approaches but also about different desired outcome. More specifically, two students claimed that in mathematics someone has to get a result in a problem whereas in statistics is to analyse and find the meaning or interpret this solution, provide an explanation, draw the conclusion and communicate it (F9-Y2-EEN; F15-Y1-NUTR; M28-Y5-RAD). Lastly, two students shared that in mathematics they were more certain of their answers whereas in statistics they were not always sure about being correct (M2-Y2-AFN; M26-Y2-COM).

5.5.7 Opinions, beliefs and feelings about mathematics and comparison with statistics

The first version of the questionnaire included six questions to assess students' opinions, attitudes, perceived difficulties, anxieties, and self-efficacy beliefs towards mathematics. During the interviews, these topics were further discussed and compared with statistics.

Firstly, the students talked about their opinions and general beliefs towards mathematics. The positive opinions exhibited by many students were due to the nature of the subject being practical and incorporating operations, calculations and numbers (F5-Y1-AFN; F8-Y2-NUTR; M13-Y3-BPA; F14-Y3-CE; M17-Y4-EE; F21-Y6-TOUR) and the perceived easiness of mathematics (M12-Y2-BPA). Some students said that they love mathematics because *engaging with mathematics is like a game* (F15-Y1-NUTR) and *the brain is growing and keep working* (F8-Y2-NUTR; F19-Y1-PSYC). The attendance at private tutorial lessons (F10-Y1-EDUP) or the acquisition of extra qualifications (such as A-Levels) in mathematics (M4-Y2-PHYS) in high school and their previous mathematics school teachers (F10-Y1-EDUP) were also sources of students' positive dispositions regarding mathematics.

Some students admitted that they liked mathematics when they were able to understand the mathematical-related concepts or solve the exercises correctly (M3-Y2-ECE; M27-Y1-PSYC). Also, a number of students reported that they felt competent about their abilities and skills in mathematics due to their perceived inclination towards mathematics (M13-Y3-BPA; M17-Y4-EE) and past good performance in mathematics courses (M17-Y4-EEN; F19-Y1-PSYC). They were students who said that they had envisioned themselves majoring in mathematics rather than in their chosen field of study (M2-Y2-AFN; M4-Y2-PHYS). On the other hand, a group of students stated that mathematics was not among their favourite subjects and the subjects that they were interested in (M1-Y1-OGS; F6-Y1-ECON; F16-Y1-PSYC; M24-Y2-AFN; M25-Y3-MEN). Among those who exhibited no favourable dispositions towards mathematics were students who stressed that they did not like mathematics since their school years (M7-Y1-PSYC; F20-Y1-EDUC; M22-Y1-PSYC). They said that they found mathematics difficult (M7-Y1-PSYC; M24-Y2-AFN; M22-Y1-PSYC) or not particularly appealing to them (M23-Y3-MEN; M24-Y2-AFN; M25-Y3-MEN). Perceptions of mathematical incompetence throughout the school life were also stated (M7-Y1-PSYC; F20-Y1-EDUC). There were also students who mentioned anxieties evoked by doing mathematics (M24-Y2-AFN) and dealing with numbers and operations (F10-Y1-EDUCP; F20-Y1-EDUC). Unpleasant experiences with mathematics courses in a previous semester seemed to heighten students' anxieties towards the subject of mathematics (F18-Y1-BPA).

In addition, a large number of students stressed the importance and the usefulness of mathematics and mathematical thinking for their everyday life. They argued that *mathematics is an essential part of our everyday life* (M4-Y2-PHYS; F16-Y1-PSYC; F29-Y1-IEE); *nowadays, whatever we do, we need mathematics* (M24-Y2-AFN; F30-Y1-CFS); and *mathematical thinking helps us in the daily life* (F8-Y2-NUTR; F16-Y1-PSYC). Many students pointed out that mathematics has contributed to and is the base of almost all sciences (F8-Y2-NUTR; F16-Y1-PSYC). Five students particularly mentioned that mathematics is the base of their field of study (F9-Y2-EEN; M23-Y3-MEN; M24-Y2-AFN; M25-Y3-MEN; M26-Y2-COM). Also, they emphasised the value and the application of mathematics in their chosen field of study and their future professional career (F13-Y3-BPA; F18-Y1-BPA; M24-Y2-AFN; M25-Y3-MEN; M26-Y2-COM; M28-Y5-RAD).

Students were then asked to compare their opinions, attitudes and perceived competence regarding mathematics and statistics. There were students who reported liking and enjoying mathematics more than statistics for reasons such as perceiving it as *easier* (M4-Y2-PHYS; M3-Y2-ECE; M7-Y1-PSYC; M17-Y4-EE) and *more straightforward* (F11-Y1-ABF) and also that mathematics *has more 'essence' and 'madness' than statistics* (M4-Y2-PHYS); *involves more operations* (F14-Y3-CEN); and *does not deal with or involve probabilities* (F14-Y3-CEN; M23-Y1-TOUR). Other students reported finding *the mathematical problems more understandable* (F21-Y6-TOUR; F14-Y3-CEN). On the other hand, there were students who perceived statistics as easier than mathematics (M3-Y2-ECE; M13-Y3-BPA; M17-Y4-EEN; F18-Y1-BPA; M24-Y2-AFN). Some students also identified statistics as more interesting than mathematics because *it was not just numbers and calculations* (F20-Y1-EDUC; M25-Y3-MEN) and the *statistical thinking was more challenging* (M21-Y1-TOUR). One representative excerpt is presented below:

> M2-Y2-AFN: I like mathematics more than statistics. It might be perhaps because we get used to mathematics from the elementary levels in school. It is more familiar to us. However, I can say statistics is more interesting than mathematics because it is something new and stimulates the interest and curiosity.

Related to the above comment, two students mentioned that they felt more confident in mathematics because they had many years of experience with mathematics, while they have introduced with statistics a bit in high school and this semester at the university (F21-Y6-TOUR; M4-Y2-PHYS). Another student felt more confident in statistics because she performed better in statistics than in previous mathematics courses (F18-Y1-BPA).

There were students who supported that statistics is more useful and applicable in their field of study than mathematics (M-Y1-NUTR; M2-Y2-AFN; M4-Y2-PHYS; M7-Y1-PSYC; M22-Y1-PSYC; M28-Y5-RAD), whereas some others they perceived the opposite (F10-Y1-EDUCP; M13-Y3-BPA; F14-Y3-CE; M23-Y3-ME; M26-Y2-COM; M27-Y1-PSYC). One of them justified his opinion by arguing:

> M28-Y5-RAD: In order to practice my profession, the machines need numbers; they need mathematics. We are technologists. In order to get a treatment plan, I will use mathematical procedures rather than statistical investigations.

Moreover, a number of students considered statistics as more useful in their everyday life (M7-Y1-PSYC; F9-Y2-EEN; F14-Y3-CEN; M25-Y3-MEN), whereas some others they perceived the opposite (M4-Y2-PHYS; F10-Y1-EDUP). Nevertheless, generally, they seemed to appreciate the value of both disciplines/subjects for every day applications.

5.6 Attitudes and opinions (e.g. liking and interest) about statistics

This main thematic category is a composition of two topics (namely students' liking of statistics and statistics course and students' interest in statistics). As previously indicated in the Quantitative Analysis Chapter (see e.g. §4.5.1), students' liking and interest in statistics were closely related. During the interviews, students tended to use phrases such as *I like it*, *I love it*, *I enjoy it* or *I find it interesting* (and the opposite direction) interchangeably. Both versions of the questionnaire included questions regarding students' liking regarding statistics and the statistics course they were currently attended as well as their interest in the course, enjoyment of studying statistics and interest in acquiring further knowledge of statistics. During the interview sessions, these topics were discussed further.

5.6.1 Changes in attitudes towards statistics and antecedents of them

Firstly, with the aim to gain an insight into students' attitudes statistics, I asked them what impressions, attitudes and beliefs they had about statistics before attending the statistics course and whether these remained the same or changed during the course. Positive changes in students' attitudes, that is bad impressions about statistics which turned into positive, were mostly mentioned by students who had not undertaken any statistics course before (M7-Y1-PSYC; F18-Y1-BPA). Their prior opinions and beliefs about statistics were commonly shaped from comments, opinions and perspectives of others (most commonly of former students and friends) as well as their own conceptions of 'what is statistics' and 'what is to do statistics'. However, after their personal engagement with statistics and their enrolment in the statistics course, these participants argued that their feelings and attitudes have changed in the positive direction. The main reason for their positive change towards the learning of statistics was the appreciation of the usefulness of statistics for their everyday and professional life. A representative example is:

> F18-Y1-BPA: I formulated a bad impression about statistics since previous students described it as the most difficult course of our degree. However, the enrolment in the statistics course has changed the way I thought about statistics. My opinions and attitudes about statistics have completely changed. Now, I am not influenced by other's opinions. I found the course useful in professional and everyday life. When you engage with a subject and keep up with it, you can understand its usefulness and it is more likely to like it.

Related to the above comments, students mentioned that they liked to learn things that make sense to them and they are applicable to real life because this makes them seem important to them (M28-Y5-RAD; F29-Y1-IEE). Those students said that they did not like statistics course content that contains things that they would probably never use again or they need to learn them just for getting a good grade and passing the course.

The influence of close environment (e.g. family members) was apparent in two students' interviews (M4-Y2-PHYS; M2-Y2-AFN). As one of them communicated:

> M4-Y2-PHYS: I liked statistics because of my mother who is a mathematician and she transferred to me her positive feelings about statistics.

There were students who had positive attitudes towards statistics before their enrolment in the statistics course and these positive attitudes remained unchanged and after attending the course. This is illustrated in the following excerpt:

> F19-Y1-PSYC: I love statistics. I had the first experience with statistics in high school and I liked it. Statistics helps me to sharpen my way of thinking and broaden my horizons.

On the flip side, some students drew on prior learning experiences and achievement with mathematics/statistics courses in high school and in university and their instructors, and the influence these experiences had on shaping their attitudes towards statistics (M1-Y1-OGM; F14-Y3-CEN; M21-Y6-TOUR). They expressed negative feelings and attitudes towards statistics before and during their enrolment in the statistics course. These students did not change their mind after the engagement with the course. A representative statement is:

> M21-Y6-TOUR: I attended the same statistics course several times in previous years. The statistics course was the only course at the university, which had produced negative feelings to me. The primary reason was the former statistics instructor and the previous unsuccessful attempts to pass the course. Even this semester that the statistics course is taught by a different instructor, my negative feelings did not change. I do not like statistics.

Another interviewee who exhibited negative views about statistics, which did not change after his engagement with statistics was psychologist student (M22-Y1-PSYC). He was disappointed about having a statistics course as a compulsory course for his degree programme. In his interview session, he repeated a few times the word ‘disappointed’ by also adding the words ‘too much’ and ‘extremely’. More specifically, he said:

> M22-Y1-PSYC: I was disappointed. I was too much disappointed. I had the impression that there I will never see in front of me mathematics after the full stop that I put on at the matriculation entrance exams. I was extremely disappointed to have a compulsory statistics course at university. I had a bad idea about statistics. It might be because of my unpleasant prior experiences with mathematics in primary and high school. I still have a bad idea for statistics.

Some students believed that statistics is mathematics or is very closely related to it. Thus, they mentioned that their attitudes and stances related to the subject of mathematics were transferred to the statistics subject (F8-Y2-NUTR; F30-Y1-CFS).

5.6.2 Sources of opinions and beliefs during the course

Students were then asked to share their sources of opinions regarding statistics throughout the course. A large number of students stressed the importance of the instructor and the way of his/her teaching along with his characteristics and attributes in generating positive attitudes to them. For example, two students who participated in a pair interview session gave the considerable credit of their positive views towards statistics to their statistics instructor (M2-Y2-AFN, M12-Y2-BPA). Also, another student attributed her positive attitudes towards statistics to the statistics instructor as exemplified in the ensuing quote:

> F16-Y1-PSYC: I think I like statistics because of the statistics instructor and her way of teaching and delivering the subject matter to us. I do not know if I would like statistics if I attended the particular course with a different instructor.

The students who were favourable towards statistics described the subject and the course as being *interesting* and *fascinating* (F8-Y2-NUTR), *practical* and *logical* (F15-Y1-NUTR). There were also students who compared and pointed out the differences between statistics and the other courses of their major, which played a role in their positive attitudes regarding statistics. They described statistics as *their favourite subject* compared to the other courses (F8-Y2-NUTR); *break from other -more theoretical- courses* (M4-Y2-PHYS; M13-Y3-BPA) and *oxygen between the more theoretical courses of their major* (F19-Y1-PSYC).

Another source of students' positive attitudes towards statistics was the good performance in examinations in statistics (F5-Y1-AFN), the perception that the course was on their capabilities and they would be good at it (M13-Y3-BPA) and the subject material which they found it understandable and easy (M13-Y3-BPA; F29-Y1-IEE).

Students' feelings and attitudes towards statistics seemed to be related to their understanding of the statistics material (M1-Y1-OGM; M3-Y1-ECE; F20-Y1-EDU). The following excerpt reveals how their opinions might alter depending on their understanding:

> F20-Y1-EDU: Whatever I do not understand, whatever I cannot 'get' it, I do not like it. Whenever I understand something (a concept or an exercise), I like it. My opinion can change 360 degrees depending on my level of understanding.

Related to the above comment, the probability component of the statistics course and the difficulty in understanding it generated negative feelings as it is exemplified:

> F14-Y3-CEN: I did not like statistics since high school years. Statistics is for me probabilities, so I did not like them because it was hard for me to understand them.

Students' negative attitudes towards statistics seemed to be influenced by the nature of the statistics course (being too mathematical-oriented as it was described), the difficulties they experienced and their bad performance (F20-Y1-EDU; M22-Y1-PSYC; M27-Y1-PSYC). The comment below is highlighted the above:

> F20-Y1-EDU: I can say that statistics is amongst my worst subjects. I hated statistics because it involves calculations. The mathematical component of statistics made it less appealing to me. I can say that if I do not perform well in an examination in statistics, I might say that I did not like statistics.

Lastly, talking about attitudes and opinions about statistics, one student referred to her instructor's attitudes and the potential influence of them in students' attitudes by saying:

> F14-Y3-CEN: I do not like statistics. I can also say that my statistics instructor does not like statistics too. She told us that. Thus, she prefers teaching statistics in a more mathematical way. I think that sometimes the instructor's opinions might influence students' opinions.

5.6.3 Interest towards statistics

There were students who shared their interest and enthusiasm towards statistics and what they found interesting and enjoyable in the statistics course they were enrolled in. A few students mentioned that the instructor and his/her approach had the potential to influence their interest in statistics (M25-Y3-MEN; F29-Y1-IEE). Many students talked about enjoying the problem-solving aspect of statistics and practising during the course (M24-Y2-AFN; F8-Y2-NUTR). One student mentioned having a keen interest in mathematics, which stemmed back to secondary school and transferred to statistics (F19-Y1-PSYC). Another student said that he was particularly attracted to mathematical and statistical-related problems and tasks (M13-Y3-BPA). Comments from two students are presented below:

> F8-Y2-NUTR: I enjoy statistics. There are inexhaustibly things that you can learn and do with statistics. You are never getting bored. It is fascinating. Finding the subject consistently interesting for me is very important. The brain is 'working' and 'growing' in statistics.

> M12-Y2-BPA: I treated statistics as a science and not as a compulsory course and that is what generated a genuine sense of curiosity and inherently interest for the statistics discipline and content.

There was only one student among the interviewees, where the statistics course was not a compulsory module for his degree programme, and he chose it as an elective (M3-Y2-ECE). He explained his decision as follows:

> M3-Y2-ECE: I preferred statistics course to other courses that were offered as electives and were more theoretical such as psychology and language courses. I find statistics an interesting and appealing subject because it is practical and you can learn a lot from it. However, I do not think I want to engage deeper with statistics.

Students' willingness and interest in engaging more with statistics (for example, by completing other statistics courses in the future) was discussed. Students' opinions were mixed and selected quotes are given below:

> M24-Y2-AFN: I am interested in taking further, and perhaps more advanced, courses in statistics if they are useful and relevant to accounting and finance major.
>
> M1-Y1-OGM: I had the experience of more advanced and demanding statistics courses, so I do not think I want to be in the same position again.

Some students mentioned an enjoyment that arose when encountered something quite difficult and challenging in statistics, such as the probabilities chapter (M24-Y2-AFN). Nevertheless, interest in statistics, which was conditioned by the perceived easiness or difficulty and understanding of the subject material, is illustrated in the following comment:

> F20-Y1-EDU: I can say that I like the things in statistics, which are simple and easy to understand. When the things started being more difficult and I might not understand them, this makes the statistics course less enjoyable for me.

In contrast, some students stated that, in general, they did not find statistics and statistics course interesting. Among the reasons mentioned were its mathematical nature and association with mathematics (M22-Y1-PSYC; M27-Y1-PSYC). Another student reflected:

> M23-Y3-MEN: I found statistics course pretty boring for me. It is far away from the 'sphere of my interests'. I believe that it is something 'extraordinary' for me.

5.7 Value of statistics

Both versions of the questionnaire included six questions in an attempt to assess students' opinions about the usefulness, applicability and relevance of statistics for their every day, educational and future professional life. During the interviews, students talked about the value they placed on statistics and the perceived benefits of undertaking a statistics course.

5.7.1 Value of statistics for students' educational and future professional life

The majority of the interviewees indicated that statistics is relevant, useful and has applications in their field of study. Since the students majored in a number of different disciplines, a variety of responses were given. For example, an oil and gas engineering student believed that statistics has applications in oil and gas industry and he explained:

> M1-Y1-OGM: We are engaged with geological issues. We can use probabilities to calculate the chances of finding petroleum in some regions by predicting some quantities (such as the number of deposits). Statistics can also help in planning exploration strategies, in real data analysis and evaluation and in decision-making.

An agricultural major stated that statistics is useful in designing and implementing experimental studies in medicine, agriculture and fishery to make informed decisions (F11-Y1-ABF). Also, two students, who were majoring in nutrition and dietetics sciences, reported that they found statistics useful in biology, medicine and medical-related sciences. They justified their opinion about the usefulness of statistics in their field of study by stating: *Statistics can aid in investigations. Many variables can be imputed in a model and this can help us to formulate a more 'concrete' conclusion* (F8-Y2-NUTR); and *Statistics can be helpful to produce dietary plans and analysis of our patients* (F15-Y1-NUTR).

The psychology majors made statements about the usefulness and the relevance of statistics for their discipline. They said that psychologists *need a lot the statistical surveys and the relational investigations to import data, extract results, compare situations, draw conclusions on various psychological investigations they do* (M22-Y1-PSYC); *describe, explain and communicate the findings of a statistical investigation* (F16-Y1-PSYC); *carry out experiments and perform statistical procedures to test, evaluate and compare theories and theoretical propositions* (M7-Y1-PSYC); *develop an argument and support their words based on relevant evidence if they want to be good scientists* (F19-Y1-PSYC).

Students who were majoring in economics, accounting, finance and management, said that there are lots of statistics involved in their field. As one student argued, economics and business sciences depend on statistics and statistical investigations (M24-Y2-AFN). They talked about its numerous applications such as to *calculate the percentage of people that are unemployed and people who are currently working* (F6-Y1-ECON); *use and apply statistics to collect information, organise and analyse data to test hypothesis about customer satisfaction* (F6-Y1-ECON); *find the relationships between supply and demand* (M2-Y2-AFN); *deal with the economic data of the companies, check the companies' accounts and investigate how well they are overall performing* (M24-Y2-AFN). One student said in a more detailed way:

> M13-Y3-BPA: If we want to run a new business, firstly we have to carry out an investigation to identify what the preferences and the needs of the customers are in order to identify and satisfy their requirements and needs. Then, we have to check the quality of the market products, estimate the costs and the profits and make informed decisions. Using statistical investigations and analysis, the probability of our business not to be successful is less.

There were students who explicitly mentioned how they envisioned themselves using statistics in their future profession (F18-Y1-BPA; F19-Y1-PSYC; F20-Y1-EDU; M22-Y1-PSYC; M24-Y2-AFN; M28-Y5-RAD). For example, a pre-primary education teacher mentioned that she can use statistics twofold in her future work (F10-Y1-EDUP). She mentioned a task design (e.g. graphical activity) where she can explain to the young learners some things using diagrams and graphs. Then, she talked about producing some tables to summarise their students' performance, which can share and explain to the parents.

Knowledge of statistics as an enhancement of their employability and an extra qualification for their future profession was stated by many students. For example, three students particularly mentioned the value and the competitive advantage of statistical knowledge and skills in future job haunting (M22-Y1-PSYC) since many professions require research, analytical and problem-solving abilities (M2-Y2-AFN; F29-Y1-IEE).

Students reported that the knowledge and skills of statistics would be a helpful tool in their future career to *comprehend, analyse and present complex data sets related to their profession (*M12-Y2-BPA) and *better understand and interpret the research being carried out in their field of study* (F15-Y1-NUTR; M28-Y5-RAD). The latter student argued that: *It is an advantage to know statistics for attaining your future educational and career goals.*

A number of students raised the relevance and the usefulness of statistics for their academic studies. Some of them recalled that they 'saw' the application of statistics (for example definitions and statistical methods) in other academic subjects (M26-Y2-COM; F14-Y3-CEN). Three students stated the usefulness of statistics for their dissertation projects (F5-Y1-AFN; M26-Y2-COM) when conducting the analysis which was the basis of the research project (M28-Y5-RAD). Also, one student said that statistics enhanced his understanding of the subject material covered in other academic subjects and courses (M2-Y2-AFN). There were students who mentioned explicitly how statistical knowledge helped them in understanding some things better and in producing more informed results. One student said that after learning what a representative sample is, he will use this information when he will need to take a sample for his future projects (M26-Y2-COM). An engineering student shared an experience of generating a website for the purposes of another course (M3-Y2-ECE). After he attended this statistics course, he noticed that he had produced some graphical representations incorrectly. He proposed that the next time he will use the knowledge he acquired to produce the graphs and report correct results and conclusions.

Students seemed to appreciate the value of statistics not only for their discipline but for other disciplines as well. They talked about the usefulness of statistics in a wide variety of fields, such as Law (M4-Y2-PHYS; F6-Y1-ECON), Sociology (F20-Y1-EDU), Medicine (M4-Y2-PHYS), Astronomy (M7-Y1-PSYC) and Sports Sciences (M25-Y3-MEN). The latter student talked about the usefulness of statistical models to inform game strategy and tactics, evaluate player value and quality, investigate previous performance before buying players and forecast future performance. A representative comment is given below:

> F8-Y2-NUTR: In my opinion, statistics can be regarded as multidisciplinary – at the boundary of many disciplines and fields of studies.

On the other hand, there was a student who although he mentioned that statistics might have some applications in his discipline (mechanical engineering), based on his working experiences so far, he has not seen any practical applications of statistics yet (M25-Y3-MEN). He concluded that an engineer might need to carry out a preliminary investigation by himself, but a specialised and knowledgeable person (e.g. a statistician) is needed to be consulted to continue and complete it. Another engineering student mentioned that he might need to use statistics if will be employed in specific positions (such as product or sales manager) in his future job (M17-Y4-EEN). A student who was majoring in psychology stated that he does not plan to engage with the research part of psychology and experiments; thus, he will not use statistics in his future profession (M27-Y1-PSYC).

5.7.2 Value of statistics for students' everyday life

The majority of the students admitted that statistics is beneficial and applicable in everyday life. Two students stressed the applicability of statistics to modern life arguing that: *Statistical thinking is applicable everywhere. It is part of our daily life* (F9-Y2-EEN) and *Statistics has numerous day-to-day applications in modern life* (M25-Y3-MEN). Some specific applications of statistics mentioned by students were to: *track your everyday budget and manage accounts* (M24-Y2-AFN); *carry out a small investigation and reach a decision based on evidence if for example one wants to buy a product and has a lot of options (*M12-Y2-BPA); and *see the statistics of a sports game (*M25-Y3-MEN). Three students talked about the applicability of statistics when playing cards, such as poker (M1-Y1-OGM; M13-Y3-BPA; F18-Y1-BPA). The students also mentioned the daily applications of probabilities in weather forecast (M2-Y2-AFN; F6-Y1-ECON) and in the stock market and indicators, in the transactions and in the change of currencies (M12-Y2-BPA). They talked about the ability to predict the occurrence of an event based on probability data (M2-Y2-AFN; F29-Y1-IEE; M3-Y2-ECE) and taking more informed decisions in everyday life based on probabilities (M7-Y1-PSYC).

Students mentioned that after their engagement with statistics, they could evaluate and think more critically about the statistics presented in the media (e.g. television), filter media reports on social and political issues and assess the value of the information are inundated with continuously (M2-Y2-AFN; M26-Y2-COM; F29-Y1-IEE). One student argued that after his enrolment in the statistics course, he could read an article (in a newspaper or a magazine) or listen to a debate on the television and understood more than before learning statistics (M7-Y1-PSYC). As he explained:

> M7-Y1-PSYC: At this time that we have elections in our country, many results from surveys and opinion polls are displayed in the social media. Except only for observing the results, I also look at other information such as the size of the sample and the sampling method. I can say that I became more critical about the information and results that are presented to me.

In addition, some students brought up general and personal skills that statistics offered to them. More specifically, they mentioned that statistics: *helps you to make sense of the world (*F15-Y1-NUTR) and *understand the people and the world around you* (M25-Y3-MEN*)*; *broadens your horizons* (F8-Y2-NUTR); *aids in developing the mind/brain (*F19-Y1-PSYC)*; teaches an individual to think* (F30-Y1-CFS)*;* and *helps you to see the things more clearly and summarised* (F10-Y1-EDUP). The ensuing excerpt highlights the personal and professional value of statistics:

> M4-Y2-PHYS: Statistics can open you a lot of doors. You can combine it with other sciences. You can make advances in your professional work and your life in general if you know statistics. It is an advantage for anybody to know statistics.

On the other hand, there was a small number of students who, although found statistics useful in their field of study and their future profession, advocated that they could not see the usefulness and applicability of statistics for their everyday life (F11-Y1-ABF; M22-Y1-PSYC; M27-Y1-PSYC). One of them stated:

> M27-Y1-PSYC: Statistics is not connected to anything that I normally do in my everyday life and I cannot think of instances when I used statistics outside of the classroom. For example, I cannot relate the problems of throwing coins or dices to

everyday applications.

Finally, students were asked whether they believed that all students should be required to learn at least basic statistics regardless of their major. Most of them found statistics a worthwhile and a necessary part of everyone's degree programme for reasons such as *statistics is something that you encounter in your everyday life and knowing statistics can be profitable for every person* (M25-Y3-MEN)*; everyone at some stage of his life he will need to use statistics even he is not aware of that* (F6-Y1-ECON); *statistics is an essential tool for any individual thus even students who follow theoretical degrees have to learn statistics* (F9-Y2-EEN). One student argued:

> M2-Y2-AFN: Every student regardless of the specialisation of his studies should attend a course in statistics because it is not just a matter of mathematics. It is a matter of general knowledge. I think it is helpful for everyone in every aspect of his life.

One comment made by an interviewee was that students should be taught statistics only if it is useful for their degree programme or their future professional career (F18-Y1-BPA). Another interviewee proposed that statistics should be taught in all the degree programmes, but in a more simplified form and by giving more emphasis on learning of statistical topics that would be helpful for their future professional work (M3-Y2-ECE; F16-Y1-PSYC).

5.8 Difficulty/Easiness of statistics

Both versions of the questionnaire included four questions with the aim to assess the students' perceived difficulty of the statistics course they were enrolled in. During the interviews, students' perceptions of the difficulty level of statistics and the sources of the difficulties they encountered were discussed.

Perceptions and expectations regarding the difficulty of the statistics course before the students attended it and whether these were changed during the engagement with it were mentioned. The perceptions of the students were based on: comments they heard from senior students or friends (F21-Y6-TOUR; M24-Y2-AFN; F30-Y1-CFS) and mathematics teachers in high school (F11-Y1-ABF); high failure rates in statistics courses (F10-Y1-EDU; F21-Y6-TOUR); and/or personal perceptions (F10-Y1-EDU). These students formed the opinion that the statistics course would be a difficult one and they continued to have this opinion even after attending it. On the other hand, there were some students who changed opinion about the perceived difficulty of statistics after their engagement with the statistics course. Before they attended the course, they perceived statistics as an easy subject and after they found it difficult (M27-Y1-PSYC) or the opposite direction (M1-Y1-OGM; F15-Y1-NUTR). The change from perceiving statistics as difficult to easy is reflected below:

> F15-Y1-NUTR: I was thankful I did not continue my studies in France and had to do statistics because I thought it was too difficult. I did not expect statistics to be so easy; I expected it to be more like astrophysics. I would like it a bit more challenging.

Some students reported finding the introductory statistics course easy until now, but they knew or they had heard that statistics in a more advanced level is more difficult (M1-Y1-

OGM; M4-Y2-PHYS; M24-Y2-AFN). Also, other students noted that the level of difficulty of the course such as the workload and the difficulty of the topics increased as the course progressed (M3-Y2-ECE; F6-Y1-ECON; F10-Y1-EDUP; F19-Y1-PSYC).

I asked students to share which chapters (content areas) of the statistics course they found the most difficult or hardest ones until the time of the interview execution. Probabilities chapter was the chapter that was stressed as being the most challenging by the majority of the students (M1-Y1-OGM; M3-Y2-ECE; F5-Y1-AFN; F21-Y6-TOUR; M24-Y2-AFN; M27-Y1-PSYC; F30-Y1-CFS). The most common reasons behind their perceived difficulties were the *requirement of a more solid understanding in probabilities than in the other chapters* (M1-Y1-OGM); *the selection and the application of formulas* (M3-Y2-ECE); *the uncertainty of its logic* (M2-Y2-AFN) and *the understanding of some principles such as the law of large numbers (*M2-Y2-AFN). Some chapters (or areas) of the statistics course were also mentioned by students to be easier or more difficult compared to others. Students considered as easier areas the following: linear regression (M12-Y2-BPA; F21-Y6-TOUR); random variables (F21-Y6-TOUR; M13-Y3-BPA); and data tables such as descriptive statistics and graphical representations (F10-Y1-EDUP; F16-Y1-PSYC). More difficult areas were probability confidence intervals (F10-Y1-EDUP) and discrete and continuous distributions (F6-Y1-ECON; F19-Y1-PSYC). As one student explained:

> F6-Y1-ECON: I find a bit hard the chapter about the probability distributions. Let us say we have to select among the geometric, the hypergeometric distribution and so on. There is a little difficulty and confusion in figuring out which distribution and type I have to select and use in each problem case.

A subset of students seemed to find it more difficult to understand and learn the theoretical aspect of the statistical course, for example, to figure out the meaning of a theoretical concept, compared to the more practical one, for example, to solve an exercise (M1-Y1-OGM; F5-Y1-AFN; F11-Y1-ABF). One representative comment is provided below:

> F5-Y1-AFN: Sometimes, I confuse a bit some terminology in statistics, for example, the mean and the median, the standard deviation and the variance, the percentiles and the percentages. However, I do not find it hard to calculate them.

Participants' references to difficulties that they experienced when studying and learning for their statistics course follow. One student described that he struggled with definitions and theory and the correct use of statistical terms and also faced difficulties in interpreting the results and writing the conclusions from statistical analyses (M28-Y5-RAD). Interpretation and explanation of statistical topics such as p-values and confidence intervals were mentioned as posing difficulty while learning statistics (F29-Y1-IEE). The mathematical and arithmetical aspect of the statistics course seemed to evoke difficulties to some students (F20-Y1-EDU; M22-Y1-PSYC). The selection and the application of formulas in statistics was another point articulated by some students (M7-Y1-PSYC, M22-Y1-PSYC). Some students talked about encountering difficulties more often in choosing the appropriate type for each exercise than subsequently applying this formula (F21-Y6-TOUR; M23-Y3-MEN). Two students said that they were not worried about memorising the formulas because a typology (in the class and in the exams) was given to them (M23-Y3-MEN; M25-Y3-MEN). Another student referred to the long and difficult formulas in statistics, which were easier to keep them in mind if the instructor explained to them from where each formula came out or how they can find it by themselves (F10-Y1-EDUP).

Two students mentioned the words *demanding* and *complicated* when they referred to the statistics course (F10-Y1-EDUP; M23-Y3-MEN). Among their comments was that *if you do something wrong or omit something by an oversight in a statistical exercise, for example, to choose the wrong formula then all the exercise might go wrong*. The combination of many things to solve an exercise (such as theory, operations, graphical representations, comparisons, results, conclusions, interpretations) was stressed from a student as heightening the difficulty level of statistics (F11-Y1-ABF). Another student mentioned that, commonly, there are a lot of steps to follow to accomplish a statistical task (M23-Y3-MEN).

One student attributed the difficulties that he experienced in the statistics course to the instructional practices. More specifically, he argued:

> M7-Y1-PSYC: I think statistics is not a very difficult course, but the way it is delivered to us makes it more complicated. It is like having to know 20 things to say but the way is taught gives the impression to the student that he must know 100 things. I think it gets more complicated or confusing than it should be.

The new (and unfamiliar) terminology (M1-Y1-OGM) and the new symbolism (M22-Y1-PSYC) that they were introduced in statistics were mentioned from students as a source of their difficulty. There were students who found it difficult the first time the subject material was conveyed to them by the instructor during the lecture class. For example, they talked about the first time they had to solve exercises using statistical tables such as the normal distribution and t-distribution tables (F11-Y1-ABF) and the first time they were introduced the theoretical framework of using statistical methods (F9-Y2-EEN; F30-Y1-CFS).

During the interviews, the issue of mastering an understanding of the statistics content was raised quite often when students referred to the difficulties they experienced in the statistics course. They talked about difficulties in understanding *the logic and the reasoning of statistics* (M3-Y2-ECE; F18-Y1-BPA); *the problem formulation, for example, what does it say and what requests from the students* (F14-Y3-CEN; F21-Y6-TOUR); and *the statistical inference* (M28-Y5-RAD). Students seemed to often relate understanding with difficulty as one student commented:

> F20-Y1-EDU: When you do not understand something, it is difficult.

The difficulty of the subject and the amount of studying were also closely related as some students stressed (M25-Y3-MEN, M26-Y2-COM). The following excerpt elaborates this:

> M25-Y3-MEN: I have not studied the last chapter yet, so I find it a bit difficult. I saw hypothesis testing for the first time and it struck me a bit. If I do not study them, things are difficult, but if I study them, they become easier and more 'accessible'.

In addition to this, some students associated the perceived difficulty with the interest and challenge (M24-Y2-AFN; M25-Y3-MEN). As one of them argued:

> M24-Y2-AFN: Even when I find something quite difficult to understand in statistics, I still consider this sort of challenge quite enjoyable. I try to consider the difficulty of statistics as a challenge.

A number of students claimed that they had not experienced any particular difficulties in the statistics course up to the time of the execution of the interviews. Two arguments made were that: statistics *does not require the learning of very difficult concepts* (M3-Y2-ECE; M12-Y2-BPA); and *just involves a set of procedures, like choosing the appropriate techniques identifying the variables, and putting them on the formulas* (M25-Y3-MEN).

When discussing the perceived difficulty of the statistics subject, students were also asked their opinion whether even excellent -high performing- students can encounter difficulties in statistics. Most of the students believed that even the high-performing students might experience difficulties and struggle with statistics at some point. Among the arguments put forward were that *it depends on whether someone is a theoretical or a practical person and if he/she is a more theoretical person, he/she will probably experience difficulties* (M28-Y5-RAD) and *those who have less difficulties in statistics are those who 'come into' and understand that logic, that way of thinking* (F20-Y1-EDU). Some students mentioned that struggle and challenge might be inevitable throughout the statistical learning process at the university level (F10-Y1-EDUP; M21-Y6-TOUR). Another student commented:

> M3-Y2-ECE: In statistics, as well as in mathematics, as good as you might be, an exercise can be given to you and you might face difficulties.

5.9 Anxiety towards statistics

Anxiety towards statistics was one of the main topics discussed during the interviews conducted with the students. The two versions of the questionnaire included six questions regarding types and situations that might evoke anxieties to students. During the interviews, antecedents, sources and effects of anxieties along with changes in anxiety and strategies to cope with them were discussed further. Students described anxiety feelings regarding statistics to a different extent and with different emphasis using words such as *stress*, *fear*, *panic*, *worry*, *anxiety*, *frustration*, *being overwhelmed*.

5.9.1 Antecedents of anxiety before the course

To start with, I asked students what were the antecedents of their anxieties (if any) before their enrolment in the statistics course. Previous mathematics/statistics experiences and performance in high school and/or in university (F18-Y1-BPA; M22-Y1-PSYC); previous failures in mathematics/statistics courses (M1-Y1-OGM); time-elapse since previous mathematics courses (M23-Y3-MEN); perceived mathematical capabilities (M22-Y1-PSYC) and involvement of mathematics in the statistics course (F20-Y1-EDU; M22-Y1-PSYC) seemed to have an impact in determining the students' anxieties towards statistics. Specifically, previous experience with statistics courses at university level appeared to increase some students' anxiety regarding statistics (M1-Y1-OGM; M21-Y6-TOUR).

A few students noted that they had their own impressions and perceptions about statistics before attending the course that played a role in their anxiety as the ensuing quotes show:

> M23-Y3-MEN: Only the word – statistics – made me feel anxious because it is something very 'different' and 'far away' from me.

> F9-Y2-EEN: I was feeling anxious before attending the course because I had the impression that statistics is a branch of economics, I did not like economics and I was not good at economics in high school.

In a similar manner to the last comment, there were students who, although they had not had any previous experiences and engagement with a formal statistics course, the perceptions and opinions of others (e.g. senior students and/or friends) regarding the statistics course and statistics instructors led them to feel anxious about statistics . The following interview excerpt represents the others' influence:

> F18-Y1-BPA: I heard from senior students that the previous statistics instructor was not good and supportive, there are high failure rates in the statistics course and is the most difficult course of our degree. All these comments made me feel very frustrated.

On the other side, a few students stated that they were not anxious about statistics before attending the statistics course. The main reasons stated were: the type of the course being an elective (M3-Y2-ECE); the previous mathematical background and foundation (M17-Y4-EEN; M25-Y3-MEN); the prior exposure and familiarity with statistics (M3-Y2-ECE); and the usefulness of statistics for their degree programme and future career (M24-Y2-AFN).

5.9.2 Changes in anxiety before and after the course

Changes in their anxiety before and after their enrolment in the statistics course were mentioned by some students (M17-Y4-EEN; F18-Y1-BPA). These changes were mainly attributed to the exposure and acquaintance with statistics subject material and to the statistics instructor as the following excerpt exemplifies:

> F18-Y1-BPA: Before attending the statistics course, I was frustrated and anxious because of my previous experiences with mathematics and the comments of others. After the attendance at the class, I feel less anxious. I believe that when you start engaging with the subject by yourself and understand its usefulness, it is easier not to be overwhelmed by anxiety. The statistics instructor played a role in that too.

The following student echoed a change in anxiety levels during the semester, which was related to the fear of unknown and the perceived difficulty of the upcoming subject material:

> F6-Y1-ECON: At the beginning, I was not nervous because the subject matter was easy. However, it started becoming more difficult and I started feeling stressed. I feel anxious about the upcoming new and unfamiliar concepts, about what is coming next. What scares me most is if I will be able to overcome the difficulties of the course.

5.9.3 Sources of anxiety during the course

Students were requested to share the main factors and situations that contributed to their anxiety regarding statistics during the statistics course. On review of the students' responses, it was evident that the content and specific aspects of the course, especially the mathematical component of statistics (F10-Y1-EDU); the perceived level of difficulty (F20-Y1-EDU); the new terminology, the unfamiliar concepts and the complexity of terms (F21-Y6-TOUR) and the symbols, which were used (F20-Y1-EDU), were among the sources of students' anxiety towards statistics. Course-related variables such as: the amount of the subject material was taught in a lesson (M7-Y1-PSYC); the great deal of information and a combination of many things such as theory, practical exercises, software (M7-Y1-PSYC); the workload of the course (M7-Y1-PSYC); the language of instruction (M23-Y3-MEN); and the evaluation methods (M27-Y1-PSYC) seemed to trigger anxiety in statistics. More than half of the students who talked about that issue referred to the statistics instructor, his/her style of teaching statistics, explanations, behaviours and attitudes as an influence on their reduced or heightened levels of anxiety.

A subset of the interviewees expressed anxiety when attending a statistics lecture class. Listening to the instructor, taking notes and understanding at the same time during the class seemed to cause anxiety to the students (M3-Y2-ECE; M7-Y1-PSYC). In addition, two students stressed the worry of grasping the subject material that was delivered to them and not falling behind in class (F20-Y1-EDU; F30-Y1-CFS). From students' responses, it was evident that understanding of the subject material in statistics was one of the primary sources of their anxiety. As one of the students commented:

> F19-Y1-PSYC: I feel anxious during the lecture class. I need to have a clear mind and be fully concentrated to write and understand the information that is presented.

Students talked about specific components and chapters of the statistics course that triggered their anxiety and discomfort feelings. There were students who mentioned the probability chapter as raising their anxiety due to the unfamiliarity of its logic (M3-Y2-ECE; F29-Y1-IEE). Solving practical exercises, dealing with numbers and performing computations evoked anxiety to some students (F21-Y6-TOUR; M22-Y1-PSYC). Students worried about *making mathematical mistakes or getting an incorrect result* (F10-Y1-EDU; F15-Y1-NUTR; F19-Y1-PSYC) and *applying mathematical formulas and doing statistical computations because they need to perform them precisely* (F20-Y1-EDU). When first encountered with a practical exercise that she could not solve, *a sense of frustration and annoyance was dominated her* as a student described (F14-Y3-CEN). For other students, the theoretical parts of statistics caused their anxiety as the following excerpt illustrates:

> F18-Y1-BPA: The theoretical part of statistics makes me feel anxious. I do not feel anxious when I have to deal with practical exercises and calculations because if you do not find it, you can try it again.

Three students stated pleasing others (such as parents and statistics instructor) as a factor that heightened their anxiety and their worry of a good performance (M4-Y2-PHYS; F5-Y1-AFN; F18-Y1-BPA). Those students were concerned about not disappointing them.

Performance and grades that would be obtained in the statistics course were among the major sources of anxiety towards statistics (M22-Y1-PSYC; M27-Y1-PSYC; M28-Y5-RAD). The fear of failing -that is getting a non-passing grade and having to retake the course- and/or the worry about not performing well or performing lower than they expected were prevalent in many students' responses (F11-Y1-ABF; M26-Y2-COM; F30-Y1-CFS).
There were students who set future achievement goals and had high expectations of themselves (M24-Y2-AFN; F9-Y2-EE; M3-Y2-ECE) which seemed to have an impact on their anxiety as the following statement shows:

> F15-Y1-NUTR: After the failures I had in my previous university in France and in high school, I worry about my performance and the grades I will get. I want to

> obtain a very good GPA to get the scholarship and continue further my academic studies. After the midterm examination in statistics, I feel more anxious because I want to maintain the high grade I achieved.

Closely related to the anxiety regarding their performance was the anxiety students described when studying for and taking an examination in statistics. Their primary concern when an examination was approaching was to master and understand the material they were taught (M22-Y1-PSYC). Some students specifically shared stressful and nervousness feelings in evaluative contexts and specifically under examination conditions. For example, a business major described general anxiety when undertaking examinations, which had begun in high school, continued in this statistics course and it was regardless of how much she had prepared and studied for these examinations (F18-Y1-BPA). The main reasons behind anxiety while taking an examination in statistics as stated by the interviewees were: *to write on the exams paper what I know and what I have studied* (F18-Y1-BPA); *to write everything clearly and correctly because of the instructor's attention to the detail* (F9-Y2-EEN); *the sequential nature of the exam paper* (M7-Y1-PSYC); and *the time pressure because we have much to do and little time for that* (M7-Y1-PSYC). Three other students said that they worried whether they would be stuck in solving the exercises in an exam in statistics (F6-Y1-ECON; F14-Y3-CEN; M25-Y3-MEN). The intensity of students' anxiety was highlighted in a comment made by a student who said that she became *real nervous* during the statistics examination and she had a *panic attack* (F20-Y1-EDU).

The evaluation methods and the way the students' final grade was composed were also stated as sources of anxiety (F6-Y1-ECON; M7-Y1-PSYC). One of the students stated:

> F6-Y1-ECON: There is stress because we only have one midterm examination. There is no second one. I am concerned because I know that I should perform well on it since my final grade would depend greatly on the midterm examination grade.

The anxiety involved when doing the assignments for the statistics course was apparent in two students' responses (F11-Y1-ABF; F29-Y1-IEE). One of them said:

> F11-Y1-ABF: I feel anxious when I have to do assignments in statistics. I want to submit all of them and correctly.

5.9.4 Effects of anxiety towards statistics

Experiences of anxiety towards statistics seemed to have an impact on students' learning process and performance in a statistics course. Some students claimed that their anxiety affected (or they can affect) their ability to learn and perform as well as they would like to (F11-Y1-ABF; M27-Y1-PSYC; F30-Y1-CFS). The following responses exemplified this:

> F11-Y1-ABF: Because of my anxiety, I might not get the grade I expect or the grade corresponds to the studying and effort I have made.
>
> M27-Y1-PSYC: When I become anxious, I do not have a clear mind and I forget what I had learned.

Two students described, by giving examples, how anxiety influenced them during an exam in statistics (F20-Y1-EDU; F30-Y1-CFS). One of these descriptions is presented below:

> F20-Y1-EDU: There was an exercise in the exam requesting to calculate a percentage. I knew it, but at the time of the exam I confused the formula and then I

> completed the whole exercise wrong. I believe that if I were not so anxious, I would not get confused.

Previous performance in an examination might affect or had affected students' anxiety as pointed out by many students (M7-Y1-PSYC; F10-Y1-EDUP) and is shown below:

> F10-Y1-EDUP: If I do not perform well on the midterm exam, I will become more anxious since this means I have some weaknesses in statistics. I will have to work on them because if I do not, I will not also perform well in the final exam.

The positive and the negative consequences of the levels and intensity of the anxiety were also stated. The interviewees agreed that anxiety in 'normal levels' could be considered as *good* (M1-Y1-OGM; F6-Y1-ECON) and *beneficial* (F10-Y1-EDUP) because it can *activate and motivate you to study* (M25-Y3-MEN; M27-Y1-PSYC). On the other side, students talked about higher - than the normal- levels of anxiety, which *can bring devastating results if you cannot control it* (F10-Y1-EDUP), *destroys you* (M25-Y3-MEN), *demotivates you for studying* (M27-Y1-PSYC) and *results on not performing well in the examination* (F6-Y1-ECON). An exemplary comment is provided below:

> F19-Y1-PSYC: I believe it is good to have some amount of stress, at moderate levels, because it keeps you in vigilance. However, during an examination, you might have the answer to the exercise in front of you and because of your high anxiety and panic, you cannot 'see it'.

As the above-mentioned comments indicated, many students feel that some levels of anxiety can facilitate the learning process. Also, some students argued that no anxiety might lead to devote less effort and time for studying and learning and pay less attention and concentration (M3-Y2-ECE; M22-Y1-PSYC; M24-Y2-AFN). One student stated the positives and negatives of being anxious:

> M17-Y4-EEN: Generally, I am not an anxious person. The reason is that when you are anxious, you might get stuck. The statistics course needs a clear mind, so it is not good to be anxious. There is 80% positivity and 20% negativity on that. The negative thing is that I do not revise the material I am not sure I know because I do not worry if it would be a topic in the exam.

5.9.5 Strategies to cope with statistics anxiety

Students were asked to describe any particular strategies they put forward to eliminate or control the anxieties experienced during a statistics course. The most common strategies mentioned were: *more time devoted for studying* (M3-Y2-ECE); *revising the subject material regularly and practising systematically over the semester* (F19-Y1-PSYC); *not leaving the studying until the last minute* (F11-Y1-ABF; F20-Y1-EDU); *studying with other classmates or senior students who are more knowledgeable and experienced with statistics* (M27-Y1-PSYC); *asking questions the instructor(s)* (F16-Y1-PSYC; F29-Y1-IEE); *having positive thoughts* (F11-Y1-ABF) and *visualising performing as well as they deserve it* (F18-Y1-BPA).

5.9.6 Absence of anxiety

A small number of the interviewees did not express any anxiety and nervousness regarding statistics and seemed to experience little or no statistics-related anxiety. For example, two students reported *no stress at all* during examination situations in statistics (M12-Y2-BPA; F16-Y1-PSYC). One student particularly mentioned *creativity stress - the stress that will help me to perform as well as I have the capabilities and potentials to do* (F15-Y1-NUTR). These students stressed the statistics instructor and his/her way of teaching and delivering the subject material (M1-Y1-OGM); his/her availability and willingness to answer questions (M2-Y2-AFN); and the structure and organisation of the course (M2-Y2-AFN) as the reasons behind the absence of their anxiety. Also, students' learning strategies and study habits such as *putting a program in their studying and managing their time* (M24-Y2-AFN); *doing a lot of practising* (F8-Y2-NUTR; F19-Y1-PSYC;) and *understanding the subject material* (F8-Y2-NUTR; M12-Y2-BPA) seemed to contribute to the lack of anxiety.

5.10 Self-efficacy regarding statistics

Both versions of the questionnaire included seven questions related to students' perceived confidence in their abilities to execute statistical-related tasks, master the theoretical part of statistics and perform well in the statistics course. The interview questions were oriented to elicit and investigate further the antecedents, sources and changes in students' self-confidence beliefs regarding statistics and the statistics course.

5.10.1 Antecedents of self-efficacy beliefs before the course

Firstly, students were asked to state their initial sense and perceived levels of competence to learn and master statistics before attending the statistics course. The main sources of positive self-efficacy beliefs shared by students were the trust in their capabilities that they will perform well (M13-Y3-BPA) and their beliefs - and expectations - that statistics would be an easy subject (M3-Y2-ECE; M24-Y2-AFN).

Some students reported general high levels of academic self-efficacy (though not using this term) which were transferred to statistics. Past experiences with mathematics, previous successes in mathematics courses and perceived mathematical abilities (e.g. being a practical personal) also seemed to determine students' self-efficacy regarding performing well in the statistics course (M12-Y2-BPA; M13-Y3-BPA; M17-Y4-EEN). Students also talked about specific experiences, which influenced their confidence to learn statistics. The following excerpt exemplifies the points mentioned above:

> F9-Y3-EEN: I believe a lot in myself and in my capabilities. Statistics is not an exception. Based on my experiences and achievement in mathematics, I am confident that I can perform very well in statistics too. I believe that I can earn the highest grade. I have always been good at mathematics.

Experiences of encouragement from teachers and family members were mentioned as antecedents of self-efficacy beliefs (M4-Y2-PHYS). For example, one student said that the appraisal of others in high school about being good at mathematics played an important role in her self-confidence in statistics (F19-Y1-PSYC). On the opposite, there was a student who said that the instructor in his previous statistics class had a negative impact on his view of himself regarding his ability to master the statistics course content (M21-Y6-TOUR).

Some students felt incapable of doing and performing well in statistics before attending it based on their personal beliefs and previous experiences, mostly with mathematics, and opinions and experiences shared by others (F5-Y1-AFN; F20-Y1-EDU). Low self-efficacy beliefs and pessimistic feelings, even before attending the statistics course, were pointed out by a few students and a representative example is presented below:

> M22-Y1-PSYC: I told my friends (psychology senior students) that I have statistics this semester, and I will fail, I will not pass the course, and so on. You know, I was pessimistic at the beginning mostly because of my previous experiences with maths.

5.10.2 Changes in self-efficacy beliefs before and after the course

Changes in self-efficacy beliefs throughout the statistics course were also mentioned. More specifically, some students talked about an increase in their confidence levels (F5-Y1-AFN) and others who described a decrease (M27-Y1-PSYC). Students attributed these changes to the understanding and learning of the subject material and their performance in evaluation assessments in statistics (e.g. midterm tests). An example of this change is presented below:

> M27-Y1-PSYCH: I came from the higher school optimistic because I was doing it well in mathematics at high school. I was obtaining 20 out of 20. Now, I feel like I do not know anything. Before attending the statistics course, I had more confidence and now, as the course progressed, my levels of confidence dropped. One of the reasons is that I did not perform very well in the midterm examination.

5.10.3 Sources of self-efficacy beliefs during the course

The sources of students' self-confidence in their knowledge and ability to deal with the content and practices of the statistics course were requested. When responding to how confident they felt about learning and doing statistics, the majority of the students pointed out that their self-confidence throughout the course depended on the level of understanding of the material was taught to them and the amount of their studying (F6-Y1-ECON; F9-Y2-EEN). They exhibited fluctuations in their self-confidence levels associated with the level of their understanding (F19-Y1-PSYC; M22-Y1-PSYC). An instance of the students' comments is presented below:

> M3-Y2-ECE: My confidence is now reduced because we have been introduced new terms that I have not found the time to study yet and I do not understand them. However, when I study and practice them, I will understand them. My confidence depends on the degree of my studying and understanding of the statistical content.

Individual's self-efficacy seemed to be affected by their performance in an examination in statistics. The direction was as expected. Students who performed or they were expecting to perform well expressed an increase in their self-efficacy levels (F8-Y2-NUTR; F14-Y3-CEN; F18-Y1-BPA; M22-Y1-PSYC). As one student mentioned, a high grade in the midterm examination -that is a grade corresponded to excellent- *gave her strength and confidence* (F5-Y1-AFN). On the other hand, students who performed poorly (or not as well as they expected) in the midterm exam in statistics reported becoming less self-efficacious and the levels of their self-confidence were dropped (M4-Y2-PHYS; M7-Y1-PSYC).

On the other hand, self-efficacy levels seemed to play a role in students' performance in statistics. One student argued that: *when you believe that you will do it well and you have positive thoughts, then you will perform well* (F10-Y1-EDUP). Another student pointed out that his self-efficacy had an impact on his psychology during the examination conditions and during the studying at home (M24-Y2-AFN).

Students also related the levels of self-efficacy to the amount of studying and effort in statistics. They described personal experiences or general descriptions of how they perceived this association. Some students argued that over-confidence might result in devoting less time for studying (M3-Y2-ECE; M24-Y2-AFN) and putting less effort (M2-Y2-AFN). However, it seemed that students tended to engage with things in statistics that they believe they were good at them or they understood them (F11-Y1-ABF; M22-Y1-PSYC; F30-Y1-CFS). One illustrative excerpt is given below:

> F20-Y2-EDU: If you have confidence this means that you understand some things easier. If you are confident that you know something, then you will not give so much emphasis. On the other hand, if you do not have so much confidence in yourself, you study more often and put greater effort.

The role of the statistics instructor and his/her teaching methods in students' levels of self-efficacy was also apparent in the interviews. Students who perceived that their instructors explained the subject material clearly and understandably to them (M22-Y1-PSYC) and who were supportive and provided encouragement (F18-Y1-BPA) reported becoming more self-efficacious regarding statistics.

There were a number of students who exhibited more confidence in their knowledge and capacity to deal with some aspects (parts) of the statistics course, whereas some others in other aspects of it. Most of the interviewees appeared to be more confident in the practical part, for example, solving exercises and applying statistics methods, instead of the theoretical part of the statistics course, for example, dealing with the statistical theory and learning definitions (M2-Y2-AFN; F11-Y1-ABF; F18-Y1-BPA; M24-Y2-AFN; M26-Y2-COM; F29-Y1-IEE). The following comment highlighted this:

> M2-Y2-AFN: If the instructor requested for me to write a rule or a definition in the examination, I would not manage to do it. I cannot memorise things. Thus, I would write it using my (own) words. However, because in statistics (and in mathematics) every word has its own meaning, I would probably not perform well in these theoretical questions of the test. I think I am better at practical questions.

Some students indicated that comparison with others and appraisal by others could boost their levels of self-confidence (M12-Y2-BPA; M17-Y4-EEN). One personal experience related to the sources of self-efficacy levels regarding statistics was shared by an engineering student (M17-Y4-EEN). He remembered gaining confidence in his abilities and knowledge in statistics when he was studying with his classmates and he understood something quicker than the others. He admitted that: *When somebody requests my help, for example, comes to me for questions or explanations; this adds to my confidence*.

A comment made by an education major (F20-Y1-EDU) was the following: *I can understand a statistical concept or solve an exercise when it is easy*. This student also claimed that she was incompetent in statistics and attributed her success to the easiness and the straightforward nature of the exercise rather than to her (personal) abilities.

There were instances where students reflected on self-perceptions of competence*: I am not a mathematics or statistics person*; *Mathematics/statistics is not my strong point*; *I am* *incompetent; I feel weak*; *I am good at statistics*. These can be considered as images of their selves as statistics (and mathematics) learners. An illustrative example is presented below:

M23-Y3-MEN: I think I am not this kind of person, I mean a statistics person.

5.11 Knowing/Learning in statistics

This main thematic category composed of three major topics ,which are presented below namely understanding; effort and amount of studying; and learning strategies and approaches to statistics.

5.11.1 Understanding

The questionnaire did not include any questions explicitly related to the students' understanding in the statistics course. Nevertheless, the issue of understanding and comprehension of the material being taught to them was raised by the students quite often during the interviews.

A number of students stressed the importance of understanding in the statistics course. They used phrases such as *the key or the most important issue in statistics is the understanding* (F8-Y2-NUTR; F18-Y1-BPA; F21-Y6-TOUR); *statistics is a matter of understanding* (F9-Y2-EEN); *the only thing is to obtain this statistical understanding and thinking* (F29-Y1-IEE); and *statistics is more or less to understand the meaning of what it says to you* (F16-Y1-PSYC). One student pointed out that, in statistics, it is necessary to *develop a deep and meaningful understanding and not only merely follow procedures* (F19-Y1-PSYC). Related comments made from students were about *the importance of understanding the topics discussed in the lecture classes and then go home to elaborate and understand them better* (F19-Y1-PSYC) and *the necessity of completely understand what is 'happening' in every chapter of the subject content* (F9-Y2-EEN).

Many students referred to the nature of statistics as a subject to be closely related to the understanding of it. For example, one student characterised statistics as being *logical* and she argued that if someone thinks logically, he/she would be able to understand statistics (F18-Y1-BPA). Another student mentioned the mathematical-oriented nature of the course (M1-Y1-OGM). He said that the understanding of the mathematical part of statistics made easier the application of the methods and the performance of calculations. In a similar vein, a student stated that those who did not have a good or strong mathematics background might experience problems with understanding in the statistics course (F18-Y1-BPA).

For some students understanding the material in the statistics course was their crucial problem. This is highlighted in the following responses: *it is the hardest for me to understand statistics* (F16-Y1-PSYC) and *my biggest trouble is with the understanding of statistics* (F20-Y1-EDU). There were students who generally talked about experiencing difficulties and having troubles (sometimes or more frequently) in understanding or they mentioned specific aspects of the subject matter. Some students found more difficult to understand the topics or exercises that required conceptual understanding than step-by-step procedures (M21-Y6-TOUR; F30-Y1-CFS). A representative example is given below:

> F14-Y3-CEN: It depends on the chapter. Some chapters which consist of formulas and I need to apply them, I think I can figure them out. However, if I have first to understand what a problem says to me and what its demands are, then it becomes more difficult for me. My main problem is understanding.

One student described challenges in understanding a statistical topic (more specifically, the probabilities) which had started from high school and continued to university:

> F11-Y1-ABF: I cannot figure out the probabilities. I have tried it. I cannot understand it since high school. I might understand a particular exercise, but if the instructor gives us a different exercise, I might not be able to do it.

The perceived lack of competence and ability in understanding statistics is also reflected in the following statement:

> F20-Y1-EDUC: Regardless of how hard I study for statistics, I think I am not able to understand it completely.

There were students who related the degree of understanding of some statistical topics and ideas to the amount of their studying and effort (M7-Y1-PSYC; F9-Y2-EEN; M13-Y3-BPA). Particularly, they mentioned that after the studying and engaging with statistics, some terms and concepts started becoming more understandable and clearer to them. Moreover, students tended to relate their understanding of the statistics content material to the course outcomes and specifically their performance. As one of the interviews argued: *Understanding goes hand in hand with performance in statistics* (F16-Y1-PSYC).

5.11.2 Effort and amount of studying

Both versions of the questionnaire included questions related to the effort students put forward in the statistics course. During the interviews, the students were asked to describe further their time and effort investments while they were studying and learning statistics.

The need and the importance of systematically studying in statistics were stressed by a considerable amount of students (F8-Y2-NUTR; F9-Y2-EEN; F16-Y1-PSYC; M27-Y1-PSYC; M28-Y5-RAD; F30-Y1-CFS). As they stated, due to the nature of the subject being practical, time and effort were required for practising and solving exercises (F8-Y2-NUTR; F9-Y2-EEN; F14-Y3-CEN). Students argued that it is better to *start the studying for statistics early in the semester* (F21-Y6-TOUR); *not leave studying all the subject material together or at the very last minute* (M3-Y2-ECE); *understand some concepts from the beginning* (M3-Y2-ECE); *not create gaps or deficiencies in statistics* (F9-Y2-EEN; F10-Y1-EDUP; F11-Y1-ABF:); *be in touch with the material during the semester and be prepared* (F18-Y1-BPA). They pointed out the necessity for studying and putting effort throughout the semester and not only when an examination was approaching (F18-Y1-BPA; M24-Y2-AFN; F29-Y1-IEE). Some students mentioned their planned effort arguing that they will work hard (F16-Y1-PSYC) and try their best in this statistics course (F6-Y1-ECON; F19-Y1-PSYC). One representative example is presented below:

> F19-Y1-PSYC: Statistics requires time and effort. If you leave the studying at the last minute, you have too many things to cover, they seem difficult and you become stressed. I believe it is more important to build brick by brick and add to your

> existing knowledge than to put all the bricks and the clay together to build the house (in our case knowledge).

Attendance in the lecture classes seemed to be important for the majority of the students. There were students who said that by missing a lecture, *you need more time to study at home* (F8-Y2-NUTR; M24-Y2-AFN) and *it is like that you have to cover the double subject material and you have to put the double effort* (M7-Y1-PSYC; M23-Y3-MEN). Three students mentioned that it happened to them to miss a lecture in statistics and they described it afterwards as *feeling lost* (F10-Y1-EDUP); *being in a 'black'* (F14-Y3-CEN); and *finding it difficult to follow the next lecture* (M22-Y1-PSYC). The usefulness of attending the statistics classes was apparent in some students' responses where they mentioned that *every time you get something new* (M13-Y3-BPA; F20-Y1-EDU); *you understand better the subject material* (F16-Y1-PSYC) and *you take your own notes instead of depending on someone's else notes* (F14-Y3-CEN; F19-Y1-PSYC). They also talked about the importance of being present in the class because *the instructor could explain and say little details that might help* (F15-Y1-NUTR; F20-Y1-EDU; M24-Y2-AFN; M27-Y1-PSYC); *you hear the voice of the instructor and where he/she puts more emphasis* (F9-Y2-EEN); *you assess the instructor's way of thinking and how he/she wants the things in the exams* (F20-Y1-EDU). An illustrative excerpt related to the above comments is provided below:

> F18-Y1-BPA: I attended all the lectures in statistics. The most important thing is the beginning - what you gain from the classroom, how the instructor will explain to you, how you will 'get' it in the first contact with the exercises. If I did not 'follow' the classes, I would probably do not like statistics too. Maybe I would not even understand that well. I strongly believe that class attendance plays an important role.

Students talked about the effort and the amount of studying they expended throughout the semester. Some of them quantified the amount of studying by stating a rough approximation of the number of hours they spent for studying statistics (F10-Y1-EDUP; F11-Y1-ABF; F18-Y1-BPA). There were students who reported studying systematically throughout the semester (M4-Y2-PHYS; F19-Y1-PSYC). Some of them mentioned that they revisited the material between the two lecture classes *to be prepared* (M7-Y1-PSYC), *to resolve any questions they had* (M13-Y3-BPA) and *for interest and curiosity reasons* (F15-Y1-NUTR). One of them stated that in every lecture class, the instructor proposed a few questions related to the previous lecture class before getting into the new material and this 'pushed' her to study more (F11-Y1-ABF). One illustrative comment is mentioned below:

> M4-Y2-PHYS: I have to study throughout the semester. I cannot leave the studying for the last week before the exam. I will get so tired that is meaningless. It is better to devote, let's say 3 hours per day, for studying and engaging with statistics.

There were students who described changes regarding the time they spent in studying statistics throughout the semester (M2-Y2-AFN; M3-Y2-ECE; F9-Y2-EEN). The workload of the semester and the studying for other courses was mentioned as the main reason.

Students also talked about the time and effort they exerted for studying statistics when an exam was approaching. Some students mentioned that they started studying in advance (two or three weeks before) to cover all the subject material and have time to revise (M3-Y2-ECE; F5-Y1-AFN; F9-Y2-EEN; F10-Y1-EDUP). Other students said that they studied a few days before the examination because *they had already covered the examined material* (F20-Y1-EDU); *they had revised it systematically* (M13-Y3-BPA) and *they 'caught' it from* *the class* (F15-Y1-NUTR; M17-Y4-EEN). The methods of assessment (such as a small test after the end of each chapter) seemed to aid a student to study more regularly (F14-Y3-CEN). Conversely, two students admitted that they left the studying for statistics for the very last minute because they did not organise and manage well their time (M7-Y1-PSYC; M27-Y1-PSYC). Moreover, previous background, foundation and performance in mathematics-related subjects seemed to be associated with less amount of studying. For example, two students reported devoting less time and effort because they performed well in previous mathematics courses and they believed they could do it well in this statistics course too (M12-Y2-BPA; M25-Y3-MEN). There were also two students who indicated avoiding studying and investing less effort because their perceptions of ability and success in statistics were low (F11-Y1-ABF; M27-Y1-PSYC). One of them further commented by relating the amount of effort and understanding in statistics:

> M27-Y1-PSYC: The amount of studying depends on how much you know the subject material; how quickly you get it; how competent you are to understand it. Someone who does not understand it, he might need to devote lots of effort and time to learn it. Also, the opposite; when someone is good, he might solve two or three exercises and he will be fine, he can really understand it and perform very well.

Changes in the amount of studying if they do not perform as they expected in an exam in statistics were mentioned by some students. They said that they would *study even more* (F6-Y1-ECON; M24-Y2-AFN; F10-Y1-EDUP); *study more systematically* (M24-Y2-AFN); and *give more emphasis* (F10-Y1-EDUP; F30-Y1-CFS) to the statistics course.

There were also students who said that they did not spend enough time for studying statistics and they should study and try even more (M7-Y1-PSYC; F10-Y1-EDUP; M24-Y2-AFN). On the other hand, one student mentioned that he devoted much time to studying for statistics, but at the end, it was not necessary (M3-Y2-ECE). The reason was that he found the midterm examination quite straightforward and he was examined in concepts he had already known them from before.

The mature students who took part in the interviews mentioned that the time they had to dedicate to studying was limited due to the situations of their life (for example, family and work obligations) and their age (F8-Y2-NUTR; M23-Y3-MEN; M28-Y5-RAD). One of them believed that if he had more time to study for statistics, he would perform better (M23-Y3-MEN).

5.11.3 Learning strategies and approaches to statistics

Both versions of the questionnaire included four questions related to students' learning strategies. During the interviews, students were requested to explain in a more detailed way their learning strategies and approaches when learning and studying for the statistics course. Firstly, students were asked to describe what they usually did during a statistics lecture class. The majority of the students reported that they took their own notes and tried to understand the lecture material that they were taught. There were students who *took organised notes* (F14-Y3-CEN; F16-Y1-PSYC); *copied whatever the instructor wrote on the blackboard* (F29-Y1-IEE); *wrote down only the exercises* (M1-Y1-OGM); *took notes using their own words based on what instructor was saying verbally* (F16-Y1-PSYC; F20-Y1-EDU); *highlighted what instructor stressed as important* (F11-Y1-ABF; F20-Y1-EDU);

used their tablets/i-pads (M23-Y3-MEN; F21-Y6-TOUR); and *audio-recorded the lecture classes* (M4-Y2-PHYS). Some students stressed that they tried *to understand before writing down the notes* (F14-Y3-CEN; F16-Y1-PSYC; F19-Y1-PSYC) or *copied the notes and then tried to elaborate what they have written* (F20-Y1-EDU). One illustrative comment is:

> M13-Y3-BPA: I take my own notes during a lecture class in statistics. This helps me to listen, write, think silently and try digesting the information I am taught at that moment. In statistics, this works.

Many students reported that they were participating in the classroom. For example, they raised their hands to say an answer to the instructor's questions (M1-Y1-OGM; M12-Y2-BPA; M13-Y3-BPA; M17-Y4-EEN) or/and they asked their questions during the lecture class (M1-Y1-OGM; F6-Y1-ECON; M13-Y3-BPA; F15-Y1-NUTR; F18-Y1-BPA; F19-Y1-PSYC; M24-Y2-AFN; M26-Y2-COM) or/and after the lecture class (F6-Y1-ECON; F15-Y1-NUTR; F20-Y1-EDU; F21-Y6-TOUR). Some of them also visited their statistics instructor to his/her office for questions (M3-Y2-ECE). Those students argued that by seeking help and asking questions *you show your interest in the subject* (F18-Y1-BPA); you *can cope with the subject material* (F18-Y1-BPA); you *will achieve a better understanding* (F19-Y1-PSYC); you *will be corrected and learn in case you say something wrong* (M17-Y4-EEN); and *you will avoid misunderstandings or misconceptions* (F29-Y1-IEE).

On the other hand, some students admitted that they were hesitant to ask questions during the lecture class. The most common reasons were being afraid of saying something wrong or giving an incorrect answer and being embarrassed by their instructor (F11-Y1-ABF; F20-Y1-EDU) or their classmates (M4-Y2-PHYS; F30-Y1-CFS). One student said that generally, he did not like asking questions in front of all during the lecture class, but he preferred to seek help individually (M3-Y2-ECE). Some students mentioned that they preferred seeking support and asking questions to their classmates or friends (F11-Y1-ABF; M23-Y3-MEN; M27-Y1-PSYC), family members (M4-Y2-PHYS; F21-Y6-TOUR; M25-Y3-MEN) and/or previous mathematics teachers (F29-Y1-IEE). One opponent of asking questions to classmates instead of the instructor argued:

> M25-Y3-MEN: I prefer to ask questions my instructor instead of my classmates. The reason is that the instructor will explain to you more quickly, more correctly or precisely and he/she will guide you better than your classmates. Instead, your classmates might confuse you somewhere; they might misinform you in some way.

The students were also requested to share how they usually study at home for the current statistics course. The students talked about the materials and the resources they used. They mentioned that they read the instructors' lecture notes (M13-Y3-BPA; M26-Y2-COM), their own notes, which they took them during the lecture class (M13-Y3-BPA; F19-Y1-PSYC) and the tutorial notes and exercises (F16-Y1-PSYC; F21-Y6-TOUR). Some of them said that they used to put together all the available notes and materials they had (F6-Y1-ECON; F19-Y1-PSYC). The majority of the students seemed to be satisfied with the lecture notes provided by the instructor (F6-Y1-ECON; M17-Y4-EEN). Also, most of the students said that they believed that the notes and exercises given by the instructor were enough for this statistics course and they did not need to search for extra information or exercises (M3-Y2-ECE; F14-Y3-CEN; M24-Y2-AFN; M25-Y3-MEN). Another student said that she sought out extra exercises on the recommended textbooks, on supporting material from previous students for more practice and for improving her understanding (F19-Y1-PSYC).

Four students mentioned that they searched on the internet to *get more information about a topic that was interesting* (M13-Y3-BPA); *take a second opinion or search for another explanation* (M17-Y4-EEN); *achieve a better understanding of the content* (M2-Y2-AFN); *understand something that they found difficult such as probabilities* (M26-Y2-COM).

Some students recounted that they were studying between the two lectures by reviewing and revising the lecture class notes (F11-Y1-ABF; F16-Y1-PSYC; F19-Y1-PSYC; M26-Y2-COM). Four students said that they prepared in advance for the class *by always trying beforehand what exercises they will do in the tutorial sessions* (M17-Y4-EEN; M26-Y2-COM; F29-Y1-IEE) or *even by pre-reading the upcoming subject material* (F18-Y1-BPA). Another student said that he preferred to have complete notes in front of him; that is to have all the notes related to a specific chapter and then started studying about it (M23-Y3-MEN).

Many students also mentioned how they studied specific parts of the statistics course. Regarding the practical part in statistics, one student described that he was going through the exercises step by step, focusing on what each exercise demanded and what methods were followed in each of them (M26-Y2-COM). Regarding the theoretical part, one student reflected that he first reviewed the theory; he always started from the theoretical part to understand it and then be able to apply the theory in practice (M13-Y3-BPA). Another student said that he studied the theory and the exercises at the same time to 'break' the monotony of the theory (M3-Y2-ECE). Four students stated that they were learning the theory by *making up a poem* (F18-Y1-BPA); *creating analogies* (M2-Y2-AFN); and *finding memory cues/associations* (F11-Y1-ABF; F20-Y1-EDU) to remember it.

A subset of students further commented about their learning strategies and approaches when studying for the statistics course. For example, one student described: *I preferred to re-write the notes down; one, two or even more times because for me when I wrote them, I learned them better. I learned with that way in statistics* (M1-Y1-OGM). Another student mentioned that, when she understood them visual and auditory, she did not need to write them down (F20-Y1-EDU). Common strategies mentioned by the students were: *rewriting the notes they were taking during the lecture class*; *generating summary notes including the main points of each lecture*; *identify main ideas to be learned*; *paraphrase the subject material using their own words; try to explain back to themselves or to others the subject material*; *write the steps to solve the different exercises; synthesise information from different chapters*; *recall relevant prior knowledge and make associations*; *find connections between concepts, ideas and methods they have already learned; checking whether the solution was reasonable or possible and relating results and evidence to conclusions.*

Students also shared how they studied when they had an examination in statistics. The majority of the students said they were studying all the subject material, but they were placing more focus on the things that they were pointed out by the instructor (M13-Y3-BPA; F19-Y1-PSYC; F29-Y1-IEE). Two students recounted that they studied only the things they perceived as important or 'candidates' for being topics in the exams because of time constraints due to other responsibilities (M23-Y3-MEN; M28-Y5-RAD). The most common approach mentioned by the students was reading the lecture notes again, solving the examples given by the instructor and trying to solve the exercises of a particular chapter

(F14-Y3-CEN; F18-Y1-BPA; F30-Y1-CFS). Two students argued that *the more exercises you solve in statistics, the better is for you* (M24-Y2-AFN; F21-Y6-TOUR).

A few students mentioned giving emphasis to detecting and routinising algorithms with applications to similar exercise types (M22-Y1-PSYC; M27-Y1-PSYC). Nevertheless, a larger number of students stated placing more emphasis on understanding the subject material and then learn or apply it. There were students who stressed the importance of understanding over only rote memorising things, especially in statistics (F19-Y1-PSYC; M23-Y3-MEN). They argued that *there is no point when studying something, not digesting it, and just going to apply it procedurally* (M13-Y3-BPA); *there is no benefit of reaching to a solution without understanding* (M28-Y5-RAD); *it is better to get the logic rather than the rote memorisation* (M3-Y2-ECE). Other students argued that when you understand something, *it is easier to learn it by heart* (M25-Y3-MEN), *you can remember it for a longer time* (F18-Y1-BPA) and *you can solve the exercises much easier and (really) know what you are doing* (M17-Y4-EEN). As one of the students contended:

> M24-Y2-AFN: I prefer to understand the exercises and not to learn them by heart. If I understand the way an exercise is solved, I can think and figure out the exercises that the instructor will give us in the examination, which might be different from the ones that you have already done in the classroom. I want to understand the steps I follow to solve an exercise. I want to understand what I am doing.

Two students admitted that they learned things by heart in some cases when they could not understand (F20-Y1-EDU) or they did not have enough time to understand them first (M26-Y2-COM). One of them explained:

> F20-Y1-EDUC: Sometimes, I memorised things in statistics when they are too difficult. When I cannot 'adopt' them to me, then I say I will learn them as they are.

Furthermore, some students mentioned preferring to solve similar exercises in statistics *to understand and familiarise themselves with the specific way of solving and thinking for this kind of exercises* (F18-Y1-BPA; M23-Y3-MEN; M27-Y1-PSYC). Two students justified it by commenting that *repetition helps me* (M1-Y1-OGM) and *repetition is beneficial and is the mother of learning* (M13-Y3-BPA). On the other hand, there were students who said that they preferred solving new exercises and practising a variety of exercise types to *acquire new knowledge* (M13-Y3-BPA); *sharpen their brain* (F18-Y1-BPA; F19-Y1-PSYC); *confront with the possible variations or alternatives of an exercise* (M25-Y3-MEN); *be better prepared for the possible unfamiliar exercises* (F29-Y1-IEE), *potential tricks or pitfalls that they will encounter in the exam* (M28-Y5-RAD).

A number of students stated that they preferred studying and co-operating with their classmates when preparing for the statistics course. Some of them had already tried cooperative studying or were willing to try it. They found it helpful because *one solved the questions of the other* (F11-Y1-ABF; F20-Y1-EDU; M23-Y3-MEN); *we interact with each other (*M13-Y3-BPA); *we think together* (M26-Y2-COM); *we can listen other's opinions, ways of thinking and explanations* (M24-Y2-AFN); *we can compare different solution strategies if any* and *we can cross-check the results of exercises* (F29-Y1-IEE). There were students who mentioned that they preferred studying the course content together with students who were more 'experienced' than them, for example, students who have attended the course again (M27-Y1-PSYC); were higher performers (F10-Y1-EDUP; F14-Y3-CEN) or understood the subject material better than them (F20-Y1-EDU; M23-Y3-MEN; M26-Y2-COM). Also, there were students who stated that they preferred studying firstly alone and then with others in small groups (F5-Y1-AFN; F14-Y3-CEN). One student stated that, by helping his fellow students, he learned from them and studying for himself at the same time (M17-Y4-EEN). More specifically, he said:

> M17-Y4-EEN: I think it is important in electrical engineering to work with others. I noticed that I benefitted from the questions of others. When my classmates asked for my help, it helped me in my revision. In essence, at the time I explain to the others, I actually study for myself. By telling and recalling the subject material, I understand it better.

On the other hand, some students preferred studying for statistics on their own (M3-Y2-ECE; M12-Y2-BPA; F16-Y1-PSYC; F18-Y1-BPA; M28-Y5-RAD). The reasons were being *more concentrated* and *attentive* (F16-Y1-PSYC) when studying on their own and *avoid confusion* if they were studying with others (M28-Y5-RAD). One of them argued:

> F18-Y1-BPA: I prefer studying statistics on my own because statistics requires logic and concentration. Everyone has his own way of thinking, perceives the subject material differently and wants his own time to absorb it. Also, group studying is not always productive.

There were two students who mentioned attending extra private tutorial sessions outside of the university to help them learn and understand the subject material of the statistics course (F10-Y1-EDUP; F21-Y6-TOUR).

Regarding organisation and management of their studying, several students stated that they organised their materials, for example, by using box files (M22-Y1-PSYC; F29-Y1-IEE) and planned their time and actions in statistics and generated a study schedule (F19-Y1-PSYC; F20-Y1-EDU). They argued that this helped them to be more *efficient* and *productive* (M13-Y3-BPA; M24-Y2-AFN) and *up-to-date* (F16-Y1-PSYC).

Some students stated that their learning strategies and their way of studying were (or might be) related to their performance in the statistics course (F19-Y1-PSYC; F20-Y1-EDU). They argued that if they would not perform well in an examination in statistics, they would probably need to alter their strategies such as solving more exercises or trying to achieve a better understanding using more efficient techniques (F16-Y1-PSYC; F20-Y1-EDU).

In addition, there were students who compared the study strategies they applied to their statistics course with these they applied in other courses. Some of them mentioned that they studied different the theoretical and the practical courses (such as statistics) because of the nature of the subject (F20-Y1-EDUC; F16-Y1-PSYC; M27-Y1-PSYC). One of them said:

> M27-Y1-PSYC: In statistics, I have in front of me the instructor’s notes (in a paper form) and the hard copy notes I take during the lecture class. I have to solve exercises by hand and understand the procedures to solve them. In psychology, I use my laptop and the lecture slides and I write them in my own words to learn them.

5.12 Resilience in statistics

Both questionnaire versions included seven questions trying to gauge students' resilient behaviours. During the interviews, the students were asked to share the approaches and strategies they adopted (or might adopt) to cope with adversities, setbacks or challenging situations that they experienced (or might experience) during the statistics course. It should be mentioned that, initially, 'Resilience was identified as a code under the main thematic category 'Knowing/Learning'. However, since the construct of resilience has a prominent role in this study, interview excerpts related to this topic is presented in a separate section.

5.12.1 Description of perceived failure and association with resilience behaviours

Firstly, the students were asked to describe what a failure in statistics for them is and how a (potential) failure have affected or might affect their perceived abilities and the subsequent effort that they put forward. A number of students defined the failure as failing the course (not obtaining a passing grade) or even obtaining a lower grade than they expected or they believed they deserved. Nevertheless, they reported that even if they might be disappointed (at the beginning), they will *continue trying and making an effort* (M1-Y1-OGM; F30-Y1-CFS); *trying even harder (*F18-Y1-BPA*); putting a greater tenacity (*F6-Y1-ECON*); being more stubborn (*F8-Y2-NUTR*); and taking the course again to improve their statistics grade* (F6-Y1-ECON). One student pointed out that failures and making mistakes is a vital part of the learning process (F29-Y1-IEE). A representative excerpt is presented below:

> F16-Y1-PSYC: If I get a grade below 70, this would be a failure for me because I know that I have the capabilities. At this time, I will be disappointed. I would say that I am not very good at statistics. Afterwards, the logic will come back, and I would say that to be good at statistics, I have to continue studying and trying.

Similar to the last comment, there was evident in many students' responses how a poor (or under expectation) performance might affect or had affected to a great extent their confidence and beliefs in their abilities (M3-Y2-ECE; M13-Y3-BPA; F20-Y1-EDU). The following excerpts exemplify this:

> F20-Y1-EDU: A failure would affect greatly my levels of confidence. The ultimate failure for me is not to pass the course. I will be desperate. I will say that the fault was all mine because I cannot understand the subject material and due to the lack of my abilities in mathematics-related subjects.

Some students defined failure not with relation to their performance, but instead as not devoting enough effort and the appropriate attention, not trying enough or giving up (F6-Y1-ECON; F9-Y2-EEN; F16-Y1-PSYC). One illustrative quote is given below:

> F6-Y1-ECON: A failure for me is to give up, be disappointed and stop trying. On the one hand, failure is to get something less than what you expected, but a greater failure is not to try for the next time. I continue trying even I had trouble. Keep going!

In the opposite direction, a good performance in an examination can be a stimulus and a motivation for some students for the upcoming examinations or challenges (F18-Y1-BPA; F20-Y1-EDU; F29-Y1-IEE). The following excerpt highlights this:

> F18-Y1-BPA: If I write well in the examination, this means that I can manage it even in the difficult situations. This gives me confidence, strength and motivation for new challenges.

5.12.2 Resilient approaches and strategies

With the aim to elicit students' resilient approaches to learning statistics, I requested to them to share what they did (or might do) when they encountered difficult, new or unfamiliar to them statistical-related tasks. Students described their strategies when struggling with learning and understanding to successfully meet the desired outcome. Most of the interviewees seemed to exhibit persistence and tenacity when they were trying to learn the subject material, understand statistical concepts or solve exercises. Common strategies mentioned among others were: *asking questions or requesting for help from a variety of sources such as their instructor* (F6-Y1-ECON; F9-Y2-EEN; F18-Y1-BPA); *senior students* (M27-Y1-PSYC), *family members* (M4-Y2-PHYS; M25-Y4-MEN), *internet* (M23-Y4-EEN; M25-Y4-MEN), *textbooks and notes* (Male-Y2-ECE; M25-Y3-MEN); and *studying collaborative or discussing with classmates* (F6-Y1-ECON; F11-Y1-ABF; F29-Y1-IEE). Nevertheless, there were students who said that they tried to solve or understand the unfamiliar and difficult exercises or concepts by their own before seeking for help or asking questions (F6-Y1-ECON; F9-Y3-EEN; F10-Y1-EDU; F18-Y1-BPA; M24-Y2-AFN; M25-Y3-MEN). Also, they mentioned their approaches and their problem-solving procedures such as *planning the steps to accomplish the exercise or the assignment* (F8-Y2-NUTR); *revising and reflecting on the information and knowledge be taught* (F18-Y1-BPA); *applying existing knowledge and skills* (F9-Y3-EEN); *finding commons/similarities with what they have already learned* (F20-Y1-EDU); *breaking the exercises in smaller (or easier) parts* (M17-Y4-EEN); *trying alternatives procedures* (F9-Y3-EEN); *trying to think of it differently, maybe more simple, in order to adjust it in their own way of thinking and understanding* (F20-Y1-EDU); *trying to understand a new or difficult theoretical concept through examples* (M3-Y2-ECE); *making a poem to remember something* (F6-Y1-ECON); *thinking hard, clearly and focused* (F6-Y1-ECON). Study and learning habits such as *spending more time on studying and practising* (F9-Y3-EEN) and *active class participa*tion (F18-Y1-BPA) were stressed by two students as strategies when they faced difficulties in statistics. Students also used words like be *optimistic, concentrated under pressure*, *determined* and *patient* as important when coping with unfamiliar tasks or situations. The following selected excerpt is representative of students' actions and behaviours:

> M26-Y2-COM: When I encounter a difficult exercise, I continued trying because it is what I do not know that I have to learn. After I try it up to the point I know, I ask my classmates or my instructor to explain it to me until I will completely grasp it.

One student described how she was confronting a difficult exercise in the past and how her approach has been changed in statistics (F20-Y1-EDU). In her interview, she reflected:

> F20-Y1-EDU: Previously, when I encountered something that it was hard for me, I quit; I did not deal with it; I did not have patience. Now, in statistics, I continue the effort. I want to finish the exercise, to reach a solution even if it is not the correct one. I might even start with the most difficult ones.

Some students distinguished the conditions and situations of having to complete an unfamiliar or difficult exercise mainly because of pressure and time constraints (M2-Y2-AFN; F10-Y1-EDU; M26-Y2-COM). The following excerpt showed that students employed alternative strategies and approaches depending on whether they had to complete the exercises at home or during an examination:

> F10-Y1-EDU: If I am at home, I try to find new ways of solving a new or an unfamiliar exercise. I try firstly on my own and then I request for help. If I encounter difficulties, during an examination when there is the pressure of time, I proceed to the next exercise and I revisit it later.

5.12.3 Relationship between resilience and a number of constructs

Arising from students' responses, students' behaviours seemed to be related to their confidence in their abilities to learn and their perceived competence of completing an exercise. It seemed that higher levels of self-confidence could fuel students' continuously engagement with statistics as the following comment shows:

> F9-Y2-EEN: I have trust and confidence in my abilities and skills. I know that I have the capabilities to solve the exercise in the end. I believe that there is not something so much difficulty in statistics. You only need to strive to do it, continue to be engaged and try as much and as hard you can and everything is understandable.

However, there were students who seemed to be unwilling to try statistical tasks if they had the perception that they could not accomplish it. More specifically, two students mentioned that they would probably even not try the task if they believed that they could not do it *quickly* (M1-Y1-OGM) or *eventually* (M23-Y3-MEN). Previous successful attempts to understand and master the topics taught or complete correctly exercises in statistics seemed to make students to use more resilient-related behaviours (F10-Y1-EDUP; F18-Y1-BPA).

Positive resilient behaviours appeared to be related to high motivation levels to reach an end- a solution or an understanding- (F8-Y2-NUTR) or to avoid failure in the course (M27-Y1-PSYC). The association between resilience and levels of anxiety, attitudes towards statistics and future goals is highlighted in the following excerpt:

> F19-Y1-PSYC: When I start to solve an exercise and I cannot do it, this makes me feel anxious. However, I would 'stay' in the exercise until I solve it because later I would find it in front of me. I have to persist to learn statistics since it is valuable for my future personal and career goals. Besides that, statistics is one of my favourite subjects.

Classroom environment and comparison with other classmates might also actuate students to exhibit positive resilient behaviours (F15-Y1-NUTR; F16-Y1-PSYC). This is indicated in the following excerpt:

> F15-Y1-NUTR: During the lecture class, when somebody says that an exercise is very difficult, this makes me being more stubborn in order to be able to solve it.

Finally, three students said that their interest, enjoyment and value of a task were essential factors to try or continue engaging with it (F6-Y1-EDU; M12-Y2-BPA; M24-Y2-AFN).

5.13 Achievement goals and Motivational Orientations in statistics

The pre-course version of the questionnaire included five questions in order to elicit students' achievement goals and motivational orientations in statistics. During the interviews, I asked students what were their goals in this statistics course and what factors they motivated them to study and learn statistics.

5.13.1 Intrinsic (i.e. internal) and extrinsic (i.e. external) motivations

Among the students' main goals in the statistics course, as revealed from the interviews, was to perform well and obtain a good grade. The reason was their desire to maintain or improve their Grade Point Average (GPA). Future (long/short-term) goals mentioned by students included *getting a scholarship* (M7-Y1-PSYC), *earning their university degree* (M21-Y6-TOUR; M28-Y5-RAD); *pursuing further academic studies such as a master or/and doctoral degree* (F19-Y1-PSYC; M22-Y1-PSYC; M3-Y2-ECE; M24-Y2-AFN; M28-Y5-RAD); and *increasing their prospects for their future career* (M24-Y2-AFN). Achievement goals often motivated students to study more, as the comment below shows:

> F18-Y1-BPA: I want to perform well in this statistics course because I intend to do a master degree in the future. This is an extra incentive in order to study more.

Some students stated that to obtain only the passing grade in the statistics course was not their goal and they would be not satisfied (F14-Y3-CEN). Oppositely, for many students their main goal was just to pass the statistics course and not to fail in it. The main justifications made were that: *they did not want to attend it again* (M27-Y1-PSYC; M23-Y4-MEN); *it was the last remaining course to obtain their degree* (M28-Y5-RAD; M21-Y6-TOUR); the nature of the course being *practical* (F20-Y1-EDU); and *among the most difficult courses of their degree programme* (F10-Y1-EDU).

The type of the course being compulsory for their degree programme seemed to motivate students to study for it *obligatorily* (M22-Y1-PSYC). Likewise, another student said:

> F11-Y1-ABF: The motivating factor for me to study for the course is that it is compulsory for my degree and I have to pass it. The grade does not bother me so much because I know that I am not very good at statistics.

From the last excerpt is apparent how the students' perceived abilities can influence their motivational orientations. Perceived abilities as motivation towards performing well in statistics is also highlighted in the interview excerpt which follows:

> F19-Y1-PSYC: Because of the abilities I think I have, I want to gain a very good grade in statistics. This is my main motivation.

Students' previous experiences and repeated success in mathematics also appeared to motivate them to engage in statistics as it is shown below:

> F19-Y1-PSYC: I have always succeeded in mathematics, so this is an extra motivation and encouragement to try my best in this statistics course.

Students' beliefs regarding the usefulness and the applicability of learning statistics for their future professional careers also seemed to be linked with their motivational orientations.

Five students commented about this (M4-Y2-PHYS; M7-Y1-PSYC; F11-Y1-ABF; F16-Y1-PSYC F18-Y1-BPA) and one illustrative quote is given below:

> F16-Y1-PSYC: The most important motivating factor for me to engage with statistics is because I believe that statistics can give me a lot. The more I study for statistics, the more I will understand and be able to apply it better in the future.

Another factor which students identified as increasing their motivation to learn statistics was interest in the subject, interesting topics and (some kind of) curiosity on how to reach a solution (M12-Y2-BPA; M26-Y2-COM). The following excerpt highlights this:

> M26-Y2-COM: It is a pleasant subject, an interesting course, and this is among the reasons I am motivated to study it. If it were not interesting, it would not be an impetus for me to study it with willingness.

Moreover, acquisition of statistical knowledge and skills was stressed as the goal orientation of many students (M3-Y2-ECE; M4-Y2-PHYS; F9-Y2-EEN). These students seemed to give emphasis on learning and understanding the subject material as it is exemplified below:

> M3-Y2-ECE: The knowledge I will gain and it will be useful for me is the most important motivating factor. I want to improve my (own) abilities. I am interested in the knowledge and the skills that I will acquire.

A combination of gaining knowledge and achieving a good grade was stated from some students as their motivation that drove them to learn and study statistics (F6-Y1-ECON; F10-Y1-EDU; M13-Y3-BPA; F29-Y1-IEE). Two selected comments are present below:

> M13-Y3-BPA: I wish I would gain some knowledge. Knowledge of statistics is power. It is better to get a grade equal to D and gain knowledge instead of getting A and rote learn and copy paste what I have studied. However, it is still very important for me to get a very good grade in statistics.

Related to the above comment, a students talked about the importance of the future use of statistical knowledge and skills. As she explained:

> F6-Y1-ECON: I want to gain knowledge and get a good grade (for the degree). But I do not want only to get a good grade and then forget what I have learned after the course. A good grade in statistics is of little value if someone cannot use and do statistics and apply this knowledge.

For some students, the knowledge and a good performance go hand in hand (M1-Y1-OGM; F16-Y1-PSYC; M17-Y4-EEN; M25-Y3-MEN) as it is reflected in the following excerpt:

> M17-Y4-EEN: In order to gain the grade, you need the knowledge. I believe that this is the case in statistics. Personally, I want first to understand statistics, then write down and apply correctly what I have learned and achieve a very good grade.

Students' desire to have a good performance and reach their goals for the purpose of self-improvement and self-satisfaction (M1-Y1-OGM; F5-Y1-AFN; F6-Y1-ECON; F18-Y1-BPA) is illustrated in the statements below:

> F5-Y1-AFN: I would like to gain a good grade in statistics to improve my general academic grade. However, I also want a good grade for myself. It will be a personal fulfilment of my goal.
>
> F6-Y1-ECON: For me, the important thing is how well I perform and how I can help myself to be improved. If I get a good grade, I will feel satisfied with myself.

Pleasing the statistics instructor as a motivator was stressed by an individual who said:

> F18-Y1-BPA: One of the motivations to achieve a good performance in statistics is my instructor. I want to please her because she believes in me.

5.13.2 Comparison of grades and displaying abilities

Students were also asked whether they tended to compare the grades they obtained in statistics with the grades of their classmates. Most of the interviewees claimed that they did not tend to compare their performance with others. An illustrative excerpt is given below:

> F6-Y1-ECON: I do not compare my grades with my other classmates because each one has his/her abilities, pre-knowledge or acquired knowledge and way of thinking. Also, it depends on the effort and studying one puts forward to statistics.

Some students mentioned that they asked for the grades of their classmates to take an idea of the general performance of the class and positioned themselves compared to it (M24-Y2-AFN). Displaying the abilities and skills in statistics will be important in the future - when looking for a job- and not in the classroom settings as one student argued (F16-Y1-PSYC). Another student asserted that he aimed to satisfy himself and then his close environment (e.g. family), but not displaying his performance and knowledge to others (M13-Y3-BPA).

There were students who stressed the sense of competition in the university environment (F11-Y1-ABF; F14-Y3-CEN; F16-Y1-PSYC; F29-Y1-IEE) as shown in the ensuing quote:

> F14-Y3-CEN: I am not competitive, but many of my classmates are competitive. I think it is because, in a way, the university promotes competition.

Nevertheless, the 'healthy' competition and comparison with higher-performing students can be a motivating factor for some students. One student commented that it is a motivation to try to *reach the higher achievers* (M4-Y2-PHYS). Another student said:

> F19-Y1-PSYC: I like to compare myself, in a positive way, with those who might perform better or they might understand better, to adopt their positive behaviours or to ask help if I need something. But, in no case, I do not like to compare myself with those who perform worse than me and try to show them that I am better.

As a last comment, there were also factors that appeared to have the opposite results – that is to demotivate students towards learning and thriving. More specifically, a student stated:

> F15-Y1-NUTR: I believe that the level of the class is low and this sometimes demotivates you to try your best.

5.14 Statistics performance

This main thematic category is composed of three major topics including students' perceived control over learning and performance, students' expectations of their performance in the statistics course and the current ways of assessment in the statistics course and their preferable ways of assessment.

5.14.1 Perceived control over learning and performance

Both versions of the questionnaire included two questions to assess students' opinions about whether they believed that their performance would be determined by their studying and effort or/and their instructor and instructional methods. During the interviews, students' perceived control over desirable outcomes in the statistics course was discussed further.

A number of students argued that their performance in the statistics course would mainly be determined by their own studying and the time and effort they will invest (M3-Y2-ECE; F5-Y1-AFN; F6-Y1-ECON). One student commented:

> F5-Y1-AFN: I believe that the performance depends on the effort and the studying you do; whether you will study hard. I strongly believe that it is a matter of studying.

It was apparent from some students' responses that they believed having the control of achieving the desired outcomes in the statistics course. They used phrases such as *with the studying you can achieve everything* (F6-Y1-ECON); *whoever works and puts effort, he pays for it* (M13-Y3-BPA); *good grades in statistics result from my effort and studying*; *if I want to learn statistics, it is up to me* (M26-Y2-COM). One student specifically mentioned that ninety percent of her good performance in the statistics exam could be attributed to the effort she put (F9-Y2-EEN). Also, another two students said that if they do not perform well in a statistics exam, the burden of responsibility will fall on their shoulders (M7-Y1-PSYC; M13-Y3-BPA).

Many students pointed out the role of the instructor and his/her instructional methods (for example, his/her transferability) in determining their learning and performance in statistics (M1-Y1-OGM; M7-Y1-PSYC; F9-Y2-EEN; F20-Y1-EDU; M22-Y1-PSYC; M24-Y2-AFN; M27-Y1-PSYC). One student stressed the role of the instructor and his control on students' performance by expressing the following opinion:

> M7-Y1-PSYC: I am of the opinion that if we had a different instructor, the grades of each student would have changed. I believe that the current grades are not representative of the abilities and the potentials that each student has. To give an example, it depends on the topics the instructor would include on the exam; if she includes practical exercises or if she asks for theoretical explanations.

Related to the above comment, the instructor's examination questions such as the structure, pattern, type, wording and difficulty level of them were mentioned by many students as possible determinants of their performance (M1-Y1-OGM; M3-Y2-ECE; M7-Y1-PSYC; F9-Y2-EEN; F11-Y1-ABF; M17-Y4-EEN). One illustrative argument is presented below:

> M3-Y2-ECE: I believe that our performance might also be at the mercy of the instructor and the exam topics; that is how she will structure them and how she will formulate the questions. For example, if she wants to distinguish each student from the other to see who really understands or if she will put a topic that needs a trick to be solved.

Two students mentioned that performance could also be related to factors such as *luck or chance and/or a bad day* (F30-Y1-CFS) and *how easily or quickly the student will 'enter into' the logic of the exam questions* (F9-Y2-EEN). Another two students further supported their arguments regarding the role of the exam topics by recalling the midterm examination topics. They talked about a mistake (F6-Y1-ECON) and some ambiguity (M25-Y3-MEN) in the formulation of a question, which 'cost' them time and probably affected their grades. On the other hand, some students claimed that the exam questions do no play a critical (or big) role (F6-Y1-ECON; F18-Y1-BPA), as it is shown below:

> F18-Y1-BPA: I think the exam questions do not play so much, or at least critical, role. When you are well studying and prepared, you will be able to solve whichever exercise the instructor would include in the examination.

The contention that both their studying (and effort) and the instructor might determine their learning process and performance in the statistics course was shared by many students (F6-Y1-ECON; F8-Y2-NUTR; M13-Y3-BPA; F19-Y1-PSYC; F18-Y1-BPA). They said that they were willing to invest time and effort, but firstly, it was depended on the instructor to transfer the appropriate supplies such as the knowledge, skills, interest and motivation to them to be able to cope and understand the subject material (F6-Y1-ECON; F29-Y1-IEE). Another student stressed the role of the instructor in explaining several times and clearly enough the subject material to them, but she concluded that *at the end of the day, statistical course-related outcomes are dependent on each (individual) student* (F16-Y1-PSYC).

5.14.2 Expectations of performance

Both versions of the questionnaire included questions to elicit students' expectations of their overall performance in the statistics course. During the interviews, students further elaborated about their outcome expectations in statistics. Students mentioned that at the beginning of the course, their expectations were somewhat affected by the previous experiences and performance in statistics or mathematics-related courses and by their first contact and experience with this statistics course.

By the time of the interviews, were conducted after the students had undertaken at least one examination in statistics, their expectations of achievement seemed to be evaluated according to their performance and grades on those exams. There were students who stated that they expected a grade corresponding to excellence. Those students said that they performed almost excellent in the midterm examination and they expected the same for their next examinations (M1-Y1-OGM; F8-Y2-NUTR; M13-Y3-BPA; F15-Y1-NUTR M17-Y4-EEN; F19-Y1-PSYC). Other reasons shared for expecting a very good grade in statistics were that they *had completed harder mathematical courses during their degree programme* (M3-Y2-ECE); *had succeeded in previous mathematical courses (*M25-Y3-MEN); *were organised, consistent and strict with themselves* (F9-Y2-EEN); and *had very positive attitudes towards statistics* (F8-Y2-NUTR). There were also students who expected a moderate performance in statistics because they perceived it *as the most difficult course of their degree* (F10-Y1-EDUP). There were students mentioned expecting a lower grade than they anticipated at the beginning of the course (M7-Y1-PSYC; F6-Y1-ECON; M27-Y1-PSYC). Moreover, students' expectations of success or failure were seemed to be related to their self-efficacy beliefs (M13-Y3-BPA; M25-Y3-MEN). It seemed from their responses that students who had higher expectations of their performance level there were students who also rated higher their perceived abilities in statistics.

Students were also asked whether they expected that they would perform as well as or better than most of their classmates in the statistics course. Many students argued that their classmates might perform better than them in statistics because *they have stronger mathematical background, experience and knowledge* (F19-Y1-PSYC; F20-Y1-EDU); they *are more clever* (F20-Y1-EDU) *or inclined* (F16-Y1-PSYC); *their minds are more 'developed' and 'practised'* (F20-Y1-EDU; M21-Y6-TOUR); they *possess more abilities in* *statistics* (M7-Y1-PSYC; F16-Y1-PSYC; M26-Y2-COM); *they would achieve a better understanding of the statistics course content* (F11-Y1-ABF; F14-Y3-CE; F16-Y1-PSYC; M22-Y1-PSYC) and *they would devote more time on studying and practicing and apply more effort in statistics* (F11-Y1-ABF; F15-Y1-NUTR; F16-Y1-PSYC; F20-Y1-EDU; M24-Y2-AFN; M26-Y2-COM).

5.14.3 Methods of assessment

The first version of the questionnaire included three questions to elicit the type of evaluation preferred by students in relation to the statistics course. During the interviews, students were described the current methods of assessment in statistics and they shared their preferences. As previously mentioned (see §3.5.3), due to the variety of universities, classes and instructors which took part in this study, there were differences in the methods of assessments. Nevertheless, in all the courses, the closed-book examination was the dominant way of assessment and took the largest part of the students' final course grade.

To start with, some students reported their preferences of examinations over assignments by characterising the evaluation using examinations as more *reliable* and *representative* (F16-Y1-PSYC; M24-Y2-AFN). More specifically, they said that *assignments might involve a little cheating because the students might copy them* (F6-Y1-ECON; M17-Y4-EE; F18-Y1-BPA) and *they might be time-consuming* (M3-Y2-ECE). Some students reported that they believed they performed better in examinations than in assignments (M26-Y2-COM).

On the other side, some students stated their preference in having assignments as means of evaluation rather than examinations. The main reason reported was the anxiety of undertaking examinations (F6-Y1-ECON; F11-Y1-ABF). One of them explained it:

> F6-Y1-ECON: I do not prefer exams as a way of evaluation. The reason is that a student might become anxious, he might have the so-called 'blackout' and he would not write what he studies or what he knows. I would prefer assignments because you can develop and investigate a particular topic. I think I would do it better in assignments than to undertake exams because I would not have the stress of it. I would have the time to read it, to see what I can do. I would also try to complete it before the deadline and ask questions, so if I have a mistake to correct it.

A combination of examinations and assignments was preferred by some students (F10-Y1-EDUP; F30-Y1-CFS). An illustrative example is given below:

> F10-Y1-EDUP: I would prefer a combination of assignments and examinations. I do not prefer only examinations because you get evaluated on what you did that time and not what you were doing the whole semester. Ideally, for me, it would be to have assignments occasionally, to work on them and give them back to the teacher for evaluation along with the midterm and final examinations.

Some students proposed that a small percentage of the final grade can be allocated to projects, for example, projects using a statistical program such as SPSS (F8-Y2-NUTR; M24-Y2-AFN). Another student was in favour of having a small project related to a specific statistical topic arguing that by working and elaborating on this particular topic a student would learn more and familiarise himself with it (F10-Y1-EDUP). Two students proposed the assessment to include additionally a research investigation on real-world projects (M7-Y1-PSYC; M23-Y3-MEN).

On the other hand, some students preferred submitting exercises for evaluation on the chapters of the subject content that they covered rather than an independent project (F14-Y3-CEN). There was a student who suggested a type of an assignment (such as a difficulty or an ‘impressive’ that could take into account the way of thinking and reasoning of students (M4-Y2-PHYS).

A following-up question was whether the students preferred group (team) or individual assignments/projects if they had this option. The students who were in favour of individual assignments argued that each student can show his/her abilities and knowledge (F15-Y1-NUTR; M23-Y3-MEN). One of them stated:

> M23-Y3-MEN: Teamwork is good too, but only with the individual project you can prove who you are and what you can do. On groups, some students might ‘hide’ behind the others or they might not try enough. So, I would prefer individual ones.

The students who were in favour of group assignments advocated that with group work *students can interact* (F10-Y1-EDUP) and *learn from each other* (M22-Y1-PSYC); *the possibility of doing them wrong is less than the individual assignments* (M26-Y2-COM); and *it would be more productive and interesting* (M21-Y6-TOUR). One student stated:

> M7-Y1-PSYC: I would prefer a group project in statistics because I regard statistics as a subject, which is team-based. Also, in the future, we will not be the only people who carry out the investigation; we will have to collaborate with other colleagues and scientists.

Some students did not prefer assignments because they would add *an extra pressure* (M25-Y3-MEN), *extra workload* (M26-Y2-COM; M27-Y1-PSYC) and *extra anxiety* (F30-Y1-CFS) to the students of having both (examinations and assignments).

The majority of the students showed their preferences in closed-book examinations rather than in open-book examinations. Their main argument was the higher level of difficulty of the examination when they were allowed to have open books and notes (M3-Y2-ECE; M17-Y4-EEN). Three students shared that they had the opportunity to undertake examinations with open books in their previous universities, but they described this experience as not pleasant. They argued that *the amount of the examined subject materials was more* (M1-Y1-OGM) and *required more searching and thinking* (M17-Y4-EEN; M25-Y3-MEN). Two students argued that open-book examinations might be a hindrance for acquiring knowledge and a solid understanding of statistics (F8-Y2-NUTR). However, some students admitted that open-books examinations might be more difficult, but they stated that they would prefer it because it would minimise the memorisation (M23-Y3-MEN; M27-Y1-PSYC). One of them justified his opinion by referring to his major:

> M23-Y3-MEN: It is well known that open-book exams are more difficult; but, I would prefer to have this type of exams. For the engineer, everything he needs, for example, to measure something, he can go back to the catalogues and find it. Thus, the open-book exam, even in statistics, is something that suits the industry of engineering. The engineer must have the knowledge to do it and where to look to find it and not to remember it.

In all the classes I entered to collect data, the students had to undertake at least one midterm examination in addition to the final examination. Students were in favour of having midterm examinations because *they forced you to study more often* (M23-Y3-MEN; M25-Y3-MEN); *you would have the opportunity to improve your performance* (F10-Y1-EDUP) and *take another chance in case you have a potential underachievement in one of them* (F20-Y1-EDU); and *the subject matter is divided, so you don't have to study all the material at once* (F20-Y1-EDU).

Moreover, three students suggested having small tests or quizzes at the end of each chapter or after a number of lectures in order to track their difficulties and weaknesses throughout the semester (F10-Y1-EDUP; M13-Y3-BPA; F18-Y1-BPA). One of them proposed:

> M13-Y3-BPA: I would prefer to have a quiz more systematically, for example, at the end of each chapter. The reason is that the instructor can see how well his/her students perform and where they experienced difficulties or are weaker. Then, he/she could call to his/her office the students who did not perform very well to help them, to boost them and their weaknesses to make them powers.

The type of questions included in an examination was also raised. Some students showed preference in multiple-choice examinations over the open-ended exercises (F5-Y1-AFN) while others had the opposite preference (M1-Y1-OGM; M13-Y3-BPA). An opponent of multiple-choice questions argued:

> M1-Y1-OGM: I prefer the open-ended type of exercises because you can solve it using your knowledge and way of thinking. The multiple choices exercises confused me because it makes me think whether there is somewhere a trick or not.

There were students who recommended and supported that a percentage of the final grade should be given to the active participation in the statistics classroom (F6-Y1-ECON) and the regular attendance of the lectures (M13-Y3-BPA). One student argued that *someone should be active in the statistics course and in the future as a researcher, and be credited about that* (M7-Y1-PSYC).

5.15 Statistics instructor and methods of instruction

Even though the questionnaire that had been completed by the students before the execution of the interviews did not include any questions regarding students' opinions about the instructor and the methods of instruction, this issue was raised from all the participants during the interviews and thus it composed a separate main thematic category.

5.15.1 Knowledge and Transferability of it

Students commented on their statistics instructor's knowledge of the subject and his/her ability to transfer it to the students. The students were unanimous in the opinion that their instructor was knowledgeable of the subject material of statistics. They also remarked on the transferability of the knowledge to the students. Most of the students were satisfied with it (M2-Y2-AFN; M3-Y2-ECE; M12-Y2-BPA; F16-Y1-PSYC; M25-Y3-MEN; F29-Y1-IEE) while others talked about lack of transferability, or transferability from times to times (F14-Y3-CEN; M22-Y1-PSYC). A representative example is given below:

> M22-Y1-PSYC: I think she has the subject content knowledge. She is a professor at the university, so I suppose she has her way of explaining it to you. However, the

> transferability is subjective. It depends on each student; in the way someone learns and understands. Sometimes she explains with clarity sometimes with not so much.

5.15.2 Instructional practices and materials used

Students described the practices and the materials used by the instructor during their statistics learning experience and stated their preferences. Two selected students' descriptions and preferences are presented below:

> F10-Y1-EDUP: I prefer that the instructor writes on the board instead of using PowerPoint slides. I also like the way that she usually says aloud the exercise and we write it down because it makes the exercise more understandable and makes you think about it before writing it and before doing it. Sometimes she gives us a few minutes to rest. Indeed, it is tiring to think continuously in statistics.
>
> M3-Y2-ECE: I do not like so much the way of teaching - writing on the board and explaining the same time. I prefer the instructor, firstly, to write the notes or the exercises and then to explain them to us. Also, I think it is more efficient to write the notes on the board as she does now rather than using the PowerPoint.

Further instructors' pedagogical practices and strategies were described by many students. They commented about finding the lesson structure in statistics to be organised, pre-planned and methodical (F18-Y1-BPA; M25-Y3-MEN). Some students reflected on the importance for the instructor to be organised and clear in both oral and written presentation of the subject matter (M17-Y4-EEN; F30-Y1-CFS). Two examples from students' responses are:

> F11-Y1-ABF: In every lecture, our instructor makes a rehearsal of the previous lecture. Definitely, the first ten minutes of each lecture class, he will ask us questions. I believe this is the most important and it is a big advantage for us.
>
> F10-Y1-EDUP: The instructor sometimes gave us space and time to participate and express our way of thinking about how we can solve an exercise. This makes us to think by our own.

On the other hand, there was an interviewee who was not satisfied with the way of teaching and the *structured*, *organised*, and *intensive* structure of the course. As he described:

> M7-Y1-PSYC: She is a good teacher, she teaches correctly, but I think her way of teaching is somewhat painful. The lesson is too organised, structured and intensive. She does not let the students breathe. We are always running to learn new things from the teacher. Continuously. New things to learn continuously.

Another issue, which was raised positively by many students, was the instructors' helping behaviour and support to them. More specifically, they talked about an instructor who *is always willing to answer questions, even at the break time.* (M7-Y1-PSYC; F29-Y1-IEE); *spends time after class to explain* (M21-Y6-TOUR)*; pays attention, listens to the students and cares if they understand the material* (F6-Y1-ECON.); *encourages them to ask questions* (M12-Y2-BPA; M24-Y2-AFN); *explains even the most obvious things from the beginning to be understood by the students who did not understand it*; (M2-Y2-AFN); *gives more or simpler examples to students when they request it (*M24-Y2-AFN) and *sometimes shows two ways of how an exercise can be solved, so that students can choose which one they prefer or understand more* (F10-Y1-EDUP).

5.15.3 Students-instructor relationship and instructor's approachability

Students-instructor relationship and communication/interaction along with the approachability of the instructor were stressed by some students as playing an important role in their learning. Students characterised and described their instructors and their behaviours using the following words/phrases: *supportive* (M2-Y2-AFN; M7-Y1-PSYC; M23-Y3-MEN; F29-Y1-IEE); *helpful* (F6-Y1-ECON; M12-Y2-BPA); *reinforces and encourages students* (F18-Y1-BPA); *says positive verbal words* (F6-Y1-ECON); *shows understanding and rapport* (F18-Y1-BPA); *shows personal interest* (M9-Y1-PSYC; M13-Y3-BPA); *invests in and cares about students' learning* (F6-Y1-ECON); *provides one-on-one help and support if the students request it* (F18-Y1-BPA; M23-Y3-ME); *is always available to the students* (M24-Y2-AFN); *is close to the students and interested for them* (F6-Y1-ECON*);*); *is like their friend* (F6-Y1-ECON); *knows students with their first names* (F14-Y3-CEN; M23-Y3-MEN). Two divergent views related to this issue emerged:

> F18-Y1-BPA: The instructor plays an important role. She is always next to us to explain the subject material. At various times, the instructor gives us exercises which we have to solve and return them. She explained to us individually where we made our mistakes and how we could solve the exercises correctly. She also tells some things that are important to keep them in mind. This is very helpful. You feel the instructor close to you.
>
> F9-Y2-EEN: The instructor is a bit impersonal. I do not feel her so close to me. I wanted my instructor to know that I am a good and hard-working student with potentials. This would give me more power to do well in statistics. I think it is important to feel that the instructor believes in you and that whatever will happen she will be next to you. For example, if you have a failure, this will not affect her opinion about you and your grade.

Some students also stressed the reciprocal relationship between instructor's behaviour and students' interest in learning and progressing (M13-Y3-BPA; M23-Y3-MEN). One of them said:

> M23-Y3-MEN: I believe that the instructor 'follows you'. If you show interest, if you give her attention, she will give it to you back. If I come to the lesson, just sit and do not ask her anything, she will not come to me. However, when you ask her, she will give you answers and explanations.

5.15.4 Instructor's personality and identity

Instructor's personality, characteristics and qualities (such as *patience*, *insistence*, *humour*, *enthusiasm, confidence*, *character* and *integrity*) seemed to play a role in students' learning (F8-Y2-NUTR; M22-Y1-PSYC; F9-Y2-EEN). As one of the interviewees mentioned:

> F8-Y2-NUTR: Definitely, the instructor plays an important role. I believe that since I was a student in high school. I am lucky to have this instructor in the statistics course, because of her way of teaching; she has enthusiasm and loves a lot what she is doing; she has patience and insistent with all of us when we experience difficulties. Also, she helps us to try our best. She is also trying her best.

5.15.5 Role of the instructor in students' opinions and feelings about statistics

The role of the instructor in shaping students' opinions about the statistics course, for example, whether they will like it, find it interesting, not be stressed about it and understand it was pointed out by several students (M3-Y2-ECE; F7-Y1-ECON). One of them said:

> M3-Y2-ECE: The instructor plays a major role whether you will like the course, whether you will be interested in it. Because you understand something when the instructor makes it understandable to you. And when you understand the subject material better, you do not get stressed.

On the opposite side, a few students were not satisfied with the instructor and his/her instructional practices which resulted in unfavourable opinions and feelings about statistics (M7-Y1-PSYC; M27-Y1-PSYC). A detailed description given by a student is:

> M27-Y1-PSYC: I do not like the statistics course because of the teacher. Teacher, teacher. If she taught the subject matter in a little better way and she did not analyse it so much, but to be more to the point, I think it would be easier. Sometimes, I might need a simple answer and she answers me one hundred different things, maybe unnecessary. This happens occasionally, not always, but it makes me feel stressed.

5.15.6 Pace of instruction

Their opinion about the current pace of instruction was shared by a subset of students. Some students found it fast/quick which resulted in not *managing to follow and synchronise with the instructor at most of the times* (M27-Y1-PSYC); *being able to absorb the new information and understand what is taught at the moment to be ready to move on to the next one* (M7-Y1-PSYC); and *having enough time to say the same thing many times, to stick to something and everyone to understand it one hundred percent* (F19-Y1-PSYC). One student described the current pace of instruction and she shared how she experienced it:

> F20-Y1-EDU: The instructor delivers the lesson very quickly. She might say something very quick and I might not 'catch' it. The pace is very fast. Sometimes I cannot write and understand at the same time. For example, we did a repetition for the midterm examination, what we have done in one month. In this month I did not get anything. I understood them in one hour (during the repetition) because she explained them slowly.

On the other hand, there were students who found the pace of the instruction *appropriate* (M2-Y2-AFN; M12-Y2-BPA) and *as it had to be to understand the lesson* (M24-Y2-AFN).

5.16 Software for learning statistics

Both versions of the questionnaire included three questions related to the students' opinions, anxiety feelings and confidence concerning using and learning computer software packages related to statistics. During the interviews, the students' opinions about incorporating technology into the statistics lessons as well as training in a software package to apply and learn statistics were discussed.

5.16.1 Previous experiences with statistical software programs

One student described his previous experiences with learning a statistical program (without mentioning the name of it) in his previous public university (M1-Y1-OGM). He stated that the students did not have a computer in front of them, instead they were writing the commands on the paper. He concluded: *I think it would be better if we used computers to apply statistics than writing the commands by hand.*

5.16.2 Learning a statistical software program in the statistics classroom

There were students who had the experience of using and learning a statistical program (that is SPSS) as a part of their statistics course. Three students shared their experiences and their viewpoints (M7-Y1-PSYC; F11-Y1-ABF; F15-Y1-NUTR) and one excerpt is cited below:

> F11-Y1-ABF: We use SPSS during the tutorials. The class is not monotonous. The software helps me to master the theory and improve my understanding of some statistical concepts. For me, it is easier to use software to apply statistics than just do it in the paper and have to memorise things and results. And if you do not know, you will play with it and you will find it.

5.16.3 Proponents and opponents of learning software programs in statistics

There were students who, although they did not have the opportunity to engage with a software program in the statistics course, they would like to use technology for learning and applying statistics. Those students said that, since technology is a part of the everyday life and these programs are available, they were in favour of the integration of it into the statistics classroom. Two students argued that it might help in the improvement of their learning and performance in statistics (F6-Y1-ECON; F29-Y1-IEE). Some students claimed that the incorporation of a statistical program would probably make the course *more valuable, especially for their future profession and career* (M1-Y1-OGM; M3-Y2-ECE; F15-Y1-NUTR; F19-Y1-PSYC; M23-Y3-MEN); *more enjoyable* (F6-Y1-ECON; F8-Y2-NUTR), *easier* (M1-Y1-OGM; F15-Y1-NUTR); *less-anxiety provoking* (F6-Y1-ECON) and *more understandable since they might understand some statistical concepts and methods better* (F10-Y1-EDUP). As one student put it:

> F15-Y1-NUTR: To give an example, I might work somewhere where I will have to sort out the customers or to check whether they have obesity, the range of their weight and so on. I might need to assess and manipulate datasets. SPSS can help me to accomplish these tasks. By learning such a program at the university, I will be more prepared in case I need to use it in my future work.

Many students expressed their preference the course to be delivered in computer-equipped classrooms (F10-Y1-EDUP; F16-Y1-PSYC; M25-Y3-MEN; M26-Y2-COM). One of them said:

> F16-Y1-PSYC: I would prefer to do the statistics course in labs and to have computers in front of us because nowadays computers are part of our lives. It would be nice to work in small groups to carry out a statistical method using computers. I would also like to have to do an assignment using a statistical program.

The desire to be taught and learn to use a software package (such as EXCEL and SPSS) as a part of the statistics course was further exemplified and justified in the following comment:

> M23-Y3-MEN: I would like to be in labs and have my (own) computer to work because it is more practical. I think doing things by hand is outdated. Technology can automate and expedite some calculations and procedures that might take a lot of time or would not be possible to do them by hand. For example, I currently use EXCEL in my work.

Some students were supporters of learning a software program in the statistics course, but they mentioned the importance of learning also to do statistics by hand, as described below:

> F18-Y1-BPA: I think statistics (and in general mathematics) is better to do it, firstly, by hand. Hand calculations are good practice. As a second stage, it would be interesting to see how we can do some things (such as representing many visualisations of the data) using the software. For example, when we want to present some data using a histogram or a stem and leaf plot (which we learned them at the beginning of the course), technology might help to do it easier and more accurate.

By contrast, there were students who stated that were against learning a statistical software program in statistics. Some of them were generally against technology (M4-Y2-PHYS; M13-Y3-BPA). The students who supported this view seemed not to like using computers, were not comfortable with using or in the prospect of using computers and even mentioned anxiety and nervousness (M4-Y2-PHYS; F14-Y3-CEN). One of them shared the perception that she would not be good at learning a statistical program (F5-Y1-AFN). A representative example follows:

> F14-Y3-CEN: I do not like technology. I do not manage it very well with it. It would make me nervous if we had to learn a program in statistics. I do not feel so comfortable with the computer, to deal with the commands and outputs of a computer program.

Other students argued that the integration of learning a statistics software program would be a 'burden on the course' (F9-Y2-EEN). However, they were open and willing to learn it if it would be useful for their professional career (F9-Y2-EEN; M13-Y3-BPA).

5.17 People

This category was composed of the main topics associated with students' references to people (such as family members, friends and close environment, previous statistics/mathematics teachers, senior students and classmates) as well as references to themselves as statistics/mathematics learners.

5.17.1 Family members

During the interviews, there were students who referred to their family members (such as parents, brother, uncle). They talked about their profession and whether this was related to the discipline of statistics/mathematics (M3-Y2-ECE; M4-Y2-PHYS; F5-Y1-AFN; M7-Y1-PSYC; F10-Y1-EDUP; F18-Y1-BPA; M25-Y3-MEN). Some of them mentioned how their family members played a role in their achievement goals (M4-Y2-PHYS; F5-Y1-AFN; F10-Y1-EDUP) and their opinions about statistics (M3-Y2-ECE; M4-Y2-PHYS; M7-Y1-PSYC; F10-Y1-EDUP). Also, many students reported that their parents had high expectations for them regarding their performance in the university. Some of them said that this was *an additional pressure* (M7-Y1-PSYC; F30-Y1-CFS) and *extra stress* (F10-Y1-

EDUP; M13-Y3-BPA) for them. However, there were students who contended that *this kept me on my toes when I skimp the studying in statistics* (M7-Y1-PSYC) and it was *a motivation to try my best* (M25-Y3-MEN). More detailed references have been provided throughout the reporting of the other main thematic categories.

5.17.2 Other students (seniors/classmates)

During the interviews, students mentioned senior students (that is, students who had already completed statistics courses), their classmates or their friends when responding to the questions. For example, they indicated senior students and friends as sources of their opinions and attitudes towards statistics before attending the statistics course. Also, some students mentioned whether they believed that their fellow students (classmates) shared the same opinions and attitudes with them regarding the current statistics course. Students seemed to position themselves as learners with regards to the other students in the class. They commented, among other things, about the difficulties they might experience and whether everyone struggled with statistics at some point, the comparison of their performance and the cooperative learning and mutual support with classmates. Also, the students mentioned their classmates when they were questioned on their opinions about the classroom learning environment and climate and the class performance level.

5.17.3 Previous mathematics/statistics teachers

When I asked students to recall any positive or/and negative (unpleasant) experiences and performance in mathematics in high school and in university, most of them referred to their previous mathematics teachers. They talked about teachers' knowledge of the subject, the transferability of it, their pedagogical practices and their (personal) qualities. Most commonly, many students stated the impact that their previous mathematics or statistics teachers had on their future engagement with statistics/mathematics, the perceptions of themselves as statistics/mathematics learners and their self-confidence, anxiety and opinions and attitudes about statistics. Students' comments about their previous teachers were presented in the main thematic where relevant.

5.17.4 Self-identity

This main code included self-references and characterisations that students made for themselves. For example, some students characterised themselves as more practical persons (M4-Y2-PHYS; M7-Y1-PSYC) or more theoretical persons (F20-Y1-EDUC; M21-Y6-TOUR). Some students claimed that they were not the mathematics kind of persons (F6-Y1-ECON; M22-Y1-PSYC). These senses and images of themselves in relation to statistics (and mathematics) as described by students were presented in the pertinent categories.

5.18 Suggestions/Recommendations

This main thematic category included students' comments and suggestions about how an introductory statistics course offered to non-mathematics majors could be improved. However, this information is provided later in the Discussion chapter (see Chapter 6).

5.19 Conclusion

In this chapter, the key findings of the qualitative analysis are presented. Both quantitative results chapter (Chapter 4) and qualitative results chapter (Chapter 5) lays the foundation for the discussion chapter (Chapter 6), where the findings are integrated, interpreted and discussed.

Chapter 6 DISCUSSION OF FINDINGS

6.1 Introductory statement

The present study resulted in several findings. This chapter reflects on the main findings and integrates the two strands of the study – the quantitative and the qualitative. It should be noted that overall the qualitative and the quantitative findings are mainly convergent. The findings have been tried to be interpreted by providing reasons and possible explanations based on the students' responses to the interviews and comments to the open-ended questionnaire question, researcher's personal experiences and perceptions, informal discussions with instructors and students, informal observational field notes from the statistics classes and evidence of the pertinent literature. When interpreting and discussing the results, the characteristics of the educational system and the characteristics of the specific population and the particular sample which provided the quantitative and the qualitative data were considered. The first section of this chapter is devoted to address and provide answers to the research questions (and sub-questions) and the second section is devoted to the discussion of the principal or/and unexpected findings along with further recommendations and implications for teaching and learning statistics. It should be reminded that italics throughout this chapter signify the exact words of students as shared by them during the interviews.

6.2 Answer to the Research Questions and Sub-Questions

This section provides a summary and a discussion of the main findings with respect to the primary and secondary research questions and sub-questions posed in this doctoral research study and outlined in the Methodology chapter (refer to §3.2). It aims to synthesise and interpret the results obtained from both the qualitative and quantitative analysis (refer to Chapters 4 and 5) and the review of the literature presented in Chapter 2.

6.2.1 Answer to the Primary Research Questions and Sub-Questions

Research Question 1: What are the affective responses and perceptions of students over the course of a semester and how do the students describe them?

> Research Sub-Question 1.1: What are the students' feelings, attitudes and beliefs regarding statistics, interest in learning statistics, perceptions about the usefulness, the worth and the relevance (for their specialisation) of statistics and perceptions about the difficulty of the current statistics course?

The two versions of the questionnaire and the interviews provided insights into the students' feelings and attitudes regarding statistics. Generally, students expressed favourable responses towards their liking of statistics and the statistics course they were attended both at the beginning and at the end of the semester (see §4.3.2). More specifically, the majority of students tended to agree with the statements whether they liked statistics as a discipline and whether they liked the subject content they were taught in the statistics course. Also, there was a tendency to disagree with the statement whether statistics was among their worst subjects. Concerning the existing body of knowledge, the findings in the international literature are mixed. Most commonly, positive or negative feelings towards statistics were assessed using an affect (i.e. feelings) subscale, which was a component of a general attitudes scale (see §2.4). There are research studies which report that students held generally positive or neutral feelings towards statistics (e.g. Clark, 2003; Mills, 2004; Schau and Emmioğlu, 2011; Tempelaar *et al.*, 2011; Gloria, 2014), whereas some other studies report that negative feelings were dominant in their sample (e.g. Fullerton and Umphrey, 1991).

The interview data further elaborated students' feelings, attitudes and beliefs even before attending the statistics course and throughout their enrolment and engagement with it (see §5.6). Students' predispositions and pre-existing opinions about statistics before attending the current statistics course were influenced by their own previous experiences with statistics/mathematics courses and instructors and their perceived statistical/mathematical knowledge and skills, their own conceptions of what is statistics and what is to do statistics as well as comments and opinions of other people in their close environment (such as senior students, friends or family members). This is consistent with the possible sources of statistics attitudes as described by Gal and Garfield (1997) which can be past experiences with mathematics and statistics and 'notions' of what is statistics.

The students who demonstrated positive attitudes towards statistics attributed them to the nature of statistics as a subject (which was characterised as *interesting*, *fascinating*, *practical* and *logical*) and the difference of statistics from the other courses of their major (for example, statistics was described as *oxygen* and *break* from other courses). The appreciation of the usefulness and applicability of statistics for their everyday and future academic and professional work was also highlighted as a source of their positive attitudes. Moreover, the students' responses revealed that confidence in learning and mastering statistics played a role in their favourable attitudes towards statistics.

Students particularly stressed the instructor and his/her instructional methods and personality (such as characteristics/attributes) as factors contributing to their positive or negative attitudes. Griffith *et al*. (2012), in a mixed methods study exploring students' attitudes towards statistics across many disciplines, identifies instructor to be associated with both positive and negative attitudes indicating the potential of the instructor (e.g. his/her characteristics and qualities) to influence students' attitudes. A similar point is also raised by Zientek *et al.* (2011), which demonstrates that students' perception of the instructor's explanations and methods are associated with their attitudes towards statistics. Ruggeri *et al*. (2008) proposes that the most important determining factor on students' attitudes regarding the statistics course is the lecturer/instructor. Moreover, the instructor's attitudes regarding the statistics subject might have an impact on students' feelings and attitudes about it, as was raised by one student during the interviews.

On the other hand, more unfavourable feelings and attitudes regarding statistics were linked to students' previous learning experiences with statistics and/or mathematics courses and previous failures in these courses. This is in accord with the findings of other studies which finds that prior mathematics experiences and achievement (Onwuegbuzie, 2003; Chiesi and Primi, 2010; Strobl *et al.*, 2010; Zimprich, 2012; Prayoga and Abraham, 2017) and perceived mathematical competence (Galli *et al.*, 2008) are factors related to students' attitudes towards statistics. It also supports the evidence reported by Verhoeven (2009) which demonstrates that previous statistics experience and perceived mathematics skills have an impact on college freshman's attitudes in an introductory statistics course. From the students' responses during the interviews, it appeared that the greater their prior formal exposure to the statistics subject (e.g. students who had (re)taken a statistics course in the university before), the more unfavourable their attitudes towards statistics were. This is a somewhat unanticipated finding, but it is found to be consistent with a study conducted by Mathew and Aktan (2014), which finds that undergraduate nursing students with a higher experience of statistics in high school and university level possessed more negative attitudes towards statistics. Furthermore, interviewees who expressed more unfavourable attitudes referred to the nature of statistics as a subject (e.g. too *mathematical oriented* as it was described) and the difficulties they had experienced throughout the learning of statistics.

An important element from the interviews, which also appeared to influence students' attitudes and liking of statistics, was their level of understanding. It is evident that when students understood the subject material and when they performed well in evaluation assessment (such as examinations) in statistics, they tended to express more favourable attitudes towards it, and the opposite direction.

Regarding changes in students' feelings and attitudes towards statistics before, during and after taking the current statistics course, positive changes (from negative to positive) and no changes (positive remained positive and negative remained negative) were observed based on the interview responses. None of the interviewees reported that they had positive attitudes towards statistics that became negative as a result of attending the course. From the quantitative part, when comparing students' responses near the start and upon completion the course, no significant movements on the liking of statistics are detected in the sample of students who answered both versions of the questionnaire. In a similar manner, as discussed above, not much consistency among the results of the studies which monitored and investigated changes in students' feelings (and more generally attitudes) towards statistics over the duration of a statistics course is detected. There are studies which show an increase in the mean scores of the feelings component (Kiekkas, 2015; Milic, 2016), whereas some other studies indicate a decrease (Zhang *et al*., 2012) or no substantial or significant changes (Evans, 2007; Tempelaar *et al.*, 2011; Schau and Emmioğlu, 2012; Beemer, 2013).

Concerning the level of students' interest in learning statistics, the two versions of the questionnaire and the interviews were used to inform this inquiry. Based on the responses to the questionnaires (refer to §4.3.2), it could be inferred that the majority of the students who participated in the study found the statistics course interesting and the studying of statistics enjoyable both the beginning and near the end of the course. However, despite their favourable answers regarding their interest in statistics, students were not found to be particularly keen on undertaking further (and probably more advanced) statistics course in the future and deepen their knowledge in this area. Also, it is found that the likelihood of choosing a course in statistics was larger than not choosing it if the students had the choice (e.g. the course was not compulsory for their degree programme) (see §4.3.1). These findings are similar to a quantitative study conducted by Coetzee *et al.* (2010) in a South African sample composed of undergraduate and graduate psychology students who displayed high levels of interest in learning, understanding and using statistics. By employing samples of postgraduate medical students from Ireland and China respectively, Hannigan *et al.* (2014) and Zhang *et al*. (2012) also report students' positive dispositions towards their interest in the subject of statistics.

During the interviews, the students discussed in a more detailed way what they found interesting and enjoyable in the statistics course (refer to §5.6). The students who displayed an interest in learning, understanding and using statistics talked about: a (genuine) sense of curiosity in statistics as a discipline; the practical and problem-solving aspect of statistics; and the numerous things someone can learn and do in/with statistics. The statistics classes and the statistical content can be *inherently interesting* and *appealing* as two students specifically mentioned. However, there were students who did not find the statistics course interesting mainly because of its mathematical nature and association with mathematics and the statistics subject was also described as being away from their field of main interests. The students' interest and enjoyment of statistics seemed to be conditioned by their perceived difficulty or easiness of the course and the understanding and mastering of the subject material. Some students admitted being more interested and engaged in statistical-related tasks when they believed that they (could) understood them. Nevertheless, the enjoyment that arose when students encountered something that it was perceived as challenging was also stated. Moreover, the interview responses revealed the role of the instructor in inculcating an interest towards statistics to the students.

Regarding changes in students' interest in statistics, no substantially significant differences are observed from the beginning towards the end of the semester in the sample of students who participated in both questionnaire administrations. This outcome is in line with the outcomes of previous research studies (e.g. Tempelaar *et al.*, 2011; Milic, 2016). From the interview data, it was apparent that either the students became more interested towards statistical topics and knowledge or they did not change their levels of interest before, during and after their exposure to a statistics course.

Concerning the students' perceptions about the usefulness, the worth and the relevance (for their specialisation) of statistics, the results from both quantitative (i.e. two versions of the questionnaire) and the qualitative (i.e. interviews) components were synthesised to answer this inquiry. The quantitative data showed that, in aggregate, students tended to appreciate and value statistics and the statistics course (refer to §4.3.2). At the beginning, as well as towards the end of the semester, almost 70% of the students gave a positive response to the general question whether they perceived statistics as a useful subject. In addition, the majority of the students were in favour of the statements asking whether statistics is useful and applicable in their everyday and future academic and professional life. These findings are consistent with the findings presented in other empirical studies (e.g. Mahmud, 2009; Naccache, 2012; Zhang *et al*., 2012; Hannigan, 2014; Gloria, 2014) which report that students tended to appreciate the usefulness and the relevance of statistics for their everyday and professional life.

During the interviews, students further commented on their perceived relevance, usefulness and applicability of statistics for their personal life, academic studies and future career (refer to §5.7). Given that a wide range of disciplines and majors were represented in the sample, a variety of responses was given indicating the students' perceptions of the wide and broad applications of statistics. Students seemed to appreciate the value and worth of statistics as a tool not only in their discipline but in other disciplines as well. Also, they mentioned examples of the applications of statistics to their future professional career and the connections with other courses in their degree programme. They seemed to believe that statistics knowledge and skills can contribute to their career development and enhancement of their future employability. However, there were students who admitted that, even though statistics might have some applications in their disciplines, based on their working experiences so far or their desired future professional position, statistics would not be so useful or relevant to their career goals. In addition to this, a large number of students considered statistics as useful and applicable in everyday life; they stressed its applicability to modern life and described it as an important tool for making informed decisions (financial, political or job-related) especially nowadays with the abundance of information. There were also students who pointed out general and personal skills (such as *making sense and understanding of the world* and *developing their brain*) that they acquired from the statistics course. As a representative example, one interviewee stated that: *It is an advantage for anybody to learn and know statistics*. In the relevant questionnaire question, the majority of the students considered statistics as a worthwhile and a necessary part of everyone's degree programme. However, during the interviews, some students proposed that statistics should be taught in a manner related to students' degree programme by giving emphasis on learning statistical topics and skills that are more related to their chosen major and they are more likely to be useful and applicable to their future professional work.

Regarding changes in the students' perceived value of statistics over a one-semester course, the results of the paired quantitative data demonstrate that the positive perceptions, although still rated as high, diminished over the semester (refer to §4.4). This finding is in contrary to some research findings in the literature which demonstrates that the perceptions of value and relevance tended to increase or remained unchanged (e.g. Schau, 2000; Cherney and Cooney, 2005; Shield and Shield, 2008; Olani, 2011; Milic, 2016). Although this outcome contrasted with my initial anticipations, negative changes are also present in other empirical studies. For example, there are studies which report slightly negative, but not significant, changes (e.g. Schau and Emmioğlu, 2011; Zhang *et al*., 2012). Significant negative changes in perceptions of the value of statistics after students' exposure to an elementary statistics course are found by Gloria (2004) in a sample of students from eighteen different degree programs and six different colleges. Also, Sizemore and Lewandowski (2009) reports a significant decline in undergraduate psychology students' perceived utility of statistics from the beginning to the end of a sophomore-level course on research and statistics. This current study finding may be explained by the conjecture that students might not find the particular statistics course as useful and applicable as they perceived at the beginning of the course and this particular course might not help in this direction (i.e. to maintain or improve the levels of their positive value perceptions). It might also be the case that students did not, by the end of the semester, appreciate the importance of what they had learnt in the statistics course. The practical importance of this finding (which is considered to be a step further than the statistically significant one) is discussed later in this chapter (see §6.2).

Concerning the students' perceptions about the difficulty of the current statistics course, both statistical information and interview data were consulted. The findings of the quantitative investigation suggest that the students had moderate levels of perceptions regarding the difficulty of the statistics course at the beginning as well as towards the end of the semester (refer to §4.3.2). The students were also neutral or undecided about the relative difficulty of the statistics course compared to their other academic courses. Moreover, a larger percentage of students agreed on finding difficult to understand the statistical concepts in statistics than agreed on finding it difficult to apply statistical methods. The quantitative findings are in line with the results of earlier studies (Emmioğlu, 2011; Milic *et al*., 2016) which indicate neutral or moderate perceptions of non-statistician undergraduate and graduate students and medical students respectively about the difficulty of statistics. However, they are not congruent with other empirical studies which report that on approximately half of the postgraduate students experienced some difficulties while learning statistics (Mahmud, 2009; Zhang *et al.*, 2012; Hannigan *et al*, 2014) and the prospective mathematics teachers had great perceptions of the difficulty of statistics (Leavy *et al*. 2013; Hannigan *et al*. 2013). Also, Verhoeven (2009), in a sample of undergraduate university students who attended a mandatory introductory statistics course, demonstrates that, in general, the participants perceived statistics as a difficult subject to learn.

The findings from the qualitative investigation generally support the findings from the quantitative investigation (refer to §5.8). There were students who talked about a moderate perceived difficulty of the introductory statistics course until the time of the execution of the interviews, with no one mentioned experiencing major difficulties. Students also stated the chapters or content areas of the statistics course they perceived as being more difficult. The probability-related topics were the most frequently content areas mentioned by the students. This is consistent with Coob and Moore (1997) which stresses that it is the probability component of the statistics course that the student reported finding it difficult. In line with the quantitative findings, most of the interviewees seemed to find more difficult to understand and learn the theoretical aspect of the statistical course (for example, to figure out the meaning of a statistical concept) compared to the more practical one (for example, to solve an exercise). Moreover, some students stressed the nature of statistics as a subject, including: the number of steps and a combination of things to reach to a solution that is the complexity of doing statistics; the new terminology and unfamiliar words; and the statistical logic, thinking and reasoning as a factor contributing towards their perceived difficulty of statistics. Besides that, understanding the definitions and theoretical propositions, selection of the statistical methods and techniques, and use and application of formulas were raised by students when teasing about their sources of the difficulties they experienced in statistics. During the interviews, students expressed greater concern about mastering and understanding the statistics subject matter. Some students often related understanding with their perceived difficulty; when they understood something, it seemed easier to them. In addition, the quantity of the information presented and the instructional practices used were mentioned by some students as being partly responsible for their perceived level of difficulty of the course. The teaching practice along with the uncertainty of the statistical content including the language, symbols and terminology used were among the causes of their difficulties as reported by secondary pre-service teachers in a study conducted by Fitzmaurice *et al*. (2014). The interview data also reveals that the difficulties of some students were associated with the evaluation, explanation and interpretation of the results and the writing of the conclusions from statistical analyses. In keeping with this study's findings, some past research investigations highlight that there were students who experienced difficulties in the interpretation of statistical results in school mathematics settings (Ridgway *et al.*, 2008; Yolcu, 2012). Also, McGrath (2004) identifies the writing of conclusions as challenging by students when completing a statistics course. As a final point, the majority of the students who completed the questionnaire(s) and the majority of those who were interviewed reported believing that even the higher-achieving students can experience difficulties and struggle with statistics at some point.

Regarding changes in students' perceived difficulty of statistics over the course of a semester, a slight, but significant, increase is detected. This could indicate that later on the course students might experience more difficulties in statistics than at the beginning. Significant differences between the beginning and the end of the semester regarding the perceived difficulty of statistics are reported in the literature (e.g. Zhang *et al*., 2012). However, there are other other empirical studies (e.g. Schau and Emmioğlu, 2012, Breemer, 2013) which do not find a substantial difference between students' pre-test and post-course answers related to the difficulty perceptions. The quantitative data are substantiated by the qualitative interview data where some students said that the level of the difficulty increased as the course progressed or might increase at a more advanced level.

> **Research Sub-Question 1.2:** What are the types and levels of anxiety related to statistics that students experience, the sources and the effects of these anxieties?

The students' answers to the two versions of the questionnaire along with the responses to the interview questions were integrated to explore students' anxieties in statistics. The overall anxiety levels of the students regarding statistics were moderate (or even below) as revealed by their answers to the general question whether the statistics course make them feel anxious. Students indicated higher anxiety regarding their performance in the statistics course whereas attending a statistics lecture class and having to complete assignments in statistics were the least sources of anxiety. On the whole, quantitative results indicate that the students who participated in the study did not (generally) experience high levels of anxiety throughout their enrolment in the statistics course (refer to §4.3.2). This outcome coincides with the findings reported by Finch and Jameson (2007) and Hagen *et al.* (2013) which employs samples of graduate and undergraduate nursing students. Also, it supports Rosli *et al*. (2016, 2017) and Brezavšček (2017) which demonstrates that levels of statistics anxiety are at moderate (or even below) levels among education postgraduate students and undergraduate social sciences students respectively. However, it conflicts with many empirical findings which find that over seventy per cent of students in their samples experienced uncomfortable levels of statistics anxiety (e.g. Zeidner, 1991; Onwuegbuzie and Seaman, 1995; Onwuegbuzie *et al.*, 2000; Baloğlu, 2003).

Based on the interview responses (refer to §5.9), one of the issues that emerged was that there were students who possessed anxiety regarding statistics even before attending the current statistics course. Previous educational or personal experiences and acquaintance with mathematics and/or statistics and performance in related courses; previous mathematics/statistics teachers; perceptions of mathematical abilities as well as their own impressions and opinions from others (such as senior students, friends or family members) appeared to initially contribute to the students' level of anxiety towards statistics. This is in line with previous studies which demonstrates that previous mathematics experience, foundation and preparation (Zeidner, 1991; Wilson, 1997; Baloğlu; 2003; Malik, 2015); perceived mathematical abilities and skills (Zeidner, 1991; Baharun and Porter, 2009); and unpleasant experiences in previous statistics classes (Pan and Tang, 2005; Baharun and Porter, 2009) are antecedents of statistics anxiety levels. In the current study, it is found that prior experiences with statistics courses at university level seemed to increase the anxiety of some students regarding statistics which conflict with the other studies which report that it led to a decrease of anxiety levels (Zanakis and Valenzi, 1997; Welch *et al*., 2015).

The most common stated forms and types of anxiety during the statistics course were test and examination anxiety (before and during the examination) as well as performance and grades anxiety. Students worried about their grades in the examinations and overall in the statistics course which resulted in anxiety when studying for and when undertaking an examination in statistics. Their main concerns were to: understand the subject material they were taught; write in the examinations what they have studied and learned; not get stuck in solving the examination topics; have sufficient time to prepare before the exams; and manage their time effectively. These findings appear to cohere with the study conducted by Williams (2010), which indicate high levels of students discomfort in statistics test situations. Moreover, Zanakis and Valenzi (1997) demonstrates that test anxiety and lack of understanding and interpretation of statistics were among the highest sources of students' anxiety in business statistics. Another cause of their anxiety frequently mentioned by the students was the fear of failure (that is getting a non-passing grade and having to retake the course) or the worry about getting a low or below their expectations grade. Fear of failure was also indicated by social sciences students as a contributing factor to their statistics anxiety in a focus group study conducted by Pan and Tang (2005). Future achievement goals, aspirations and high expectations of themselves as well as pleasing to others (such as family members and statistics instructor) also seemed to heighten students' anxiety related to the statistics course.

Anxiety levels were also found to be associated with: course-related factors (such as the subject content, the workload of the course and the evaluation methods); confronting with new, unfamiliar and perceived difficult topics; understanding the thinking and logic of statistics; and dealing with computational and practical exercises. The quantitative nature of the course (for example, solving practical exercises and performing mathematical/statistical computations) seemed to be the reason of exhibiting higher anxiety about statistics compared to their other theoretical courses especially for students majoring in non-mathematically oriented or demanding degrees. Some interviewees stated specific chapters and components of the statistics course (such as the probabilities component) which raised their anxiety. Research studies in the literature also support the view that the nature of the statistics course (Zeidner, 1991; Onwuegbuzie *et al*., 1997), uncomfortable feelings in doing mathematical computations (Ali and Iqba, 2012), dealing with formulas and statistical calculations (Williams, 2010; Lalayants, 2013), and lack of problem solving skills and abstract thinking and reasoning (Kaiser, 1992) were among the main reasons for evoking anxiety in statistics.

The positive and negative effects of anxiety on students' learning were stated. From the one hand, students felt that high levels of anxiety could impair performance and decrease learning effectiveness in statistics, but also there were students who claimed that anxiety in 'normal levels' could be considered as *good* and *beneficial* since it could motivate students. Some students mentioned that absence of anxiety might lead to exert less attention and concentration, effort and amount of studying, for example, when preparing for upcoming examinations. These students' comments are in line with Paechter (2017).

Based on the interview responses, students tried managing and overcoming anxiety in statistics by utilising a wide range of strategies such as cooperative studying with classmates, consistent and regularly studying and rehearsal, preparation and practising. Also, the comments of students taking part in the interviews highlighted that the instructor's methods, explanations, attitudes and behaviour had influenced (heightened or reduced) their anxiety towards statistics. This supports previous qualitative studies which point out that the instructor's attitudes and strategies were among the crucial contributing factors for statistics anxiety levels experienced by the students (Pan and Tang, 2005; Malik, 2015).

Regarding changes in the students' anxieties manifested towards statistics, the quantitative analyses revealed that, even though the levels of these anxieties diminished towards the completion of the course, the differences between them are considered not significant. The current finding supports earlier studies on changes in statistics anxiety which indicate that anxiety towards statistics decreased from the beginning to the end of the instruction of the statistics course (Davis, 2004; Pan and Tang, 2005; Huang, 2018). Moreover, Zanakis and Valenzi (1997), when investigating anxiety of students attending a business statistics course, find that their levels of anxiety, even though still high, decreased towards the end of the course. From the qualitative investigation, it appeared that potential changes in the levels of students' anxiety in both directions could be attributed to the exposure and familiarity with statistics and statistics material, the performance in midterm evaluations (such as examinations) and the statistics instructor (and his/her instructional methods).

> **Research Sub-Question 1.3:** What are the levels of students' perceived self-efficacy regarding statistics and the main antecedents and sources of them?

The combination of the quantitative and qualitative findings provided support to answer this research question. Overall, arising from the responses to the questionnaires (refer to §4.3.2), students were positive in rating their confidence regarding learning and doing statistics in the beginning and upon the completion of the statistics course The majority of the students who took part in the study exhibited a positive self-perception of their capability to perform well in the statistics course. This relatively quite high level of self-reported confidence in statistics is a somewhat unanticipated finding. Nevertheless, it can be explained by the arguments of some authors (e.g. Bong and Skaalvik, 2003; Afolabi, 2010) that self-efficacy judgments are more concerned about what individuals believe about their competencies rather than the actual skills and abilities they may possess and their actual performance. This quantitative finding is in line with Lalayants (2012) which reports that on average graduate students had relatively confidence in the prospect of taking a statistics course.

During the interviews, students explained further their perceived confidence regarding statistics (refer to §5.10). Some students exhibited perceptions of success (or failure) even before attending the statistics course and engaging with it. The most common antecedents and sources of their self-efficacy beliefs as reported by the students were: general confidence in their abilities and academic skills; previous mathematics/statistics experiences and achievement in mathematics-related courses; perceived mathematical knowledge and skills; nature of statistics as a subject (such as being practical) and the level of their understanding. It seemed that students who perceived that they had weak or insufficient mathematical background and skills and/or experience a poor previous performance in mathematics/statistics, they might doubt their abilities to learn and acquire knowledge in the current statistics course. These findings are parallel to those of Verhoeven (2009) which indicates that self-confidence in statistics is associated with prior experiences with mathematics. In a similar manner, some researcher studies provide evidence that mathematics attainment (Pampaka *et al*., 2011) and the grade students received in previously completed university mathematics course (Locklear, 2012) impact the students' self-efficacy towards mathematics. During the interviews, students also shared their confidence in specific content and components of the course. For instance, in line with the quantitative results, most of the interviewees seemed to have more confidence in the practical part (for example, to understand the ways of solving exercises and apply statistical methods) instead of the theoretical part (for example, to understand theoretical concepts or learn definitions) of the statistics course. There were cases where students reflected on their self-perceptions of competence by using phrases such as *I am not a mathematics or statistics person*; *I am incompetent*; *I feel weak; I am good at statistics*. These could be considered as images of their selves as statistics (and mathematics) learners.

Another prevalent topic emerged from the interviews is the key role of the statistics instructor and his/her instructional methods in students' levels of self-efficacy regarding statistics. A supportive and encouraging instructor along with an effective and understandable explanation of the subject material seemed to have a positive impact on students' self-efficacy. This outcome is aligned with the arguments of other authors (e.g. Pintrich and DeGroot, 1990; Olani, 2011) who suggest that those students, who considered their teacher as more supportive and encouraging, exhibited greater self-efficacy than the other students who experienced less support and encouragement. In addition to this, some students indicated that the comparison with other students and appraisal by others could boost their levels of self-confidence. Also, explanation and answer to their classmates' questions seemed to influence students' self -efficacy levels. This finding is somewhat related to Hall and Vance's (2010) propositions who claim that students' self-explanations and reception of peer feedback can impact their statistics self-efficacy in a positive way. The attribution of success to the ease of the exercise or task instead of the personal abilities was reported by a student who shared low levels of self-efficacy regarding statistics. The tendency to ascribe their successes externally (e.g. task difficulty) rather than internally (e.g. abilities, skills, and effort) was mentioned by Lane *et al.* (2004) as a characteristic of students who have a low sense of self-efficacy beliefs.

Concerning the pre-to-post course changes in students' levels of self-efficacy, the quantitative investigation reveals that these were not significant in the sample of students who completed both questionnaires. In other words, the students' confidence appeared to be somewhat in the same levels and remained well above the moderate levels from the beginning of the statistics course through the completion of it. This finding does not appear to cohere with findings from other studies (e.g. Finney and Schraw, 2003; Olani, 2011) where an improvement in students' self-efficacy perceptions over the duration of a college statistics course is reported. From the qualitative investigation, it seemed that any changes in students' levels of self-efficacy could be attributed to the level of their understanding of the statistics subject matter and their performance in the assessment evaluations (e.g. midterm examinations). A similar point is raised by Finney and Schraw (2003), which indicates that students' self-efficacy perceptions fluctuated as they became acquainted with the subject content in statistics.

Research Question 2: Can the concept of resilience be adapted in the context of statistics education so that we can introduce the term 'statistical resilience'? What is the relationship between statistical resilience and other examined variables, and performance?

> **Research Sub-Question 2.1:** How can the concept of statistical resilience be conceptualised, what are the students' resilience levels, how does resilience develop over the course and what are the resilient strategies and approaches they apply in statistics?

The concept of resilience has been investigated in many contexts including the educational and academic context. In the field of mathematics, Johnston-Wilder and Lee (2010, 2012) introduce and explain the term of 'mathematical resilience' (refer to §2.8). The current study attempts to refine and apply the concept of mathematical resilience to the specific context of statistics so that concept 'statistical resilience' can be introduced. It is believed that statistical resilience might be analogous to mathematical resilience and these two constructs might be interrelated since statistics is regarded as a mathematical science and it still forms a part of the mathematics curriculum in high school and universities. Nevertheless, it is considered as a discipline-, subject-, course- or even content-specific.

Parallel to the definition of mathematical resilience, statistical resilience can be regarded as a positive affective stance in relation to statistics. Statistical resilient learners are portrayed as the individual students who have developed and applied strategies to deal with statistical-related topics and tasks, which allow them to continue trying and achieve their target goals even in the face of adversity, difficulties or challenges. It is believed that each student might perceive and experience those difficult situations differently, which can be related to the individual's competence, tolerance to the struggle or previous experiences.

In the current study, both qualitative and quantitative strands were employed to address the construct of resilience in relation to the statistics education context. Students' resilient behaviours were assessed through seven items in both questionnaire administrations. Data analysis (more specifically, exploratory factor analysis) demonstrated that the two items which were oriented to general resilient behaviours and the five items which were oriented to resilient learning behaviours towards statistics (i.e. they included the word 'statistics') form two different factors which might indicate that statistical resilience could differentiate from the general resilience (refer to §4.8).

Based on the questionnaires' responses (see §4.3.2), the majority of the students believed that they could deal effectively with the challenges and the pressure of the university life and they did not leave a perceived failure (such as a bad grade in the exams) to influence their levels of confidence. Also, students tended to espouse an 'agree' perspective in the statistical resilience component both at the beginning and near the end of the semester. This outcome demonstrates that most of the students reported having the will and the persistence in learning statistics by keeping trying to understand the statistical concepts or solve the exercises, trying alternative strategies when experienced difficulties, not giving up in the face of setbacks and working until they finished when they did not find a task interesting.

During the interviews (refer to §5.12), students generally described failure as the situation when their performance expectations are not fulfilled, for example, when they obtain a failing grade or even a lower grade than they expected or they believed they deserved based on their abilities, effort and studying. Some students stated that they might be disappointed and discouraged (in the beginning), but they will *continue trying* by *putting forth greater effort*, *putting a greater tenacity*, *working even harder* and *be more stubborn*.

Regarding the factors that might contribute to positive resilient behaviours in the statistics course, from the students' responses, it seemed that the interplay between personal and environmental factors was involved. This is in line with the Luthar's *et al.* (2000) propositions as described in §2.8. More specifically, a set of characteristics and strengths of the individuals, such as tenacity, determination, patience, commitment, optimism and the ability to work independently as well as collaboratively were mentioned by the students and are deemed as playing a role in promoting and sustaining positive resilient orientations. Besides that, friends' and classmates' network and support, classroom environment and 'comparison' with other classmates seemed to also contribute towards positive response and adaptation. For example, when students 'compared' themselves with others and acknowledged that they were not the only ones who struggled and experienced difficulties or stressful situations in statistics, this made them to continue, try more and strive longer.

Students were requested to characterise themselves whether they believed they were or acted as statistical resilient learners and whether they exhibited statistical resilience-related skills. Students described the learning approaches and strategies they applied or planned to use to confront and cope with difficult, new or unfamiliar statistical-related tasks. Among the strategies employed when struggling with learning and understanding to successfully meet the desired outcomes were: asking questions or requesting for help from a variety of sources (e.g. instructor, senior students, family members, internet, textbooks, notes); studying collaboratively and discussing with classmates; revising and reflecting on the information and knowledge be taught; applying existing knowledge and skills; trying alternatives procedures; thinking hard, clearly and focused; and spending more time on studying and practising. More information is provided in §5.12.

Various statements by students showed that they distinguished the conditions and the situations of having to complete a novel, unfamiliar or difficult exercise or task – that is, whether they had to do so when they were undertaking an examination in statistics or when they were studying at home. This was mainly explained due to pressure and time constraints. It was also apparent that students behaved in a more resilient way when the examinations were approaching rather than during a typical week. This somewhat supports Luthar *et al.* (2000) which argues that resilience might be time specific and it is not fixed but can change and fluctuate over time.

Since resilience is regarded as a developmental process, it was assessed quantitatively both at the beginning and towards the end of the semester (refer to §4.4). A significant decrease, although still above the moderate level, in resilient levels of the students who completed both versions of the questionnaire is observed towards the end of the semester. This decrease did not emerge from the qualitative strand of the study and there is no specific data (i.e. students' responses) that I can refer to. There might be several possible explanations for this result. For example, the decline may be due to students not having experienced major setbacks or failures throughout the course that trigger them to use resilient-related skills. Also, students might not utilise the resilient behaviours they were planning to use at the beginning of the course. Following Goodall and Johnston-Wilder (2015), as the concept of resilience might include the belief that effort is both required and rewarded, the decline in effort levels, which is also observed in the current study, may be related to the decline in resilience levels. More research is needed to explain this finding.

> **Research Sub-Question 2.2:** Is statistical resilience related to other examined affective, motivational and cognitive variables and is it a significant predictor of academic performance in a statistics course?

Based on the quantitative results (refer to §4.5), significant relationships are found between students' attitudes towards statistics (in terms of their liking of statistics, interest in statistics, the value of statistics) and their statistical resilience. Students' comments during the interviews offered further insight into these associations (refer to §5.12). More specifically, some students mentioned that the interest, enjoyment and perceived value of a task were important factors for them to try or continue engaging with it. These findings seemed to agree with Johnston-Wilder (2013) which supports the view that the more value the students place on mathematics, the more likely is to persist when they faced difficulties and setbacks. Moreover, Hutauruk and Priatna (2017) demonstrates that the students' conviction that mathematics is valuable and worth studying, which was used as an indicator of mathematical resilience, is significantly and strongly correlated with their level of mathematical resilience.

Based on the quantitative investigation (refer to §§4.5.1 and 4.10**),** when anxiety and difficulty were combined and included along with resilience in a structural model which aimed to predict performance in statistics, the relationship between anxiety and difficulty variable and resilience variable is found to be positive. More specifically, anxiety and difficulty variable has a direct positive effect on resilience variable indicating that the experience of more difficulties and anxieties in statistics might lead in putting forward more resilient approaches to eliminate those difficulties and anxieties. However, this pattern is not consistent with the bivariate correlations between these variables, which are found to be negative. Students who scored high on perceived difficulty and anxiety tended to have lower resilience while those scored low on perceived difficulty and anxiety tended to show higher resilience. A possible explanation might be that anxiety impeded the use of resilient behaviour strategies. During the interviews (refer to §5.12), some students described feeling nervous, frustrated and annoyed when they encountered exercises or concepts that at first they could not do or understand it.

The strongest relationship among the investigated variables is detected between the statistical resilience and the self-efficacy regarding statistics - a finding which confirmed my initial anticipations. A possible explanation for this association might be that students who had more confidence in their knowledge and competencies and trust themselves, it was more likely to behave in a stronger resilient way and try for longer to get to the desired end. The close relationship between self-efficacy beliefs and resilient behaviour is also evident in the interview responses. Some students described how a potential poor (or under expectation) performance could have the potential to affect or had affected their confidence levels in statistics. Also, it seemed that behaviours and approaches when faced difficulties or challenges (being more or less resilient) were related to students' confidence in their abilities to learn the statistics course content and depended on their beliefs that they would be able to understand it or solve an exercise at the end. There were students who appeared to be unwilling to start trying statistical tasks if they believed that they could not do it *quickly* or *eventually*. Previous successful attempts to 'get to an end' (that is, understanding a concept or solving an exercise) seemed to foster their resilience-related behaviours in the statistics course. A significant relationship between self-efficacy and academic resilience is also identified in many empirical research studies (refer to §2.8).

Arising from the interview responses, positive resilient behaviours appeared to be related to high intrinsic and extrinsic-related motivational orientations - that is to acquired knowledge and skills or/and get a good grade and avoid the perceived failure in the statistics course. Moderate and weak significant relationships are identified between statistical resilience and intrinsic and extrinsic motivation respectively. These associations might demonstrate that students who had mastery and performance-related goal were more likely to show greater resilience by developing and applying strategies in response to difficulties and stressful situations. This finding supports Dweck's theory of learning (Dweck, 2000) which argues that students who were motivated by mastery-oriented goals, developed problem-solving strategies and sought alternative ones when confronted with academic challenges and adversities. Moreover, moderate relationships are detected between resilience and learning strategies both at the beginning and towards the end of the semester. This association is further supported by the interview data where students who mentioned strategies such as putting together information from different sources, looking for additional information and readings related to the statistics course, solving extra exercises, and focusing on understanding than only memorising things in statistics were turned to be more resilient learners. Furthermore, moderate significant relationships are identified between statistical resilience and effort towards statistics. This association might reflect that students who recognised and valued effort, they understood that if they worked hard, they could obtain the desired outcome and thus they developed more resilience skills.

Regarding differences in demographic and educational related factors (refer to §4.4), in both questionnaire administrations, a significant difference is detected among males and female students in statistical resilience, in favour of females. This could demonstrate that the female students were more likely than their male counterparts to exhibit positive resilient behaviours by embracing the difficulties and trying to overcome them. No significant differences were found among other demographic factors (e.g. age group) and academic factors (e.g. faculty) and statistical resilience.

The role and the effect of statistical resilience on students' performance in the statistics course were investigated by employing several statistical methods such as correlational analysis, regression analyses and SEM techniques (refer to §§4.5.3, 4.7 and 4.10). Significant, although weak, positive relationships are detected between statistical resilience and performance. Moreover, regression analyses demonstrate that statistical resilience (as assessed at the beginning and at the end of the course) was a significant predictor of students' performance in statistics and explained on each own 5.6% and 12% of the variability accordingly. When this variable was entered in a regression model with a set of other predictors (e.g. liking, interest, anxiety), resilience is found to be a significant contributor to performance in statistics. In the literature within the broader academic context, resilience is found to be a significant predictor of academic achievement (e.g. Kwek *et al*., 2013; de la Fuente *et al*., 2017 and see §2.8). As a final piece of evidence regarding the role of resilience in performance, in the investigated structural models, statistical resilience, both at the beginning and towards the end of the semester, is found to have a direct positive effect on statistics performance.

Research Question 3: What is the nature, the interrelationships and the potential influences of examined affective, motivational and cognitive factors on the statistics course performance?

> **Research Sub-Question 3.1:** What are the students' achievement goals and motivational orientations, expectations of their performance, perceived control over learning and performance? How much study and effort do students put into statistics and what are the learning strategies and approaches they use?

The combination of quantitative and qualitative findings provided answer to this research sub-question. Regarding the students' achievement goals and motivational orientations, from the students' responses to the questionnaire (refer to §4.3.2), it is revealed that getting a good grade to maintain or improve their GPA was the strongest motivating factor for them in learning and studying statistics. This is followed by their goal to gain knowledge and skills in statistics and then by the personal satisfaction when mastering statistical topics. Displaying abilities to others is found to be the least motivating factor.

During the interviews (refer to §5.13), students shared their goals which were associated with their university studies and/or their future professional life and their aspirations with regards to statistics and the statistics course. There were students who talked about performance approach-related goals. These students seemed to be extrinsically motivated and engaged with statistics for reasons such as achieving high grades and meeting social/environment expectations. There were students who talked about mastery (learning) development-related goals. These students seemed to be intrinsically motivated and engaged with statistics for reasons such as understanding the subject material, mastering knowledge, acquiring capabilities and skills as well as personal satisfaction. There were also students who mentioned both performance and mastery-related goals. Almost all the students commented on the importance of the grade and the majority of them on the desire and the need to obtain a good grade in the statistics course. This could indicate that they were dominantly focused on the outcome evaluation, which is not a surprising finding, considering the competitive environment of the university and the job-search competition in the future. This finding corroborates the findings of Marinan (2016) which reports that the pre-business students who participated in the study exhibited very high extrinsic motivation in learning statistics. Also, Lee *et al*. (2002, 2004) report that the students' major motivation in an introductory statistics course was their goals, which were related to the statistics grade, their major and their future career. As one interviewee argued: *A good grade in statistics is of little value if someone cannot use and do statistics and apply this knowledge*. This might indicate the students' focus on the knowledge and learning they acquired in statistics to be exchanged and of use, for example, in their further education and future job and workplace. Many researchers (e.g. Williams, 2002; Noyes, 2016) construe the 'use value' and the 'exchange value' of education and learning where 'use value' is related to the eventual production and consumption (i.e. value of the knowledge and skills in practice such as in the future professional position) and the 'exchange value' which is related to the acquirement of grades and qualifications. Moreover, the instructor's behaviour and instructional practices, as well as the student-instructor relationship, seemed to play a role in students' motivation and engagement with the subject; a point which is also raised by earlier studies (Findlay, 2013; Lee *et al*., 2004; Brezavšček *et al*. 2017).

From the students' responses, it seemed that the majority of them did not tend to compare their grades with other classmates (at least in the statistics course) and when they did, it was for positioning themselves regarding the overall performance of the class and as a means to self-evaluation and self-improvement. One of the interviewees argued that displaying knowledge and skills in statistics would be important in the real world - outside of the university classroom - when searching for a job or while working. However, the 'healthy' competition and the comparison with higher achiever or more 'successful' classmates appeared to be a motivating factor for some students to strive for better performance and acquirement of the subject content. On the other hand, the absence of competition and the low classroom level could bring the opposite results by being a demotivating factor. It seemed that learning environment could be considered as an essential element of learning motivation in statistics classes.

Concerning students' expectations of their performance in the statistics course, these were evaluated using their questionnaire and interview responses. In both questionnaire administrations (refer to §4.3.2), over half of the students responded expecting to perform well in the current statistics course. However, almost a third of the students reported expecting to perform equally well or better than their classmates and almost half of the students being undecided or neutral. It may be that these participants did not have an opinion or they did not want to position their performance with regards to the performance of their classmates. Regarding the students' expected grade in the statistic course (refer to §4.3.1), it was observed a tendency of the students to increase their expectations of success from the beginning to the end of the course where the majority of them stated expecting a grade above 75 out of 100 towards the end of the semester. This could indicate that the current sample of students generally had quite high expectations towards their achievement in the statistics course. Gougeon (2016), in a sample of 386 undergraduate students who were surveyed the first day of a compulsory introductory course in Business statistics, finds an ‘anomalous expectation’ of getting a high final grade in the course - more specifically, no one of the students anticipated a grade of B or below (the author does not conceptualise in which numerical grades the grade B corresponds).

Due to the fact that the interviews were conducted after the students had some exposure to the statistics course content and they had undertaken at least one examination in statistics, their expectations of performance in the course by the time of the interviews seemed to be evaluated taking into account their so far experiences and the actual or anticipated results (refer to §5.14). It seemed that, at the beginning of the course, students’ expectations were partly affected (positively or negatively) by their previous experience and performance in statistics or mathematics-related courses - a finding which also stressed by Verhoeven (2009). However, as the course progressed, their expectations were mostly affected by their experiences and performance in the current statistics course. Regarding their expected performance compared to this of their classmates, the students stated that their classmates might perform better than them for reasons such as stronger mathematics background, knowledge and skills, mathematics/statistics inclination or intelligence as well as gaining a better understanding and exerting more effort and amount of studying in the course.

Concerning the students’ perceived control over their performance in statistics, both questionnaires and interviews aided to investigate it. From the questionnaire responses near the beginning of the course (refer to §4.3.2), it is revealed that an overwhelming majority of the respondents had an internal locus of performance control since they were in favour that their performance would be determined by their own studying and effort. These findings support Ng (2012) which employed a sample of distance learners enrolled in an educational psychology course and finds that students had strong (internal) control beliefs. However, in the current study, around one-third of the respondents reported having an external locus of control that is they believed that their performance would be influenced more by their instructor (and the instructional methods) rather than by their own studying and effort.

During the interviews (refer to §5.14), a considerable number of students shared the perception that their personal effort, studying and commitment with the statistics learning would be a determinant factor in their performance in the course. Students mainly believed that they had the control of achieving their desired statistics course-related outcomes. Nevertheless, there were students who pointed out the role of the instructor and his/her instructional methods (for example, his/her transferability and explanation of the subject material) in determining their learning and performance in statistics. They said that they might be willing to devote time and effort in statistics, but they were ‘in need’ of their instructor to convey to them the knowledge and understanding and instil in them the motivation, confidence and interest in statistics. Moreover, some students mentioned factors that were beyond their control, such as the topics of the examinations and *luck* or *chance*.

Regarding the effort expenditure in statistics, from the quantitative results (refer to §4.3.2), it can be observed that students were willing to spend or spent a great deal of effort and time to learn and study for the statistics course. In the questionnaire administrations, both at the beginning and towards the end of the semester, an overwhelming number of students reported that they attended the statistics lecture classes and they did their best in statistics. Moreover, about the half of those surveyed indicated that they were planning to or they were studying throughout the semester and not only when they had upcoming examinations. These findings are in agreement with other studies (e.g. Li, 2012; Ghulami *et al.*, 2015; Rosli, 2017) which find the students had given great effort to learn statistics. For example, Li (2012) reports a well above the middle point total mean score for the effort component with the highest mean score to be found for the attendance of every class section in statistics. Also, Lee *et al*. (2004) demonstrates that approximately one-third of the participants were studying only when the examination in an introductory statistics course was approaching. In addition to this, the majority of the students in the current study reported studying on average less than three hours weekly for the statistics course with the numbers of the hours increased (between three and six hours) when the examinations were approaching (refer to §4.3.1). In their study, Bandalos *et al*. (2003) assessed effort regulations in an introductory statistics course using the students' reported average numbers of minutes per week at both times of the administration and these are found to be approximately ninety (one and a half hours).

During the interviews (refer to §5.11), students talked about the nature of the subject (for example, being practical) which required time and effort for understanding the material, practising and solving exercises. They stressed the necessity of putting effort into the subject throughout the semester, the importance of the attendance in (all) the lecture classes and the frequent revisit and revision of the material. However, inclination in mathematics/statistics and previous background and foundation in mathematics-related subjects were considered from students as factors contributing to devoting less effort and time to the current statistics course. More specifically, students who believed that they were inclined to mathematics or/and statistics or they had previous exposure to mathematics-related subjects, they mentioned putting less effort into the studying of statistics.

Regarding the potential changes in students' effort levels throughout the semester (refer to §4.4), from the quantitative investigation, it can be deduced a significant decrease by the end of the semester, although these remained above the moderate levels. This could indicate that the students might perceive that the statistics course did not require expending as much effort as they believed at the beginning of the course or they did not devote by themselves as much effort as they were planning to do. It is claimed that post-course students' answers were concerned more about a reflection of how much effort the students put into the course and could be considered as more realistic than their pre-course questionnaire responses. These outcomes are further supported by the findings and arguments of other studies (Carnell, 2008; Tempelaar *et al.*, 2011; Gloria, 2014). For example, Tempelaar *et al.* (2011) finds a high pre-course first-year university students' level of effort in statistics, which decreased at the end of the semester, but still remained above moderate. From the interview data (refer to §5.11), it is revealed that students attributed changes in their amount of effort and studying to their performance in the midterm examinations in statistics, the workload of the semester as well as other responsibilities (e.g. family and work obligations). For instance, some students mentioned exerting less effort than they intended because of the perceived easiness of the course and the straightforwardness of the midterm exam.

Concerning the students' learning and study strategies (approaches) in the current statistics course, based on the questionnaire responses (refer to §4.3.2), the majority of the students were planning to or they took well-organised notes in the statistics course. In both questionnaire administrations, considerable amounts of students were in favour or against with the statement whether they were looking for extra information related to the statistics course apart from the lecture notes. Especially towards the end of the semester, the majority of the students disagreed with this statement. The interview data (refer to §5.11) further clarified this quantitative result. Some students commented about searching for more information about the statistics content (for example, in the recommended bibliography, in high schoolbooks or on the internet) for doing more practice, gaining more understanding, clarifying things and/or for interest and curiosity reasons. However, there were students who believed that the notes and the exercises they had in the course were enough to understand and perform well in the particular statistics course and they did not need to look or utilise extra information and resource materials. Furthermore, larger amounts of students were in disagreement than in agreement with the questionnaire statement whether they put together information from different sources (such as lecture notes, tutorial notes, books) when they were studying for the statistics course in both questionnaire administrations. From the students' interview descriptions, it seemed that students preferred studying from the notes they took by themselves during the lecture class, the exercises solved during the lecture or/and tutorial sessions and the lecture materials given by the instructor. Moreover, almost two-thirds of the respondents, at the beginning as well as at the end of the course, reported that they preferred understanding rules and steps in statistics rather than just memorising them. This preference and the intent to understand in learning was also apparent during the interviews. It might indicate that the students recognised the importance or value of gaining a deep understanding and comprehension of the subject matter rather than only rote learning it. The current study's finding is inconsistent with Lee *et al*. (2004) which find that about eighty per cent of the students attended an introductory statistics course reported trying to remember the different steps for solving problems while studying statistics. In addition to this, the interview responses revealed that collaborative learning and studying was among the preferred learning strategies of students. There were students who pointed out their need for cooperation and mutual support but also indicated the importance of individual studying in statistics.

During the interviews, students further explained their learning strategies and approaches when studying for the current statistics course (refer to §5.11 for a more detailed description). When describing what they were usually doing during a statistics lecture class, students mentioned taking their own notes, trying to understand the lecture material they were taught and participating in the class by asking questions. Some students sought help from their instructor during the lecture, after the lecture or at office hours, whereas some others shared hesitance to do that for reasons such as feeling embarrassed and being afraid to say something wrong. There were students who preferred asking for help and support from their previous mathematics teachers, private mathematics tutors, classmates, friends or/and members of their close environment. Furthermore, students shared approaches to learning statistics during a typical week (when they did not have any evaluation assessment in statistics) as well as when a statistics test/examination was approaching. Many students also talked about how they were studying specific contents of the statistics course (for example, the theoretical and the practical component of the course). They mentioned learning approaches, which were associated, among others, with time management, reflection, the organisation of time and materials, rehearsal and elaboration. The three latter strategies shared common characteristics with learning strategies components included in the Motivated Strategies for Learning Questionnaire (Pintrich *et al*. 1991, 1993) and investigated by a number of studies (e.g. Rodarte-Luna and Sherry, 2008; Kesici *et al*. 2011). As a final remark, some students stressed that, due to the nature of statistics as a subject, it was important not only the amount but also the quality and the understanding of what they were studying, the use of appropriate strategies and the sufficient preparation.

> **Research Sub-Question 3.2**: What, if any, relationships hold between students' attitudes, anxiety and self-efficacy regarding statistics, and other affective, motivational and cognitive factors?

To start with, the relationships between students' attitudes, anxiety and self-efficacy to learn statistics are found to be in the expected direction in both questionnaire administrations (refer to §4.5.1). Significant positive and moderate relationships are detected between attitudes towards statistics (in terms of liking, interest and value) and self-efficacy regarding statistics. In short, the more favourable the attitudes of the students towards statistics, the higher their self-efficacy to learn the statistics subject were more likely to be. This finding is in accord with the findings of previous research studies (e.g. Finney and Schraw, 2003; Perepiczka *et al*., 2011; Li, 2012). Also, negative (weak or moderate) relationships are found between attitudes towards statistics (in terms of liking, interest and value of statistics) and anxiety towards statistics. This can be explained as that those students with more positive attitudes towards statistics were more likely to be less anxious about it. These findings confirm previous empirical studies on the association between these two constructs (e.g. DeVaney, 2010; Perepiczka *et al*., 2011; Khavenson *et al*., 2012; García-Santillán *et al*., 2013; Sesé *et al*., 2015, Brezavšček, 2017; Rosli *et al*., 2017). Also, Macher *et al*. (2013) finds that interest is negatively related to statistics anxiety. As expected, a moderate inverse relationship between anxiety towards statistics and self-efficacy towards statistics is found. Higher perceived competence in statistics seemed to be accompanied with low levels of anxieties. This finding supports previous research studies which link self-efficacy to learn statistics and anxiety regarding statistics (Perepiczka *et al*. 2011; Schneider, 2011). Escalera-Chávez's research from 2014, in a sample of two hundred ninety-eight university students from several profiles (e.g. management, accounting), demonstrates close associations between the students' likeness, usefulness, anxiety and confidence in statistics.

The qualitative findings corroborate the quantitative ones regarding these associations. For example, students' perceived abilities in the statistics course (which is conceptualised as self-efficacy) was pointed out as a source of positive or negative attitudes towards statistics. The qualitative findings that provide additional support to these associations are reported in the Research Question 1 in the relevant answers to the Research Sub-Questions associated with students' attitudes, anxieties and self-efficacy regarding statistics.

In addition, both quantitative and qualitative portions of the study are used to shed some light on the inquiry whether there are associations among students' attitudes, anxiety and self-efficacy regarding statistics and several other affective, motivational and cognitive factors. From the quantitative investigation (refer to §4.5.2), it is found that there are positive associations between students' attitudes in statistics (in terms of their liking, interest and value) and their motivational orientations and achievement goals at the beginning of the statistics course. More specifically, moderate associations are detected

between attitudes and intrinsic motivation (mastery-related goals) and weak associations between attitudes and extrinsic motivation (performance-related goals). This might indicate that students who were motivated to engage with statistics for reasons such as mastering knowledge and skills and personal satisfaction were more likely, compared to the students who were motivated to engage with statistics for reasons such as achieving high grades in the course and displaying abilities to the closed environment (such as family, friends or classmates), to like, enjoy and value statistics. The finding of the current study is in line with the study of Marinan (2016) which provides evidence of significant relationships between students' intrinsic motivations and beliefs in an undergraduate business statistics course. In a similar manner, Nasser (2004) reports a positive, albeit weak, relationship between college students' attitudes towards statistics and their motivational orientations in a required statistics course. Also, Brezavšček *et al.* (2017) considers statistics' learning value as one of the most important contributing factors in students' intrinsic motivation to learn statistics. The qualitative findings affirm the quantitative ones where students' positive attitudes towards statistics, interest and curiosity in statistics and the value they placed on learning statistics were factors which were identified as raising their motivation to learn and engage with the subject (refer to §5.13). These results reflect those of Lee *et al*. (2004) which find that an overwhelming percentage of the students taking part in their study agreed that they were motivated to engage with statistics when the topics were interesting and relevant to their major. Related to this, and in congruence with Mery's (2011) study, during the interviews, some students reported being motivated by challenging topics in statistics.
The quantitative investigation shows that there are non-significant relationships between students' anxiety and extrinsic motivation (performance-related goals) at the beginning of the course (refer to §4.5.2). Nevertheless, there are significant, but weak, negative relationships between students' anxiety and intrinsic motivation (mastery-related goals). Similar patterns are observed when investigating the relationships between students' perceived difficulty, and performance and mastery-related goals. It might be the case the students who perceived the subject as less difficult and exhibited less anxieties towards it tended to be motivated by mastering knowledge and skills in statistics. This result confirms the finding of Dunn (2014) which supports that statistics anxiety is inversely and negatively related to intrinsic motivation. However, these findings contradict the results reported by Zare *et al.* (2011) which does not confirm a significant effect of mastery goals on anxiety towards statistics but corroborates a positive effect of performance-approach goals on statistics anxiety. Somewhat contrary to this study's finding, James *et al.* (2013) demonstrates a strong positive relationship between anxiety towards mathematics and achievement motivation indicating the significant effect of mathematics anxiety on students' motivation related to their achievement. Another finding emerged from the investigation of the interview responses (refer to §5.13) is that having no or low levels of anxiety could cause a demotivation (i.e. lack of motivation) for some students, whereas a certain amount of anxiety could be a motivation for engaging and learning statistics.

The quantitative results display that there are significant positive relationships between the students' self-efficacy beliefs in statistics and the students' motivational orientations and achievement goals at the beginning of the course (refer to §4.5.2). These relationships are higher with the intrinsic motivation (mastery-related goals) than with the extrinsic motivation (performance-related goals). This might indicate that higher confidence in statistics is more likely to be associated with the motivation to engage with statistics for reasons such as mastering knowledge than the motivation to engage with statistics for reasons such as achieving high grades. From the qualitative results, it is deduced that the students who had a stronger sense of self-efficacy, they also tended to be more motivated to engage with the learning of statistics (refer to §5.13). This is congruent with the significant positive relationships which are demonstrated between competency beliefs and achievement goals in statistics and close associations between students' goals (mastery development, performance approach and extrinsic work) and efficacy beliefs in the studies conducted by Chouinard (2007) and Ng (2012) respectively. Moreover, in a recent study carried out by Lindsey (2017), a significant relationship (with a medium effect size) between students' motivation and their statistics self-efficacy at the end of the semester is reported.

The quantitative analyses suggest that students' expectations of performance are moderately related to students' attitudes, perceived difficulty and anxiety and strongly related to self-efficacy towards statistics (refer to §4.5.2). More specifically, students who had higher expectations towards their achievement in statistics tended to believe more in themselves regarding their abilities in statistics, had more positive feelings and greater interest in statistics, appreciated and valued the statistics more and exhibited less difficulties and anxieties regarding statistics. These quantitative findings are also supported by the qualitative data obtained during the interviews (refer to §5.14). Also, similar patterns have been reported in the literature. For example, Paul and Cunnington (2017), in a mixed methods study, finds that students with higher outcome expectations (that is, expected grade) placed more value and interest in statistics content and they considered themselves as more capable of mastering it. In her study, Larwin (2014) reveals a significant association between students' expected grade in the current statistics course and their statistics-related self-efficacy beliefs. By investigating the relationship between self-confidence, attitudes and expectations, Verhoeven (2009) finds that those students with low levels of self-confidence in learning statistics had lower outcome expectations and less positive attitudes than the students with higher levels of confidence did. Also, Bude *et al.* (2007) reports a statistically significant direct effect of undergraduate health science students' outcome expectations regarding success in statistics on their affective responses towards statistics.

The quantitative analyses reveal weak, but significant, relationships between control over performance and liking, interest, value, anxiety, perceived difficult and self-efficacy related to statistics. More specifically, students who believed that they had the control over their performance outcomes in statistics tended to have more positive attitudes (in terms of their liking, interest and value of statistics), possess stronger self-efficacy beliefs, perceive the statistics course less difficult and experience less anxiety in the statistics course. The analyses of the qualitative responses support some of the quantitative findings mentioned above (e.g. see §5.9 and §5.14). For example, students who perceived that they did not have the control of their learning and performance outcomes, that is, it was dependent on external factors (such as instruction, instructional methods, topics and structure of the examination) tended to report being more anxious regarding statistics, finding the course content more difficult and have low confidence in their abilities in statistics. The current results tend to confirm a previous research study on the associations between control beliefs, self-efficacy beliefs and learning attitudes conducted by Ng (2012).

Quantitative analyses show that students' effort is weakly, but significantly related to the liking, interest, value and self-efficacy in both questionnaire administrations (refer to §4.5.2). As expected, students who showed greater effort in studying and learning statistics were students who tended to have more favourable towards their liking and interest in statistics, value more the statistics subject and possess higher confidence regarding statistics. These findings are consistent with the findings of Li (2012) which demonstrates a positive relationship between students' effort, attitudes towards statistics and academic self-efficacy. The current findings also support the motivational and self-efficacy theories as described by Li (2012), which explains the associations between positive attitudes (e.g. the students regard the subject as meaningful and relevant to their educational studies and future job) and self-efficacy beliefs respectively with the effort students put forward into studying statistics. In a similar manner, Emmioğlu (2011) and Arumugam (2014) conclude that the greater the students' interest in statistics, the more the effort they devoted to the learning of the subject. Moreover, Awang-Hashim *et al.* (2002) states the role of the students' high self-efficacy in expending more effort when engaging with tasks and during an examination in statistics.

However, and contrary to my initial anticipations, negative, although weak, associations between effort and anxiety as well as between effort and perceived difficulty are detected (refer to §4.5.2). This might indicate that students who experienced more difficulties and anxieties in statistics were more likely to exert less effort. It was anticipated that students who regarded statistics as more difficult and had more anxiety would plan to invest or they invested a greater amount of effort to overcome them compared to the students who had less anxieties and difficulties. This contradicts with Tempelaar *et al*. (2007) which finds a negative relationship between difficulty and effort as measured by the SATS instrument proposing that this is rational study behaviour for students.

From the interview responses (see, e.g. §5.9 and §5.11), it seemed that students who had more favourable attitudes, expressed more interest and enjoyment in learning statistics and valued the statistics education more, they put greater effort into the statistics course. In addition, some students stated that some levels of anxiety led them to exert more effort in learning statistics whereas no anxiety might lead to investing less effort and time for studying statistics. More specifically, they argued that anxiety in 'normal levels' could be considered as good because it is a motivation for studying and putting effort. This supports the arguments of many researchers (e.g. Owuegbuzie and Wilson, 2003; Slootmakers, 2012; Macher *et al.*,2013; Griffith *et al*, 2014) who consider that a certain amount of anxiety regarding statistics can have a facilitative effect, meaning that it may motivate learners to work harder and exert more effort. Moreover, during the interviews, students also related their levels of self-efficacy to the amount of studying and effort they devoted to statistics. Some students mentioned that higher levels of confidence in statistics might result in less effort and studying since they felt confident about their abilities in mastering and doing statistics and they did not try 'enough'. On the other hand, some students mentioned avoiding studying and devoting less effort because their perceptions of ability and success in statistics were low. It seemed that the students' perceived incapability of doing or understanding statistics might result in trying to avoid or postpone the engagement with it. This is not in agreement with Schunk (1991) which supports that students who lack academic self-efficacy might put more effort and adopt effective learning strategies to compensate for their perceived lack of capability.

Based on the quantitative findings (refer to §4.5.2), utilisation of the investigated learning strategies are found to be positively and weakly associated with their liking, interest, value and self-efficacy and negatively and very weakly associated with their anxiety and difficulty in statistics. This might indicate that students who tended to utilise the investigated learning strategies (e.g. taking notes during the lecture class, putting together information from different sources, searching for extra information and exercises and focusing on understanding than on memorisation) were more likely to like, enjoy and value statistics, possess higher confidence in their abilities and experienced less difficulties and anxieties. The qualitative data provided further insights into these associations (refer to §5.11). For example, students who were searching for extra information (e.g. the on internet) were students who were more interested in the subject or faced difficulties with the statistical content. In the pertinent literature, the results of a study conducted by Mondéjar *et al.* (2008), using a sample of university students attended a course with statistical content, show how a more in-depth study process (where students adopted a more detailed way of study) eliminated their levels of anxiety and nervousness and raised the level of their interest and perceived utility to their university degree and future professional career. In a similar manner, many research studies have investigated the association between students' learning strategies and their levels of anxiety (e.g. Onwuegbuzie, 2004; Lavasani *et al*., 2011; Vahedi, 2011; Kesici *et al*., 2011) where students who employed rehearsal, elaboration, organisation, critical thinking, and effort regulation approaches reported lower levels of statistics anxiety.

Arising from the quantitative results (refer to §4.5.2), intrinsic and extrinsic motivational orientations are weakly, but significant, associated with the control over performance. This might indicate that students who perceived that they had more control of achieving the desired outcome, tended to be more motivated in statistics. Based on the interview responses, it seemed that students' attributions of the control over learning and performance to external factors, made them less motivated. These results are in keeping with Ng's (2012) study, which finds that mastery development, performance approach and extrinsic work goals are positively (although weak to moderate) associated with perceived control beliefs.

The expectations over performance in statistics are found to be weakly associated with intrinsic and extrinsic motivations, effort and learning strategies indicating that students who had higher expectations of success tended to be more intrinsically and extrinsically motivated (i.e. had mastery and performance-related goals), devote more effort and utilise the investigated learning strategies. The significant positive relations among value, effort and expectations support the Expectancy-Value theory (which is described in §2.12). In addition, a weak association is detected between expectations and control over performance indicating that students who had higher perceptions of control over their performance tended to have higher expectations of success. This is consistent with Bude *et al*. (2007) which evidences that the Health Sciences students' perceived control was significantly and positively related to outcome expectations in an introductory statistics course.

Students' effort in statistics is found to be weakly associated with their intrinsic motivation and extrinsic motivation. The relationship between achievement goals and effort in mathematics is corroborated by Chouinard (2007) which reports that mastery achievement goals had a significant impact on the high school students' effort in mathematics. In addition, effort in statistics is found to be weakly related to the control over performance indicating that students who believed that they had the control over their learning tended to exert more effort in statistics. During the interviews, the students who believed having control over the desired outcomes in the statistics course particularly stressed that their performance in statistics would be determined by the amount of effort and studying would put forward in statistics (refer to §5.14). This finding appears to cohere with those of Ng (2012), which demonstrates a positive association between effort regulations and control beliefs. Lastly, students' learning strategies are found to be weakly associated with intrinsic (i.e. mastery goals) and extrinsic (i.e. performance goals) motivations and control beliefs in statistics. This finding support Elliot's study (1999) which indicates achievement (mastery and performance-approach) goals as predictors of study strategies (e.g. deep and surface processing). As anticipated, near the beginning and towards the end of the course, effort and learning strategies are found to be moderately related indicating the students who put more effort in statistics, tended to use the investigated learning strategies – a finding which is also collaborated by the qualitative data (refer to §5.11).

> **Research Sub-Question 3.3:** Are the examined affective, motivational and cognitive engagement variables related to statistics performance and which of them can explain and significantly predict the performance?

Questionnaire data and statistical analysis (e.g. correlations and regression procedures) were employed to answer these research sub-questions (refer to §4.5.3 and §4.7). In the pre-course administration, with respect to the seven variables of interest, namely liking, interest, value, difficult, anxiety, self-efficacy and resilience (the concept of resilience is described later in Research Focus 5), weak relationships are found between the students' liking of statistics, interest in statistics, perceived difficulty of statistics, self-efficacy regarding statistics and resilience applied in statistics and the final grade the students obtained in the statistics course. The strongest associations are detected between self-efficacy and performance and resilience and performance in statistics indicating that students with higher self-efficacy and more positive resilient behaviours tended to earn higher grades in statistics. Contrary to my initial expectations, students' anxiety regarding statistics and the perceived value of statistics near the beginning of the course were not significantly related to their overall performance in the statistics course. In the post-course administration, the results indicated significant relationships between the seven variables and the final grade in statistics. Stronger associations are observed between self-efficacy and overall performance, followed by the associations between resilience and performance and anxiety and performance. Overall, based on the findings of the correlation analyses, the most of the significant correlations between the investigated variables are found to have signs (i.e. directions of relationships) as anticipated from empirical and theoretical investigations, and they also matched researcher's expectations. However, the magnitudes (i.e. strengths) of these relationships are revealed to be weaker than anticipated.

The regression analyses using the pre-course sample data indicate that six out of the seven variables of interest (except the value variable) are single predictors of performance. The multiple linear regression predicting final grades in statistics using the six significant variables (e.g. liking, interest, anxiety, difficulty, resilience, self-efficacy) accounted for 6% of the variance in statistics performance. Of those variables, students' self-efficacy and resilience behaviours in statistics are found to be the only significant predictors of performance making the largest contribution to it. Value variable is not found to either be a significant predictor of performance or significantly correlated with it indicating that the value the students placed on statistics, at least near the beginning of the course, was not so much related to the final grade they obtained in the statistics course. The regression analyses using the post-course data showed that each of the seven variables under consideration is significant on its own in predicting course grade. The multiple linear regression predicting final grades in statistics using the seven variables explain 20% of the variance in statistics performance with the anxiety, self-efficacy and resilience remained significant predictors of performance with self-efficacy followed by resilience being the strongest ones. Overall, it might be inferred that post-course students' responses were more likely to explain and predict students' overall performance in the statistics course compared to their pre-course responses. Nevertheless, the amount of the explained variability in performance is found to be relatively small. More discussion and interpretation of the relationships between these seven variables and performance is provided when answering the Research Question 19 which concerns the best fitting model for explaining performance in a statistics course.

The important role that self-efficacy has in predicting performance is aligned with results from previous studies (e.g. Naccache, 2012) which report that the most important factor associated with performance is the cognitive competence (measured as a component of the SATS attitudes scale) in both final average and final exam statistics grade. In the same conclusion reached Milic (2016) which adds that, except for the cognitive competence, affective responses and difficulty are also related to students' achievement in statistics.

Concerning the relationships between students' motivational orientations and cognitive engagement (e.g. intrinsic motivation, extrinsic motivation, expectations of performance, control over performance, effort and learning strategies) and statistics course grade, these are found to be significant, except for the relationship between control over performance and course grade. The strongest relationship is detected between expectations of performance and final grade in statistics indicating that students who had higher expectations of performance tended to (actually) perform better in the statistics course. This result confirms Verhoeven's (2009) findings that the higher the expectations of performance, the higher the outcome might be. Both near the beginning and towards the end of the course, students who reported expending more effort and using the investigated learning strategies tended to achieve higher grades in the statistics course. This is consistent with Kiekkas (2015) which reports a weak correlation between effort and examination performance in statistics. Also, Rautopuro and Vaisanen (2003) investigates and confirms the association between several learning strategies (such as reflection, self-monitoring, rote learning and elaboration) and learning outcomes (i.e. course achievement) in a Quantitative Research Methods course.

In the pre-course data, all the investigated motivation and cognitive engagement-related variables, except the control over performance variable, are found to individually and significantly predict performance. When these variables were entered in a general linear model (excluding the control over performance variable), they are found to account for 23% of the variance. The expected grade and the learning strategies variables are found to be the only significant contributors to this model developed to explain and predict performance. In the post-course data, results show that among the motivational and cognitive engagement-related variables, the effort and expected grade remained significant and the strongest predictors and determinants of students' performance explaining significant amounts of variance in the performance (namely 46.5%). These findings are consistent with Tempelaar *et al.* (2007) which demonstrates a significant direct effect of effort on statistics performance using a sample of economics and business students. This paper also suggests that both surface and deep learning-oriented strategies can aid students to achieve adequate performance grades in the statistics course.

The findings of the current study regarding the relationship and the predictive ability of various motivational and cognitive factors in performance are in line with findings from other empirical studies. For example, Marinan (2016) reports evidence that intrinsic motivation significantly predicted university students' examination performance in a business statistics course. In a similar manner, Mohsenpour, (2008), using path analysis techniques, demonstrates a positive direct impact of performance-approach goals on mathematics achievement. Also, Woodward and Galagedera (2010), using regression techniques, confirms that effort and motivations are significant predictors of achievement in an elementary statistics course. Moreover, Hood *et al*. (2012) reports that effort and expectations made significant direct contributions to performance.

In her study in 2013, Clark initially run a general linear model and then a regression model since she finds that categorical variables included were not significant predictors of students' test courses. Although, she finds that the model which incorporates pre-course measures does not explain much of the total variance in students' test scores, she reports that the factors which are more strong predictors of the achievement are measures of effort (e.g. labs and homework completed), followed by the attitudes subscales (e.g. cognitive competence, value and appreciation of statistics, affect, and the perceived difficulty of statistics). Then, she concludes that factors related to students' study habits and post-course scores on the investigated measures might account for further variability in performance which is something confirmed in the current investigation.

> **Research Sub-Question 3.4:** What is the overall best-fitting model that describes the relationships among selected affective and cognitive variables and performance in statistics?

This doctoral study proposed and tested alternative factor structures based on a sample of non-mathematician undergraduate students attending statistics courses. With regards to the overall examination using explanatory and confirmatory factor analyses (refer to §§4.8 and 4.9), a five-factor model is considered to provide the best explanation and fit of the pre-course and post-course data. The five-factor solution is also considered to be meaningful and theoretical sensible. The five factors, which are identified and defined, are: liking and interest; value; difficulty and anxiety; self-efficacy; and resilience. In order to predict the existence of causal relationships between these variables and statistics performance, a refined version of the hypothesised theoretical model (after adjustments as a result of the EFA and CFA procedures) was empirically tested using Structural Equation Modelling (SEM) techniques (refer to §4.11). The non-significant paths were eliminated from the initial models and the final pre-course and post-course models are reported.

Self-efficacy towards statistics was postulated and confirmed to have a direct influence on liking and interest, value, difficulty and anxiety, and resilience both at the beginning and at the end of the course. The results support that students' beliefs in their confidence regarding statistics could shape their dispositions towards the subject in terms of their liking, interest and value and influence their perceived anxieties and difficulties and resilient behaviours. Consistent findings are reported by Wisenbaker *et al*. (2010), which finds significant moderate standardised path coefficients linking cognitive competence to affect, value and difficulty aspects of the SATS instrument. This paper concludes that students' initial feelings, value and perceived difficulty of the course were, to some extent, derivative from their initial levels of cognitive competence to learn statistics. The direct link of self-efficacy to value, is also consistent with Hood *et al.* (2012), which shows that cognitive competence (i.e. ability belief) predicted value and also with the Eccle's (1993) expectancy-value model (see §2.12), which proposes that values are influenced by individual's self-concept and ability beliefs. Furthermore, the significant direct effect of liking and interest on difficulty and anxiety in the expected direction (that is negative) could indicate that more unfavourable dispositions in terms of liking and interest in statistics might be converted to anxieties and difficulties or might intensify them (e.g. higher levels of anxiety in statistics). The latter finding confirms claims of other researchers (e.g. Wisenbaker and Scott, 1997; Nasser, 2004). It is also found that greater value attributed to statistics resulted in more favourable dispositions towards statistics. Moreover, direct links from difficulty and anxiety to resilience towards the end of the course indicate that greater anxieties and difficulties experienced might result in applying positive resilient behaviours when learning statistics.

Furthermore, the results from SEM show that, contrary to my initial hypotheses, only two among the five investigated variables (constructs) included in the hypothesised model are found to have a consistent direct influence on students' performance. Statistics self-efficacy and resilience constructs, as defined and measured in this study, are found to be the most important (and influential) among the factors included for modelling the structure of performance in an introductory statistics course. Although both effects (i.e. structural paths) are found to be statistically significant, the effect of self-efficacy on statistics performance was larger, although not substantially, than the resilience. The finding regarding the predictive ability of self-efficacy in performance is supportive evidence of the expectancy-value model and self-efficacy (and self-concept) related theories (e.g. Bandura, 1997). It also corroborates the views of Linnenbrick and Pintrich, (2003) who proposes that students are more likely to engage and achieve when they have the belief that they have the potential and the abilities to do so. Moreover, it is also consistent with several prior empirical research studies. For example, Tempelaar *et al*. (2007), by applying SEM techniques, demonstrates that cognitive competence (which was considered as an aspect of the attitudes factor) is a strong predictor of performance in the statistics course. Moreover, Bandalos *et al*. (2003) shows that self-efficacy both directly and indirectly influences achievement in an introductory statistics course. Mohsenpour *et al*. (2008) finds evidence that self-efficacy has the strongest direct effect on mathematics performance compared to the other variables included in the model (e.g. performance goals, learning strategies and persistence).

The hypothesised direct path between difficulty and anxiety towards statistics and performance is not supported by the pre-course data. This finding is in agreement with the findings of earlier studies (e.g. Lalonde and Gardner, 1993; Nasser, 2004; Chiesi and Primi, 2010) which report a lack of direct effect of statistics anxiety in statistics performance. However, the post-course data supports the direct link between difficulty and anxiety to performance which is in agreement with other empirical studies (e.g. Tremblay *et al*., 2010; Onwuehbuzie, 2003).

From the results, it seems that the value variable does not substantially contribute much to the hypothesised model (for example, value is not found to have a direct effect on performance). The findings of this study come in somewhat contrast with the Expectancy-Value model which explains how value directly influences achievement. Nevertheless, it is consistent with other empirical studies in the pertinent literature which failed to find a significant direct path from value to statistics performance (e.g. Wisenbaker *et al*. 2000; Tremblay *et al*., 2000; Sorge and Schau, 2002; Hood *et al*., 2012). For example, Sorge and Schau (2002) reports that value's impact on statistics achievement in a required introductory course is small and not statistically significant. Moreover, in the current study, liking and interest factor is found to be significantly correlated with performance, but not directly related to performance when other factors included in the structural equation model both in the beginning and towards the end of the course. However, towards the end of the course, liking and interest factor along with the value factor are found to influence performance indirectly through anxiety. This could be explained as that the students who had more favourable dispositions towards their liking, interest and value placed in statistics were more likely to experience less difficulties and anxieties in statistics and eventually achieve higher grades in the statistics course.

6.2.2 Answer to the Secondary Research Questions and Sub-Questions

Research Question 4: What are the students' opinions about the nature of statistics and mathematics and what is the role of the previous statistics/mathematics learning experiences and background in the current statistics course?

> **Research Sub-Question 4.1:** What are the students' perceptions about the nature of statistics as a discipline/subject, the similarities and the differences between statistics and mathematics and the relation between them?

During the interviews, students shared their opinions about the (distinctive) nature of statistics as a discipline/subject (refer to §5.5). There was one student who characterised statistics as a *language*, which is accompanied by its own rules and concepts. Another student argued that one should expect and be able to cope with ambiguity and uncertainty at every stage. An illustrative comment made by a student is the following: *In statistics, you will never say that you are certain about something*. Furthermore, some students described statistics as a *methodological discipline* and talked about a *procedural nature,* where, by following the procedures, someone can reach the result. Moreover, some students touched on the logical nature of statistics, the rationale that underpins it and the necessity to have, get into or understand this logic. The requirement of thinking and reasoning (logical and critical) in statistics was pointed out along with and a *new* or *special/unique* way of thinking that statistics cultivates which other subjects are not able to do. These students' comments support the argument of Leavy *et al.* (2013) about the uniqueness of statistical thinking and reasoning. Also, some students referred to the hierarchical nature of statistics by describing it as a *logical pyramid;* a *puzzle*; a *tower*; and a *chain*. They talked about the interrelations between some chapters and they generally agreed on the necessity of building and adding to the existing knowledge and achieving a good understanding of every single chapter, topic and concept delivered in the course. The importance of developing a conceptual understanding along with acquiring interpretative skills in statistics were emphasised by most of the students. Some students pointed out the need for a (sustained level of) *dedication and commitment in statistics* and the importance of *concentration* and *focus* both in classroom settings and examination conditions. In addition, they stressed the demand for *practising and doing exercises* and the need for *paying attention to details*. This is related to a comment made by Fitzmaurice *et al*. (2014) which argues that statistics necessitates a great deal of discipline and time to learn. Lastly, one student remarked perceiving statistics as a subject that students cannot study on their own, but they require the explanation from an expert (in their case, the instructor).

During the interviews, students shared and justified their perceptions of whether they considered mathematics and statistics as different or the same thing (refer to §5.4). They talked about similarities as well as differences between statistics and mathematics they had identified from their so far learning experiences. A group of students pointed out that mathematics and statistics are different sciences/disciplines, but they cannot be separated because they are *related*, *linked with each other* and *based on one another*. These comments corroborate some authors' contention that statistics and mathematics are two distinct methodological disciplines (e.g. Moore, 1992; Chance and Garfield, 2002; Zieffler *et al*., 2008; Carmichael *et al*., 2009). Many students reported that there is a close relationship between mathematics and statistics since statistics *come from mathematics* and has *its roots in mathematics* and they recognised that statistics *involves mathematics*, *borrows things from mathematics* and particularly has a *mathematical base*. The perception that statistics is more specialised whereas mathematics is more general and broader was also stated. They considered statistics as a *branch*, a *subset*, a *subfield* and a *part* of mathematics, which has other pre-requisites, other applications and uses and different outcome aims from mathematics. There were students who mentioned similarities in the problem-solving techniques, but differences in the methods, approaches and tools when dealing with problems and exercises. Notably, one interviewee stated: *Both mathematics and statistics are tools we use to model and understand the world, but they do so in very different ways using different approaches.* Some students believed that in statistics is not only about reaching to the solution - which in the most cases represent something - but also to be able to understand it, interpret it and write conclusions. This comment stands in line with the prepositions shared by Gal and Garfield (1997) that when solving context-bounded statistical tasks, students need to render reasoned interpretations of data, reasoned descriptions, judgments and inferences. A few students also compared the reasoning and the way of thinking and understanding in mathematics and statistics. and they claimed that a distinct way of thinking and logic is required when doing statistics. This claim supports the proposition that “statistics requires a different kind of thinking because data are not just numbers, they are numbers with a context” (Cobb and Moore, 1997, p. 801).

In addition to this, students were asked to compare the statistics course they attended the current semester with mathematics courses (such as Algebra) they had already completed in previous semesters at the university level (refer to §5.4). The students mostly commented about the course content (for example, about the chapters and the interrelations between them) and the involvement and connection between theory and practical applications. In general, they found the way of teaching and delivering the subject material quite similar.
The students’ perceptions about the involvement of mathematics in the current statistics course were assessed using both the quantitative and qualitative components. In the questionnaire statement whether statistics involves lots of mathematics, at the beginning of the course, approximately half of the students were in agreement with it whereas towards the end of the course this number was diminished (refer to §4.3.2). This finding could be possibly explained by the claim that students after their exposure to the statistics course, recognised that statistics course might have some mathematics pre-requisite knowledge and skills, but the emphasis is placed more on the statistical practice rather than on strict mathematical foundations and is not heavily mathematically oriented. Based on the interview data (refer to §5.5), the majority of the students contended that the statistics course involved basic mathematical knowledge, required simple operations/calculations and did not need an advanced knowledge of mathematics or a very good background on it. Some students particularly noted some basic mathematics pre-requisites such as: doing operations with numbers; mastering of equations and inequalities; solving integrals and derivatives; and reading and producing graphs and tables. On the other hand, one student argued that statistics involved a lot of mathematics that cannot be avoided.

> **Research Sub-Question 4.2:** What are the students’ previous mathematics and/or statistics background, performance and learning experiences and are these related to their affective perceptions and performance in the statistics course?

Both questionnaire responses and interviews were consulted to assess students’ previous mathematics and/or statistics background and performance in high school and university. Almost two-thirds of the students, which participated in the pre-course administration, attended an advanced mathematics class and nearly one-third a core mathematics class in high school. The mean score of the reported matriculation examination grade in mathematics was approximately 15 out of 20 which is considered as an ‘average grade’. Regarding the previous university mathematics background and performance, the majority of the students (43.6%) had not completed a mathematics course before followed by the number of students (32.4%) who had attended two or more courses, and then by the number of students (23.9%) who had completed one mathematics course. The average mean score of the reported mathematics course grades was approximately 67 out of 100 which corresponds to a ‘good grade’ based on the public universities grading scheme. More information is provided in §4.3.1.

During the interviews, students described and reflected on their previous background, performance and overall learning experiences with mathematics and statistics courses in previous years (secondary and high school). They also shared their experiences with mathematics/statistics courses they had completed at university level before entering the current statistics course (refer to §5.4). Students tended to attribute their engagement, learning process and ultimately their good or bad performance in mathematics to: the mathematics teachers and their way of teaching; the perceived difficulty of mathematics (e.g. problem-solving difficulties); the amount of studying, effort and attention they had personally devoted; their opinions, attitudes and interest in mathematics; their perceived mathematical abilities and their personal characteristics or attributes. The mathematics teachers seemed to greatly influence students' opinions about mathematics, interest towards mathematics, perceived confidence and uncomfortable feelings regarding mathematics. These findings broadly support earlier research studies (e.g. Eden *et al.*, 2013; Prayoga and Abraham, 2017) which reports evidence that prior bad experiences with mathematics could be transferred to future mathematics-related or –based learning experiences.

In addition, some students compared the statistics component they had been taught in high school (as a part of the mathematics course) and the current statistics course. Especially, some students from educationally-related degrees stated that the subject matter of the university course (at least, the chapters which included descriptive statistics and probabilities) was related to the statistics they were exposed in high school, but at the university level, these were delivered to them at a more advanced and deeper level. Nevertheless, a point stressed by an interviewee was that even she perceived the level of statistics in the university more advanced than in high school, some things were more understandable and clear to her now (in university). The good preparation in high school (for example, solving university-level exercises from high school) seemed to help the students in the current statistics course.

During the interviews, students were also requested to recall any exposure to statistical-related topics they had and any statistics concepts they remembered they had been taught before attending the current statistics course (refer to §5.4). Many students noted that some things were familiar to them from high school mathematics, such as the probabilities and combinations, the distributions and the measures of centre and dispersion (such as the standard deviation). Similarities between high school and university statistics were noted on the way of thinking and the logic, but also differences on the symbolism and the way of solving the exercises However, the weakness of recall any statistical knowledge was mostly shared by males (who mentioned the gap between high school and university due to the military responsibilities). Notably, one student argued that he could not remember anything from the statistics he had done in high school (a *blackout* as he described it).

Concerning the role of the previous mathematics background and performance in the students' attitudes, anxiety and self-efficacy towards statistics, the quantitative analyses demonstrate significant associations between the type of the mathematics course and the high school grade in mathematics and their liking, interest, value, difficulty, self-efficacy and anxiety in statistics at the beginning of the course (refer to §4.5.4). It can be postulated that attitudes (e.g. liking, interest, value) and self-efficacy were significantly greater and anxieties and difficulties were significantly lower for the students who attended a higher level of mathematics course in high school (that is, advanced mathematics) and/or achieved a better mathematics grade in the matriculation exam. In addition to this, the majority of the students at the beginning of the statistics course were in favour with the questionnaire statement whether previous experiences with mathematics (positive or negative) have influenced their opinions about statistics (refer to §4.3.2). These quantitative findings are indicative of the importance of prior learning experiences with mathematics in shaping student's affective responses and perceptions regarding statistics. In the pertinent literature, Carmona (2005) shows evidence that students' self-reported mathematics grade obtained in secondary education were significantly related to students' affective responses and self-perceptions regarding statistics (i.e. cognitive competence). Paul and Cunnington (2017) also reports that the students, who self-rated higher the perceptions of their performance in mathematics subjects they had taken in the past, had greater perceptions of cognitive confidence. Moreover, the findings of this study are in line with Birenbaum and Eylath (1994) and Paechter (2007) which identify that mathematics grades at school were negatively associated with statistics anxiety.

The results of the quantitative analyses suggest that students' liking, interest, value, difficulty, anxiety and self-efficacy in statistics also varied as a function of the number of mathematics course they had previously completed at the university level (refer to §4.6.4). More specifically, students who had completed two (or more than two) mathematics courses had more favourable attitudes and behaviours (regarding their liking, interest, value and self-efficacy) towards statistics than those who had not attended any mathematics courses before or they had attended just one. A plausible explanation might be that the more mathematics classes taken were likely to give the students the experience and provide them with a closer engagement with mathematics-related subjects in order to like, enjoy, value, have more confidence in statistics (note that causation cannot be inferred in this analysis). This finding coincides with Larwin (2014) which presents evidence that the number of college-level mathematics courses completed is significantly associated with the students' level of statistics-related self-efficacy. Moreover, students who had completed one mathematics course perceived the statistics course more difficult and experienced more anxieties than those who had attended none or two (or more than two) mathematics courses before. Responses in the interviews helped in interpreting this finding. It might be the case that students, who had already undertaken a course in mathematics, found the current statistics more difficult and experienced more anxieties because they had already had some exposure in mathematics and they might have experienced difficulties and anxieties in these courses that they transferred to the current statistics course. Nevertheless, more research is needed to explain this phenomenon.

Moreover, weak, but significant, relationships are found between the average grade achieved at previous university mathematics courses and the students' liking, interest, value, anxiety and self-efficacy in statistics with the strongest relationship being with their self-efficacy beliefs (refer to §4.5.4). Thus, it can be postulated that previous performance in mathematics-related courses might impact students' attitudes, behaviours and perceptions of competence in statistics, especially at the beginning of the course. The findings of this study are congruent with those of earlier studies, which report an association between previous mathematics background and students' attitudes towards statistics. For example, Hannigan (2014) finds a strong association between how the students felt they performed in mathematics (in school or college) and various attitudes components (e.g. affect, value, cognitive competence, interest) indicating that the higher the self-rating performance in mathematics, the more favourable the students' attitudes towards statistics were.

From the interview responses (refer to §5.4), it is revealed that students' feelings and attitudes regarding statistics (especially at the beginning of the course) were associated and somewhat influenced by their previous learning experiences with mathematics courses, achievement in these courses and previous mathematics teachers. It seemed that, at least at the beginning of the course, a previous good performance in mathematics and positive experiences with mathematics might give confidence in the students that can perform well in statistics and counteract the presence of anxiety towards the subject and the opposite direction. It is worth noting that the majority of the students who had previous experience of attending the same or another statistics course at university level shared unpleasant and/or unhelpful experiences with statistics and previous instructors in statistics. Based on the questionnaire responses (refer §0), the quantitative analyses indicate that students who had attended a statistics course in the past were less interested in engaging with statistics at the beginning and at the end of the course compared to the students who had never attended a statistics course. The findings of the current study are somewhat contrary to some other studies (Mills, 2004; Rhoads and Hubele, 2010; Lalayants, 2012) which report that previous exposure to statistics and attendance in college-level statistics courses respectively was related to more positive attitudes towards the current statistics course.

Both quantitative (refer to §4.5.4) and qualitative (refer to §5.5) strands of the research study provided insights into the extent to which attitudes, anxiety and self-efficacy regarding statistics are parallel with those regarding mathematics. Students' attitudes (e.g. liking, interest, value) towards mathematics are found to be moderately associated with the students' attitudes towards statistics. Also, weak to moderate relationships are found between anxiety and difficulty in mathematics and students' attitudes towards statistics. This outcome might indicate that higher levels of mathematics anxiety and perceived difficulty of it was more likely associated with low levels of liking, interest and value of statistics. The direction, but not the magnitude of the relationships, is consistent with Nasser (2004) which presents evidence of a strong adverse effect of mathematics anxiety on students' attitudes towards statistics. In the current study, a moderate relationship is found between the students' anxiety towards mathematics and their anxiety towards statistics. This empirical finding might to some extent support the proposition of Onwuegbuzie and Wilson (2003) which argues that the anxiety towards mathematics is transferred to statistics courses and it can be transformed into statistics anxiety. In addition, students' self-efficacy in mathematics (including perceived mathematical abilities, and numbers and calculations competence) is found to be weakly to moderately correlated with students' attitudes towards statistics. This is somewhat consistent with Coetzee *et al.* (2010) which shows evidence of significant associations between students' attitudes regarding statistics and their perceptions of their performance in mathematics in high school and their current performance in mathematics in university. Particularly, moderate significant correlations are found between students' self-efficacy regarding mathematics and self-efficacy regarding statistics. This outcome is in agreement with the findings reported by Finney and Schraw (2003), which demonstrates that in the two questionnaires that were explicitly designed to measure statistics self-efficacy, this was found to be related positively to mathematics self-efficacy.

Based on the interview responses, students who considered statistics as being more interesting than mathematics stated reasons such as that: statistics was not just numbers and (mechanical) calculations; the unfamiliarity and novelty of statistics stimulated their interest and curiosity; and they found the statistical thinking more challenging. On the other hand, students who stated their preferences towards mathematics perceived it among others: as easier; more straightforward; does not deal with probabilities and uncertainty; and does not require interpretations. Regarding their perceived competence in both subjects, students' confidence in mathematics was influenced by previous performance and mastery experiences, social comparisons with classmates or peers, opinions from teachers or closed environment (e.g. parents) whereas confidence in statistics was more influenced by their performance and mastery experiences in the current statistics course. Concerning which discipline/subject they perceived as more valuable and applicable to their field of study and future career path, divergent views were stated. Also, it seemed that students recognised the value of both mathematics and statistics for their everyday relevance and application.

To what extent do the students' prior mathematics background and achievement were related to their statistics performance was assessed using the quantitative component of the study (refer to §§4.5.4 and 4.6.4). Students' prior mathematics achievement in high school and in university (in terms of the high school mathematics matriculation grade and the average grade in mathematics-related previous courses obtained) is found to be weakly related to their performance in the current statistics course. Significant differences in students' performance in statistics and the number of mathematics courses they had previously attended are also detected. Unexpectedly, the average grade obtained in statistics by the students who had not attended any mathematics course was higher than the average grade obtained by the students who had attended at least one mathematics course in the past. Also, students who had previously attended two or more mathematics courses are found to perform higher on average than those who attended one. The latter finding is somewhat expected since it is believed that the better the students' performance in previous mathematics-related courses, the better would be their performance in the current statistics course. Moreover, the students who attended a core mathematics course in high school are found to significantly perform better on average than the students who attended an advanced mathematics course. A review of the high school curriculum along with the students' interview responses aided in explaining this finding. One possible explanation is that the curriculum of the core mathematics course in high school includes a larger component of statistical topics compared to the advanced mathematics course. The students who had completed a core mathematics course might have been exposed to statistical content to a greater extent than students who had completed an advanced course, and this might benefit and help students to perform better in the statistics course at university level. Our findings are not entirely in agreement with Dupius's (2012) study, which in a sample of college students in the United States, reports that those with stronger prior high school mathematics performance (which was reflected in success in mathematics courses completed in high school) obtained higher grades in an introductory statistics course. However, the above study fails to find a significant relationship between the type of the mathematics curriculum students completed in high school (which might include less or more exposure to statistical topics) and the grades they obtained in the statistics course. Moreover, it was somewhat unexpected to find the students who had attended the current statistics course for the first time performed better than the students who had previously attended a statistics course in the university. This result may be explained by the fact that commonly students who had taken the statistics course before were students who failed on passing it the previous time (s) or students who attended the course in other universities.

Nevertheless, the results mentioned above (especially the anticipated ones) have to be interpreted with caution. First of all, the students who had completed a core mathematics class in high school and had not attended a mathematics course in university before, there were students who, in the majority of them, came from educational, social and life sciences-related degrees. Thus, the attainment of a good grade in the statistics courses offered in these degree programmes might be easier than in the courses provided to more mathematically demanded degree programmes. The level of the difficulty and the demands of these courses might also be different. Statistics courses, which are designed for more mathematically oriented degree programs, are considered to have greater difficulties and demands compared to the ones, which are designed and offered to the social and life sciences-related degree. As a final remark, it is acknowledged that there was a variation in mathematics courses offered at the university level in different departments at various higher institutions. There might be variations, among others, on the credits earned in these courses (which might reflect the difficulty of the course), the course content and learning objectives (see §§3.5.3 and 7.2 for more information).

Quantitative analyses results (refer to §4.7) show that the number of mathematics courses completed in university and the average grade obtained in these courses as well as the mathematics grades achieved in high school matriculation exams, when combined, were significant predictors of the performance in the statistics course explaining almost one fifth of the total variability of it. This finding collaborates with earlier research studies which evidence that past mathematics background and performance are significant predictors of achievement in statistics (e.g. Hood *et al*., 2012 and see §2.3).

In addition to this, at the beginning of the course, more than one-third of the students were in disagreement with the questionnaire statement whether someone should be good at mathematics in order to succeed in the statistics course with that percentage to increase to nearly the half of the students towards the end of the semester (refer to §4.3.2). During the interviews (refer to §5.4), there were students who mentioned that those students who had any previous or recent contact with mathematics or/and statistics, they might face fewer difficulties and challenges when engaging with statistics in the current statistics course. The opinion that a previous introduction to statistics (at university) might benefit the learning process and performance in the current statistics course rather than the number of mathematics courses completed and the performance in these courses was also stated. Moreover, it was pointed out by many students that the mathematical background can be an advantage while learning statistics since it might help in *practising and sharpening someone's mind*, *developing mathematical thinking* and *gaining familiarity when dealing with numbers and operations*. Nevertheless, one student claimed that the absence of a previous strong or appropriate mathematical background could be compensated with more studying and effort in the current statistics course.

<u>Research Question 5:</u> Are there any significant differences in affective, motivational and cognitive orientations related to statistics, and in students' performance, with respect to various socio-demographic characteristics?

Various demographic and educational-related factors were examined whether they had an effect on the constructs of interest including students' overall course performance. This investigation was carried out using the questionnaire data (refer to §4.6). Regarding the gender factor (refer to §3.11.1 for the gender breakdown), in both questionnaire administrations, no differences are identified between male and female students in their liking, interest and the value they placed on statistics, their perceived difficulty of statistics and their levels of self-efficacy towards statistics. Earlier research studies also demonstrate that gender does not significantly influence attitudes towards statistics (e.g. see §2.10). Nevertheless, there are studies, which find evidence of female students displaying more negative attitudes towards statistics than male students (e.g. Coetzee *et al.*, 2010; Bechrakis, 2011; Tempelaar *et al*., 2011; Paul and Cunnington, 2017). In the current study, differences are obtained between the two genders regarding their self-reported anxieties towards statistics both at the beginning and near the end of the course. More specifically, as indicated by the higher mean values, female students reported experiencing significantly higher levels of anxiety than male students. This might reflect real gender differences, but it might also be the case that male students avoided admitting that they were nervous or anxious about statistics. This finding is consistent with a research study conducted by Papanastasiou and Zembylas (2008) in a sample of 472 undergraduate students (87.3% were women) in the Department of Education at the University of Cyprus. The study shows evidence that females who had completed a research methods course (including the quantitative component) reported higher levels of anxiety compared to males. In the current research work, even females are found to be more anxious towards statistics, a significant effect of gender on effort expenditure and learning strategies also indicate that females appeared to be more likely to utilise the learning strategies investigated in the study and exert more effort in statistics. This chimes with the findings of Fullerton and Umphrey (2011) which demonstrates that even though women were more anxious than men, they applied more effort and worked harder than them. Other studies also report that female students tended to utilise more often a wide range of learning/cognitive strategies than male students (Lee and Oxford, 2008; Rodarte-Luna and Sherry, 2008).

At the beginning of the statistics course, females are also found to be more intrinsically and extrinsically motivated to learn statistics than males. These differences might suggest that females were more likely to be motivated and set up current and future goal orientations to attain the desired outcomes. In the pertinent literature, Bude *et al*. (2007) reports no significant differences between the female and male students on all the examined variables related to the motivational processes (e.g. control, outcome expectancy and effort). Lastly, the quantitative analyses disclose no significant differences in students' final grade obtained in the statistics course with respect to their gender. This finding is consistent with the results reached by earlier studies (e.g. Cashin and Elmore, 2005; Haley *et al*., 2007; Bechrakis *et al*., 2011) which find no significant differences between male and female respondents in statistics course performance and contradicts with other studies (e.g. Dupuis *et al*. 2012) which report that females obtained higher grades in college statistics than males.

Regarding the age group factor (refer to §3.11.1 for the age group breakdown), students in the age group of 17-24 do not find to significantly differ in their answers from the students in the age group of 25 and above regarding their affective responses and perceptions (e.g. liking, interest, value, difficulty, anxiety and self-efficacy) towards statistics. This finding is consistent with a study conducted by Bui and Alfaro (2011) which shows evidence that the two group of students, traditional students and non-traditional students (age 25 or older) did not differ in their anxiety levels regarding statistics. However, contrary to this study's findings, there are studies which report that older students held more negative attitudes (Zhang *et al*., 2012), exhibited higher levels of anxiety (Watson, 2003; Baloğlu, 2003; Zhang *et al*., 2012) and had more difficulties in mastering the material presented in statistics courses compared to their younger counterparts (Zhang *et al*., 2012). On the other hand, Coetzee *et al*. (2010) shows that older students found statistics to be less difficult and Nguyen *et al*. (2014) reports that older students experienced lower anxieties in statistics compared to the younger students. In this study, students in the age group of 17-24 appeared to be more extrinsically motivated (e.g. had set up performance approach-related goals) than students who were in the age group of 25 and over. Moreover, no significant differences are detected in students' final grades in the statistics course regarding their self-reported age group.

<u>Research Question 6:</u> What suggestions and ideas do the students propose for improving the statistics education experience at the university level?

This research study intends to elicit students' experiences and opinions about the statistics course they attend and congregate their ideas to improve the statistics education learning process and experience. During the interviews, students offered their suggestions and ideas about how the statistics course can be improved and how the teaching and learning of statistics can be more effective. These issues were addressed and further suggestions are offered by drawing on students' ideas and feedback and relating them to the pertinent literature. It is worth mentioning that one student pointed out that he could not make any (constructive) suggestions since, prior to the current statistics course, he had not had any experience of doing and learning statistics in a formal level to have a point of reference and say which things could be better or could be improved. It might be the case that students who had previously attended a statistics course at university and might have experiences of different learning environments and instructional approaches in statistics, might be in a better position to reflect on them, compare them and offer suggestions.

Among the changes that students suggested was related to the content of the course and more specifically to the incorporation of more practical exercises and less theoretical-related subject matter. Students seemed to prefer applying the theoretical things in practical applications and practising instead of abstract ideas and thinking (see §5.5). One student recommended that the theory should only be taught for informative purposes and constitute the basis and foundation for solving the practical tasks, but students should not be examined on it. Some students claimed that the course would be more interesting and useful if it were more practical. These commented further support the suggestion of Bude *et al*. (2007) that the statistics course could be more attractive and interesting for the students if it is less theoretical. The importance of learning to work with real - and often big or/and messy- data was also stated by the students. There were interviewees who particularly proposed that the students could be offered the opportunity to carry out a small research investigation (e.g. on a topic of their choice that is related to the statistical subject material) and engage by themselves with the phases of a statistical and research investigation process such as the development of the measures (e.g. questionnaires), the collection and the analysis of the data and the reporting of the results. As one of them further noted, the statistics course should provide to the students - except for the knowledge- the essentials of being good researchers including *active participation*, *vigour* and *cooperation*.

Moreover, there were students who preferred to be given more exercises for practising in statistics. In addition to the greater amount of exercises, a greater variety of examples was also requested by the students in order to be able to: *understand the theoretical concepts better*; *be more prepared for the examination topics;* and *be familiar with the possible ways of encountering different kind of problems in further academic studies (and not only).* Two students recommended giving to them a set of exercises at the end of each week or each chapter for more practise and understanding. For these reasons, the extension of the tutorial sessions' time (for example, to last more than one hour) was also proposed. Although it was in case in some statistics classes, some students suggested that, except the practise exercises, previous examination papers (preferably by the same instructor) should be available to the students to aid them formulating their expectations regarding the structure, the types and the difficulty of the exam topics and questions. Related to that, many students stressed the importance of clarity and wording of exercises (especially exam exercises).

The suggestion more frequently shared by the interviewees was the integration into the statistics course of more real-life applications and real-world connections as well as major-related and career-oriented examples. It was apparent from the interview responses, the students' desire to be exposed more explicitly to the usefulness of statistics and be taught examples that they have relevance, application and meaning in a realistic sense. For example, one student mentioned the 'throwing a dice' examples and he stated preferring to be taught examples that are more tangible. The connection of statistics with other disciplines (and foremost with their discipline), the relevance to their chosen degree and future career path and the applicability to practical situations were flagged as crucial by the students. One student particularly mentioned that the instructor could inform the students how the examples can be practically applied. In the same vein, there were students who stated that the statistical topics and the choice of the examples could be more specialised and oriented to the field of their studies. In addition, some students argued that there were topics in statistics, where the instructor covers them in a greater depth than the students believed it was necessary. Thus, they recommended the consideration of the level of depth of each topic based on students' major or specialisation.

The incorporation and the use of technology in the statistics course was another suggestion made by the students (see §5.16 for more information). There was a general agreement among the students that the use of technology (e.g. computers, projectors and interactive whiteboards) and the incorporation of learning a statistical software program should be done in appropriate ways. One student notably mentioned that technology should be used as an adjunct to learning statistics. Some students stressed the importance of learning to do statistics by hand before learning to apply it using statistical software programs. Most of the students did not support either only face-to-face traditional lecture approaches using boards or just technology-based lectures, but a blending or a combination of these methods.

A hybrid teaching approach in statistics is proposed by other researchers as well (e.g. Boora *et al*., 2010; Judi *et al*., 2011; Zheng and Zhou, 2011). Also, both paper-based and technology-enhanced learning resources in a statistics course were recommended by some students. The supporters of the incorporation of technology and the learning of a statistical program argued that it would probably make the course more understandable, practical, enjoyable, relaxed and useful especially for their future profession and career. However, there were mixed views, whether it would make the course easier or more difficult. As it was stated, it would make it more difficult since it might be an extra burden of the course adding to the already existing heavy workload. For the small number of students who did not support the incorporation of learning a statistical program in the statistics course, this opinion seemed to be related to the lack of technology competence, perceived difficulty of using technology and the lack of perceived value of the affordances of learning such a program.

The opinion that the incorporation of technological and visual tools (such as pictures, videos, tables, graphical representations, statistical illustrations) and the learning of a statistical program might help in the improvement of their learning process and performance was shared. Nevertheless, it was particularly stressed the importance of the instructor's methods of teaching the statistics program, the guidance and the support that he/she offered in order to promote the students' learning instead of impeding it. One student, who was exposed to the learning of a statistical program (that is, SPSS), mentioned that she needed to devote more time on learning how to use the particular statistical software than carrying out the statistical tasks. Related to that, another student, pointed out that a greater amount of time on exploring and familiarising with the program is needed before introducing the more advanced topics in statistics. Moreover, a recommendation made by a student was that another course (which can be called Computational Statistics), as a supplement to the current introductory statistics course, could be offered to the students. This course can include the learning of basic programming rules, organising and analysing data and solving tasks related to statistics.

A considerable number of students reflected on their preferences for instructional approaches and styles when learning statistics (see §5.15 for more information). The majority of the students referred to the existing ones. However, the was a group of students who generally seemed to be unsatisfied with the current pace of teaching – which they found it quick – and proposed a more appropriate pace which takes into account the diversity of the prior background and abilities and the level of understanding of the students in each class. Also, the intensive structure and the substantial amount of the course content along with the need to learn new things continuously were mentioned with a possible suggestion given to be the reduction of the curriculum demands and the workload of the statistics course. Moreover, some students talked about the explanations of the material presented to them and mentioned that they wanted it in a more simplified form and to the point. In addition, there were students who talked about the improvement of the design of activities in the statistics course so that the students can learn and work independently as well as collaboratively in order to exchange ideas and shares methods and results. As a last remark, there was a student who mentioned preferring to have lectures in statistics – which would be presented in power-point slides instead of writing notes – and discuss them in the classroom. He would like, if it was possible, to have more discussion in statistics, see debates to be taking place and the students to have the opportunity to express opinions, for example, how to alternatively solve an exercise or what other solutions might exist.

6.3 Further discussion, recommendations and implications of the findings

In this section, the key findings of the present study and the findings which are considered as particularly important or interesting are revisited, summarised and discussed further along with emergent findings, which are not covered when addressing the research questions (and sub-questions) in §6.2 and warrant further discussion. The data analysis yielded some findings, which might be worth investigating further in future studies. Some of the results of this study are expected and supported previous empirical studies and theoretical propositions reported in the literature. However, some unanticipated findings are observed. It is believed that the findings of the current study can provide some educational implication for practice. Accordingly, recommendations and implications of the results for teaching and learning statistics at the university level (to the local and general context) are proposed and briefly discussed. It should be noted that the instructional strategies recommended throughout the section are informed by and considered evidence from the research study (e.g. students' suggestions and recommendations), the researcher's suggestions and suggestions extracted from the literature. However, it is acknowledged that there is not a 'perfect' learning-teaching environment and some of these suggestions might not be feasible. The context and the nature of tertiary institutions (such as university standards) might influence instructors' teaching practice and impose (real-world) constraints in them which might not make it possible in crafting instruction the way they might want. The instructor's 'task' is often not easy taking into account several factors such as the regulations of each university, the pre-determined statistics course curriculum and the degree of flexibility, the availability of the resources and the allocated class time. It is not the intention of this discussion to necessarily 'point out' to the statistics stakeholders, instructors or students what can they do; instead is to provide a reflective account to inform and 'stimulate' them. Moreover, it is not contended that the instructors do not follow particular instructional practices; however the instructors (and not only) could use the knowledge generated from this study and gather information that might aid them to enhance their own instructional practices and consequently, the students' learning in statistics.

6.3.1 Favourable dispositions and attitudes towards statistics

Both quantitative and qualitative strands of the study inform the evidence and the arguments made in this subsection. The majority of the students who participated in the current research investigation expressed favourable dispositions and attitudes towards statistics, including liking of statistics (as a discipline and regarding the subject content of the course) and interest towards learning statistics and studying for the statistics course. The tendency of more positive dispositions was present both near the beginning and towards the end of the semester. Also, in general, favourable dispositions towards statistics before attending the statistics course seemed to be sustained and after attending it, while some pre-existing negative or unfavourable dispositions found to be improved after the enrolment and the engagement with it. There were students who had not previously attended a statistics course and despite any possible initial reservations about it, they shared favourable dispositions regarding statistics at the time of the interviews. This general picture of prevailing positive attitudes might be a possible reflection of the experience with the current statistics course. The interview data highlights that students' perceptions and attitudes towards statistics sustain or are open to alter. The nature of the course (being quantitative and practical), the statistical content, the perceived ease of the subject, their self-confidence regarding statistics, their understanding of it, the appreciation of the usefulness and applicability of statistics the instructor have the potential to positively influence their attitudes towards statistics. Also, the qualitative findings suggested that the students might enter a statistics course with pre-determined opinions and attitudes, for example, a negative bias or misconceptions regarding the statistics discipline/subject (which were related to previous negative or unpleasant experiences with mathematics/statistics courses and instructors; previous perceived or actual failures in these courses; and/or opinions transferred to them from others (such as family members, friends, senior students) but the statistics course experience could probably alter them. It seemed from the interviews that initial negative perceptions related to mathematics, which might be transferred to statistics, tended to be reduced over the course of the semester. Thus, it might be postulated that students throughout the statistics course had their own experience in statistics, became more informed about it and formulated their dispositions and attitudes based on this experience. Nevertheless, it is proposed that more attempts and greater efforts are needed to sustain or engender more positive attitudes and views towards statistics.

A finding of the current study, which is deemed as worthwhile to be re-stated is that students' liking of statistics and interest in studying and learning statistics are found to be closely related. This is supported by both the quantitative part (e.g. strong correlations between these two variables and they form one single factor in factor analysis, see, for example, §§4.5.1 and 4.8) and the qualitative part (e.g. where students seemed to use the words like, love and enjoy interchangeably, see §5.5) of the study. In the pertinent literature, there are numerous research studies which have investigated the liking aspect as a part of the affective component of an attitudes subscale and the interest construct as an additional component of the attitudes subscale (e.g. Coetzee *et al*., 2010; Tempelaar and van der Loeff, 2011; Stanisavljevic *et al*., 2014). In some other studies, interest in statistics is treated as a motivational-related characteristic or construct (e.g. Schiefele, 2011; Sproesser *et al*., 2016). Future research studies could investigate more thoroughly and provide a better picture of the potential distinction between these two constructs.

An additional finding of this study was the general awareness of the usefulness, applicability and relevance of statistics for the everyday life and their respective degree of choice and future profession among students from a variety of disciplines and majors. However, the quantitative analysis reveals that the students' perceptions about the value of statistics, although they stayed favourable, tended to decline from the beginning to the end of the statistics course. It was prudent to search for possible reasons behind these changes and interview data helped towards this direction. A reasonable explanation might that the students embarked on the statistics course with positive dispositions towards the value of the subject and near the end of the course, they might believe that they had not 'seen' the applications or the realistic examples they had anticipated. Students, by the end of the course, might not be necessarily convinced regarding the utility and the benefit of the statistics course they currently attended which might be a result of potential lack of real-life and career-oriented examples or tasks. There were also students who reported not finding statistics useful in their academic studies or their specific professional goals or/and they could not see any applications of statistics in everyday life. These findings suggest the need for statistics courses stakeholders to nurture and promote an (even) greater appreciation of statistics as a discipline and as a subject by trying to design the courses in ways and means that these changes would be in a more positive direction. It is not unreasonable that students were in pursuit for finding relevance, application and 'meaning' of statistics in their field of specialisation and they did not wish to learn things that they might never use or practically apply outside of the statistics classroom (now or in the future). To this end, the curriculum of the statistics courses, as well as the instructors and their instructional approaches, can focus on improving students' appreciations and perceptions of the power and the benefit of the statistics course content especially outside of the educational classrooms. I propose that instructors could initiate or intensify their discussions regarding the usefulness and the relevance of statistics for all the disciplines, but give more emphasis on the particular students' field of specialisation, especially for those where this relevance might not be so explicit or obvious. It is believed and supported by the findings of the current study that if the students see or recognise the value and the importance of the statistics subject (and the course) beyond and above the exercises or tasks they are required to carry out, they are more likely to like the subject and be enthusiastic about it.

6.3.2 Moderate levels of anxiety and perceived difficulty towards statistics

Results from both qualitative and quantitative parts of the study informed the comments and arguments posed in this subsection. Regarding the perceived difficulty of the subject, in general, the participants of the study considered the statistics course neither difficult nor easy. I was more interested in exploring the particular topics and aspects of statistics that students found or perceived as difficult. Probabilities chapter was revealed in the interviews to be the content that was associated with the most difficulties and challenges experienced by the students. Also, both quantitative and qualitative results indicate that students found it more difficult to understand statistical concepts than to apply statistical methods. The nature of statistics and its inherent uncertainty (the language, terminology and symbols used and the need for interpreting the statistical results and writing justifications and conclusions) were among the aspects, which were found to engender more difficulties to the statistical learners rather than others based on the interview responses. Some students mentioned 'sudden' exposure to new or unfamiliar things because they had no or inadequate previous introduction and exposure to statistics at the high school (secondary) level or/and because of the gap between high school and university. This is unsurprising taking into consideration the possible lack of (or little) exposure to statistical-related topics and concepts during high school (or even primary school). Other causes of difficulty included the quantity of the information to be digested (usually in a short period of time) and the workload of the course. As might be expected, greater difficulties were more frequently shared by social science-related majors, including psychology, sociology and education (primary and pre-primary). Future research studies could focus on these particular groups of students, concentrate on the 'problematic' topics mentioned above, try to explore and understand further students' sources of difficulties and identify how instructional practices could help in overcoming them. Some recommended instructional approaches are provided throughout this section.

Regarding anxiety towards statistics, the main antecedents of it even before attending the course, as mentioned by the students, were previous experience with mathematics/statistics courses and teachers and perceived mathematical/statistical abilities. Based on the quantitative data, on average, the participants demonstrated moderate levels of anxiety towards statistics both near the beginning and upon the completion of the statistics course. I was more interested in the sources and antecedents of any types of anxieties that students experienced throughout their enrolment in the statistics course, which lasted one semester. From both the quantitative and qualitative strands of the study, it is apparent that examination and test anxiety, as well as performance and grade anxiety, were among the most dominant and common sources and states of evoking anxiety and nervousness to the students. The students seemed to be anxious regarding aspects of the course that might affect their performance in the course. For example, students were more concerned about an upcoming test/examination in statistics, were more anxious during a test/examination in statistics and worried about their performance on it. However, the students did not seem to be anxious about attending a statistics class or completing an assignment in statistics. The reason might be attributed to the nature of assignments (e.g. exercises, projects) and whether they were formally graded or not. This is not unsurprising if we consider the competitive nature of a university degree programme and the uncomfortable feelings that examination preparations and conditions can promote. More related to the statistics discipline/subject, the nature of statistics and the nature of learning statistics such as being quantitative and practical, mathematical/statistical computations involved, new, unfamiliar or perceived difficult topics, specific chapters such as probabilities, requirement of thinking and reasoning along with problem-solving techniques were among the main reasons stated by the students as raising their anxiety levels throughout their engagement with statistics.

Except for the strategies that students can utilise to cope with any potential anxieties related to statistics (some strategies mentioned by the interviewees are reported in §5.9), instructors could also put forward strategies which aim at preventing and eliminating high, and undesirable, levels of anxiety in statistics. In the pertinent literature, Chew and Dillon (2014) offers an update of the research regarding statistics anxiety and proposed interventions and recommendations for the statistics instructors. Instructor’s attentiveness and support are believed that might help positively towards the elimination of statistics anxiety. As Williams (2010) proposes statistics instructors should increase the use of behaviours that demonstrate a psychological availability, also known as immediacy, in order to diminish students’ anxieties towards statistics. The constant availability inside as well as outside of the class for answering students’ questions and concerns could help in alleviating anxiety among students (Maschi *et al.*, 2012). Also, D’Andrea and Waters (2002) suggests that the use of short stories to give the context for the statistical problems that students have to solve lessened their levels of statistics anxiety in introductory statistics courses. In addition, Kinkead (2015), after conducting a qualitative assessment, proposes collaborative learning (e.g. collaborative problem solving) as an effective instructional method for eliminating the negative effects of statistics anxiety. Moreover, many researchers reported the use of humour (Schacht and Stewart, 1990; Forte, 1995; Wilson, 1997, 1998; Earp, 2007; Lesser and Pearl, 2008) in statistics classes or the humorous teaching style (Pan and Tang 2005) as recommended practices.

It should be noted that even though perceived difficulty and anxiety were initially hypothesised and measured as different conceptual constructs, statistical analyses (e.g. factor analyses, see §4.8) suggest that they are moderately related and could form one single construct. This close relationship is also substantiated by the qualitative findings where students who reported experiencing anxieties in statistics were more likely students who reported encountering difficulties when learning the subject and the opposite direction. Moreover, anxieties and difficulties are found to share common antecedents and sources and have related dimensions in the current statistics courses. A closer investigation of the relationship between these two constructs is needed in future research.

6.3.3 Relatively high levels of self-efficacy beliefs towards statistics

One of the most intriguing findings of the present study is the relatively high levels of confidence associated with their competence in statistics regarding their capabilities of performing well in statistics, learning and mastering the statistics course material that participants reported at both questionnaire assessments. Based on the interview responses, the students' judgements of their self-efficacy regarding statistics, at least at the beginning of the course, seemed to be linked to their previous experiences and performance with statistics or mathematics-related classes and tasks over the past school or/and university years, pre-judgements about their statistical abilities if they did not have a formal exposure to statistics or even based on their actual or perceived general educational abilities. However, the students' judgments of their self-efficacy by the end of the course were more likely to be framed on their performance, experiences or even expectations while they were engaging with statistical-related tasks and undertaking formal assessments (e.g. tests/examinations) in the course. It should be kept in mind that these were the students' self-reported perceptions of their statistical competence. It is a matter of conjecture whether students tended to regard themselves as being more capable of performing statistical-related tasks than they actually were. According to evidence in research, students at different academic levels have a tendency to over-estimate their capabilities (Hackett and Betz, 1989). A reasonable approach to assess this issue could be to evaluate students' perceived ability as well as actual ability to execute tasks aligned with the learning outcomes in an introductory statistics course. To this end, a set of statistical tasks could be given to the students to measure the congruence between statistics self-efficacy beliefs (or estimates) and actual performance scores on those tasks and explore whether students accurately prejudge or judge their abilities at the beginning and at the end of the course respectively. From both the quantitative and qualitative strands of the study, it is found that students had more confidence in solving exercises and applying statistical methods than in understanding theoretical concepts. They also felt less confident in interpreting the results and writing their conclusions after statistical analyses. Thus, it is imperative for the instructors to aid students by fostering their confidence, particularly in mastering theoretical concepts and ideas, interpreting the results of their analyses and writing down their conclusions by giving them the appropriate explanation and guidance. Moreover, although the statistical analyses did not indicate any changes in students' self-efficacy beliefs from the beginning towards the end of the course, it is proposed that educational efforts and instructional strategies could be applied aiming to support, maintain and enhance self-confidence beliefs over the span of a statistics course. It is claimed that strategies such as practise and self-assessment could help students to strengthen their confidence. Instructional practices and assigned activities could also help students to value their statistical competence. For example, instructors could organise and distribute to the students smaller and easier tasks and activities which would be developed gradually and progressively. Furthermore, statistical concepts, especially theoretical ones, could be introduced from easier to more complicated ones. These strategies are deemed as allowing the students to build up more confidence in their abilities and skills when achieving intermediate successes.

6.3.4 Relatively high levels of positive resilient behaviours in statistics

Another important finding emerged from both strands of the present study is related to the students' overall positive dispositions to apply resilient approaches to enable them to learn and comprehend the statistics course content. A possible explanation for the students' relatively high reported resilient behaviours might stem from the perceptions shared in interviews that statistics is a discipline and a subject that requires these particular types of behaviours to master the content, perform well and thrive in the course. Students seemed to recognise the role of positive resilient behaviours while learning statistics. More specifically, they seemed to acknowledge that their own effort, hard work and persistence when the topics or tasks were unfamiliar, difficult or even challenging would empower them to reach the desired outcome. As some students admitted, statistics generally needs a great deal of discipline and involves tasks and exercises that, most of the time, were more cognitively demanding or they were a different type of tasks they had encountered previously. The contention that someone has to be prepared and ready for the struggle and challenge they might experience throughout the statistical learning process at the university level is also shared. Also, both quantitative and qualitative results indicate that participants perceived that even higher-achieving students might experience difficulties and struggle with statistics at some point. Moreover, it is revealed that positive attitudes and interest towards learning statistics could make students stronger in the face of the adversities and be or remain resilient.

A set of personal characteristics and personality traits (e.g. patience, determination) were mentioned by the interviewees and are deemed indispensable for the process of resilience in educational settings. These characteristics can also be identified in Martin and Marsh's (2003, 2006) papers concerning academic resilience. The decline in the resilience levels that is observed from the beginning to the end of the course based on the statistical investigation could lead to the support (which was also mentioned by the students' standpoints in the interviews) that instructors could also help them to develop and sustain resilient learning behaviours. For example, instructors could stress that all the students have the capability to understand or solve what might seem to them as being initially difficult or impossible by following and adapting resilient-related strategies. They could also emphasise to the students that they should not interpret any potential challenges or difficulties in statistics as a sign of lacking intelligence or talent. Students mentioned during the interviews that making mistakes is a vital part of the learning process. Instructors could further instil in the students the perceptions the mistakes (and possible failures) can be used as means for learning and better understanding statistics. Lee *et al.* (2013) proposes that choice of tasks, collaborative learning and active engagement could aid in contributing to greater persistence, building resilient behaviour and boosting students' self-efficacy. Related to this, another suggestion to the instructors is that instead of providing the correct solution immediately (if they do so), they could initially give time and space to the students to think and try it and then guide them towards the right direction if they request it. It is suggested that students should be encouraged to be more statistical resilient learners and thus more independent learners when learning statistics.

It is hoped that the current research study might lay the foundation for further investigation and research on the construct of resilience. First of all, a more in-depth understanding and conceptualisation of resilience, particularly within the context of statistics education, is needed along with an examination of what are the best ways and methods to evaluate it. Moreover, a possible area of future research could be the investigation of domain-specific resilient strategies that is to explore and clarify whether resilient behaviour strategies used (and which appeared to work) for statistics differ from those applied to other quantitative subjects (e.g. mathematics). This could be done, for example, through the direct observation of resilient behaviours in classroom settings or when students are studying statistics at home. Also, even though the focus of the present study was on student-level resilience towards statistics, future research could attempt to investigate potential university and classroom factors which promote the resilience process and examine which and how features of instructional methods, as well as classroom learning environment, work better towards the development of resilient learning behaviours in statistics. The aim would be to identify individual-level behaviours and explain them within the broader context of the university, the classroom, the instructor and the classmates.

6.3.5 Is there a close relationship between self-efficacy and resilience?

One of the considerations of this study was the extent to which self-efficacy and resilience, as defined and measured for the purposes of the study, could be regarded as distinct constructs. A strong statistical relationship was found between them but not high enough to consider them as the same construct. This close relationship between self-efficacy beliefs and resilient behaviours are also apparent from the interview responses which met our initial hypothesis that they are distinct, but related concepts (see, e.g. §4.5.1). Significant relationships between self-efficacy and academic resilience are also reported in other research studies (e.g. Borman and Overman, 2004; Martin and Marsh, 2006). Nevertheless, as Ee and Chang (2010) proposes, highly resilient people are individuals who are reactive to stressful, adverse and disruptive situations meaning that they show a response to a stimulus. On the other hand, highly self-efficacious people are individuals who are proactive and they do not just respond to a situation after it has happened. That means that students, by building their confidence and perceived competence, could try to control or minimise the possibility of a bad situation (e.g. a bad performance) rather than acting in response to it (e.g. by showing resilience). However, it is acknowledged that such situations might be inevitable in the learning process, for example, potential difficulties and challenges that someone might experience in a statistics course. The interview data suggests that those students who had more confidence in their knowledge and competencies and trust themselves, it was more likely to behave in a stronger resilient way and try for longer to get to the desired end. It seemed that students' behaviours and approaches exhibited when faced with difficulties or challenges were related to their confidence in their abilities to learn and their perceived competence in solving statistical-related tasks. Future studies on the association between these two constructs are therefore recommended.

6.3.6 Self-efficacy and resilience as the strongest determinants of performance in statistics

The investigation of the relationships among several affective, motivational and cognitive factors and statistics performance was flagged as crucial for fulfilling the objectives of this research study. These relationships are found to be stronger when the investigated factors and performance were assessed closer in time (see, e.g. §4.5.3). In other words, stronger bivariate relationships between post-courses measures and performance than between pre-course measures and performance are observed. An absence of moderate or strong relationships between individual factors and course performance is observed. This might suggest that each factor cannot stand alone for explaining or determining performance, but a combination of them might explain it better. From my point of view, all the investigated factors have their unique importance and practical significance in the students' learning process and ultimately their performance in statistics. The current study demonstrates the direct and indirect relationships between selected variables and achievement in statistics. When discussing the Structural Equation Modelling findings in previous sections (refer to §§4.10 and 6.2), an attempted was made to consider and interpret each predictive (significant or not) path in the model.

Statistical analyses (e.g. correlation analyses, regression analyses and structural equation modelling analyses) show evidence that the self-efficacy and resilience constructs, as assessed by the questionnaire statements, were important contributors and significant predictors of performance in an introductory statistics course. For example, the tested theoretical-conceptual model integrating five factors (namely liking and interest, value, difficulty and anxiety, self-efficacy, and resilience) and using SEM procedures indicates the direct relationship of self-efficacy and resilience in performance. The practical implication of the significant effect and direct influence of students' self-confidence and positive resilience behaviours on their performance might be that students who feel more capable of successfully carry out tasks in statistics or gradually see that they can master the material taught to them and students who develop positive and adaptive resilient behaviours could achieve in a statistics course. The quantitative findings are supported by the qualitative findings, where students who had confidence in their abilities and were not discourage by stressful or adverse situations, not easily quit and try to find alternative ways coping with tasks, those students appeared to have an overall better performance in the course.

The central position of the self-efficacy construct in the tested structural equation model is highlighted since it is found to have a direct impact on all the investigated constructs and on the performance. Thus, it is deemed as crucial not to neglect, over the duration of the statistics course, the students' sense of competence and ability to deal with statistical-related content material and perform well. From a practical point of view, it is of vital importance for the interventions to work towards improving students' self-efficacy, not only because higher confidence might lead to a better performance, but also because it is likely to engender more positive dispositions towards the subject (including liking of statistics, interest and enjoyment of statistics and value placed on it) and reduce the levels of anxieties and difficulties that the students might experience. It is, therefore, suggested that future research studies could investigate further and determine what makes students confident regarding statistics before and after engaging with it. More attention could be placed on those antecedents, and interventions could be directed at fostering students' confidence in order to increase competence.

It is worth restating that a substantially larger percentage of the variance in the performance was accounted for by the students' reported affective and cognitive reactions towards the end of the course (e.g. 21%) than by the students' affective and cognitive reactions at the beginning of the course (8%).

6.3.7 Higher external than internal motivations and achievement goals in statistics

In the current study, the quantitative results show that students tended to be more extrinsically than intrinsically motivated. It was also not surprising that the majority of the interviewees shared that they pursued to obtain a (very) good grade in the statistics course. Some of them mentioned the importance of the grade in the statistics course for their academic and future career goals. Perhaps students' high external motivations and achievement goals can be explained by the competitive environment in higher degree education. It is believed and supported by the students' answers that achievement goals and aspirations might stem from the general university and future job environments and pressures. Also, the entry-level university examinations at the end of the high school are regarded as promoting the competition among students, which might be transferred to the university environment. In this regard, it is recommended to the instructors to not encourage and amplify among their students the 'unhealthy' competitive spirit, but the 'healthy' one, and not show to the students that they place a large emphasis on the grades. Future research could investigate whether meeting social norms (such as obtaining a very good degree in terms of the grade point average) and social expectations (for example, closed environment and parental expectations), which I believe that exist in Cypriot culture, contribute towards the external motivations pertaining to examination grades and distract students from chasing more internal motivations, especially in the learning context of statistics.

Nevertheless, mastery (learning) developmental-related goals were also demonstrated in both quantitative and qualitative components of the study. During the interviews, some students mentioned being intrinsically motivated and sought for mastering knowledge, acquiring skills and understanding the subject material. As Ryan and Deci (2000) proposes and Dunn (2014) further explains, students' intrinsic motivation can be increased through three conditions: autonomy (e.g. when students are offered options with regard to their homework assignment or the topic of their final project), competence (e.g. when students are provided with positive and specific feedback) and sense of belonging or relatedness (e.g. when students are provided with opportunities for interactions and discussions between students and teachers). Also, the challenge could evoke and sustain students' intrinsic motivation throughout the statistics course as was evident in interview responses. However, the degree of challenge of the tasks – too easy or simplistic as well as too difficult or complex tasks- might lead to the opposite desired direction. Thus, the instructors could pay attention and attempt to find the optimal level of challenge taking into account the specific students' skill level and background in order to promote and not hamper students' intrinsic motivations (Deci and Ryan, 2000; Dunn, 2014). Moreover, Lee *et al*. (2002) proposes that instructor's clearly-explained expectations regarding the learning objectives of the statistics course, instructor's concern for students' learning progression, active interactions with them, and willingness to offer help can have motivation enhancement effects.

6.3.8 Considerable effort expenditure in statistics

Based on the quantitative findings, a considerable number of students reported that they were willing to put or put forward a great deal of effort and time to learn and study for the statistics course. This outcome might be attributed to the students' perceptions, as shared by them during the interviews that statistics as a subject (and course) required devoting effort and time for understanding and mastering the material and practising and solving exercises. The finding emerged from the quantitative analysis concerning the decrease in the students' effort levels by the end of the semester was investigated further in the students' responses to the interviews. The students attributed any changes in their effort expenditure to their performance in the midterm examinations, their perceived inclination or talent in statistics/mathematics, their perceived abilities in statistics, the workload of the whole semester as well as other responsibilities. It is proposed that instructors could advise and promote students' continued engagement with statistics irrespectively of their performance or their perceived abilities. According to Paechter *et al*. (2017), instructors should particularly stress to the students the importance of investing effort and time in order to succeed in statistics. The qualitative findings also suggest that a little of challenge might urge students to expend extra effort in the course.

6.3.9 Use of deep-related learning strategies and study approaches to learning statistics

A considerable number of students report giving more emphasis on understanding than only memorising the subject material in statistics in both strands of the study – quantitative and qualitative. In addition, they mentioned employing strategies, which are more related to deep learning and cognitive learning approaches (such as source management, organisation of the material, seeking for extra notes, elaboration, reflection). These strategies are generally regarded as more effective than more shallow or surface ones since they create fields for understanding and learning that lasts longer and not only for the duration of the course (see, for example, Biggs, 1987). However, I am of the opinion that, the advantages of rehearsal strategies and memorisation processes should not be underestimated. Instead, they should be accompanied by more deep-processing strategies after the initial encounter with a new or unfamiliar topic. Moreover, during the interviews, students mentioned adopting different approaches while learning statistics compared to other more theoretical subjects, but they did not explicitly talk about different approaches to other quantitative or mathematics-based courses. Students' approach to a quantitative in nature discipline at the university level, such as statistics, seemed to be affected by their prior experiences with high school or university numerical subjects such as mathematics. However, it was not clear from their responses whether and which statistics-specific learning techniques they employed which they did not use in other subjects. Future research could investigate more thoroughly what specific strategies and approaches are employed by the students in the statistics course and which of them are more likely to be associated with success in statistics – that is effective learning and mastering of the subject content and desired performance outcomes in the course. Observational or experimental studies could also be carried out where the researcher would have the opportunity to observe how the students approach problems and tasks in statistics both practical and theoretical ones. Then, the reported and observed learning strategies could be compared. As Dunn (2014) suggests, instructors could include learning strategies applied specifically to statistics (i.e. domain-specific learning strategies) as a part of the subject curriculum and the statistical assignments. Also, the instructors, through their instructional practices and the tasks they assign to the students, is recommended to promote deep learning approaches and cognitive and metacognitive learning skills and strategies (such as planning, organising, monitoring and elaborating) aiming to develop and promote meaningful and conceptual learning and long-term retention of the subject material they have taught them.

6.3.10 Importance of understanding in statistics

One of the main issues, which are stemmed from the qualitative investigation, but it has not been assessed through the quantitative investigation, is students' understanding. During the interviews, students were found to be keenly aware of the importance of understanding in statistics due to its nature as a discipline and as a course. The students seemed to perceive, as more difficult or challenging, the parts or the topics of statistics which required conceptual understanding and interpretation than those which followed standard or systematic (e.g. step-by-step) procedures. Particularly, the topic that was mentioned by the students as being more difficult with respect to reaching an understanding was probabilities. Students' difficulties in learning and understanding probabilities have also been demonstrated in several research studies (e.g. Garfield and Ahlgren, 1988; Pfannkuch, 2005; Leavy *et al*., 2013; Fitzmaurice *et al*. 2014). Perhaps this is associated with the nature of probabilities (for example, it is associated with randomness/chance and judgements under uncertainty). It might also be stem from the lack (or little) prior exposure to the logic of learning and doing probability-related problems.

The prominence of understanding within the context of learning statistics is also evident in the relationships between understanding and students' affective reactions, motivational orientations and cognitive engagement with statistics. Specifically, students' liking of statistics and interest and enjoyment when learning statistics are found to be conditioned by their level of understanding and mastering the subject material. It was also evident that achieving an understanding could raise students' self-efficacy perceptions and diminish anxiety towards statistics. Moreover, arising from the interview responses, the understanding of the subject matter is found to be closely associated with the students' perceived difficulty of the course; when students understood and mastered something, they reported perceiving it as easier. In addition, students tended to relate the level of understanding to the amount of study and effort and the learning strategies used. Several students acknowledged that greater effort, studying and use of 'appropriate' learning strategies lead to achieving greater understanding. Related to this, students seemed to relate their understanding to their course performance – when they understood the course content, they perceived it as more likely to achieve good grades in the course. As one of the interviewees argued: *Understanding goes hand in hand with performance in statistics.*

Many students mentioned instructors and instructional practices as prominent in their process and progress in achieving an understanding of the statistics course content. Instructors are deemed as responsible for helping students to understand and clarify abstract topics and ideas presented to them in the statistics class, especially if these are novel or unfamiliar to them. The instructors through diverse and frequent practice with progressively complex examples or exercises over time could help the students to develop a conceptual understanding in the statistics course. In an earlier study, Rittle-Johnson and Koedinger (2009) examines the idea of presenting the tasks to the students iteratively; that is an interchange between conceptual tasks and procedural skills aiming to achieve both conceptual and procedural understanding and knowledge. In addition to this, the interaction and discussion between students and instructors and among students themselves could arouse elaboration and reflection, which in turn might enable statistical learners to reach a greater level of understanding. It is also believed that students learn and understand something better through trying to do it by themselves rather than just passively listening to the instructor describe it. This point was also stressed by one interviewee who talked about difficulties in the high school mathematics due to the lack of practising in classroom settings.

From my point of view, the ultimate goal of achieving an understanding in statistics is the students to be able to retain, recall and apply the gained knowledge and skills in statistics outside of the statistics classroom. Introductory statistics education could help towards this direction by focusing on promoting a solid understanding of the statistical topics that would help students in their further academic studies, career choices and everyday life situations. As Garfield and Ben-Zvi (2007) proposes, the essential thing in statistics is the students to comprehend the statistical ideas presented to them and be able to apply and use them when is needed in real-world situations.

6.3.11 The important role of the previous mathematics/statistics background, learning experiences and performance in statistics

Returning on the results of the quantitative and qualitative investigations, it is apparent the essential role and influence of students' prior learning experiences, background and performance in statistics or/and mathematics courses on their affective, motivational and cognitive engagement with statistics at least at the beginning of the course. The overall impression was that the more positive affective reactions towards statistics, especially at the beginning of the statistics course, are stronger associated with previous positive mathematics-related learning experiences rather than only with greater exposure to mathematics-related courses that students might have. It seemed that previous positive experiences with mathematics/statistics courses, good performance on those courses and/or supportive mathematics/statistics teachers might give students the confidence that they can master the statistical-related content and perform well in the statistics course and counteract the presence of any potential high levels of anxiety and vice versa.

Based on my interpretations of the qualitative findings, students' higher levels of self-efficacy and lower levels of anxieties were not greatly associated with the number of the mathematics or statistics courses the students had previously attended, but instead on how well they performed in these courses and the overall learning (and mastery) experience they had in terms of the subject content and the instructors. Also, a vital role seemed to play how good they believed they were in these classes, how well they felt they had performed and their gained mathematics/statistics competence level. Besides that, difficulties and challenges that students might encounter during an introductory statistics course appeared to be partly consequent of earlier experiences and deficiencies or gaps. These findings support my assertions that drawing on and be familiar with students' prior experiences, background and performance in mathematics-related subjects are critical in statistics.

The quantitative findings provide evidence about differences in current statistics performance based on students' mathematics/statistics background and past achievement in high school and in university. The qualitative findings further highlight the key role of the prior mathematics learning background, experiences and achievement on the students' performance in the current statistics course. Also, based on the study's findings, I would highlight the importance of the amount and depth of exposure to statistical content even prior to an introductory statistics course at the university level and as early as the secondary school. Further recommendations regarding this issue are offered later in this section.

6.3.12 The influential role of the instructor and instructional practices in statistics

Although the role of the instructor and his/her instructional methods employed in a particular statistics course was considered by the researcher as of high importance, the questionnaires which were administrated to the students did not include any questions related to the students' opinions about the instructor and the methods of instruction in the statistics course they were attended. However, this role was very evident in the data collected during the qualitative collection since it was raised by all the students who participated in the interviews. The perceived importance of the instructor in the statistics course is captured by a students' comment: *Instructor is the alpha and the omega in the statistics course*. Consistent with Lee *et al*. (2014), the overall impression is that students' learning experiences in a statistics course were greatly influenced by their statistics instructor (and his/her practices and behaviour). Students' responses to the interviews direct the following discussion.

During the interviews, students commented on the instructional practices and the supporting materials used and reflected on their preferences and appreciations of instructional techniques and approaches when learning statistics. The students' preferred instructional approaches most of the time seemed to coincide with the instructional approaches used in the statistics course they attended. This is considered a positive outcome; nevertheless, instructors need to (continually) search for alternative instructional approaches -new or innovative ones- that they could incorporate into their teaching. I am of the opinion that they should not rest on only conventional or traditional approaches and they have to possess the ability to be flexible. A number of activities (such as quizzes, games, individual and group activities) also could be introduced. The instructors could evaluate the new applied styles and techniques from their perspective and from their students' perspective and might adapt those approaches that are more likely to enhance the learning experience and learning effectiveness. This is deemed as a way to improve the quality of teaching and thereby the learning of statistics. In the literature, there are a lot of recommended teaching practices which are deemed as effective and statistics instructors and educators could apply them to their teaching (e.g. Dunn *et al.*, 2007; Garfield and Everson, 2009; Kotecha, 2012; Everson *et al*., 2013). For example, Everson *et al*. (2013) proposes how social media, such as Facebook, Twitter and YouTube, can be incorporated into the statistics classes.

Based on the interview responses, some students seemed to be not satisfied with the pace of delivery of the statistics course, which they found too it fast resulting in usually losing the flow of the instructor's explanations. As explanation is deemed as crucial in statistics, due to the nature of the course which requires understanding and building knowledge, a well-paced instruction is recommended. Instructors should create and preserve an appropriate pace of the statistics course -for example, by slowing down the pace when necessary- to provide the students with sufficient time to digest the material, especially the new information presented to them. The learning objective should not be only oriented towards delivering as much as statistical subject content to the learners as possible, but instead as much understanding and reasoning as possible.

The qualitative findings of this study emphasise the importance of the instructors' statistical content knowledge and the transferability of it. How the instructor transmits the statistical knowledge to them is deemed for students as essential as instructor's content knowledge about statistics subject. Specifically, students argued that the statistics instructors do not need only to have the in-depth knowledge of the statistics subject content or the relevant qualifications to teach it, but also the ability to impart this knowledge to the students, by having (or training to have) the necessary pedagogical knowledge. Some students proposed that they need their instructors to provide to them clear, simple and step-by-step explanations and explain statistical concepts and ideas using simple terms and words. Adding to the students' propositions, preparing and providing activities and learning resources that are as clear and understandable as possible to the students is recommended. Rodríguez *et al.* (2010) outlines that statistics educators should use an intelligible language for the students. In a similar manner, Bandalos *et al*. (2003) argues that statistics teachers should make the subject material of statistics more accessible to the students. Instructors are urged to provide clear definitions, clarify the statistical terminology and theoretical concepts, explain the statistical theory and provide clearly defined statistical exercises, tasks and examination topics. Moreover, instructors could take any abstract statistical topics and make them concrete, give emphasis and build on the logical progression of statistical topics, concepts, ideas and procedures and make explicit connections between those that are related. (Again, I do not claim that the statistics instructors do not already do these).

Pursuant to Berg (2004), instructors ought to create an atmosphere in the statistics class where it is acceptable to ask for further explanation or clarification, and it is also accepted that everything delivered to the students, especially the new or unfamiliar information, might not be grasped and understood by the students immediately. The instructors could consider the possible diverse background of the students attending a statistics course, bearing in mind the low or insufficient background in mathematics and the possible different time that students need to process and internalise statistical material that they have been introduced to them. Some students might it find tough (or need time) to cope with and absorb the material delivered to them in the lectures and they might need additional support and guidance. Instructors are urged to encourage students to share any difficulties or challenges might experience throughout the process of learning and understanding statistics without the fear of feeling dumb or incapable. They could try to 'be in their students' shoes' and explain the subject material so that it can be understood by (almost) all the students. This is believed to be among the greatest challenges that instructors face during the process of delivering a statistics course, especially to non-mathematics majors.

As pointed out by Griffith (2012), students' perception of the attitudes and the characteristics of the instructor is a distinct dimension from his/her teaching style and approach in the statistics course. Qualitative data highlights the prominent role of the instructor's personality and identity, instructor's approachability, and relationship and communication between the instructor and the students. The students identified their preferred key instructional behaviours and characteristics such as patience, guidance, responsiveness, approachability, friendliness, supportiveness, acceptance, fairness, enthusiasm and sense of humour. It is believed that instructors' characteristics and personality have an impact on their instructional style and approach and the classroom atmosphere and environment they create (Goodykoontz, 2008) as well as on the relationships that they build with their students. It is proposed that the instructors might adopt or improve the skills mentioned above, create a supportive and mentored learning environment, build a rapport with students and treat them equally.

The importance and the contribution of the instructor, his/her instructional competence and/or strategies being used in generating positive feelings and dispositions to students and ability to inculcate an interest in the subject are also highlighted during the interviews. Some students attributed positive changes in their feelings and dispositions (if they were negative) or unchanged ones (positive remained positive or negative remained negative) to their statistics instructor and his/her approaches and behaviours while teaching statistics. It can therefore be recommended that instructors attempt to (frequently) imparting positive attitudes towards statistics (even though they might personally have negative ones) to their students via their teaching. They should bring enthusiasm into the statistics classroom and provide an environment, which prompt students' interest, enjoyment and curiosity in statistics, alleviate anxieties and build students' self-beliefs in their competencies to execute successfully statistical-related tasks. Also, it is proposed the instructors to provide an outline of the course structure and set up clear learning goals and objectives and requirements or expectations of the course at the beginning of the course instruction. Aligned with that, students could build up their own goals and expectations for the statistics course. In return, instructors could believe in and empower the students by encouraging them to work towards and reach their goals and expectations along with fostering a sense of students' control over learning and performance. Nevertheless, it is suggested the instructors show their students that they do not only care about their attained targeted learning and performance in statistics, but also about their feelings, attitudes, interests, motivations and expectations throughout this process. Prior research studies have also noted the role of the instructor on the students' perceptions, affective reactions and motivational orientations. For example, in a case study conducted by Kotecha (2012), it is underlined the difference an instructional approach and style can make to students' perceptions of statistics, engagement, motivations, self-efficacy and overall learning experience. Moreover, Tremblay *et al.* (2000) reports a direct effect of students' attitudes towards the instructor on their motivational intensify (which was defined as the amount of students' effort in learning statistics) which in turn has a positive influence on students' achievement in statistics. They also find a positive relationship between attitudes towards the course and attitudes towards the instructor, which highlights the association between students' and the instructor's affective reactions within the statistics education context.

'Effective teaching' is defined by Hattie (2009) and reported by Lee *et al*. (2013) as 'active', 'reflective', 'collaborative' and 'grounded in the real world'. Also, during a conference I attended, Hahn (2017), argued: "Pedagogy is an art, not only knowledge and professional competence". As it is mentioned elsewhere in this document, there are differences across type of universities, universities and courses/classes, but it is reasonable to speculate that the instructor could make the difference (in either direction) on students' learning experience with the statistics course. Instructors are admittedly among the most important influences on students' learning process, progress and achievement in statistics. Future research work could assess and evaluate students' opinions about the instructor and the instructional methods used by including the relevant items in a questionnaire aiming to obtain a broader picture of them. Also, instructors' perspectives and opinions could provide additional context for the students' comments and suggestions. It is deemed helpful to investigate how the instructors view themselves as sources of knowledge and information as well as resources for students. Investigations of these aspects are considered as important contributions to inform and enhance the quality of the instructional practices in statistics.

6.3.13 Appropriate and effective incorporation of technology into statistics classes

Even though Information Technology (IT) nowadays is an indispensable part of everyone's life, it was observed that in some statistics classes – mainly in the public universities – the teaching of statistics was carried out without the use of any form of technological or visual support. In some other classes – mostly, in the private universities – the statistics classes were delivered in traditional classroom classes using a computer projector (e.g. interactive whiteboards), or they were taken place in classroom laboratories with every student to have a computer in front of him. Some students had an experience of being taught a statistical software program and they mentioned during the interviews the need for appropriate instruction, guidance and support. As Brezavšček *et al.* (2016) proposes, comprehensive step-by-step tutorials and guides should be provided to the students on how to conduct particular statistical analyses using statistical packages. This, some claim, can reduce anxiety and enhance self-confidence of learning and employing a statistical software program to carry out statistical analyses and perform statistical methods. In her paper, Jatnika (2015) reports evidence that students after following an SPSS course, they felt more confident in their statistical science knowledge and skills.

As Chance *et al.* (2007, p.21) advocates, the effective incorporation and use of technology in the statistics classrooms necessitate "thoughtful and deliberate planning as well as creativity and enthusiasm". Bakker *et al*. (2017), by drawing on research on probability and statistics education, states the importance of incorporation of computer-based tools in the teaching and learning statistics and probability. To my point of view, the use of technology should not be used for the sake of incorporating into a statistics class, but instead in a way which would enhance and profit students' learning of statistical material (for example, developing students' conceptual understanding about particular statistical concepts and methods), promote cooperation and collaboration among students and enhance the interactions between the students and the statistics instructor. Especially within the context of statistics learning, it could afford the opportunity for the students, for example, to observe variability and pattern in data, reconstruct their knowledge and cultivate their interpretative skills. Also, teaching and learning with technology should not merely place emphasis on procedures, formulas and results, but also help students to achieve a conceptual understanding of the process of the various statistical procedures.

6.3.14 Further recommendations and implications for teaching and learning in statistics

Taking into account the findings of this research study, further general recommendations to be applied in practice are offered. The recommendations and points of considerations made are related to the statistics course planning and design and the development and implementation of pedagogical strategies and instructional interventions. These are based and derived from the students' responses during the interviews and the researcher's standpoints and personal experiences as a mathematics graduate student who attended statistics courses at university level and as a mathematics/statistics tutor. Also, the pertinent literature of mathematics and statistics education research, as well as the educational psychology research, was consulted. The aim is to provide suggestions for potential improvement of an undergraduate introductory statistics education experience and process taking into consideration the outcomes of the current study, other empirical and experimental findings, theoretical propositions and personal experiences. Statistics stakeholders, policymakers, educators and instructors might use the findings and the recommendations of this study as an impetus and guidance to take empirical evidence-informed decisions.

Since this investigation focuses on students' affective reactions, motivational orientations and cognitive engagement throughout the statistics learning experience, recommendations are given based on this study's premises and supported by its findings that these factors can play a role in statistics education including learning process and performance. It is believed that internal factors (such as individual students' characteristics, perceptions, and behaviours) and external factors (such as instructor's qualities, strategies and behaviours, curriculum and assessment design, classmates, classroom characteristics) are critical and are interrelated in the teaching-learning process of statistics.

To start with, from my point of view, the role of the high school (and secondary school) should be not neglected. For the sample under consideration (i.e. students who were attending tertiary institutions in Cyprus), some statistical topics are introduced to the students as a part of the core or advanced mathematics course in the high school. It is proposed that a pure statistics class or a statistically- oriented course should be incorporated into the high school curriculum in the educational system in Cyprus. If this is not feasible, a larger presence of statistical (and probability)-related topics in the curriculum of both core and advanced mathematics courses is proposed. This could provide the students with the opportunity to be introduced to some basic statistical topics and familiarise with statistical concepts and statistical thinking as early as the secondary (or even primary) level. The argument behind these propositions is the students to be better prepared for a university statistics course or/and the statistical content that they might encounter at the university level. It is speculated that the earlier the exposure to statistics, the more familiar the students would be with it and the less likely to not understand statistics at a higher level. Also, the integration of a statistics course into a pre-university level curriculum is believed to aid in developing better statistical thinking and statistical literacy, which are deemed as indispensable for achieving in a statistics course at the university level. Moreover, students' lack of (explicit) exposure to statistics at high school compared to mathematics and the absence of statistics intimacy might be among the reasons behind any affective reactions formulated and any problems met during the completion of a statistics course at university level. This is supported by the students' responses to the questionnaire. Related to the above proposition, one student suggested that statistics could be offered as a separate course of mathematics in high school. She justified her opinion by arguing that someone might like and be interested in statistics so that he/she wants to specialise on it or choose it later at the university if it is not compulsory for his/her undergraduate degree programme. I extend this idea further by claiming that if statistics and mathematics are taught separately in high school, this might help students to distinguish between them as disciplines/subjects. Also, this might even work towards to not 'transfer' and reproduce previous unpleasant or negative experiences that students might have related to the subject of mathematics in the statistics classes.

In addition to this, having in mind that a large percentage of students who participated in the present study were first-year students, the issue of the transition from the high school to the university is raised. The high school-university transition for some students might not be an easy or smooth process, but a challenging one. The lecture classes are much bigger, the pace of the delivery of the courses proliferates and there is little repetition or rehearsal, the subject material covered is commonly greater and more advanced (or difficult) and the individualised support and attention by the instructor is less (or none). At university, learning is considered to be more 'independent'. In high school mathematics, students commonly learn to handle the exercises procedurally instead of conceptually and focus on memorisation of types, formulas, step-by-step procedures and computations. However, when entering the university world and starting to be taught more advanced and complicated things, these techniques might not always work. Especially, for students in the first year, or even the first semester, of their studies should be prepared to adapt learning approaches, which are appropriate for higher education demands and especially statistics education demands. Thus, might be useful for the school mathematics curriculum to be structured and delivered using instructional practices more related to the university ones with the aim to smooth the transition from the high school environment to the university environment. Also, high school teachers could focus on a combination of procedural thinking and logical and critical thinking which are deemed as valuable tools in statistics. They could also take advantage of any opportunities to promote positive attitudes towards statistics before the students' enrolment in the university.

Students' gaps and difficulties in mathematics at different levels or stages of their educational journey might accumulate and thus, at university level, might experience difficulties achieving an understanding as a consequence of them. A possible remedy could be online teaching materials and resources or face-to-face mathematics support tutorials to be offered to the students in any discipline in order to assist them to bridge and fill the gap between high school-level mathematics and university-level mathematics/statistics. The materials or tutorials could cover certain mathematical principles, fundamental mathematical concepts and skills, which are used in or applied to the current statistics course. This would aid in addressing students with low or insufficient prior knowledge and background in mathematics and help them to increase their ability and confidence in performing basic mathematical methods. It is believed that even a statistics course might not have been designed to be heavily mathematical-oriented, the familiarity with basic mathematical techniques, skills (such as problem-solving skills) and thinking/reasoning is deemed as a necessary tool and advantage for students attempting statistics.

As previously stated (refer to §3.5.3), in some introductory statistics classes, follow-up tutorial or seminar classes are offered as a supplement of the main lecture classes. These classes mainly include applications of the material covered in the main lecture class through examples. Even though there were students, during the interviews, who claimed that the amount of lecture time in statistics should not be increased since a clear mind is needed to absorb new information, the increase of tutorial classes' time was requested. Among the reasons mentioned were more time for practising and reflecting on the subject material covered in the lecture class so far through exercises and the opportunity to ask for more explanations and questions. My further recommendation is that additional tutorial classes which would cover selected lecture class material, but at a slower pace, and give emphasis to theoretical ideas or practical exercises which students struggled with and experienced difficulties could be offered. These statistics support classes should be provided to all the undergraduate students in any discipline and should be not served for just the 'less-capable' students. Also, the university could provide regular study groups, especially for the statistics course, where the students can have the opportunity to (informally) study together in groups on statistical-related tasks. This is deemed as a form of peer learning and support. Moreover, small groups or even one-to-one support tutorial classes could be provided to cater target student cohorts, for example, students with learning difficulties (such as students with dyslexia).

I firmly believe that efforts should be made and particular emphasis should be given to how the statistics courses are structured, designed and delivered to the students within the current structures and confines of the higher education. Curriculum developers and statistics instructors are expected to pay attention when they develop statistics courses, especially for non-mathematics students. The statistics curriculum design should be taken into account the students' chosen degree of study and their possible diverse backgrounds (and abilities) with the intention of accommodating statistical learners' needs. Among the central objectives might be to: provide a quality learning environment in statistics; promote effective learning and support the meaningful learning of statistics; and establish long-term retention of acquired statistical knowledge and skills.

First of all, the selection of the instructional approaches and methods and the design and development of the statistics course content should be made in such a way to promote and encourage students' engagement with it. Instructors ought to carefully employ strategies and create and develop activities, which cover the subject content, but additionally tailored towards making the statistical learning more interesting, enjoyable, attractive and motivational. The information can be presented by employing diverse and changing methods and formats- such as using of appealing presentations of the subject content, graphical representations, diagrams and tables and several multimedia alternatives or initiatives (such as audio, video, interactive examples).

According to Cobb (1993), the learning of statistics must be active in order for students to construct their own learning and develop a sense of responsibility for their learning process. Given that active learning process is considered as any instructional approach that engages students in the learning process (Bonwell and Eison, 1991; Prince 2004), it requires the collaboration and the interaction of students and instructors on several levels and ways. For example, Carlson and Winquist (2011) proposes and evaluates an active learning approach in introductory statistics course where students required reading the content before and during the statistics class, work in small groups to perform tasks and answer questions from their instructor. Moreover, Dolinsky (2001) describes an active learning approach where less emphasis is given to the statistical theory and abstract concepts and more emphasis is placed on collaborative learning environment. He concludes that this approach resulted in more positive attitudes and self-confidence, a greater understanding of the material and more insight into the strengths and weakness of students' learning strategies in statistics. Related to this, as one interviewee mentioned, especially in statistics, in the journey of acquisition of knowledge and skills students need the guidance and explanations of their instructor. This is consistent with other authors (e.g. Garfield, 1995; Lee *et al*. 2004) who state that one of the principles that underlie students' learning in statistics is by discovering and constructing statistical knowledge themselves but also through guided processes (e.g. instructors). Instructors could promote active learning by encouraging students to make comments or ask questions during the lecture class or office hours and also students could take advantage of any opportunity to ask questions and further explanations.

From my point of view, both individual and collaborative learning are important in statistics. I believe that the nature of statistics and the nature of learning statistics promote cooperative learning and group tasks and activities. Nevertheless, students need to learn how to work individually as well as a part of a team. To this end, a combination of individual as well as group activities could be given to them. Instructors could assign to students in-class activities (e.g. problem-solving exercises) to apply the new knowledge and statistical techniques that they have learned. Students can work individually, but also to have the opportunity to use their classmates or their instructors as helping resources. With this tactic, it is contended that students would engage with the statistical material in a more 'active' and 'energise' way. Instructors also could encourage their students to work during the class in small groups – help and discuss with each other, exchange ideas and compare answers. Then, the answers can be shared in front of the class and feedback from both classmates and instructors can be received. As Chiesi and Primi (2010) suggests, working in small groups could enhance students' perceived self-confidence, perceived easiness of the course and understanding of the statistical topics and eliminate the negative feelings towards statistics. Also, Paul and Cunnington (2017), by conducting focus group discussions with students attended an introductory statistics course, demonstrates that they had the desire for collaborative or cooperative projects as they were familiar with working in groups in other academic courses. Collaborative learning in mathematics (and also, I would add in statistics), where students can be engaged in teaching and explaining to one another, solving classmates' questions and concerns and sharing methods, ideas and results is supported by Swan (2006). Furthermore, as a student proposed during the interviews, statistics classes could involve more discussion giving the students the opportunity to express and exchange ideas, discuss and argue. In the related literature, Lee *et al.* (2013) highlights the importance of collaboration, discussion and variety in mathematics classes to keep the students motivated and interested in it.

The quality and the frequency of constructive feedback given to the students regarding the exercises they have been assigned to or the examination questions they have not done correctly could help. Hall and Vance (2010) proposes that real-time feedback along with real-time evaluation (e.g. assessment and progress indicators) in order the students to see the outcomes of their efforts can influence students' self-efficacy beliefs positively. In the same vein, Kotecha (2015) suggests that instant feedback might promote students' self-efficacy, interest and engagement with the course. Regarding what the students can do, peer feedback or review, which is a form of collaborative learning, is recommended. Students can provide feedback to each other, which might aid in improving their understanding of the statistics course material.

Strangfeld (2013) suggests that the teaching of statistics should be learner-centred rather than instructor-focused. I recommend a student-centred learning environment in statistics with the catering of a mix of student-designed and instructor-designed tasks and projects. Students, as statistical learners, to the extent possible, could be provided with opportunities and activities to develop skills related to independence, autonomy and choice. To this end, statistics could be introduced to the students in a way that they can have a sense of choice and autonomy, for example, to choose and work on projects or data sets that they have a personal interest and employ statistical methods and tools for investigating their areas of interest. This might enhance students' enjoyment, engagement, motivation and appreciation of the subject matter as well as assist in promoting statistical mastery. As one interviewee proposed, the opportunity to carry out a student-designed data collection and analysis project and be actively involved with the required stages of a statistical investigation cycle (e.g. collection, analysis, interpretation, and conclusion) should be given to the students who attend a statistics course. In a step further, I propose that students could then present and communicate their statistical findings in a series of presentation seminars in front of their classmates and instructors (with or without formal assessment). It is believed that through this process, students can learn, appreciate and feel comfortable with the statistical investigation process. Several lines of evidence suggest that students' engagement with statistics projects that employ samples of real data or student-gathering data can have a positive impact on students' attitudes and opinions regarding statistics (Smith, 1998; Holcomb and Ruffer, 2000).

As mentioned elsewhere in the document, more emphasis should be placed on the practical utility and realistic applications of statistics. The findings of this study suggest that students preferred to learn and be engaged with applied fields of statistical knowledge. This could be achieved through more engagement with real-world problems and less exposure to abstract concepts. This view is supported by other researchers (e.g. Cobb, 1992; García-Santillán *et al*. 2014; Mutambayi, 2016) who propose that students favour the real-life examples to help them to comprehend a statistical concept presented to them. During the interviews, students frequently mentioned that a statistics course should offer knowledge and skills, which are relevant and applicable to their field of study using practical and tangible examples. Taking into account the students' expressed desire to acquire major-specific knowledge and skills, textbooks and lecture notes which are provided to the students in the statistics course needs to be not quite general, but more oriented and rely on applications, examples and exercises which are drawn on contexts of relevance to the students. I also recommend that instructors invite presentations by professionals who are currently employing and applying statistical knowledge and skills to their professional positions since this might help to increase students' awareness and appreciation of the importance of statistics for their future careers. Students need to learn to understand, internalise and practise the subject material delivered to them and the new knowledge gained in statistics in different contexts - both in general contexts and in context of their chosen area of specialisation. The integration of statistical topics and methods into other courses of students' degree curriculum programme might help towards this direction. Also, the instructors could, when appropriate and possible, make explicit interdisciplinary connections - that is to connect and relate statistics content and applications to other disciplines and domains. As Chiesi and Primi (2010) argues, it should be transmitted to the students that statistics is not an isolated course in their undergraduate degree programme, but instead, it has applications and relevance to it.

Statistics courses curriculum developers and instructors may seek to design and create activities and tasks that could aid students to augment their background knowledge and link the new material taught as much as possible to the students' prior knowledge and ideas that they are accustomed to. Then, students could be encouraged to apply prior and new knowledge to understand or solve current statistical-related problems. As some students mentioned during the interviews, statistics (and the statistics course) involves problem-solving skills, logical thinking and reasoning. Thus, one of the main aims of course planning and teaching is to instil and foster these skills to the students. It is suggested that statistical operations are not taught to the students in a purely mechanical way and the complexity of the exercises (for example, exercises which involve massive calculations) be eliminated when they are not needed. The students should focus more on understanding and learning concepts, and dealing with data instead of calculating complicated and big formulas. As Ciftci *et al*. (2014) states, in order to handle the prominence of data generating and the concept of variability, students should focus more on data and concepts than mainly on formulas and calculations. In addition to that, it is advisable for the students to concentrate not just obtaining the results, but also understanding the meaning and implications of them and being able to explain and communicate them. Solving a problem in statistics should be regarded as important to understand the statistical task, the procedure that is followed and why the final answer is correct. The aim is the students to achieve a conceptual understanding of statistics than just a procedural fluency and reached to results and conclusions that are based on evidence, logical flow and appropriate reasoning. This, it is contended, might facilitate future retrieval and application of the statistical knowledge.

To this end, instructors could pose probing questions to the students that call for students to justify and explain their answers and their way of thinking. They could also guide and inspire them to think before they act and stimulate the development of reasoning about executing a statistical task than only to get the correct answer. The correct answer should not be promoted as an end in itself. This proposition is related to Clement *et al.*'s (2010) statement which stresses the importance for students to develop argumentation competence in statistics over and above the mathematical/statistical execution and computation. Moreover, during the interviews, a student with dyslexia proposed that students could be offered the opportunity to explain verbally the steps they follow and the thinking they develop to solve a statistical-related problem. This is considered as a kind of self-explanation and thinking-aloud and a self-reflection technique. In an earlier study, Bude *et al.* (2007) recommends the use of directive tutor guidance as an effective supplement to the problem-based learning of statistics with regard to the students more positive perceptions and higher achievement.

Based on the course content that they have to cover, it is proposed that instructors design and develop activities aiming to produce not only students who perform well in the statistics course, but also students who formulate favourable dispositions towards statistics. Instructors need not only to consider students learning process and acquired knowledge but also their opinions, attitudes, motivations and expectations (if possible). An instructional implication is that the instructors could profit by and take advantage of this knowledge to inform and tailor their instructional practices and approaches.

Students could be encouraged to provide evaluations of the course and the instructor by giving their opinions and their satisfaction rates. Then, the students' opinions and feedback, expert opinions and constructive ideas (e.g. university, faculty, instructors, policy makers) along with the results of empirical, experimental and theoretical studies (especially of the studies conducted on the population of interest) should be taken into consideration. As Brezavšček *et al*. (2016) recommends, students should be encouraged to evaluate their own learning by giving them the grounds to reflect on the teaching-learning process. Further research could examine the particular course design and pedagogical techniques in terms of their effectiveness (e.g. performance and learning outcomes), in terms of the students' satisfaction as well as with regards to their impact on students' affective reactions, motivational orientations and cognitive engagement in statistics.

Regarding formative methods of assessment, Iannone and Simpson (2015), in a mixed-methods study assessing students' preferences of assessment in mathematics, demonstrates that students tend to prefer traditional assessment methods (such as closed book examinations) and put multiple choice examinations amongst their least preferred option. The findings of the current study, both quantitative and qualitative, show that students tended to prefer closed book examinations over other methods (opened-book examinations and assignments) by characterising them as more *fair*, *reliable* and *representative*. The students' concern for a fair assessment of their mathematical abilities is also shared in Iannone and Simpson's (2015) study. Students seemed to prefer methods of assessment that they are familiar with or those that they believe they are more likely to perform well in. Regarding the assessment methods, from my point of view, that the multiple choice questions do not have the potential to represent and assess the learned materials adequately, give room or chance to the students to develop their way of thinking and promote the appropriate reasoning and thinking. It is suggested the students be evaluated through a variety and multiple forms of assessment techniques and throughout their learning process (over the course of a semester). The questions on the examinations can be designed to focus on conceptual understanding of the subject material but also to include procedural, computational and definitional problems. I support Leong (2012) which proposes the planning and implementing of appropriate evaluation methods and kind of questions that assess students' 'genuine' understanding of statistics. In their study, Garfield and Gal (2007) provides examples of typical (innovative) assessment approaches in introductory statistics courses (such as individual or group projects; portfolios of student work; concept maps which assess students' understanding of conceptual connection) accompanying by current challenges and future directions.

Overall, it is suggested that the aim of the universities, instructors, curriculum developers should not solely focus on how to make the course more informative, but also how to make a statistics course more attractive, enjoyable, valuable, relevant, enlightening, challenging (up to a threshold), motivating, engaging, less frustrating and anxiety-producing to the students, and helpful in reinforcing self-efficacy beliefs. Intervention strategies and approaches need to be planned which would take into account not only knowledge and actual aptitude but also perceived knowledge of and competence in statistics. It is imperative that instructors create opportunities to promote and inspire positive feelings, value and enthusiasm to the students so that the students to perceive it at the end the statistics course as an overall positive and rewarding experience.

The main empirical, practical and theoretical implications of the findings of this research study and the general recommendations to the statistics stakeholders are summarized below:

- The study aimed to add to the understanding of the phenomenon of interest and contribute to the field of knowledge in local (and international) context. More specifically, it aimed to add further insights into the constructs under investigation, how these constructs 'operate' in specific culture settings and the interrelationships between then, advance the literature regarding academic (and mathematical) resilience and pave the way for future studies in the construct of resilience within the statistics education learning context.
- The study aimed to inform, support and contribute to instructional and classroom practices and issues related to curriculum structure, content and pedagogy.
- Self-efficacy beliefs and resilient behaviours should be promoted and encouraged due to their important role in students' learning process and performance in statistics.
- The importance of the amount and depth of exposure to statistical content even prior to the introductory statistics course at the university level and as early as secondary level is recommended.
- Statistics could be offered as a separate course of mathematics in high school level.

- Online teaching material and resources, face-to-face mathematics/statistics support tutorials, follow-up tutorial or seminar classes, study groups and peer learning groups could be provided.
- Active and energise learning (i.e. students take responsibility, construct their own learning and engage in the learning process); guidance and clear explanation from instructor; quality, frequent and instant feedback; individual and co-operative learning environment; collaborative and student-designed data collection and analysis projects; student-centred learning environment rather than instructor-focused; practical and realistic applications of statistics; variety and multiple forms of assessment techniques and throughout the course; and enhancement of problem-solving skills, logical thinking and reasoning, argumentation competence and procedural understanding are recommended.
- Appropriate and effective incorporation of technology into statistics classes is suggested.

As a final remark in this chapter, the overall findings of this research study support its initial hypotheses that non-cognitive factors, along with the cognitive ones, work together and cannot and should not be neglected or isolated in the process of teaching and learning statistics. Consequently, academics, educators and policymakers (i.e. persons in charge of the statistics course curriculum design and development) should direct their attention and put effort into developing and implementing targeted interventions through both cognitive and non-cognitive lenses. This may help in facilitating better experiences and increase the likelihood of non-mathematics students to achieve in an introductory statistics course.

Chapter 7 SUMMARY, LIMITATIONS OF THE STUDY, DIRECTIONS FOR FUTURE RESEARCH AND CONCLUSIONS

This chapter begins with a brief summary and an overview of the key findings of the current study. Next, the main limitations of this study (along with possible approaches to tackle these issues) and directions for future research are provided. Finally, a concluding statement about the study as a whole is stated.

7.1 Summary of the study and overview of the key findings

This doctoral study aimed to scrutinise and shed some light on the interactive role of cognitive and non-cognitive factors in learning and performance in statistics and makes an endeavour to untangle and understand the (intricate) relationships among these factors and students' performance. The core of the research problem was to get and provide an insight into non-mathematician students' perceptions, perspectives and experiences of introductory-level statistics courses offered at tertiary institutions. Even though this study was based in Cyprus, it utilised a sample of students across different universities and a variety of disciplines and degree programmes, and it appears to reflect common patterns and themes found in the relevant literature along with some new insights. It is hoped that these experiences can be located and framed within the learning context of other groups of students from other populations and provide implications for a wide range of audiences (such as students, instructors, educators, researchers and curriculum developers).

It is important to keep in mind that although statistics courses, which are offered to different classes, different universities and different countries, might not share similar curriculum choices, learning goals, taught materials or requirements, methods of instruction and assessment, they have the common denominator 'the nature of statistics'. According to Wisenbaker (2000), the very nature of statistics and the unique perspective for successfully mastering and learning it establishes its own 'microculture' with common features experienced by most of the students engaging with it. As Verhoeven (2009) argues, the value, the interpretation and the informative level of the data and the results provided are deemed as more crucial than the generalisability of them. Thus, even though the current study is based on a specific population, it aims at providing empirically grounded findings and prepositions that others (e.g. mathematics and statistics educators and researchers) could replicate or adjust to their local or learning contexts and situations.

This doctoral investigation intended to take the students' perspective, examine what drives their achievement and explore their experiences when undertaking a statistics course. In order to achieve the goals pursued throughout the study, a combination of theoretical, methodological and analytical approaches was adopted. For example, a triangulated mixed-method methodological approach using both quantitative and qualitative methods was employed. A longitudinal quantitative component (i.e. students' affective reactions and cognitive engagement evaluated at the beginning and at the end of the statistics course), statistical analyses (including multivariate analyses such as structural equation modelling techniques), and qualitative analyses (using thematic analysis approach within and between cases) were utilised. Both questionnaire information and interview data contributed to the exploration and understanding of the total picture of the introductory statistics education experience and journey. The quantitative data through statistical summaries and results provide a general picture and information of students' affective reactions, motivational orientations and cognitive engagement enhanced by the qualitative data, which helped in explaining and interpreting those statistical results and providing more in-depth and rich information about students' perspectives and reflections on their statistics education experience. The qualitative information was used to complement and simultaneously challenge the quantitative information ensuing in joint knowledge creation and a balance of perspectives. The findings of the quantitative and qualitative components of the study were reported separately and then synthesised to address the research aims and questions of this study.

Several results have come out of both the pre-course and post-course quantitative assessment and qualitative investigation. Overall, the current study has largely confirmed previously reported empirical results and theoretical propositions, arguments and educational expectations, supported some of the relationships that were hypothesised or expected as well as uncovered some emerging issues. Since it was deemed as difficult to compile and summarise the wealth of information and subsequently the findings in the thesis document and in this concise conclusion, the key conclusions stem from the results are used to inform this section.

Drawing upon the qualitative empirical evidence reported in the previous sections (see Chapter 5), the overall impression is that students' learning experiences in a statistics course were greatly influenced by their statistics instructor (and instructional practices/behaviour). In addition, the understanding of the statistics course material is inferred to be related to the learning process and influenced students' affective reactions, motivational orientations and cognitive engagement in statistics.

Based on the quantitative findings (see Chapter 4), the investigated affective, motivational and cognitive-related factors are found to be significant, although weak and moderate, related to performance (except for the value, the anxiety and the control over performance variables as measured at the beginning of the course). Even though these results can only indicate statistical associations and not causation (i.e. a cause and effect relationship could not be inferred), they allow shedding some light on the associations between these factors and academic performance in statistics.

Given that a relatively large number of factors were examined in the current study, the quantitative investigation was narrowed by focusing on some key factors (more specifically, liking of statistics, interest in statistics, the value placed in statistics, perceived difficulty of statistics, anxiety towards statistics, self-efficacy towards statistics and resilience in statistics). At both pre-course and post-course assessment times, among the seven main variables of interest, regression analyses showed that self-efficacy and resilience played a significant and positive role in predicting students' grade. These seven factors were afterwards subjected to factor analysis. The resulting five-factor structure is considered meaningful and is confirmed as adequately fitting the current data (both pre-course and post-course data samples) using undergraduate non-mathematics students. There is a clear factor structure underpinning the selected set of factors and each factor is found to be internally consistent. The five factors are: liking and interest; value; difficulty and anxiety; self-efficacy; and resilience. For exploring the interplay of these variables and predicting statistics performance, the proposed theoretical model was analysed and explored through the SEM approach with the incorporation of the final grade variable. Among the variables included in the model, two of them stand out as key consistent predictors of performance in statistics courses – namely, self-efficacy and resilience. More specifically, the SEM results indicate that, near the beginning of the course, higher self-efficacy and resilience levels make significant direct contributions to performance (i.e. have positive direct effects on students' performance) and near the end of the course, additionally, less anxiety levels have direct positive effects on it. Liking and interest towards statistics and value placed in statistics are not found to have direct relationships with performance in either questionnaire administration; rather they have an impact on performance (make an indirect contribution to performance) through anxiety by the end of the course. It should be noted that each component associated with students' attitudes (liking, interest and value) are found to be significantly correlated with performance, but not directly related to it when other factors included in the structural equation model. In addition, self-efficacy has a prominent position in the model since it is also found to have an impact on all the variables incorporated into the model.

Qualitative analyses confirm the hypotheses of this study that students' self-efficacy and resilience can enhance performance in statistics. These findings add further support to the Bandura's self-efficacy and social learning theory and are in line with the earlier research indicating self-efficacy as an important factor and predictor of academic achievement (e.g. Bandura, 1986, 1997; Schunk, 1995; Schunk and Pajares, 2002, and refer to §§2.7 and 6.2). Also, the findings might indicate that since students' confidence in their abilities and skills is associated with their performance, then it may stand to reason that improvement in confidence beliefs (that is self-efficacy), through a simple result of successful exposure to or engagement or as an outcome to formal evaluations, would correspond with improved performance in the course. According to Pajares and Miller (1994, p. 200), "It should come as no surprise that what people believe they can do predicts what they can actually do. How could it be otherwise?" In addition, it was evident from the findings of the current study that statistical resilience can be a useful tool and an advantage for examining and predicting course outcomes. These findings are a further confirmation of research studies (refer to §§2.8 and 6.2) in which it has been reported that resilience is significantly associated and can predict academic achievement. The above findings indicate the importance of positively changing or maintaining resilience and pre-gained confidence, but also students' perceptions of gained confidence and resilient behaviours throughout the course.

The key conclusions from the current research study are summarized in the following points:

- The research on the investigated affective, motivational and cognitive-related factors provides evidence supporting the effect of these factors in learning statistics and subsequently in students' performance.
- The important role of self-efficacy and resilience in achieving well in statistics is highlighted. More specifically, self-efficacy and resilience are found to be directly and positively related to the performance. This indicates that students with higher self-efficacy and more positive resilient behaviours are more likely to earn higher grades in a statistics course.
- Self-efficacy variable is inferred to have a prominent role in the tested structural equation model since it is found to have a direct impact on all the variables (such as liking, interest, value, difficulty, anxiety, and resilience) included in the model.
- The qualitative findings highlight amongst other things, students' statistics education learning process and experiences are greatly influenced by the instructor (and instructional practices and behaviours). Moreover, the understanding of the statistics course material seems to be related to students' affective reactions, motivational orientations, cognitive engagement and performance.

Overall, this doctoral study focused on some indicators of affective, motivational and cognitive engagement. It is hoped that its results may reinforce and contribute to the knowledge about the structure of achievement in statistics as a function of several variables. The findings also could further indicate that performance (and learning) is a complex process and a multitude of factors (affective, motivational, cognitive and skill-based) may interplay. From my point of view, the integration and the combined consideration of affective, motivational and cognitive-related variables is required since each one has its unique importance in students' performance and learning statistics.

7.2 Main Limitations of the study and Suggestions for future research

Similar to the most research studies, which are empirical and deal with real data, the current study has several potential limitations, which should be considered. Some of the considerations concerning, for example, procedural choices, methodological and data issues, have been already mentioned and discussed in the relevant sections (see for example §§3.10 and 3.11). In this section, some major general limitations (such as any deficiencies that could influence the internal and external validity of the current study) are underlined. Approaches that were attempted (if these were applicable or feasible) along with directions for future research that could address these issues are also discussed. Moreover, further suggestions for future research studies are offered.

7.2.1 Clustered/Hierarchical order of the data

The first limitation of the current study resides in the population under consideration and subsequently in the population sample used. The research study was conducted in all the recognised universities operate in Cyprus and information was gathered from thirty-four classes. Even though the sample sizes for both components of the research study (refer to §3.6.2) are considered among the strengths of the study, the main limitation lies in the fact that there are differences among the tertiary institutions where the data were collected. More specifically, public and private universities in Cyprus have distinct admission requirements/criteria and different regulations and conditions (refer to §3.5.3). Also, each university might offer different types of courses with different demands and level of difficulty, and various instructional and evaluation methods might be applied. There might be differences between types of universities, but there might also be differences within single institutions (or departments and faculties) (Mutz *et al.*, 2013) and within classes. Even if the investigation of class differences was not among the aims of this research study, an attempt was made to account for the natural clustered data structure of my data and the modelling of the class dependency. This was accomplished by using a multilevel modelling analysis approach following the recommendations of many researchers (Heck *et al*., 2013; Tabachnick and Fidell, 2013) and LEMMA (Learning Environment for Multilevel Methodology and Applications) course (Steele, 2008). A two-level analysis was conducted (i.e. students were nested with classes) by incorporating student-level explanatory variables (such as students' liking and enjoyment of statistics and self-efficacy towards statistics). A three-level model (i.e. students were nested within classes and within universities) was not developed and tested in the present study, as the sample size of the universities available was not sufficient. The results of the two-level model show that approximately one-fifth of the variability in the dependent variable (i.e. course performance) came from the variability between classes and can be attributed to the differences between them. Future research efforts could further address and explore whether students' answers to the questionnaires differ as a function of higher-order effects (such as institution, department, instructor and classroom). Future studies could also investigate the multilevel modelling approach by including not only student-level information but also class-level information (such as class size).

7.2.2 Students' performance outcomes (grades)

Another weakness of the current study concerns the dependent (outcome) variable of the current study that is the students' performance in statistics. Participants' final grade obtained in a statistics course was used as the indicator of their overall statistics performance. The extent to whether the grades of students attending different statistics classes were comparable is a critical issue. The concern lies in the equivalence across different types of universities (public versus private) regarding the grading system, the marking criteria along with the grade level and the relative difficulty of achieving these grades. The issue of equivalence might also be apparent within universities and within classes. There might be differences in the evaluation assessments (such as the topics and structure of the examinations) and approaches and rigour in grading across each instructor. A reasonable approach that was employed to tackle this issue was the standardisation of the grades (i.e. to have mean of zero and variance equal to 1) obtained by the students within each statistics class taught by the same instructor (see §3.11.1). However, preliminary analyses did not reveal differences in the conclusions of these analyses and the overall interpretations of the results. Thus, it was decided to carry out more advanced statistical methods and report the results using the actual grades of students as the dependent variable. Furthermore, although the scope of the current study was mainly to investigate the factors related to students' performance in a statistics course, future studies, besides statistics course grades, could also use students' acquired knowledge and skills as an indicator of their learning in statistics. As many authors have argued (e.g. Chance and Garfield, 2002; Zieffler *et al*., 2008), outcome measures (such as final exam and course grades) may not be regarded valid (or reliable) indicators of students' statistical knowledge or reasoning.

7.2.3 Homogeneity of the sample in terms of some socio-demographic characteristics

The population from where the data were collected (and thus, the data sample of this study) is relatively homogeneous in terms of ethnicity and nationality. Only Greek-speaking students participated in the study and more specifically the participants came either from Cyprus or from Greece. Also, it is relatively homogeneous regarding age group since the majority of the students in this population tend to go onto the higher education after the end of the secondary school (or after the military service for the males). However, although homogeneity might be considered as a weakness of the current study, it can also be seen as an advantage because it can reduce the possible effects of other variables such as race, ethnicity, cultural background and language on students' performance. Moreover, although the study sample is regarded homogenous regarding some characteristics, it is believed that it is broadly representative of the population of interest since the participants of the study represented a broad range of students attending an introductory statistics course with regards to the major degree programmes and field of study.

7.2.4 Non-probability sampling techniques

The non-probability sampling techniques (and specifically convenience sampling and purposeful sampling techniques) that were employed for the qualitative and quantitative data collections can be regarded as another limitation of the current study (Cohen *et al.*, 2007). Also, the voluntary nature of the methodological approach (including the instructors who consented to give the researcher access to their classes and the students who completed the questionnaire and participated in the interviews) could be considered as a threat to the generalizability of the findings (i.e. external validity) to a larger population even probably to the population of interest. From a statistical perspective, it is acknowledged that non-probability samples may not be appropriated for applying inferential statistics and subsequently making inferences. According to many authors (e.g. Baker, 2013), when non-probability sampling methods are employed transparency in describing the methods used (e.g. collection of the data) and the appropriateness of the sample concerning the assumptions of each statistical tests used is essential. Nevertheless, it should be noted that to generalise, transfer or projected to other populations the findings of this study was not an end itself, but instead was to understand and document the students' perceptions and experiences and to examine relationships among constructs of interest that might exist in this population (McMillan, 1996; Sharma, 2010). As argued by Gray (2009), the non-probability sampling data collection methods are not a 'sin' as long as researchers acknowledge the deficiencies that these methods impose on the interpretation of the data and on the claims and inferences that are drawn from the results. Future studies could employ probability sampling techniques such as random sampling for the selection of the classes and the participants. However, in practice, this might not be feasible since, for example, random sampling techniques necessitate the list of all universities, all classes and all students who enrol in an introductory statistics course to be available to the researcher.

7.2.5 Self-reported data

A potential methodological problem of the study concerns the self-reported and self-rated data. More specifically, the quantitative results obtained were based on the students' responses to the self-reported questionnaires. In the same vein, the qualitative results were based on what the students said during the interviews. Thus, it is acknowledged that the data gathered might involve several possible sources of bias or subjective judgements. For example, some participants might not be entirely accurate or frank with their answers. Also, during the interviews, they might select or exaggerate the things or situations they shared. Among the methodological deficiencies of self-reported instruments is the social desirability bias, where students tended to give answers that they believe are more favourable to the researchers (e.g. Van de Mortel, 2008; Li, 2012). In addition to this, the use of the Likert-type format in questionnaires (along with the number of possible responses and the inclusion of the neutral or undecided point), above its simplicity and versatility, has its weaknesses as well (DeVellis, 2003). Students might feel that they were forced to choose a response in the Likert-type continuum that it might not be entirely representative of their opinions (Breakwell *et al*., 2006). Another inherent challenge of the Likert-type agreement scales is that each student might perceive the scales in a different way, for example, what it means to agree or strongly agree and even the same student might interpret it differently in the first in the second measurement times (Pearl *et al.*, 2012). Thus, "a student's rating may change even though the underlying construct the researchers are trying to measure may not have" (Pearl *et al.*, 2012, p.13). In order to accommodate the shortcomings of self-reported data, additional, and more objective, measures could be employed in future studies. For example, instead of (only) requesting students' self-reported answers regarding their previous mathematics/statistics academic background and performance, their actual grades could be retrieved from the official university records. In the current study, gaining access to the students' previous grades (at least in university) would have proved impossible because of the information security policy of the universities. Also, Wigfield and Cambria (2010) recommends that researchers not only employ and rely on self-report measures to gauge different constructs (such as attitudes, achievement values, motivational orientations and interest), but also to use alternative approaches and sources (such as phenomenological or qualitative approaches, behavioural observations and other people's ratings, such as instructors or parents) to assess the same constructs. For example, Bude *et al*. (2007), in addition to the students' self-reported amount of effort put forward in statistics, instructors' ratings and records of students' activities and engagement with statistics were used. Accordingly, in future investigations, other data sources (and perhaps more objective measures) regarding the students' cognitive engagement and behaviours, which might not always be adequately represented by their answers to the questionnaires or/and interviews, could be collected. This information could be obtained through classroom observations (classroom-based evidence), observations of the students while they would be working at home conditions and instructor's judgements and reports. For example, instead of only evaluating learning strategies or resilient-related approaches through the employment of self-report measures, in an experimental setting, statistical-related tasks could be given to the students to determine what learning approaches they use to execute it and whether they persist during the process. Then, the congruence between perceived and actual actions and behaviours such as the perceived and actual competence, reported and the actual level of effort, reported and observed learning strategies could be tested (refer to §6.3).

7.2.6 Research instruments and methods of analysis

Another concern of the current study, which is related to measurement issues, is the design and the development of a new questionnaire for the purposes of this doctoral study. Even though the objective of this methodological decision was to develop a questionnaire, which would be more applicable and relevant to the population of interest and measure the constructs of interest, some shortcomings were possible. As Gal *et al*. (1997) argues, the development of a new survey instrument entails some challenges - methodological and conceptual ones. Both versions of the questionnaire were developed solely by the researcher and under time (and other) constraints. Besides the helpful comments and guidance from my supervisors, the content of the questionnaire was not further discussed with experts (e.g. statistics instructors) or other fellow researchers. Also, despite the fact that some of the questionnaire items were borrowed and modified from questionnaires used and validated in other published studies, none of these has been previously validated in the population under consideration. Thus, there is a need for further studies to examine and establish its psychometric characteristics (i.e. reliability and validity) in samples of the same population or populations beyond the local context. Also, future research efforts could be made to optimise the current questionnaire (e.g. structure and questions). In addition to this, the theoretical/conceptual model proposed in the current study was developed and empirically evaluated using the same sample of students. It is proposed that the findings need replication and calibration using a different sample of students. The objective would be to design and develop a model that could be replicated and cross-validated across other samples of the same population and obtained an overall acceptable model fit. This would indicate the model's stability (Diamantopoulos, 2010). The established model could then be tested and verified using samples from different countries and cultures. This would indicate the model's validity extension (Diamantopoulos, 2010). Moreover, the interview plan designed and utilised in the current study might be revisited, refined and improved in future research studies. To sum up, both the survey instrument and the interview plan might (still) necessitate further development and empirical examination.

It is acknowledged that the factor analysis method (both in its exploratory and confirmatory forms) formally requires scale-level (interval or ratio) data and the Likert-type scaling data violates this assumption. According to many authors (e.g. Bond and Fox, 2007; Apple and Neff, 2012), using Likert-type scores from questionnaires in correlational analyses can potentially lead to erroneous conclusions. Pampaka and Williams (2010) suggests that the Rasch is the most appropriate method for measures where items are assessed in the form of Likert-type scales. Rasch model (Rasch, 1960) is a special case of Item Response Theory (IRT) models. It can be used to calibrate test difficulty item and person ability and detect misfit responses in the data set to allow the data to be fitted to the model (Musa *et al*., 2011). Therefore, it is recommended to use Rasch modelling approach for avoiding factor analysis limitations and for enhancing the quality of questionnaire data and subsequently study results. In future studies, these approaches (such as item response theory, Rasch modelling) could be attempted for the purposes of further evaluation and validation of the questionnaire.

7.2.7 Measuring multiple constructs together

Another weakness of the quantitative assessment tool is the common-method variances among the constructs (and items) (see for example Podsakoff *et al.*, 2003). In other words, one single survey instrument (questionnaire) was employed to assess all the constructs of interest; thus the strength of the relationships between these constructs (i.e. inter-correlations) might be overestimated (i.e. inflated) or deflated depending on some factors (Williams and Brown, 1994; Little, 2013). Also, short-rated measures were used to assess each latent variable (construct). I am aware of the fact that some constructs (e.g. learning strategies and resilience constructs) might not be easily or adequately assessed by a few questionnaire statements. Future studies might focus on measuring a group of constructs (two or three) simultaneously with larger scales.

7.2.8 Absence of experimental research which uses a control group design.

In the current study, a pre- and post-course research design was employed to monitor changes in students' affective and cognitive engagement from the beginning to the end of the statistics course. However, it is acknowledged that the lack of the randomisation and/or the use of a control group within the current sample render it difficult to interpret any changes that were obtained between the pre-course and post-course questionnaire responses. These changes were explored and explained using students' responses to the interviews, researcher's experiences and perceptions and earlier empirical and theoretical studies. They might be related to the particular statistics class, the instructor, the instructional strategies and environment. However, other factors might have been contributed to these changes and a closer inspection of the interactive role of various factors is needed. Further research investigation through experiments and learning interventions (e.g. learning enhanced activities) might contribute towards better explaining the reasons for any potential changes and making the interpretation and the reporting of the results more conceivable and based on evidence. To this end, experimental designs could be implemented to assess, for instance, the effectiveness of potential instructional interventions and new applied instructional practices or strategies. Also, it could be tested whether the constructs of interest (such as self-efficacy and resilience) would be enhanced in the desired direction as a result of the implementation of them. According to many authors (e.g. Torgerson, 2001; Torgerson and Torgerson, 2009), randomised controlled trial design is among the best evaluative techniques that the stakeholders could rely on for decision making, policy development and answering 'what works' in educational contexts.

7.2.9 Broad scope of thesis and large amount of data

As a final remark, another problem was that the scope of this thesis which might be too broad. Although a large amount of information was collected and stored (for example sixty-five interviews were performed), limitations of time and space inhibit the analysis and the reporting of all the information. Future research investigations could analyse, share and discuss this information. In the section that follows, further suggestions and directions for future research are provided.

7.3 Additional suggestions for future research studies

It is hoped that the findings of the current study could provide a foundation and pave the way for more research in the future at least in the specific learning and location context. The findings raise certain issues and provide a number of directions for future additional research studies. There is undoubtedly much investigation ahead to pursue in this field.

To start with, to the best of my knowledge, the current research study is among the first research studies, which investigated the phenomenon of interest (e.g. students' perceptions and experiences of an introductory statistics course) in university settings in a Cypriot educational context. The research in the international literature could be useful; however, it is deemed as more preferable to conduct investigations in the specific population of interest to take into account specific characteristics such as characteristics of the higher education system. Although for the purposes of the current doctoral study, data were collected from six recognised universities operate in Cyprus, in the future, it is hoped that permission from more instructors could be obtained to have access to more statistics courses and classes across various disciplines and degree programmes.

As previously mentioned, several affective reactions and cognitive engagement orientations were assessed at two times - at the beginning and at the end of the course. Future studies could assess and measure these - if it is feasible – at selected times throughout the semester. This might provide a more accurate evaluation of potential changes in students' feelings, reactions and behaviours. Also, the second questionnaire distribution was carried out towards the end of the instruction of the statistics course before the students had undertaken their final examination in statistics. A follow-up evaluation could be performed after the students take the final examination statistics and their overall course grade is available to them. Kerby and Wroughton (2017) carried out three questionnaire (i.e. SATS) administrations - in the first weeks, in the middle and in the last weeks of the academic semester- and recommends that it would be advantageous to follow, track and understand students' opinions and attitudes trends throughout the semester. With regards to experimental designs, instructors could administer the proposed questionnaire at the beginning of the instruction to get to know students' perceptions and then administrate it again two or more times (e.g. in the middle and in the end of the semester) and monitor whether their instructional practices and environment have an effect on students' perceptions. The above-described longitudinal designs might prove informative to untangle and understand further the intricate developmental and learning process.

The qualitative strand of the study involved face-to-face interviews (one-to-one or in groups of two) with the students who consented to be interviewed. Additional studies could extend the present investigation by conducting additional in-depth qualitative approaches (e.g. interviews, focus groups) to elicit and understand better students' perspectives and experiences of undertaking an introductory statistics course. Particularly for the resilience construct which has a prominent role in the current study, future research efforts could provide a more insightful and richer understanding of it especially within the context of statistics education. Also, in the present study, among the interviewees, was a student with dyslexia. Future investigations could explore, for example, the experiences of students with learning difficulties in a statistics course, the challenges that these leaners might face and their approaches to learning and mastering statistics.

On the relevant literature, Gordon (2004) conducted a phenomenographic research study and concludes that it is crucial to look at the ‘big picture’, that is the social and the cultural environment that surrounds the teaching and learning in statistics service courses. To this end, more focus could be placed on the influence of various aspects of the institutional and instructional learning environment and course design on the students’ learning process and course-related outcomes. Also, future research studies could attempt more formal observations (e.g. audiotaping or videotaping) in statistics classrooms to elicit better insight into the classroom climate and atmosphere; the methods of instructions; the structure, organisation and flow of the lessons; and the interactions between students and between students and instructor. Statistics stakeholders (such as instructors) could provide additional context for the students’ comments and remarks.

In addition, this doctoral study examined only linear relationships between the variables of interest (e.g. correlational relationships and causal relationships). Keely *et al*. (2008) finds evidence of a curvilinear relationship between statistics anxiety and achievement and concludes that this kind of function better explains the relationship between them. This aspect was not considered in the present study, but it provides a research opportunity for the future work. Moreover, in the present study, seven variables were subjected to factor analysis and eventually, five variables were included in a structural model, which purported to explain performance in a statistics course. These variables were found to explain a significant, yet relatively small amount (8% and 21% in the pre-course and post-course administration respectively) of the variability in the performance. It is acknowledged that other relevant and key factors influencing student performance have been excluded from the model (and general the investigation) since in the current study the focus was placed on the impact of a set of variables. This leads to additional inquiries and future studies to consider other affective, motivational and cognitive-related factors that might better explain and account for the variation in students’ performance in an introductory statistics course. Moreover, in the current study, background (i.e. background) variables (such as gender, age group) were not included in the theoretical model that was built and subsequently subjected to the structural equation modelling approach. In future studies, efforts could be made to build models in SEM where demographic traits of the population could be taken into account. Furthermore, in future research, the pre-course and the post-course variables could be incorporated into the same theoretical and subsequently statistical models. This might provide a better model for predicting statistics achievement. More specifically, models of change using the pooled data set that consists of data drawn from different time periods instead of considering them as separate points of analysis could be developed and tested.

The key ideas for future research are presented below:

- Further investigation on the construct of resilience especially within the statistics education learning context is recommended.
- Collection of data at several times throughout the academic semester could be conducted and from other sources (e.g. statistics instructors, textbooks).
- Instead of only relying on students' self-reported data, alternative approaches (such as classroom observations, observations of the students while studying) to measure some of the constructs under investigation and elicit better insight into the classroom settings could be employed.
- Experiments and learning interventions could be used to investigate the reasons for any potential changes in the investigated constructs. It could be tested whether the constructs of interest (such as self-efficacy) would be enhanced in the desired direction as a result of the implementation of them. For example, Randomised control trial designs could be carried out.
- Future models for predicting statistics achievement could incorporate other affective, motivational and cognitive-related factors, demographic and educational-related factors. Also, models of change using the pooled data sets could be performed.

After noting limitations of the current study and suggesting areas for future research work, I proceed in the last section of this thesis providing a general concluding remark of the current study.

7.4 Concluding remarks

This study provides an insight into how the population under investigation respond to introductory statistics and constitutes a starting point for a future richer and more in-depth population-based investigation (e.g. quantitative, qualitative, and experimental) at higher institutions in Cyprus. It is anticipated that the knowledge produced either qualitatively or quantitatively, might have both theoretical and practical impacts and implications for learning and teaching statistics within a statistics education context. Theoretically, this study intends to add to an understanding of the phenomenon of interest and contribute to the overall field of knowledge and understanding in local (Cypriot) and international context. Practically, this study intends to propose implications to be applied in practice and make (general) recommendations to students, mathematics and statistics researchers, instructors, educators and so on. The findings and the information gathered from this doctoral study may act as a valuable document that can be used to develop multiple teaching and learning activities to supplement or enhance students' opinions. Some pedagogical implications and strategies are offered in the Discussion chapter (see Chapter 6) and could be used to improve the quality and effectiveness of the statistics education learning experience for students and instructors and can be adopted and adapted by similar learning contexts.

The present study is regarded as an attempt to perform research on the students to research for the students. It should be noted that the results and the implications reflect the needs and the preferences of non-mathematics students. These could be investigated in the future but with additional research incorporating 'voices' not only from students but also from instructors and other stakeholders.

Even though general claims to a wider population cannot be made based on the data and the findings of the current study, it is reasonable to propose that one of the goals of a statistics course is produce not only competent but also confident and resilient students. Students need to possess a strong sense of self-efficacy (mainly context-bounded) tied together with resilient characteristics and behaviours to meet and overcome the challenges and demands of an introductory statistics course. These findings are deemed as crucial within the context and process of statistical education since students are advised trying to preserve, be resilient and be confident instead of promptly or effortlessly giving up. When students struggle or experience problems while learning and studying the statistics course content, instead of feeling incapable or weak, they should try to perceive this challenge as inherent in the very nature of the discipline and subject matter of statistics and an inevitable part of the learning process journey. Also, it is believed that resilient behaviour skills – similar to problem-solving skills – can be practised, developed and fostered throughout the course and can have long-term benefits.

As a final remark, an introductory statistics course can be considered as a key to mastering the basic statistical concepts and methods, and also to stimulating the students' eagerness and genuine interest in engaging with more advanced statistics in the future. It is a well-known fact that nowadays statistical knowledge and skills are becoming more and more essential not only in sciences and in academic settings but also in terms of statistical literacy in society. Interwoven with that, feelings and behaviours are also fundamental requirements for an individual to function in modern society. For instance, the sense of self-efficacy and resilient ability are not only crucial for academic purposes but most importantly, it is a crucial life skill. In the face of external demands and in times of challenges that we are now confronting with, the capability to 'bounce back' is one of the important strengths, which can assist people to not only adapt and surmount difficult, stressful and challenging situations but also to succeed and thrive.

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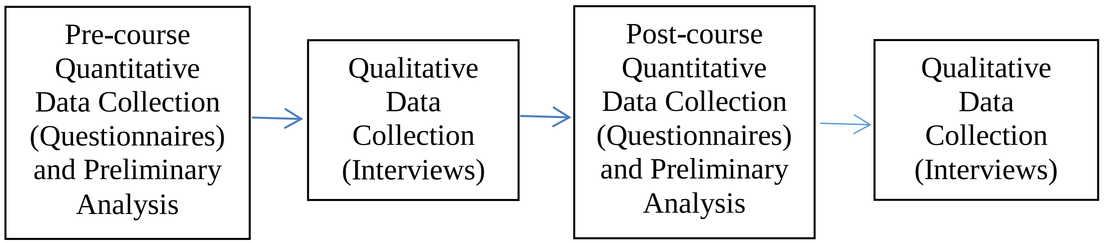
APPENDICES

Appendix A METHODOLOGY

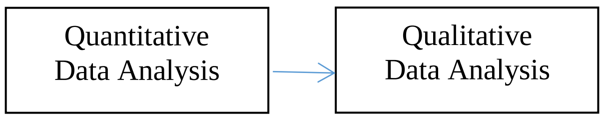
A1 Research design

The diagram A1 represents a visual model for the design of this study. Rectangles are drawn to illustrate the quantitative and qualitative data collection and analysis stages. Ovals are drawn to display the place in the research process where the connection, the integration and the discussion of the results of both quantitative and qualitative processes occurred. The single-headed arrows are used to indicate the sequence and the flow of the research design procedures.

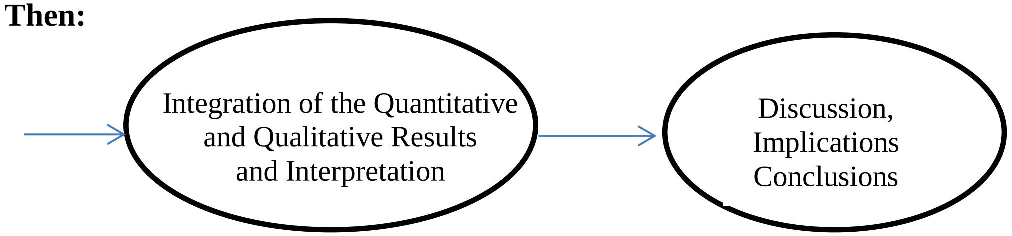
Diagram A1 Explanatory sequential design



Then:



Then:



A2 Sample version of the questionnaire

A translated sample version (in English) of the questionnaire that I administered to the participants in the pre-course administration is presented below. The following table consists of the two parts of the questionnaire. The first part provides information about the questions asked, the topic area (domain) related to these questions along with the type of the questions and the possible responses to them. The second part provides information about the Likert-type questionnaire items, the topic area (domain) related to each item along with the index number of each item/variable. An additional column was added to give information about the inspiration for each item (e.g. theory, previous literature, existing questionnaires, my own ideas).The possible responses to the Likert-types items were: 1(Strongly Disagree); 2 (Disagree); 3 (Neither Agree nor Disagree); 4 (Agree); and 5 (Strongly agree). It should be noted that the layout of the questionnaire and the ordering of the questions presented here was different from the final form of the questionnaire. In addition, the headings of the topic areas were not included in the distributed questionnaire.

Table A2 Sample version of the pre-course questionnaire

FIRST PART			
TOPIC AREA/ DOMAIN	**Question**	**Type of question**	**Possible responses**
SOCIO-DEMOGRAPHIC CHARACTERISTICS	What is your gender?	Closed-ended	1. Male 2. Female 3. No response
	What is your age group?	Closed-ended	1. 17-25 2. 25 and above 3. No response
	What is the highest educational level of your father and your mother?	Closed-ended	1.None 2. Primary Education 3.Secondary Education/ Vocational Education 4. Undergraduate Level 5. Master/Doctoral Level
EDUCATIONAL BACKGROUND	What is your major (degree programme)?	Open-ended	
	What is your academic year of study?	Closed-ended	1.1st year 1.2nd year 3. 3rd year 4.4th year 5.> 4th year
	What is the nature of this statistics module?	Closed-ended	1.Compulsory 2. Elective
	If you had a choice how likely is that you have taken any	Closed-ended	1.Very unlikely

	course in statistics?		2.Somewhat unlikely 3.Neutral 4.Somewhat likely 5.Very likely
MATHEMATICS BACKGROUND AND PERFORMANCE	How many mathematics courses have you taken at university level?	Closed-ended	1.None 2.One 3.Two 4.More than two
	Which mathematics courses, have you completed at university level?	Open-ended	
	What grades did you obtain in these courses?	Open-ended	
	What type of mathematics did you study in high school?		1. Core Mathematics 2. Advance Mathematics 3. Else
	What grade did you obtain in mathematics at the entrance matriculation exams in the end of the high school?	Open-ended	
CURRENT ACADEMIC PERFORMANCE	What is your current grade point average?	Closed-ended	1. 0-4.9 (Fail) 2. 50-64 (Satisfactory) 3. 65-74 (Good) 4. 75-84 (Very good) 5. 85-100 (Excellent)
EXPECTATIONS OF PERFORMANCE	What grade do you expect to receive in this statistics course?	Closed-ended	1. 0-4.9 (Fail) 2. 50-64 (Satisfactory) 3. 65-74 (Good) 4. 75-84 (Very good) 5. 85-100 (Excellent)
EFFORT	In a usual week, how many hours did you spend outside of class studying for this statistics course?	Closed-ended	1. Less than 3 hours 2. Between 3 and 6 hours 3. More than 6 hours
	Do you have any comments about statistics and the current statistics course?	Open-ended	

SECOND PART (Likert-Type Questions)			
TOPIC AREA (DOMAIN)	**Sample Questionnaire Item**	**Index number**	**Inspiration of each item**
DISPOSITIONS AND ATTITUDES			
LIKING (LIK) (3 items)	I like statistics as a discipline.	LIK1	Modified SATS item
	I like the subject content of the statistics course.	LIK2	My idea
	Statistics is my least favourite subject.	LIK3	SATS item
NATURE OF STATISTICS (NAT) (5 items)	Statistics course involved more theory than practical applications.	NAT1	My idea
	Statistics involves a lot of mathematics.	NAT2	My idea
	I believe that statistics has as a necessary prerequisite the knowledge of mathematics.	NAT3	My idea
	Everyone struggles with statistics at some point even the high performing students.	NAT4	Modified MRS item
	Females can do as well as males in statistics.	NAT5	My idea
DIFFICULTY (DIF) (4 items)	Statistics is a demanding subject.	DIF1	My idea
	I find it difficult to understand many of the statistical concepts.	DIF2	Modified SATS item
	I find it easy to apply statistics methods.	DIF3	Modified SATS item
	Statistics is relatively difficult in comparison to other academic subjects	DIF4	My idea
VALUE (VAL) (6 items)	Statistics is a useful subject.	VAL1	Previous literature and my ideas
	All students should be required to learn at least basic statistics regardless of their major.	VAL2	
	Statistics has applications in everyday life.	VAL3	
	I will not use what I have learned in statistics in the future.	VAL4	
	Learning statistics will benefit me in my future professional career.	VAL5	
	Statistics is irrelevant and has no applications in my field of study.	VAL6	
INTEREST (INT) (3 items)	Statistics is an interesting subject.	INT1	Modified SATS item
	I would be interested in enrolling in more advanced statistics courses in the future.	INT2	Modified SAS item
	I feel bored when I am learning statistics.	INT3	My idea
ANXIETY (ANX)			

(6 items)			
	Statistics course makes me feel anxious.	ANX1	Modified STARS item
	I feel anxious when I have to attend a statistics lecture class.	ANX2	My idea
	I feel anxious when I have to do assignments in statistics.	ANX3	Modified STARS item
	I feel more nervous when I study statistics than when I do it with other academic subjects.	ANX4	My idea
	I worry more than usually when thinking about an upcoming examination in statistics	ANX5	Modified STARS item
	I worry that I will not perform as well as I want in the statistics course.	ANX6	Modified SAM item
SELF-EFFICACY (SE) (7 Items)			
	I believe that I have the abilities to perform well in this statistics course	SE1	Theory, previous literature and my ideas
	I am confident that I can master the statistical theory presented in this statistics course.	SE2	
	I am confident that I can apply statistical methods.	SE3	
	I feel confident in my ability to explain the statistical findings after a statistical analysis.	SE4	
	I feel confident that I can understand the basic ways of solving exercises in statistics.	SE5	
	Statistics is the subject that I have the least confidence.	SE6	
	I am confident that I can learn even the most difficult parts of this statistics course.	SE7	
MOTIVATIONAL AND COGNITIVE ENGAGEMENT			
MOTIVATIONS AND ACHIEVEMENT GOALS (MOT) (5 items)			
	I want to get a good grade in the statistics course in order to maintain or improve my current academic grade average.	MOT1	Theory, previous literature and my ideas
	All I want is to pass in this statistics course.	MOT2	
	I want to do it well in the statistics course because it is important for me to display my abilities to others (such as family, classmates).	MOT3	
	I hope to gain as much knowledge and skills as I can in this statistics course.	MOT4	
	I feel personal satisfaction when I master the statistical content.	MOT5	
EXPECTATIONS OF PERFORMANCE (EXP) (2 items)			
	I expect that I will perform well in this statistics course.	EXP1	Modified MSLQ item
	I expect to perform as well as or better than the other students in this statistics course.	EXP2	Modified

			MSLQ item
CONTROL OVER PERFORMANCE (CON) (2 items)			
	The performance in the statistics course would be determined by my effort and amount of studying.	CON1	Theory and Modified MSQ item
	The achievement in the statistics course would be determined by the instructor (and the teaching methods) rather than by personal efforts.	CON2	Theory and my idea
EFFORT (EFF) (4 items)			
	I plan to attend every statistics lecture class.	EFF1	Modified SATS item
	I plan to do my best in this statistics course.	EFF2	Modified SATS item
	I plan to study throughout the semester and not only when I have an examination in statistics.	EFF3	My idea
LEARNING STRATEGIES (LES) (5 items)			
	I take well-organised notes in this statistics course.	LES1	My idea
	When I study for this statistics class, I put together information from different sources, such as lectures and tutorial notes.	LES2	Modified MSLQ item
	Apart from reading the course notes, I also look for extra information related to the statistics course.	LES3	My idea
	I prefer memorising the statistics course content than trying to understand it.	LES4	Theory and my idea
RESILIENCE (RES) (7 items)			
	I think I can deal effectively with the challenges and pressures of the university everyday life.	RES1	Modified item from Martin and Marsh (2006)
	I do not let failures (e.g. bad mark in an examination) to affect my confidence.	RES2	Modified item from Martin and Marsh (2006)
	If I get stuck on completing a statistical task or exercise on my first try, I will quit.	RES3	Modified item from Miller (1996)
	If I cannot understand something (e.g. a statistical concept) at first, I will keep trying until I do it.	RES4	Modified item from Miller

			(1996)
	If I face difficulties in statistics, I will search for alternative strategies.	RES5	Theory and my idea
	I will continue working on a statistical task until I finish even if I do not find it interesting.	RES6	Theory and my idea
	I will keep trying even if my studying and effort do not have the desired results.	RES7	Theory and my idea
TECHNOLOGY (TEC) (3 items)			
	The use of technology (e.g. statistical software programs) in the class would make the learning of statistics more enjoyable.	TEC1	Modified SASTSc item
	I feel anxious even with the thought of using technology in the statistics course.	TEC2	My idea
	I believe I would be able to use statistical packages to complete statistical-related tasks.	TEC3	My idea
PREFERRED METHODS OF ASSESSMENT (ASS) (3 items)			
	I prefer mid-term and final examinations as methods of assessment in the statistics course.	ASS1	Previous literature and my ideas
	I prefer open book examinations that test understanding rather than memory abilities.	ASS2	
	I prefer group or/and individual projects as a method of assessment rather than examinations.	ASS3	
MATHEMATICS (MAT) (8 items)			Previous literature and my ideas
	Mathematics is one of my favourite subjects.	MAT1	
	I have always enjoyed the learning of mathematics	MAT2	
	Mathematics is a useful subject to learn.	MAT3	
	I find the mathematical thinking difficult for me.	MAT4	
	I feel anxious when doing mathematics.	MAT5	
	I feel confident with my mathematics abilities and skills.	MAT6	
	Mathematics is among the subjects that I am not strong	MAT7	
	Previous experiences with mathematics have influenced (positively or negatively) my attitudes towards statistics.	MAT8	

*where Survey of Attitudes Toward Statistics (SATS) by Schau (1995), Students Attitudes toward Statistics and Technology Scale (SASTSc) by Anastasiadou (2011), Statistics Anxiety Measure (SAM) by Earp (2007), Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich and DeGroot (1990), Motivation toward Statistics Questionnaire (MSQ) by Bude *et al.* (2007), Mathematical Resilience Scale (MRS) by Kooken *et al.* (2013), Academic Resilience subscale by Martin and Marsh (2006), Attitude Toward Mathematics Survey by Miller (1996).

A3. Sample Interview Plan

A translated version (in English) of a sample interview plan is provided below. It includes the major topic areas that were discussed along with selected main and additional questions that were asked during the interviews. These questions were based on ideas from existing theoretical and empirical studies and my own ideas.

Table A3 Sample interview plan

TOPIC AREA	MAIN QUESTIONS	ADDITIONAL QUESTIONS
FEELINGS, ATTITUDES AND BELIEFS	• Overall, can you say that you have positive or negative attitudes towards statistics? • What are the reasons behind your current attitudes towards statistics?	• Before enrolling in this statistics course, what views and beliefs did you have about statistics? What were the main sources of your beliefs regarding statistics? • After attending course, did your attitudes and opinions regarding statistics change or remain the same?
INTEREST	• Overall, do you enjoy this statistics course?	• What components of this statistics course do you find more/less interesting?
USEFULNESS, WORTH AND RELEVANCE	• How useful do you think is statistics for your personal, academic and future life?	• Do you believe that statistics has applications in everyday life? Why/why not? • Do you think that statistics is relevant to your field of study, and what areas of statistics, if any, do you find the most useful or relevant? • Do you think that you will apply what you have learned in statistics in your future academic studies and your future professional job?
PERCEIVED DIFFUCULTY	• Overall, do you find this statistics course difficult or easy?	• What components of the course do you find the most difficult and what are the easiest parts for you?
ANXIETY	• Overall, how would you characterise yourself with regards to anxiety related to the statistics course that you are enrolled in?	• What factors do you believe have contributed to your heightened or reduced levels of anxiety? Did any aspects of this statistics course raise your anxiety? • How did you attempt to cope with and overcome any anxieties that you have experienced? • Did your anxiety change or remain the same over the duration of the statistics course?

SELF-EFFICACY	• Overall, how would you describe your levels of confidence regarding this statistics course?	• In which components of the statistics course do you feel more/less confident? What factors have contributed to being more or less confident in statistics? • Did your levels of confidence change throughout the course? If so, how and in what extent?
STATISTICS VERSUS MATHEMATICS	• What are your perceptions about the nature of statistics as a discipline/subject? • Do you believe that statistics is the same thing with mathematics?	• Do you see any similarities or differences between mathematics and statistics? • Do you believe that statistics involves mathematics? • Do you find statistics more or less interesting/useful/relevant/difficult than mathematics?
PRIOR MATHEMATICS/ STATISTICS BACKROUND, AND EXPERIENCES, ATTITUDES, ANXIETY AND SELF-EFFICACY REGARDING MATHEMATICS	• What is your prior mathematics/ statistics background and performance? • Can you recall any learning experiences with maths and statistics that you want to share with me? • Did any prior maths and/or statistics experiences play some role in your attitudes, levels of self-confidence and anxiety towards statistics?	• Can you recall any exposure to statistics topics in your high school or university-level mathematics classes? • Do you believe that, any previous mathematics background and skills that you have, assist your learning process and your performance in this statistics course? • What are your general attitudes towards mathematics? Do you feel anxious when you have to engage in mathematics or mathematical-related tasks? Do you feel confident with your mathematical abilities and skills?
MOTIVATIONS AND ACHIEVEMENT GOALS	• What factors do they motive you to study and learn statistics? • What are your achievement goals in this statistics course?	• What is the most important motivating factor for you to engage with statistics? • Do you want to acquire a broad and in-depth knowledge of statistics when you will complete this course or do you care mostly about the grade that you will obtain?
EXPECTATIONS OF PERFORMANCE	• What are your expectations of performance in this statistics course?	• Do you expect to perform as well as or better than your classmates and why?
CONTROL BELIEFS	• Do you believe that you have the control over your learning and your performance in statistics?	• Do you believe that the amount of time and effort that you apply in statistics will mainly determine your performance in the course? • Do you believe that the statistics instructors (and their teaching methods) can influence learning and performance?
EFFORT	• Do you think that you apply a satisfactory amount of effort when you are studying and	• Do you usually study throughout the semester for the statistics or when an examination is approaching?

	learning statistics?	
LEARNING STRATEGIES AND APPROACHES	• What learning strategies and approaches do you most frequently use when you are studying for this statistics course?	• How do you usually study the practical and theoretical components of this course? • When you are engaging with statistics, do you use different learning approaches than when you are studying for other academic subjects?
RELATIONSHIP BETWEEN SEVERAL FACTORS AND PERFORMANCE	• What factors do you believe that may affect your performance in this statistics course?	
RESILIENCE	• Do you believe that you can deal effectively with higher education challenges, pressures and stressful situations? • Have you experienced any difficulties and setbacks during this statistics course? How did you cope with them?	• What do you do when you confront with study pressures and stressful situations in your academic studies? • What did you do when you faced some material in statistics of which you could not make sense at first? What did you do when you had to complete unfamiliar or difficult statistical-related tasks? • What is a perceived failure for you? • Did a bad grade obtained in a test or an assignment discouraged you or motivated you to study harder? Did a very good grade in a test increase your level of confidence in statistics?
RECCOMENDATIONS /SUGGESTIONS	• Do you have any general recommendations for improving a statistics educational experience?	• What changes do you want to see in a statistics course to make the teaching and learning of statistics more effective/more interesting /less fearful? • Do you believe that the incorporation of the technology in a statistics course will facilitate or impede the learning process (and performance)?
EXPERIENCES RELATED TO THE STATISTICS COURSE	• Are there any particular experiences (positive or negative) that you had in this statistics course and you want to share with me?	
OPINIONS ABOUT THE STATISTICS COURSE	• What are your opinions of the statistics course that you are currently attending?	• Do you think is good that the statistics course is compulsory for your degree programme?

A4 Data collection

The following tables present information about the data collection in both academic semesters (Fall semester 2015 and Spring Semester 2016).

Table A 4.1 Data collection (Fall semester 2015)

Type of University	University Indicator	Name of the Course (Class/Group)	Programmes of study	Instructor Indicator	Pre-course Administration (# of collected questionnaires)	Post-course Administration (# of collected questionnaires)	# of interviews
Public	U1	Statistical Methods (1st)	• Psychology • Primary Education	I1	44	26	2
Public	U1	Statistical Methods (2nd)		I1	35	28	5
Public	U1	Statistical Analysis (1st)	• Business and Public Administration • Accounting and Finance • Economics • International European and Economic Studies	I2	38	23	1
Public	U1	Statistical Analysis (2nd)		I2	53	39	1
Public	U1	Statistical Analysis (3rd)		I2	51	43	2
Public	U1	Statistical Analysis (4th)		I2	20	16	3
Public	U1	Introduction to Probability and Statistics	• Computer Science	I3	38	21	2
Public	U2	Statistics for Rehabilitation Sciences	• Language and Speech Therapy	I4	24	20	1
Private	U3	Statistics I (1st)	• Accounting • Economics • Finance and Investments • Business Studies • Marketing • Management	I5	20	15	-
Private	U3	Statistics I (2nd)		I5	13	11	2
Private	U3	Statistics in Psychological Science	• Psychology • Social work	I6	19	10	2
Private	U3	Biostatistics (1st)	• Physiotherapy	I7	12	12	-
Private	U3	Biostatistics (2nd)	• Physiotherapy	I7	34	29	1
Private	U3	Biostatistics (3rd)	• Nutrition and Dietetics • Sports Science and Physical Education	I7	15	14	2

Private	U3	Biostatistics (4^{th})	• Radiology and Radiotherapy • Pharmacy • Biology	I7	32	29	2
Private	U4	Statistics in Education	• Primary Education • Pre-primary Education	I8	28	23	1
Private	U4	Statistics I (1^{st})	• Accounting • Marketing • Business Administration • Nutrition and Dietetics • Sports Science • Psychology	I9	15	11	2
Private	U4	Statistics I (2^{nd})		I9	13	11	3
Private	U4	Statistics I	• Accounting • Business Administration • Psychology • Nutrition and Dietetics • Tourism, Leisure and Events Management • Digital communications and Mass media • Marketing • Sports Management	I10	0	20	-
Private	U5	Probability and Statistics for Engineers	• Civil Engineering • Mechanical Engineering • Electrical Engineering • Computer Science • Quantity Surveyor	I11	17	18	4
Private	U6	Statistics	• Business Administration • Accounting, Banking and Finance • Economics • Real Estate	I12	31	25	1

Table A4.2 Data collection (Spring Semester 2016)

Type of University	University Indicator	Name of the Course (Class/Group)	Programmes of study	Instructor Indicator	Pre-course Administration (# of collected questionnaires)	Post-course Administration (# of collected questionnaires)	# of interviews
Public	U1	Statistical Methods	• Psychology • Primary Education • Pre-Primary Education • Sociology	I1	27	20	5
Public	U1	Introduction to Probability and Statistics	• Biology • Civil Engineering	I1	26	21	1
Public	U1	Introduction to Probability and Statistics	• Civil Engineering	I13	28	21	2
Public	U1	Statistics for Medicine	• Medicine	I4	19	15	-
Public	U2	Statistics/Biometry	• Agricultural Sciences	I14	31	26	1
Public	U2	Statistical theory of errors and Least squares method	• Civil Engineering • Quantity Surveyor • Geo-Informatics Engineering	I15	41	35	6
Public	U2	Statistical Analysis (1st)	• Commerce, Finance and Shipping • Hotel and Tourism Management • Management	I7	47	25	1
Public	U2	Statistical Analysis (2nd)		I7	30	27	2
Public	U2	Statistical Analysis (3rd)		I7	6	5	2
Private	U3	Statistics in Psychological Science	• Psychology • Social work	I6	15	10	3
Private	U3	Statistics I	• Business Administration • Business Management • Accounting • Pre-primary education	I5	16	12	1
Private	U5	Probability and Statistics for Engineers (1st)	• Electrical Engineering • Mechanical Engineering • Computer Engineering	I11	19	0	3
Private	U5	Probability and Statistics for Engineers (2nd)		I11	0	13	1

A5 Frequently used abbreviations

Table A5.1 Abbreviated variable/construct names

Full variable/construct names	Abbreviated variable/construct names
LIKING	LIK
INTEREST	INT
VALUE	VAL
DIFFICULTY	DIF
ANXIETY	ANX
SELF-EFFICACY	SE
RESILIENCE	RES
INTRINSIC MOTIVATION	IM
EXTRINSIC MOTIVATION	EM
EXPECTATIONS OVER PERFORMANCE	EXP
CONTROL OVER PERFORMANCE	CON
EFFORT	EFF
LEARNING STRATEGIES	LES

Table A5.2 Statistical abbreviations

Term	Abbreviation
Number in subsample	n
Total number in sample	N
Mean	M
Standard deviation	SD
Standard error	SE
Degrees of freedom	df
Pearson's correlation	r

A6 Model development

Certain assumptions regarding the variables under investigation were set during the model development process. For example, a classification/list of variables was initially made, including (a) which variables were designated to be the dependent or outcome variables of the study and they were presumed to be caused or influenced by the independent variables and (b) which variables were treated as independent in order to understand distributions and patterns of relationships (Fowler, 2009). Moreover, latent variables can be distinguished in terms of endogenous and exogenous variables. Exogenous variables are variables, which their causes are not included in the model, but usually, they influence one or more variables in the model (Byrne, 2010). Endogenous variables are variables which may be caused by the exogenous variables in the model, and they may also influence other endogenous variables in the model, either directly or indirectly (Byrne, 2010). In this study, as it is explained in §4.10, self-efficacy was treated as an exogenous (independent) variable whereas other variables (such as anxiety) were handled as latent endogenous (independent) variables. The final statistics course grade constituted the dependent variable in the model.

Appendix B QUANTITATIVE RESULTS

B1 Data screening and exploratory analyses

Amount and distribution of missing data

With regards to the missing pattern analyses, missing data can be characterised as Missing Completely At Random (MCAR) or Missing At Random (MAR). MCAR means that the missing values are not related to any of the values in the dataset, missing or observed (missing values occur randomly), whereas MAR means that the missing values are not associated with the values of the variable with the missing data, but can be related to another variable of the data set (Graham, 2009; Bhaskaran and Smeeth 2014; Newsom, 2017). Ideally, the missing data should be found to be MCAR, meaning that there is not a systematic pattern to the missing responses and least amount of bias can be reached. Before conducting CFA and SEM approaches, the Expectation-Maximization technique was employed. The EM - a single imputation method of handling randomly missing values - relies on maximum likelihood techniques for imputing missing values (Alison, 2002). This method is supported when variables have a small proportion of missing observations and there is no pattern to the missing responses (Allison, 2002; Moss, 2009). As many authors advocate (e.g. Enders, 2001; Scheffer, 2002), a single imputation method (e.g. the EM method) can yield unbiased parameter estimates and improve the statistical power of the analyses.

Detection and treatment of outliers

Osborne and Overbay (2004) advocates that outliers can have devastating effects on statistical analysis by reporting 3 main arguments: they can (a) inflate the error variance and lessen/diminish the power of statistical tests, (b) decrease the normal distribution of scores (and in multivariate analyses, violate the assumptions of sphericity and multivariate normality) and (c) bias or have an effect on the parameter estimates' accuracy and also influence Type I and Type II errors. For the above reasons, the questionnaire subscales which were used in the multivariate analyses (such as factor analysis and SEM) were inspected for the presence of both univariate and multivariate outliers. Initially, for locating univariate outliers to the subscales, I performed some visual inspections to graphs (such as histograms, box plots and normal probability plots) as well as a calculation of the standardised values (that is z-scores). A few univariate outliers were detected in some of the subscales in both datasets. Given that the elimination of outliers resulted to sample size reduction, I decided not to remove the univariate outliers from the data sets. I also decided not to apply data transformation (such as square root, log transformation or inverse transformation) to the independent variables as many authors suggested as a good way to deal with them (e.g. Tabachnick and Fidell, 2013).

Tests for normality assumptions

In order to check whether the variables' distributions were significantly different from the normal distribution, several methods and criteria were consulted. To begin with the graphical and visual inspection, normal probability plots of the questionnaires' subscales were assessed showing an acceptable alignment with the normal distribution assumptions. Also, histograms did not appear to have a symmetrical bell shape, with the most of the subscales were positive or negative skewed. Moreover, box plots were not perfectly symmetric, that is median and mean did not appear to have the same value in the middle of the box. With regards to the formal normality tests, significant results were obtained from both the Kolmogorov-Smirnoff and Shapiro-Wilk tests suggesting that the data did not follow the normal distribution. According to Elliot and Woodward (2007), these tests are recommendable for sample sizes of less than 50. The Kolmogorov-Smirnoff test may be unreliable (Kim, 2003) and has low power (Ghasemi and Zahedias, 2012) for large samples. The violation of normality assumption is quite common in large data samples as also pointed out by Field (2009) and Pallant (2016). They argued that the normality tests (e.g. Kolmogorov-Smirnoff and Shapiro-Wilk) can be found to be significant even if the distributions only slightly differ from a normal distribution. Thus, the authors recommended always to be taken into account along with graphical inspections and the values of skewness and kurtosis. The normality assumptions were then examined by inspecting the and the kurtosis values. Skewness and kurtosis values, ranging from -1 and 1, can be treated as acceptable and they do not lead to appreciable distortions (Muthén and Kaplan, 1985). Also, George and Mallery (2010) recommends that values of kurtosis and skewness between -2 and +2 are also usually considered as acceptable to indicate normal univariate distribution. In the current data sets, after the elimination of the multivariate outliers, all the subscales under consideration had acceptable values of skewness and kurtosis within the range of -2 to +2**.** The absolute values of the skewness and kurtosis of each variable were not substantially deviated from 0 indicating that the distribution of the variables could be considered as being close to the normal distribution (Emmoglu, 2011; Tabachnick and Fidell, 2013) and suitable for the subsequent bivariate and multivariate statistical techniques (Hair *et al*., 2013). Many authors propose transformations of the variables which might improve the normality of their distributions (e.g. Quinn and Keough, 2002; Chen and Deo, 2004; Tabachnick and Fidell, 2013). However, according to Osborne and Overbay (2006), transformations, firstly, alter the relationship between the original variables and secondly, the values after the transformation might be difficult to be interpreted. Thus, I decided not to apply transformations. Also, when normality assumptions are not met, non-parametrical methods where the normality assumption is not required can be employed. I carried out some analyses (e.g. correlations) using both parametric and non-parametric tests and the patterns of the results were very similar. As Zimmerman (1998) argues, non-parametric tests of analysis are also sensitive to violations of normality assumptions. Thus, I decided to employ parametric statistical tests for the subsequent analyses. For multivariate normality checking, the Mardia coefficient was used to examine two conditions (i.e. multivariate skewness and multivariate kurtosis) which are necessary conditions for multivariate normality. According to many authors (e.g. Bentler and Wu, 1993; Newsom, 2005; Walker, 2010), a Mardia's value smaller than 3 and larger than 30 is a sign of problematic multivariate kurtosis.

Homoscedasticity and Linearity

The assumption of homoscedasticity or homogeneity of variance (when grouped data are used) is that the variability of one variable should be stable at all levels of the other variable (Field, 2009; Warner, 2008; Tabachnick and Fidell, 2013). Homoscedasticity of variance was inspected (but not presented here) graphically using bivariate scatter plots. The band of data was distributed in a rectangular shape and no systematic pattern or clustering of scores was identified (as explained by Tabachnick and Fidell, 2013) indicating that the homogeneity of variable assumption was not substantially violated.

Appendix B2 Confirmatory Factor Analysis results

Table B2.1 Pre-course and post-course inter-factor correlations for the five-factor solution

PRE-COURSE MODEL					
Factor/Component	**LIKING /INTEREST**	**VALUE**	**DIFFICULTY /ANXIETY**	**SELF-EFFICACY**	**RESILIENCE**
LIKING /INTEREST	1	0.71	-0.59	0.65	0.48
VALUE	0.71	1	-0.40	0.49	0.36
DIFFICULTY /ANXIETY	-0.59	-0.40	1	-0.56	-0.33
SELF-EFFICACY	0.65	0.49	-0.56	1	0.65
RESILIENCE	0.48	0.36	-0.33	0.65	1

POST-COURSE MODEL					
Factor/Component	**LIKING /INTEREST**	**VALUE**	**DIFFICULTY /ANXIETY**	**SELF-EFFICACY**	**RESILIENCE**
LIKING /INTEREST	1	0.71	-0.54	0.62	0.47
VALUE	0.71	1	-0.36	0.48	0.34
DIFFICULTY /ANXIETY	-0.54	-0.36	1	-0.58	-0.33
SELF-EFFICACY	0.62	0.48	-0.58	1	0.73
RESILIENCE	0.47	0.34	-0.33	0.73	1

Appendix B3 Structural Equation Modelling results

Table B3.1 Fit Indices for the three tested SEM models (Pre-course and post-course)

	FIT INDICES						
PRE-COURSE MODEL	χ^2	**df**	**Sig.**	χ^2**/df**	**RMSEA**	**CFI**	**SRMR**
MODEL A (initial model)	946.46	363	0.00	2.61	0.05	0.93	0.05
MODEL B (final model)	955.98	370	0.00	2.58	0.05	0.93	0.05
MODEL C (without value variable)	606.62	225	0.00	2.70	0.05	0.94	0.05

	FIT INDICES						
POST-COURSE MODEL	χ^2	**df**	**Sig.**	χ^2**/df**	**RMSEA**	**CFI**	**SRMR**
MODEL A (initial model)	1005.10	363	0.00	2.77	0.06	0.93	0.05
MODEL B (final model)	1013.95	367	0.00	2.76	0.06	0.93	0.05
MODEL C (without value variable)	857.42	245	0.00	3.50	0.07	0.92	0.08

Table B3.2 Standardized Direct, Indirect and Total effects in the pre-course and post-course final models (Model B)

PRE-COURSE FINAL MODEL							
VARIABLE	**EFFECT**	**LATENT VARIABLE**					
		To LIK/INT:	**To VAL:**	**To DIF/ANX:**	**To SE:**	**To RES:**	**To FG:**
From LIK/INT:	Direct			-0.41*			
	Indirect					-0.04	-0.01
	Total			-0.41		-0.04	-0.01
From VAL:	Direct	0.47*					
	Indirect			-0.19		-0.02	
	Total	0.47		-0.19		-0.02	
From DIF/ANX:	Direct					0.09*+	0.02+
	Indirect						
	Total					0.09	0.02
From SE:	Direct	0.42*	0.46*	-0.28*		0.68*	0.12*
	Indirect	0.22		-0.26		-0.04	0.12
	Total	0.64	0.46	-0.54		0.64	0.24
FROM RES:	Direct						0.19*
	Indirect						
	Total						0.19

POST-COURSE FINAL MODEL							
VARIABLE	**EFFECT**	**LATENT VARIABLE**					
		To LIK/INT:	**To VAL:**	**To DIF/ANX:**	**To SE:**	**To RES:**	**To FG:**
From LIK/INT:	Direct			-0.30*			
	Indirect					-0.05	0.03
	Total			-0.30			0.03
From VAL:	Direct	0.54*		0.12*			
	Indirect			-0.16		-0.01	-0.01
	Total	0.54		-0.04		-0.01	-0.01
From DIF/ANX:	Direct					0.16*	-0.11*
	Indirect						0.03
	Total					0.16	-0.08
From SE:	Direct	0.36*	0.47*	-0.47*		0.82*	0.25*
	Indirect	0.26		-0.12		-0.09	0.19
	Total	0.62	0.47	-0.59		0.72	0.44
FROM RES:	Direct						0.17*
	Indirect						
	Total						0.17

Note: *indicates that p-value ≤0.05