Learning in Virtual Environments: An Integrative Approach for Understanding the Adoption, Engagement and Learning Achievement in Digital Contexts

By

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ABSTRACT

The main goal of the research presented in this doctoral thesis is to extend and enhance knowledge about the use of information and communication technology for learning purposes and its effects on the learning output. An integrative approach was utilised to combine elements from different perspectives – including attitudes, motivations, learning profiles, and behaviour – to build a theoretical framework which takes into account the learner characteristics and their interaction with virtual learning environments (VLE) in the achievement of learning goals. It is proposed that by accurate representation of the learner, and identifying relevant milestones along the learning process, it would be possible to enhance both the adoption of learning technology and the attainment of learning goals with a single framework.

In order to accomplish the research goal four studies were conducted. Study 1 tested the most utilised approaches on adoption and effectiveness of learning technology, based on Davis' Technology Acceptance Model (TAM) and a selection of indicators of learning effectiveness in virtual environments. The participants were 168 teachers enrolled in a 5-week e-learning course, who were asked to complete two questionnaires. The first questionnaire was delivered the first week of the course and it aimed to assess the variables related to the adoption of the learning technology (perceived ease of use and usefulness, previous experience with computers, intention of use, and behavioural planning). The second questionnaire was delivered once the course was finished and aimed to assess the time spent on the learning activities (online and offline), the

satisfaction with the course, and the self-perceived learning. The final mark of the participants was collected as an objective indicator of learning achievement. Results showed that a significant pathway can be observed from individual attitudes towards learning achievement through behavioural planning and actual use. Nonetheless, the explained variance was low, indicating that the model must be improved.

The second and third studies were aimed to test variables that could be included in the model in order to improve it. The second study was cross-sectional and included 268 participants. It tested the relationship between learning approach, academic locus of control, and the learning environment characteristics – comparing one highly structured and one unstructured environment – with the core of the adoption of TAM. Structural Equation Modelling revealed an important effect of learning approach on attitudes and intention of use, and a significant improvement of the explained variance over study 1. The third study collected the responses of 115 participants, assessing the role of learner goals, thoughts about technology, learning style, and learning approach on attitudes and behaviour. As in the previous study, an important effect of learning approach was found on attitudes and on the behavioural indicators. The effect of learning style, goals, and thoughts about technology was not significant for the adoption parameters. The overall power of the adoption model was highly improved.

Study 4 aimed to test a new version of the model comprising adoption and effectiveness of learning technology. It involved the use of specially developed software to assist students in learning programming. Based on the previous studies and considering their limitation, a repeated measures design was chosen involving 30 students of higher education for 12 weeks, assessing their learning process each week. A baseline of the knowledge on programming was measured at week 1, and was re assessed at week 6 and week 12. The marks of 4 assessments along the course were collected, and every week the attitudes towards the software, the module and its contents, and the time spent on the learning activities were collected. The results showed a strong effect of learning approach on attitudes and on the behavioural parameters, and how that effect decayed with time. Nonetheless, the engagement of the students with the learning activities and exercises was reinforced by the proximity of each assessment.

The main conclusions of the present research are that the adoption of learning technology, the engagement with it over time, and the achievement of learning goals lie on the interaction of individual characteristics, the learning environment design, and the instructional design utilised. Being more precise, three stages on the adoption and use of learning technology can be distinguished, namely adoption, engagement, and goal achievement. The adoption of learning technology is strongly influenced by individual characteristics that shapes the attitudes towards the use of technology to achieve learning goals. Later on, the engagement with the technology will be sustained by the satisfaction of the user with it, especially considering its functional aspects. Finally, the materials and activities together with the plan of instruction will play a role on the level of achievement of the learners. The limitations of the research, and the theoretical and practical implications of these findings are discussed.

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1.1. General context of learning in virtual environments.

1.1.1. Defining learning in virtual environments.

Learning is a concept used so commonly that its definition is not always easy. Depending on the reference background it may be related to words such as change, acquisition, process, or construction, but more generally it may be defined as a process by which a person gains more knowledge about something, or develops the skills to do something (Pritchard, 2013). The first element to have in mind is the individual that goes through this process: the learner. The learner is in this case the one who processes the information, the one who deploys its cognitive, affective, and interpersonal resources in order to broaden its potential and, as a result, the one who embodied the change (Jarvis, 2014). The acquisition of knowledge or the development of skills may occur by different methods – repetition, practice, reflection, and so on – depending on the complexity of the desired learning output, but it needs a source of information (or many) and a space (or multiples) to enable the learning to take place. In other words, the learning process does not occur in a vacuum. It is required to have a learning environment that supports both the information and the learner.

Commonly, a traditional learning setting can be identified as an in-classroom face-to-face interaction, utilizing stimuli delivered by conventional technology, such as speech, words and printed images, video and audio. However, the advance of computer technology has resulted in a fast increasing of virtual learning environments [VLE], a term that can be applied to a large number of resources and functionalities. Gillespie et al. (2007) argue that the boundaries between different learning environments – such as managed learning environments or learning platforms, in its different presentations – are blurred more and more due to the continuous advance of computer technology. For this reason, analysing the effect of specific characteristics or particular media formats seems useless, and so the efforts should be focused on understanding the general variables that affect the learning process. Among the main characteristics of a virtual learning environment might be the capability of sharing files and information, using discussion boards, organize time and resources, support learning applications and activities, among others (Gillespie et al., 2007).

For the purposes of the present research, the process of learning within a virtual environment is going to be understood as the acquisition of knowledge or the development of skills by an individual (learner) that uses its cognitive, affective, and relational resources for the processing of information delivered through a computer based application.

1.1.2. The role of virtual environments on learning.

The previous definition may seem too broad or unspecific, nonetheless literature suggests that despite the characteristics of the learning environment or the stimuli displayed by them, the learning output varies little or not at all when controlled by instructional design, this is, the strategy by which the instructional process and its resources are managed and implemented (Reiser, 2001) . One of the first researchers to state that learning technology by itself has little or no effect on the learning output was Clark (1983). Clark found no significant benefits from utilizing any particular learning environment, and warned on serious problems in the research about learning performance supported by computer technology due to uncontrolled effects related to instructional methods and to the novelty of the situation. The same author in a subsequent study (1985) analysed the results of a series of meta-analysis by Kulik conducted between 1980 and 1984 arguing that the evidence suggests that the learning results can be related to the instructional design implemented by the learning environment and not by particular characteristics of it.

Since then, various meta-analyses have reached similar conclusion. For example, Fletcherflinn & Gravatt (1995) found no significant effect of computer-based instruction when it was controlled by instructional design and learning materials, and when something was gained, it was due to a better quality of the instructional design rather than the delivery method. Lou et al. (2006) analysed 103 studies finding no difference between traditional instruction and different formats of instruction delivered by computer technology, suggesting that there is no particular feature of the virtual learning environments that made them intrinsically better than others. Another meta-analysis (Sitzmann, Kraiger, Stewart, & Wisher, 2006) found no difference between the results of different virtual learning environments and classroom instruction when the same instructional design was used, adding support to Clark’s idea.

It could be considered that computer-based technology would not be useful, given the previous arguments that it does not directly contribute at the learning outcome.

Nonetheless, a different approach is to understand that when things are made in the same way - despite using new technologies - the results tend to be the same. The previous studies show the underlying elements of learning acting in the same way independently of the learning environment (traditional or virtual). However, digital environments possess characteristics that can affect or stimulate certain components of the learning process while interacting with the learner, and by this means, they can influence the learning output. Pintrich et al. (1986) emphasized the favourable effect of technology on different respects of learning which found on different studies and meta-analyses, but indicated that the variables involved are entangled in many ways, thus its effects are not easy to observe consistently among different conditions.

For example, Bangertdrowns (1993) investigated the effect of word processing on writing instruction, finding a positive effect of technology on learning. The positive effect was achieved by acting on the way learners operate on writing tasks, making texts more flexible and thereby allowing the user to elaborate more complex materials, reaching higher quality outputs than those obtained by traditional (mechanical) ways. Nonetheless, the positive effect was significant mainly to those considered “weaker writers”, possible because those that have good writing skills can elaborate high quality output even without word processor tools, and thus the gaining of the technology is only marginal for them. A study by Moreno & Mayer (1999) also found a positive effect of technology on reducing cognitive overload with benefits on learning outputs in different scenarios. The effect of learning technology in these cases is to allow learners to deploy their cognitive resources in a better way, and therefore achieving better results.

Another example of technology assisting learning in a meaningful way is by its capacity for supporting interaction. Johnson and colleagues (2000) conducted a meta-analysis on the effect of learning technology within cooperative contexts, this is, learning environments that allow participants to interact between them and in this way to exchange information, to discuss contents, and ultimately to build knowledge collectively. They compared collaborative methods with competitive methods, finding that collaborative methods are more effective, and that learning technology that can support such collaborative methods is playing a role in the construction of knowledge by allowing participants to reflect on the contents and improving learners' engagement with the course. Again, the effect of the technology was to support the learning process, and by this action to impact on the learning outcome.

More evidence on the effect of learning technology on the learning output can be found in the literature about learning attitudes and the use of learning technology. The main argument is going to be presented and illustrated by the following three representative studies, and presented in detail later in section 1.2.

The first of these three studies was conducted by Connolly, MacArthur, Stansfield & McLellan (2007), a quasi-experimental study of three years of length. They aimed to investigate to what extent learning was enhanced by technology in comparison to face-to-face instruction, and to identify the variables that could explain such variation. They looked for differences in student performance at the end of the module, between coursework and exam performance, and in dropout rates. The results showed a better performance of those enrolled on virtual learning environments, and higher levels of satisfaction from students and faculty on the use of learning technology. Student satisfaction was related to the intention of using learning technology in the future. Despite that very positive results were obtained, people enrolled in virtual learning environments showed a lower rate of use of the learning materials than those in the traditional course, and also missed more sessions than those in the face-to-face courses. The authors indicated that while promising, quality learning environments demand more time to be designed and implemented, and even so the learners can evaluate learning materials as not completely satisfactory. This study highlights two issues that will be observed in forthcoming studies: first, virtual learning environments are attractive for students and they are usually enthusiastic with them, which is reflected by the high levels of satisfaction reported. The second is such positive attitudes do not imply more engagement with the course, reflected as time invested on the platform or as utilizing the learning materials, and so the participation may be lower than required.

The second study, conducted by Johnson, Hornik, & Salas (2008), was focused on the factors that contribute to successful virtual learning environments. They included two dimensions in their research model. The first dimension was labelled as “human dimension”, which comprised the variable application-specific computer self-efficacy. The second dimension was named as “design dimension”, and comprised the perceived usefulness of the learning environment, the evaluation of the exchange of information between the stakeholders in the course – labelled as interaction –, and social presence – the evaluation on the importance of the interpersonal relationships. The outcome variables, which should reflect the success of the learning environment, were self-perception of learning – named as course instrumentality –, satisfaction with the course, and student performance as the final mark in the course. The results shown that computer self-efficacy and perceived usefulness were related with all three outcomes variables, peer interaction was related to course performance and course satisfaction, and social presence was related to course satisfaction and self-perceived learning. These findings present the important role of learners' evaluations about their own performance and about the learning environment as good predictors of overall success, and the relevance of considering not only the technical aspects of virtual learning environments when designing them but also the learners' characteristics that would facilitate their successful adoption. Nonetheless, it is important to note that this model only explains a variance of 0.18 of the performance output, while the course satisfaction was the most represented output with a 0.41 of explained variance. The correlation between the variables included in the model and performance ranged between 0.18 and 0.36. It can be said that this model, whether useful to understand the importance of the interaction between the learning environment and the learners' reactions to it, is not completely satisfactory to understand how to improve the learning outcome.

The third study attempted to illustrate the relationship between learners' attitudes, the use of learning technology, and learning performance. It was conducted by Hassanzadeh, Kanaani & Elahi (2012) by measuring the success of virtual learning environments in universities. In their study, they included variables given account of learners' evaluation of the system quality, content quality, and service quality as predictors of intention of use and satisfaction. The last two variables were predicted as related to the use of the system and loyalty to the system. Intention of use, user satisfaction and loyalty, and actual use of the system were predicted as related to the perception of benefits of using the system, and as affecting directly the achievement of learning goals. The results showed that system and content quality positively affect satisfaction, and satisfaction influences directly intention of use, perception of benefits, loyalty to and use of the system, and goal achievement. The key role of user satisfaction implies that users' comfort with the learning environment is fundamental to ensure its usage, the engagement with it, and consequently the achievement of learning goals.

1.1.3. Current situation and main challenges for virtual learning environments.

So far, it could be said that learning technology has a positive effect on learning, and that when learners are satisfied with it, then the achievement of learning goals is going to be assured. Nonetheless, the reality is a little bit more complicated than that. A number of studies have analysed the high rates of dropouts from different modalities of virtual learning environments, especially those complementing university courses (Levy, 2007), and the so called massive open online courses [MOOCs] (Rivard, 2013; Yang, Sinha, Adamson, & Rosé, 2013), where dropouts reach up to 90%.

This is a serious issue, mainly because of the increasing participation of learning technology in the formal learning system. According to projections, the global market of learning technologies will reach USD 51.5 billion by 2016 (approximately £34 billion), with an annual worldwide growth rate of 7.9% over the period 2012-2016 (Docebo, 2014). This volume will impact the educational systems of all the countries and its institutions, especially those who will lead this growth such as the Latin-American region (14.6%), Africa (15.2%), Eastern Europe – driven by Russia – (16.9%), and Asia – driven by China, India and Australia – (17.3%). The task for designers and practitioners of learning technologies seems to be clear: to face the challenge of increasing the rates of effective adoption and effective use of learning technology, and to improving the learning process supported by it. If this goal cannot be achieved, learners would face increasing rates of educational failure, and the important investment of resources – both, of specialized staff and of money – from Governments, universities, and companies will be worthless.

Based on the previous literature, this research will be focused on the understanding of two processes related to the use of learning technology. The first of them is the well-studied process of adoption of technology, specifically learning technology. The second process is the achievement of learning goals in virtual environments, with particular focus on the variables affecting the learning outcome, considered as the main benchmark for this context. Moreover, these goals will be addressed pursuing not only the understanding of each isolated process, but looking for the variables which allow a theoretical and practical integration of them, stating that they are not two separate process, but two interdependent aspects of learning with computing technologies.

Before explaining the research objectives and strategy in detail, it is necessary to examine the literature on the two main processes to be investigated. The next section is going to comprise the most relevant studies on adoption of learning technology and on learning achievement with virtual environments, finishing with an integrative proposal which will guide the present research.

1.2. Learning technologies in action: a literature review on the introduction and effect of technology on the learning practice and its results.

The influence of different types of technology such as written and drawn materials, video, television, radio, and computer devices, has been studied through decades, since the pioneer work of Thorndike in 1912 (Clark, 1983). The general aim has been to make a comparison between distinct kinds of learning technologies and its effects on learning achievement. Since more than three decades, computer technology has been scrutinized from different approaches, whose main difference is the base role of technology on the learning process. One perspective claims that technology directly affects learning, just by using it, due to the particular symbol system employed by them (e.g. letters, images, sounds, concepts), and the processes that they allow to perform, resulting on different ways of information processing which would be specific to determined media (Kozma, 1991; Kozma, 2003). An opposite approach claims that technology does not affect the learning outcome, neither positively nor negatively, being just a delivery medium of the information, and any effect is due only to the instructional design utilized (Clark, 1983, 1994). The literature review that follows will summarize the relevant research on learning technology and its effects with focus on two aspects: the introduction and adoption of technology on learning practices, and the effectiveness of instruction supported by technology.

1.2.1. Introduction and adoption of learning technology.

The introduction of technology in any human activity involves the adoption of behavioural patterns that modify the manner a person has been developing its activities. To understand why people do or do not adopt a certain technology a number of explanations have been developed, taking as reference more general elements from three theories. Bandura's theory of social learning (1977) states that humans are active information processors, and as such the consequences of any action can make them more or less keen to perform in a certain way. The idea taken from this theory, and applied to adoption of technology, is that if something is perceived as beneficial, people will tend to adopt it. Ajzen's reasoned action and planned behaviour theories (1977; 1985) propose that people's behaviour is influenced by the valence of the attitudes towards that behaviour, in other words, if people perceive an action as positive, then the chance to be performed will increase. Last, the cost-benefit paradigm of Beach & Mitchell (1978) states that when the benefits of a behaviour are higher than the effort involved, then that behaviour will be performed more likely. In summary, when an action is considered as positive and the effort is less than the benefit, that action has a better chance to be performed than other that cannot fulfil these requirements. Therefore, the basis of technology adoption should be that when the technology is perceived as useful and easy to utilize, the users will have a good reception of it.

Specifically centred on technology adoption, the main perspective on the topic has been Davis' technology acceptance model [TAM], proposed in 1989 to explain why people would use computer technology within a working context. This explanation was extended later to other contexts so different as sales, design, and education. The base of the model is that users' behavioural intention and actual use are influenced by attitudes towards the technology, such as how useful and easy to use it is considered. In other words, it is proposed that while easier and more useful the technology is considered, then the rate of use will be higher. A number of modifications have been made since then, including social factors or context-specific variables, nonetheless the original core of the model remains the same.

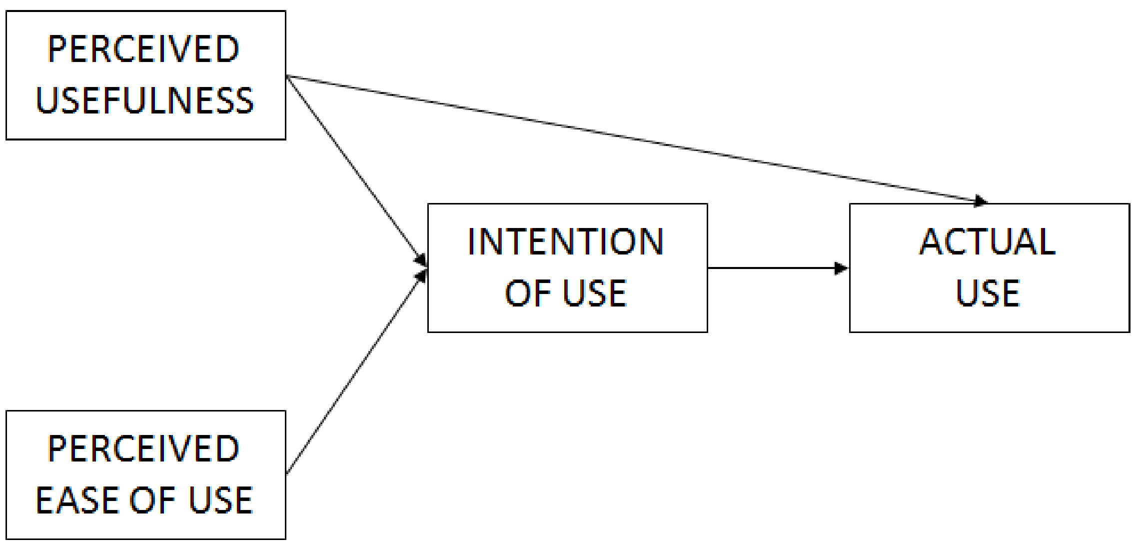

Figure 1. Davis' Technology acceptance model (1989)

Several researches on learning contexts have utilized the technology acceptance model trying to assess and explain the results of the introduction of certain technology to support or enhance learners' achievement, using different approaches and reaching varied conclusions. A systematic literature review was conducted as part of the author's Master Dissertation (2012) in order to achieve understanding on how the model works, how it has been modified, and what are the key variables that should be taken into account. It included an initial summary of 5 meta-analyses and 3 systematic published between 2000 and 2012, as an overview of the main finding up to date. The highlights of such summary can be found in table 1. The second part of that work was to conduct a systematic literature review aiming to detect relevant variations of the original model proposed by Davis. The inclusion criteria comprised the availability of full text, the study had to be related to the use of learning technology, the study had to report quantitative data including beta values, and sample size equal or higher than 100. The first selection of articles was 69 out of 613, and the final selection included 16 (table 2). The main results were (i) the finding of several competing models based on TAM, and (ii) a consistent support to the key variables of TAM, but non-conclusive support for the variables which extent or modified the model.

Table 1. Summary of meta-analyses and systematic literature reviews included as theoretical background.

Author (Year)	Type of Study	Articles included	Major Findings
(Legris, Ingham, & Collerette, 2003)	SR	22	1. TAM variables measured inconsistently among researches, but model is supported. 2. They found 39 factors affecting system satisfaction. 3. The model would include social and individual change process.
(Ma & Liu, 2004)	MA	26	1. Diverse findings on TAM. 2. Mean effects of the relationship between perceived ease of use and perceived usefulness and between perceived usefulness and technology acceptance are large. 3. Mean effect of perceived ease of use on technology acceptance is medium. 4. All mean effects are positive and significants.
(King & He, 2006)	MA	88	1. Relationship between perceived ease of use and behavioural intention is highly variable among studies. 2. Relationship between perceived usefulness and behavioural intention is strong and consistent. 3. Confirm Davis' model, but high variability is observed in correlation loads among studies. Influence of moderator variables is suggested. 4. Results suggest a complete mediation effect of perceived ease of use through Perceived usefulness on behavioural intention.
(Sun & Zhang, 2006)	SR	54	1. Experimental designs have higher explanatory power than field designs. 2. Additional factors have to be included in posterior researches, because inconsistent relationships have been observed. 3. Distinction among Organizational Factors, Technology Factors and Individual Factors should be taken into account.

(Schepers & Wetzels, 2007)	MA	51	1. Original TAM relationships were confirmed. A stronger relationship between perceived usefulness and attitudes towards technology than between perceived ease of use and attitudes relationship was observed. 2. Correlations between social norms and behavioural intention, and between social norms and perceived usefulness passed the fail-safe N test, and possess large effect sizes. 3. Strong relationships on student samples than non-student samples. 4. Cultural differences are observed.
(Turner et al., 2010)	SR	73	1. Behavioural Intention is better predictor of actual use than perceived usefulness and perceived ease of use 2. Association between variables and objective actual use and subjective use were different.
(Sumak et al., 2011)	MA	42	1. Davis' TAM is supported. 2. Relationship between perceived ease of use, perceived usefulness and attitudes were similar for different groups of users. 3. A large effect size was found to relationship PU-A; whereas a medium one was found to PEOU-A.
(Wu, Zhao, Zhu, Tan, & Zheng, 2011)	MA	128	1. Davis' original model is supported. 2. Attitudes appear as an important factor in the (extended) model. 3. High relationships between trust (on the technology) and positive attitudes, trust and behavioural intention, trust and perceived usefulness, and trust and perceived ease of use.

Table 2. List of studies included in the literature review (2012).

Authors	Sample Size	Model	Supported
(Yang & Yoo, 2004)	211	TAM	No
	211	Extended TAM	Yes
(Drennan et al., 2005)	248	Extended TAM	Yes
	256	Extended TAM	Yes
(Saadé & Bahli, 2005)	102	Extended TAM	Yes
(Pituch & Lee, 2006)	259	Extended TAM	Yes
	260	Extended TAM	Yes
(Tung & Chang, 2007)	263	Extended TAM	Yes
(Saade & Kira, 2007)	114	Extended TAM	No
(Rezaei et al., 2008)	120	Extended TAM	Yes
(Chang & Tung, 2008)	212	Extended TAM	Yes
(Lau & Woods, 2008)	481	Extended TAM	Yes
(Park, 2009)	628	Extended TAM	Yes
(Lau & Woods, 2009)	312	Extended TAM	Yes
(Lee et al., 2009)	214	Extended TAM	Yes
(Arteaga Sanchez & Duarte Hueros, 2010)	226	Extended TAM	Yes
(Djamasbi et al., 2010)	134	Extended TAM	Yes
(Liu et al., 2010)	436	Extended TAM	Yes
(Sanchez-Franco, 2010)	431	Extended TAM	Yes

Considering the results of the previous literature review, it can be said that albeit the existence of other models to explain why technology is adopted, TAM appears as consistent and adequate to be included in an integrative model of adoption and effective use of learning technology. The following theoretical background include the more relevant and illustrative studies to update the previous work.

The first of them is a research conducted by Drennan, Kennedy & Pisarky (2005) on the factors affecting student satisfaction in flexible online learning, using a two-step design. Their results showed that perceived usefulness have the strongest relationship with course satisfaction, while perceived ease of use showed the opposite. Besides, the effect of students' skills to use information technology does not appear as important for the prediction of course satisfaction. Another variable that was included on the research model was locus of control, which was observed having a direct effect on course satisfaction at the beginning of the training (first step of the research design), indicating that students with autonomous locus of control were more satisfied with flexible online learning, however since the stability of the variables was assumed, they were not assessed at step-two. The results suggest that perceived usefulness is the strongest predictor of course satisfaction, and that perceived ease of use plays just a secondary role.

The role of cognitive absorption – the level of user involvement – as an extension of TAM was examined by Saade and Bahli (2005). Their objectives pointed out to measuring the predictive value of absorption, perceived usefulness, and perceived ease of use over intention of use within an online course. The core relationships of TAM were supported by the data, were perceived usefulness appears a better predictor of intention of use than perceived ease of use ($\beta=0.43$, $p<0.001$, and $\beta=0.16$, $p<0.05$, respectively). Cognitive absorption was observed as directly related to perceived usefulness and to perceived ease of use, but the variance explained by cognitive absorption for perceived ease of use was just $R^2=0.06$, while for perceived ease of use was $R^2=0.26$. This research gives some light on the links between adoption of technology and the level of user's involvement, but the current design does not allow to capture the variations of cognitive absorption over time or due to other circumstances, such as task novelty or different difficulty of the tasks.

In 2006 Pituch and Lee, using TAM´s perspective, assessed students' intention of use for two virtual learning scenarios that they considered related between them, as one should be used as a consequence of the intention of using other. The proposed research model stated that system characteristics and use beliefs will be directly related to the use of a virtual environment for supplementary learning (scenario1), and that system characteristics altogether with the supplementary learning environment will be directly related to the use of a virtual environment for distance education (scenario 2), given their shared characteristics. The results confirmed that TAM is a strong predictor of intention of use, but additionally showed that the characteristics of the environment, and how they are evaluated by learners are also important, since while more quality and reliability of the system are perceived there is a better disposition of the students towards using it.

The role of a negative emotion – such as anxiety – on the adoption of technology has also been explored. Tung and Chang (2007) conducted a study on the relationship between computer anxiety, computer self-efficacy and adoption of technology with a sample of adolescent students. They found a positive relationship between computer self-efficacy and behavioural intention, and an inverse effect of anxiety on both self-efficacy and behavioural intention. In other words, when feeling confident about using technology users will have a higher intention of using it, and less anxiety associated to that use. At the same time, the direct effect of perceived usefulness and perceived ease of use on behavioural intention was confirmed. Another study, this time focused on the effect of anxiety on the perception of easiness of technology (Saade & Kira, 2007) found that the negative effect of computer anxiety might be cancelled out by the mediator role of computer self-efficacy. In 2008, Rezaei and colleagues tested a modified version of TAM, including computer self-efficacy, computer anxiety, and previous internet experience. The results showed a positive relationship between perceived usefulness and intention of use, and between computer self-efficacy and intention of use, and a negative effect of computer anxiety on intention of use. These results are similar to those previously presented, suggesting that while computer anxiety plays against the intention of using learning technology, a good sense of self-efficacy might counteract that effect.

The role of computer self-efficacy on technology adoption was tested again by Chang and Tung (2008), this time in addition to the perception of system quality and the perception of compatibility with user's values, experience, and needs. The analyses confirmed the relationships between the core variables of TAM, but also showed that the perception of compatibility has a significant direct effect on perceived usefulness, and that computer self-efficacy is significant and directly related to behavioural intention. In the same line that the perception of compatibility, Lau and Woods (2008) investigated the effect of attitudes and beliefs about learning objects – any pedagogical resource being part of a learning system – on the adoption of learning technology containing those objects. It was observed that positive attitudes and good perception of usefulness are significant predictors of behavioural intention, although their effect on actual use is only indirectly expressed through user's intention. Lau and Woods (2009) continued on the track of user's thoughts about learning objects, this time evaluating the perceptions about the technical quality, content quality, and pedagogical quality.

In 2009 Lee and colleagues conducted a study testing a modified version of Davis' model measuring the adoption of e-learning instruction. In that study the model was extended by adding variables accounting perception of instructor characteristics, teaching materials, the design of the learning contents, and playfulness. The analyses, besides of confirming the relationship between the core variables of TAM, noted a direct effect of instructor characteristics and teaching materials on the perceived usefulness of the learning environment. Additionally, the evaluation about learning contents design had a positive effect on the perception of easiness of the tool. Furthermore, the reported level of playfulness elicited by the virtual environment – a variable that includes individual pleasure, psychological stimulation, and interest – was directly related to the intention of using it. These findings suggest that such as a rational evaluation of the learning environment is linked to user intention of use, the emotional response is also important and strong.

A later study of Djamasbi, Strong, and Dishaw (2010) also explored the effect of emotions on the technology adoption. Starting with the assumption that positive mood affects people's cognition and behaviour, the researchers designed an experimental approach where subjects interacted with a computer-based application to complete a decision task. The mood state was manipulated (positive, negative, and neutral), as well as the degree of uncertainty of the task (moderate or high uncertainty levels). Results showed that under moderate uncertainty, positive mood influences perceived ease of use, but not perceived usefulness, both perceptions mediating the effect of mood on intention of use. Under high uncertainty the relationship was maintained, and no significant difference was found between the groups. From this research two major findings must be highlighted: i) that the effect of a positive mood is stronger than the effect of negative mood, and that ii) the uncertainty of the task, which should affect the perception of suitability of technology to complete the given task, was not as relevant as expected.

In the same track, Sanchez-Franco (2010) conducted a study on the role of affective quality on the adoption of educational technology in higher education. In his research a modified version of the technology acceptance model was utilized, mixed with elements from human-computer interaction theory such as flow and perceived affective quality – a measure of how pleasant and interesting is the reaction to a stimulus. It was observed that the inclusion of affect quality significantly improved the power of the model ($\Delta R^2=0.19$), being positively related to a higher intention of use. The result suggests that a positive emotional response is a strong predictor of intention of use, a good complement for the traditional evaluation of the usefulness and easiness, although the stability of the variable might be questioned.

A similar approach was followed by Lin (2012) when carried out a research on the role of perceived fit and satisfaction with the course in the adoption of a web-based learning system and its learning outcome. The results shown that perceived fit and satisfaction are strong predictors of adoption and continuance of using learning technology. Furthermore, it was observed that these variables are related to self-perception of learning, although data is not sufficient to determine the real impact of these variables on the learning outcome. Notwithstanding, this research suggests the idea that the adoption of learning technology can be interweaved with the learning process supported by it, measured as a learning output.

So far, the role of attitudes on technology adoption looks as irrefutable. While many context specific variables may be added to the model, the core variables of Davis' model are strongly supported by data and theory. Nonetheless, the relationship between intention of use and actual use is not as good as expected, and just a few studies have related adoption to learning achievement consistently. The next section will address the literature on learning achievement within virtual environments, with special focus on the variables that allow learners to perform successfully.

1.2.2. The assessment of the effectiveness of learning technologies.

A key aspect regarding the use of technology on learning settings is the attaining of the proposed learning goals by using it, a basic and fundamental objective within this context. The complexity of this issue starts with the very definition of what is an effective learning environment, mainly because the success of a given instruction might include a large number of pedagogical, economic, and social factors that contribute to its result (Halachev, 2009). Therefore, a variety of indicators can be found in literature to give account of learning achievement or learning effectiveness, including objective measures, subjective measures, and a combination of several of them. Therefore, the results and conclusions among studies might vary, or be difficult to compare, because either the conceptual or the operational definition of effectiveness components could be different. Some of these are going to be revised below for its methodological implications.

One approach focuses on evaluating the components of the learning process by an objective measure, such as the final mark (Kekkonen-Moneta & Moneta, 2002), or the time logged onto the learning platform (Lim, Lee, & Nam, 2007). The main advantage of such approach is to allow the collection of reliable data and the comparison of objective learning achievement indicators. Nonetheless, it is not always suitable to give into account of the learning process as a whole, since some variables cannot be easily measured in an objective way.

This leads to the second approach, which is predominantly subjective. It considers self-reports of learning and other variables, as in the study conducted by Liaw (2008), but specifically the reliability of the self-perceptions of learning can be questioned by being subject of personal biases. The most common approach is a mixture of both objective and subjective measurements, including self-reports and tests to assess learning achievement marked according to a pre-set guideline (Bhuasiri, Xaymoungkhoun, Zo, Rho, & Ciganek, 2012; Buzzetto-More & Mitchell, 2009; Stonebraker & Hazeltine, 2004).

For the purposes of this research, the effectiveness of the learning technology is going to be defined as the degree of achievement of the desired learning outcomes, and therefore reflected on a quantitative, objective measure of it: the higher the mark or score the student achieve in a test on the course subject, the more effective the course is. The intention of this definition is trying to avoid subjective biases, even when in some respects the marking parameters can be discussed, but at least this approach can set a comparable indicator of learning achievement.

Notwithstanding, the definition of the appropriate indicator to assess the learning effectiveness is only one part of the matter. To understand and eventually be able to improve learning effectiveness it is necessary to identify the learner-related characteristics on the learning process in digital environments.

In the same way that there is not a unique criterion to define the concept of effectiveness in digital environments, there is not a unique theoretical framework to give account of the process and the variables taking part in it. Throughout the literature, some variables have been used frequently and consistently to explain how learners and technology interact in order to achieve the desired learning output. These variables comprise behavioural indicators, attitudes, and perceptions, which drive the learning process towards certain goals according to the valence of the elements and the interactions between them. Specifically, three variables will be highlighted by their relevance and consistency across the literature.

The first variable to be considered is the actual use of the learning environment. This variable has a dual importance, since it is the final element of the adoption of technology process (as presented in section 1.2.1 and illustrated by Figure 1. Davis' Technology acceptance model (1989), and also the basic behavioural component of the learning process by reporting the time spent accessing to the learning materials and activities. This dual role posits actual use as a suitable bridge between adoption of learning technology and learning achievement, one of the aims of the present research.

Continuing with the trend of the literature, there is more than one way of measuring the actual use of the learning environment. Just as an example, Lim and colleagues (2007) considered actual use as the time spent by learners while logged into the platform. Other studies included logs to retrieve information about the activity of the users (Barab, Bowdish, Young, & Owen, 1996; Delialioglu & Yildirim, 2007; Gee-Woo, Sang Cheol, & Yanchun, 2010). The advantages of this method are the reliability of the data and the automated collection of the information. On the other hand, other studies had used self-reports of the time spent in different system activities as a valid estimate of the actual usage of it (Igbaria, Schiffman & Wieckowski, 1994; Mathieson, 1991; Roberts & Henderson, 2000), being such measurements validated by Davis (1989) as sufficiently accurate estimates of the time spent in those activities. The positive aspect of the self-report of actual use is that it can include the time spent on activities related to the learning environment while offline, such as completing the learning activities or reading the learning materials. Nonetheless, it is important to understand that an objective log-based report can be very different of the self-report indicator, as had been noted by a number of studies that include both of them (Horton, Buck, Waterson, & Clegg, 2001; Junco, 2013; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010). Therefore, the choice of one or other method is more related to what is attempted to be investigated, and the suitability of the indicator with the theoretical framework.

This research is going to consider actual use as the time spent both online and offline, attending that most of the learning activities are done in a variable mixture of online and offline time. Consequently, a self-report of actual use is going to be utilized in the upcoming studies when necessary.

Another relevant variable that has been related to a successful learning process in digital environments is the satisfaction with the course. It is conceived as the level of agreement with the design and content of the course (Johnson et al., 2008). Satisfaction with the course is supposed to play an important role as enhancer of the learning process, due to its reinforcing effect on the usage behaviour as a consequence of a positive evaluation of the experience with it, increasing the chance of adoption and engagement with the virtual environment (Higgins, 2006; Levy, 2007). This variable has been widely studied as related to the adoption process, but according to several studies it may be linked to the effectiveness of the learning process by influencing the student's preferences on the delivery media (Arbaugh & Duray, 2002), as an indicator of success of the course from the perspective of the designers/implementers (Eom, Wen, & Ashill, 2006; Sun, Tsai, Finger, Chen, & Yeh, 2008), or because a relationship between satisfaction and actual use was found (DeBourgh, 1999; Johnson et al., 2008; Jung, Choi, Lim, & Leem, 2002). Satisfaction with the course is going to be considered as an antecedent of learning effectiveness because of its role as a booster of learning behaviours, under the assumption – based on previous research – that a satisfied, highly motivated learner, will be significantly engaged in a the learning activity and hence he or she is able of achieving better learning results.

The third and final element to be considered as a holder of the learning process is the self-perception of learning, which might be defined as the perception made by the learner about how much improvement he/she made because of the course (Alavi, Yoo, & Vogel, 1997; Johnson et al., 2008). Literature has linked this variable to objectives measures of learning and to satisfaction with the course, being a logical component of a model for understanding learning effectiveness. Self-perceived learning is going to be included in this research project as an antecedent of learning achievement because its monitoring role on the learning process, because people's self-perception acts strengthening the behaviours that drives to the desired goal. Nonetheless, it is necessary to notice that people can hold inaccurate self-perceptions, especially when emotional states interfere (Heath, 1995; Stanley & Burrow, 2015).

Up to this point, learning effectiveness has been defined as the achievement of measurable learning goals. As the present research is focused on the utilization of virtual learning environments, the achievement of learning goals is going to be circumscribed to this particular context. Previously it was stated that despite any specific characteristic of the virtual environment due to its similarities and commonalities, it will be relevant to the discussion those variables that can affect that process. This section proposes three variables – actual use, satisfaction with the course, and self-perceived learning – as antecedents of learning effectiveness, based mainly on their effect supporting and enhancing the learning process. The next section is going to be focused on the research proposal, its aims, and the research strategy to follow.

1.3. Research proposal and aims.

As it was mentioned earlier in this chapter, the main goal of the present research is to identify the key variables involved on the achievement of learning goals through virtual learning environments. It is proposed that to attain that goal it is fundamental to understand the learning process in virtual environments from an integrative perspective, considering the interaction of the learner with the learning environment from the beginning – the first contact with the learning setting – to the end – the consecution of the learning goals. Therefore, the research proposal is going to include the study of the adoption of learning technology and how the variables that participate in it are related to learning achievement. The first challenge is to improve our understanding on the adoption of learning technology and then, the second is to integrate it to the variables related to learning achievement mentioned previously on section 1.2.2.

This first chapter has been focused on the theoretical and practical background to understand the proposed research. The following three chapters are going to be focused on the empirical component of the project.

Chapter 2 is going to test the initial approach towards the research goals. By integrating an extended version of Davis' technology acceptance model with the proposed model of learning effectiveness in a design of two steps – assessments at the beginning and at the end of the learning process – this chapter will undertake the discussion about the ways to improve the understanding of the adoption of technology, about the feasibility of a theoretical and empirical bridge between adoption and effectiveness, and the ways to improve this initial proposal.

Chapter 3 will take into consideration the results of chapter 2, by incorporating new variables into the theoretical approach. The chapter is going to include a brief literature review on the new variables that could affect technology adoption, following by two cross-sectional studies to test the new relationships proposed. The results will feed the theoretical understanding on the topic, opening new paths, and tuning up the research model.

Chapter 4 will incorporate the results of the previous two chapters in order to build a more suitable model to address the research goal. Following a new update of the literature review, in order to settle down the theoretical implications of the empirical examination, the last empirical study of the research project will utilise a repeated measures design to assess the learning process supported by an educational software from the beginning up to the end.

Finally, chapter 5 will focus on integrating the results, discussions, limitations, and highlights of previous chapters. It will attempt to reach a suitable solution to our research problem, by gathering the information obtained through the course of this research project, analysing it, and considering its theoretical and practical significance. A novel approach to the effective use of technology on learning settings is going to be presented, characterized by the importance of the learner, its active role on the learning process, and the key part that technology has on supporting the individual learning achievement.

2. TOWARDS AN INTEGRATIVE APPROACH OF COMPUTER-BASED LEARNING.

2.1. **Introduction**

The first empirical chapter of this thesis is going to be focused on testing a first approximation towards the understanding of the learning process supported by technology. Specifically, an approach based on a mix of attitudinal and behavioural variables will comprise a model to explain the learning outcome of a group of learners enrolled in a 5-week e-learning course.

A brief summary of the theoretical foundations of the model will be presented in the next section, which was explained in detail in previous chapter. The method and results will follow, ending with the discussion about the relevance and implications of the findings.

2.2. **Theoretical framework.**

As it was discussed previously, computer-based instruction has been frequently used to complement or substitute for traditional face-to-face lessons, mainly due to its advantages such as easy and flexible access (Lee, Cheung, & Chen, 2005), easier maintenance, updating, and lower costs (Saade & Bahli, 2005; Welsh, Wanberg, Brown, & Simmering, 2003), and better self-perception of learning (Alavi et al., 1997). Computer technology can support a wide range of formats and stimuli, having the potential to satisfy multiple requirements related to the design of virtual learning environments. However, the continuance of usage of learning technology in the middle- and long-term is affected by low levels of user satisfaction (Levy, 2007; Roca, Chiu, & Martínez, 2006), and low acceptance of the design (Reiser, 1994; Sitzmann et al., 2006), producing a lack of effectiveness through drop-out and/or underuse of the learning programs. On this scenario, and with an increasing demand for developing and implementing learning technology at all levels of the educational system, the main challenge seems to be to understand which variables are involved in the adoption of and the engagement with learning technologies, and how they could be related to the effectiveness of the learning process.

The present study, being the first of the current research, introduces a novel perspective in exploring the relationship between the adoption of learning technology and the effectiveness of the learning process. The approach includes new variables - and relationships between them - to more traditional approaches that seem to be struggling to explain and prevent the high rates of dropouts and low learning outcomes faced by a great number of learning programs supported by virtual environments.

As it was presented in length in the first chapter of this thesis, the proposed model bring together the Technology Acceptance Model with relevant effectiveness indicators, with the objective of represent the learning process assisted by computer technology from the beginning to the end.

We expect to find – as it is suggested by the literature - support for both adoption of technology and learning-technology effectiveness processes as independent clusters, but we aim to establish a link between them to support our proposed integrative perspective that technology-supported learning is a single process that starts with the encounter of an individual and a VLE, and finalizes with a desired learning outcome.

2.3. **Research questions and hypotheses.**

The main goal of the present study is to identify the key variables that could improve student's adoption of learning technology - in this case, e-learning - and its effectiveness. Specifically, three issues will be explored. First, we examine the best predictors of intention of use and actual use within the VLE, in order to improve the way VLEs are designed or adapted for distinct audiences, so as to enhance engagement and reduce dropout rates. Second, we investigate the interactions between behavioural and attitudinal variables in the achievement of learning goals. Third, we examine the linkage between the technology adoption process and the learning process, in order to advance towards an integrated framework that might be useful for practitioners from different disciplines entailed on the design and/or implementation of computer-supported learning programs.

To address these goals we selected a set of variables that might predict the adoption of an e-learning environment, the engagement with it, and the final marks of the student (as an indicator of learning effectiveness). These variables were selected based on their consistency in the literature – as showed previously – and because of the theoretical relationship between them. Mediations and moderations were explored to better understand the interaction among the variables. Our **first hypothesis** is that the scores on perceived usefulness, perceived ease of use, and previous computer usage will be directly related to intention of using the e-learning platform. **Hypothesis 2** is that the scores on perceived usefulness, perceived ease of use, previous computer usage, and intention of use will be positively related to behavioural planning; the **hypothesis 3** states that intention of use and behavioural planning will be directly related to the scores on satisfaction with the course, actual use, and self-perception of learning. The **fourth hypothesis** proposes that actual use, satisfaction with the course, and self-perception of learning will be directly related to students' final mark; and **hypothesis 5**, that satisfaction with the course and self-perceived learning will have a positive effect on actual use. Our full theoretical model is depicted in figure 2.

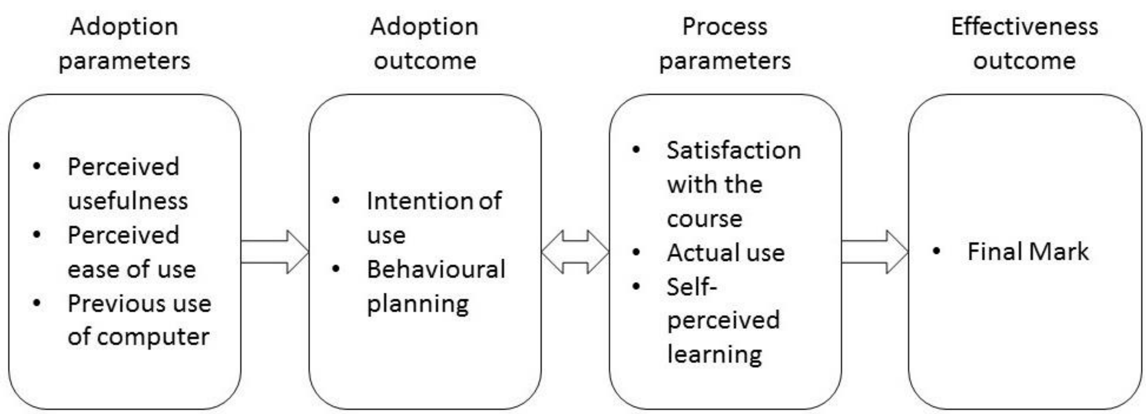

Figure 2. Theoretical model

2.4. **Method**

2.4.1. Participants.

Participants were one hundred and sixty-eight Chilean teachers from primary and high school, both urban and rural, which voluntarily took part in this study. All of them were enrolled into a five-week online-delivered course on teaching methodologies, suitable for practitioners with diverse backgrounds. From them, thirty-seven were male (22%), although no significant differences were found due to gender. The age of the participants ranged from 24 to 62 (M=39.4, SD=10, Q1=30, Q3=48), and no significant correlation was found with the main variables of the research model.

2.4.2. Design.

The design chosen to attain the research goal included two measuring times along the course: the first at the beginning of the course – week one –, right after the first utilisation of the learning platform. The learning platform was Moodle based, serving as a content repository – texts, images, and videos – and as a social platform – discussion boards, private messages, chat. The contents were organised in 4 modules delivered weekly, and a final assessment on week five. The second measuring time was on week five, after final assessment was submitted.

The first measuring time aimed to assess attitudes towards technology, intention of use, and background information (Questionnaire 1). The second measuring time assessed individual evaluations about the course, its contents and its design, and the time spent on the course activities (Questionnaire 2). The final mark of each participant was collected after explicit permission granted.

As the participants were territorially dispersed, and the course was delivered via online, the data was collected in the same way. A link to the online questionnaires was sent via personal email in week one and week five. The rate of response was dissimilar, and from the whole sample a group of 54 participants completed only the initial questionnaire, 58 completed only the second questionnaire, and 56 completed the two questionnaires.

2.4.3. Instruments.

A set of previously validated instruments was adapted to suit this specific e-learning environment. The instrument were organized onto two sets of questionnaires as detailed below.

Questionnaire 1

Perceived ease of use & perceived usefulness: Perceived ease of use and perceived usefulness were assessed by adapting items developed by Davis (1989), which tapped respondents' perceptions regarding how straightforward the e-learning environment would be for them to use (example item: “Learning to operate the e-learning platform would be easy for me”), and about how convenient they thought it would be (example item: “Using the e-learning platform would enable me to accomplish tasks more quickly”), respectively. Respondents rated the items on a seven-point Likert scale (1=”Strongly disagree”, 7=”Strongly agree”). The scores were summed.

Intention of use: To assess respondents’ intention to use the e-learning environment, we used an adaptation of the statement used by Davis (1989). Item tap the extent to which the respondent intends to use the resource (item: ‘I will try to use the e-learning platform on many occasions as possible’, 1=”Strongly disagree”, 7=”Strongly agree”.). A summed score was obtained.

Behavioural planning: To augment the intention variable described above, we developed three new questions in an attempt to capture respondents' level of planned engagement with the e-learning platform. These questions refer to a projection of the frequency of use: "On average, how many days a week do you plan to use the platform?", "On average, how many hours a week do you plan to use the platform?", and "Considering the next seven days, how much time do you think you will dedicate to the platform activities?". These questions were scored on a 1 to 7 Likert scale (1= 1 day a week/0 hours 7=7 days a week, 10 or more hours) and summed to obtain and indicator of how strong is the subject intention.

Computer use: The frequency with which respondents use the computer for a range of activities was measured with a 8-item questionnaire used by Tan & Teo (2000) (example item: "Please indicate the extent to which you use a computer to perform the following tasks: 1) Gather information, 2) Communicate (e.g., email, chat), 3) Download free software, etc."). Each statement was scores 0 to 7 depending of the number of days a week these behaviours are done. The scores were summed.

Questionnaire 2

Satisfaction with the course: We measured students' contentment with the learning environment using the 6-item Course Satisfaction Scale (Johnson et al., 2008), (example item: "I am satisfied with the clarity with which the class assignments were communicated"), which uses a 7 point Likert scale (1= "Strongly-agree"; 7:="Strongly-disagree"). A general score is obtained by summing the scores of each item.

Self-perception of learning: The students' perception about how much they have learned through the course was assessed with the 6-item adaptation of Alavi's Self-Reported Learning Scale (1997), (example item: "I learned to interrelate the important issues in the course material"). Items are rated on a 1 ("Strongly disagree") to 7 ("Strongly agree") Likert scale, and summed to get a general score.

Actual use: The time students dedicated to the course activities was measured using five items asking about the amount of hours per day, and days per week, that participants spent engaging in learning activities (example item: "On average, how many days a week did you access to the e-learning platform?"). This measure asked about both the time spent online and offline, in order to tap total time spent working on course materials and activities. Items were scored on a 1 to 7 Likert scale (1="1 day a week" / "0 hours"; 7="7 days a week", /"10 or more hours"), and then added to obtain an indicator of the strong of the behaviour.

Final Mark: As regular part of the course, participants were required to complete a formal assessment task, which involved the application and discussion of the course contents. The tutors of the e-learning course assessed this work using a scale, which scores were from a minimum of 1.0 to a maximum of 7.0, according to how well the work reflected the course contents, discussions, and goals. These scores were given to the research team by the tutors - with the consent of the participants - as a measurement of the level of learning achievement.

2.5. **Procedure.**

Participants were enrolled in a five-week e-learning course on teaching methodologies about sexuality and affectivity. The course consisted on five modules, which explained the methodology, presented and discussed relevant topics on the matter, and proposed practical exercises to put all the theory, readings and discussions onto real teaching materials by the teachers. The first stage of the study was in week one of the course, with the second stage in the last week of the course, using online administration of the questionnaires described in section Instruments. Participation was voluntary at both stages. The data of the participants that answered both questionnaires was matched by an identification code assigned to each of them. In the case that any participant answered only one questionnaire, the unaccounted information was treated as missing data. The research model, proposed relationships, and the procedure are illustrated by the figure 3.

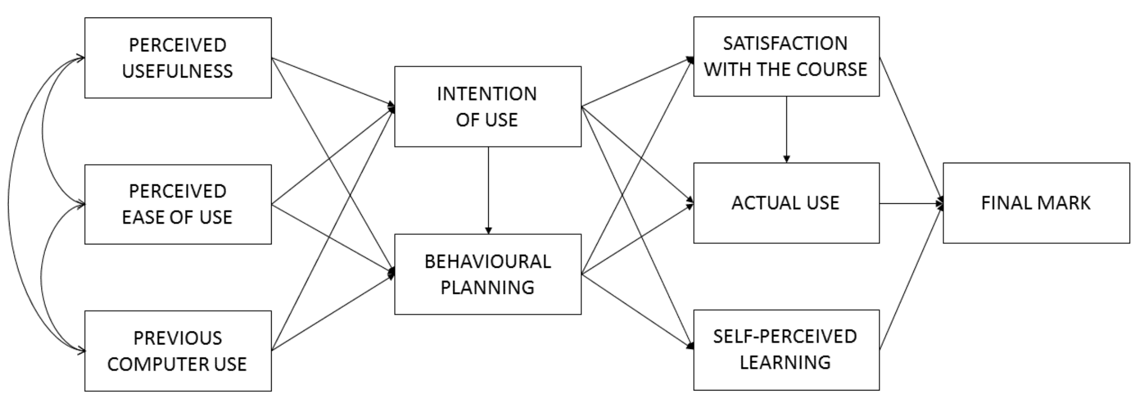

Figure 3. Research model - Study 1.

2.6. **Results**

The data were processed using SPSS Statistics and SPSS Amos v22. We present first the quality of the instruments utilized in the study and the general coherence of the proposed relationships, and then we evaluate and develop the research model in order to confirm or dismiss the proposed hypotheses.

2.6.1. Scales reliability and correlations

Internal consistency reliability (ICR) as Cronbach's alpha scores for all measures ranged from 0.73 to 0.95, which is consistent with previous literature (table 3). ICR was not calculated for intention of use and behavioural planning since there were three or less items for these variables. The correlations between variables (table 4) were coherent with the relationships proposed in the research model in figure 3, where variables related to technology adoption correlate between them, and the variables related to learning effectiveness do the same between them. Control variables such as age, gender, teaching expertise area, previous knowledge about the topic, and whether or not the participants have had previous experience with e-learning showed no significant effect nor interactions.

Table 3. Mean, standard deviation, and internal consistency reliability of the variables included in the model.

Observed Variable	Mean	SD	ICR
Perceived usefulness	5.74	0.31	0.91
Perceived ease of use	5.89	0.08	0.92
Computer experience	4.20	1.50	0.79
Intention of use	5.93	0.80	-
Behavioural planning	6.51	2.07	-
Satisfaction with the curse	5.58	0.13	0.90
Self-perceived learning	5.88	0.08	0.95
Actual use	3.54	1.08	0.82
Final mark	5.90	1.12	-

Table 4. Correlation coefficients of the variables included in the model.

Observed Variable	1	2	3	4	5	6	7	8
1. Perceived usefulness	1.00							
2. Perceived ease of use	0.54*	1.00						
3. Computer experience	-0.04	0.17	1.00					
4. Intention of use	0.67*	0.47*	0.07	1.00				
5. Behavioural planning	0.26*	0.25*	0.22	0.17	1.00			
6.Satisfaction with the course	0.21	0.07	-0.07	0.10	0.24	1.00		
7. Self-perceived learning	0.39*	-0.07	-0.09	0.13	0.27*	0.66*	1.00	
8. Actual Use	0.19	0.09	0.10	0.26	0.38*	0.26*	0.42*	1.00
9. Marking	0.00	0.06	0.01	-0.01	0.20*	0.18	0.20*	0.22*

Note: *p<.05 ; **p<.001

2.6.2. Analytic strategy for the research model

Structural equation modelling (SEM) was performed using SPSS Amos v22, through Maximum Likelihood, to test the proposed hypotheses. SEM has become more than a statistical technique and nowadays is one of the most utilised methodologies to test theory-derived hypotheses, comprising four stages: i) the conceptualization of the model, ii) the identification and estimation of the parameters, iii) the assessment of data-model fit, and iv) the potential modification of the model (Mueller & Hancock, 2008). The main advantage of the structural equations is their explanatory power of the relationships described in the model, reporting direct and indirect effects of a group of interactions. For the purpose of this study, it gives an important benefit over other multivariate analysis techniques.

It was decided to use parcels as indicator of the constructs included in this structural equation modelling. As described by Little (Little, Cunningham, Shahar & Widaman, 2002), the parcelling technique consists in aggregating the scores of individual items which belong to the same theoretical construct. As a result, the structural model is centred on a factor-solution opposite to an item-solution approach – for example, as in a Confirmatory Factor Analysis of a scale –, resulting in less parameters to be estimated, and avoiding potential item-level issues such as lower reliability, or greater likelihood of distributional infringements. In order to use this technique it is required that the variable is a) one-dimensional, and b) explicit and clearly defined. The variables included in our model fulfilled these conditions. Total scores were obtained for each variable, and then centred in order to avoid biases due to their differences in maximum scores.

Four parameters were considered to assess the model quality: a) the chi-square statistic, whereby a non-significant result indicates good fit; b) the relative chi-square ratio [CMIN/DF], which is expected to be 3 or less in case of good fit; c) the comparative fit index, where model fit is considered good when CFI $\geq$0 .95; and d) the root mean square error approximation, which is considered acceptable when RMSEA $\leq$0 .06.

All the variables composing the research model were included in the analysis. The results indicated a poor fit of the model in general, with χ^2 (16) =96.165, p$<$0.000, CMIN/DF=6.010, CFI=0.652, and RMSEA=0.173. As can be observed on Figure 4 and Table 55 , the variable perceived usefulness was a strong predictor of intention of use with a good standardised estimate (beta-value or β) associated, but neither perceived ease of use nor previous experience with computers were significantly related to intention of use. It is interesting to observe the null relationship between previous experience and perceived usefulness of the learning environment. Both perceived usefulness and previous experience with computers were significantly related to behavioural planning, although the amount of explained variance was low. The almost null relationship between intention of use and behavioural planning is particularly interesting. On the right hand of the model, the major finding is the lack of relationship between intention of use and all the variables composing the Engagement cluster, whereas behavioural planning has a positive relationship significantly related to satisfaction, self-perceived learning, and actual use. Finally, satisfaction with the course and actual use were directly related to final mark, with a small effect of satisfaction on actual use.

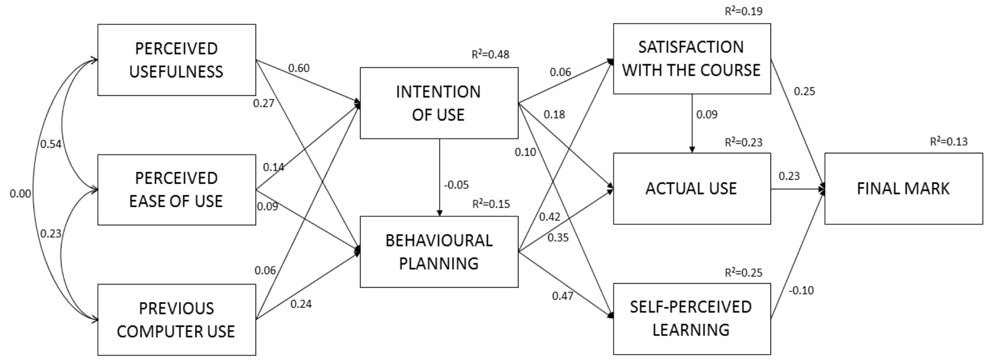

Figure 4. Standardised beta values of the research model

Table 5. Results of the research model

Observed Variable	Standardised Estimate (β)	Est./S.E.	Two-tailed p-value
Intention of Use ON			
Perceived Usefulness	0.60	7.29	0.00
Perceived Ease of Use	0.14	1.63	0.10
Computer Use	0.06	0.79	0.43
Behavioural Planning ON			
Perceived Use	0.27	2.08	0.04
Perceived Ease of Use	0.09	0.79	0.43
Computer Use	0.24	2.57	0.01
Intention of Use	-0.05	-0.40	0.69

Actual Use ON			
Intention of Use	0.14	1.57	0.12
Behavioural Planning	0.35	2.94	0.00
Satisfaction	0.10	0.93	0.35
Satisfaction ON			
Intention of Use	0.06	0.48	0.63
Behavioural Planning	0.42	3.99	0.00
Self-perceived Learning ON			
Intention of Use	0.10	0.89	0.38
Behavioural Planning	0.47	4.52	0.00
Final Mark ON			
Satisfaction	0.25	2.74	0.01
Actual Use	0.23	2.49	0.01
Self-perceived Learning	-0.10	-1.15	0.25
R-SQUARE			
Intention of Use	0.48		
Behavioural Planning	0.15		
Satisfaction	0.19		
Self-perceived Learning	0.25		
Actual Use	0.23		
Final Mark	0.13		

On the basis of these results the testing model was modified, excluding the variables perceived ease of use, intention of use, and self-perceived learning, which had been demonstrated to be non-significant components in the model. The fit of the revised model was significantly improved, with χ^2 (8) = 6.850, p=0.553, CMIN/DF=0.856, CFI=1.000, and RMSEA=.000. The new model (Figure 5) is much simpler, with less crossed paths mainly due to the exclusion of intention of use, and with perceived usefulness and previous computer use as direct predictors of behavioural planning, and then behavioural planning directly related to satisfaction with the course and actual use, and then actual use positively related to final mark. Satisfaction with the course is also directly related to actual use and final mark, although its p value is slightly over 0.05. The detailed information can be seen on Table 66. Despite the positive and significant relationships between the variables comprising the model, overall percentages of explained variance were disappointingly low, with R^2=0.12 for behavioural planning, R^2=0.07 for satisfaction with the course, R^2=0.22 for actual use, and R^2=0.11 for final mark.

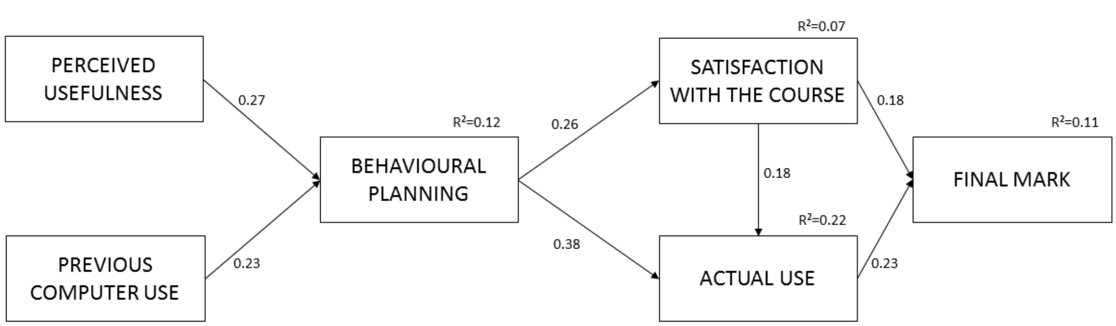

Figure 5. Standardised beta values of the corrected research model.

Table 6. Results of the optimized research model.

Observed Variable	Standardised Estimate (β)	Est./S.E.	Two-tailed p-value
Behavioural Planning ON			
Perceived Usefulness	0.27	3.00	0.00
Computer Use	0.23	2.51	0.01
Satisfaction ON			
Behavioural Planning	0.26	2.21	0.03
Actual Use ON			
Behavioural Planning	0.38	3.39	0.00
Satisfaction	0.18	1.90	0.05
Final Mark ON			
Satisfaction	0.18	1.94	0.05
Actual Use	0.11	2.50	0.01
R-SQUARE			
Intention of Use	0.12		
Satisfaction	0.07		
Actual Use	0.22		
Marking	0.11		

According to these results, hypothesis 1 that perceived usefulness, perceived ease of use, and previous use of computer would be directly related to intention of use, is partially supported, due to the weak relationship between previous computer usage and intention of use. The second hypothesis, which states that perceived usefulness, perceived ease of use, and previous use of computer would be directly related to behavioural planning is also partially supported, because of the non-significant relationship between ease of use and behavioural planning. The third hypothesis, which states that intention of use and behavioural planning would be directly related to satisfaction with the course, actual use, and self-perceived learning, is also partially supported, due to the non-significant effect of Intention of use on the other variables. The fourth hypothesis, stating that satisfaction with the course, self-perceived learning, and actual use, would be predictors of learners' final mark finds support for the effect of actual use, while the p-value of satisfaction with the course is slightly over 0.05, and the effect of self-perceived learning is non-significant. The fifth and last hypothesis, proposing that satisfaction with the course would have a positive effect on actual use was not supported, since its p-value was slightly over 0.05. Theoretical and practical implications will be discussed next.

2.7. **Discussion and implications**

In this study with Chilean teachers embarking on an e-learning environment, we found that i) behavioural planning was a better predictor of actual use of the learning platform than was intention of use; ii) it seems to be a mismatch between the self-perception of learning and actual learning, showing that the usage rate of the platform was a better predictor of performance than the learner's perceptions; and iii) that both adoption and effectiveness of learning technology can be seen as parts of an integrated technology-enhanced learning model in which personal attitudes are related to behaviour, and behaviour is related to learning achievement. These findings are important both theoretically and practically, as we will discuss in turn.

2.7.1. Adoption of learning technology

Our findings do support Davis´s model for predicting intention of using technology (in this case an e-learning environment). Nonetheless, the poor relationship between intention of use and the actual use suggests that other variables may be involved on learning technology adoption. We found that behavioural planning predicted actual use, suggesting that variables other than attitudes, such as those tapping motivation and intention, might influence the adoption of learning technology. At the same time, actual use was significantly related to the students' final mark (a measure of learning achievement), reinforcing the idea that the first step towards improving the effectiveness of computer-based instruction is to achieve higher rates of adoption and continued, engaged use.

As a second issue, it is important to consider that the correlation between learners' declared intention to use the e-learning environment assessed at the beginning of the course, and their declared time dedicated to the course reported five weeks later, was relatively low ($r = 0.38$). Thus, what participants thought they would do was not a good predictor of what they actually did. The effect of satisfaction on actual use ($ß=0.18$, $p=0.05$) combined with the fact that the high initial expectations of use were not reflected in the actual use of the platform, suggest that the adoption of learning technology varies through time and that other variables are involved, which would likely explain an important amount of the remaining variance. Therefore, the adoption of learning technology should not be seen as a passive, static response of the user that starts with an intention and ends with the execution of a plan of action, but as a dynamic and iterative process that may evolve over time and through changing circumstances. In future research, a design including repeated measures should help to clarify whether or not these ideas are correct.

2.7.2. Learning achievement

The results revealed only a small effect of the attitudinal variables - satisfaction with the course and self-perceived learning - on the learning outcome. There seems to be a mismatch between the self-perception of learning and the objective measure of the learning achievement, in other words, learners' view about their own learning was not accurate when compared with the mark obtained. This might be related to a self-discrepancy between people's representation of their self and their actual self (Higgins, 1987; Stanley & Burrow, 2015).

Satisfaction with the course was slightly related to actual use (ß=0.18, p=.05) and to final mark (ß=0.18, p=.05), which suggest that satisfied learners spend more time doing the course activities, and hence they achieve better results. However, from the current study, we cannot determine how these results were achieved. It might be due to differences on the individual attributes and the social capital of the learners - such as learning orientation and shared understanding, respectively (Kankanhalli, Pee, Tan, & Chhatwal, 2012), or to the role of motivation as an enhancer of self-directed learning

(Shinkareva & Benson, 2007) and self-perceived learning (Chang, Chen, Huang & Huang, 2011).

The time spent using the platform and developing the learning activities was the most relevant variable explaining students' mark. Nonetheless, the explained variance was low ($R^2 = 0.11$), which suggests that other factors not included in the model must be considered. For instance, variables related to the way that people learn that might influence the learning outcome, such as their learning approach (J. Biggs, Kember, & Leung, 2001; Kember, Biggs, & Leung, 2004) and learning styles (Dağ & Geçer, 2009; Felder & Spurlin, 2005; Tulbure, 2011). Additionally, the marking criteria, while known beforehand, might have been inconsistently applied. Finally, the initial knowledge of the participants about the topic of the course was assessed by a self-perception rating, correlating low but significantly ($r = 0.21$, $p < 0.01$), but had a non-significant contribution to the path analysis and made a worse fit for the overall model. In future, an objective baseline of the knowledge on the topic must be included in order to compare the results and get more reliable results.

2.7.3. Integrated model of computer-based learning

One of the main objectives of the present study was to develop a theoretical and empirical bridge between the learning technology adoption process and the effective use of learning technology for the achievement of learning goals. From the perspective of technology usage, it must enhance the way people develop their activities, hence a well-integrated model would be useful for a better design and improved adaptability of the VLEs to specific learner characteristics, goals, and conditions. The proposed model was based on the individual attitudes and evaluations widely considered in the literature to explain these phenomena, but nonetheless resulted in a low overall power ($R^2 = 0.11$).

From this, two ideas emerge as central for discussion. The first idea – relating to one of our main hypotheses – is that it is possible in a logical and empirical way to connect adoption and effectiveness of learning technology. The path from individual attitudes towards learning achievement, through behavioural planning and actual behaviour, indicates that strong planning and then implementation of such a plan is related to a better outcome. Our future research will focus on understanding which aspects of the interaction between learners and virtual learning environments are more important to improve the engagement with and the effectiveness of learning technology, and whether they are related to the learner (user) or to the learning environment (design).

The second idea – which is a consequence of the first – is that the model must be augmented, probably through the inclusion of two kinds of variables: i) individual variables related to cognition and motivation, and ii) those related to the dynamic aspects of the process, even including some modifications to the testing design. Regarding the individual variables, locus of control has been found directly related to attitudes towards the use of virtual environments and to continued use (Broos & Roe, 2006; Coovert & Goldstein, 1980; Eom & Reiser, 2000; Joo, Joung, & Sim, 2011). In the same line, internal dispositions such as learning approach (Biggs et al., 2001; Kember et al., 2004) and learning styles (Dağ & Geçer, 2009; Tulbure, 2012) have been related to instructional designs and learning achievement. Perhaps the inclusion of these variables will give some insight about individual attitudes towards learning technology, the rate of use that learners are willing to accomplish, and how learners deploy their cognitive resources to achieve the proposed learning goals. Finally, to understand the time-dependent aspects of the model (e.g. actual use among different weeks or key events of the course, or satisfaction with the course regarding specific activities) it is important to utilise a design with repeated measures capturing the role and response of variables such as actual use and satisfaction with the course over the time (Nezlek, 2012).

3. EXPLORING THE EFFECTS OF LEARNER CHARACTERISTICS ON THE ADOPTION OF LEARNING TECHNOLOGY.

3.1. **Introduction**

Building on the results of Study 1, this chapter presents two studies exploring variables to modify the initial research model in order to improve it. Specifically cognitive variables such as Academic Locus of Control, Learning Approach, and Learning Style will be included on the left side of the model. Additionally, the variable Perceived Fit will be included among the adoption parameters on the left side of the model.

The rationale for including these variables and the theory that supports them are presented in the next section, followed by the research question and hypotheses that lead to the studies of this chapter. Following, the method and results of each study will be presented, finishing with the discussion section, integrating the highlights of both studies.

3.2. **Theoretical framework.**

As explained in the Introduction to the thesis, each chapter contains a brief theoretical section in order to contextualise, extend or complement the understanding of the variables included in the studies. Below the theoretical foundations to include new variables into the research model will be presented, highlighting their main definition, and some studies demonstrating their connection with the present research project.

3.2.1. Academic Locus of Control.

The concept of locus of control was introduced in a series of studies from 1950s and 1960s about the influence of personal beliefs on own behaviour and chance, and its consequences on an individual's current situation. Locus of control refers to the degree of personal responsibility that people accept for what happens to them (Lefcourt, 1966). Known as well as "control of reinforcement", it states that people's attribution about the source of the event that originated a current state or consequence is going to affect how they evaluate their own behaviour and consequently reinforce it in a positive or negative way (Kormanik & Rocco, 2009).

Academic Locus of Control refers to a continuum – from internal to external – of students' perceived responsibility for their own academic performance (Arlin & Whitley, 1978). In other words, when students have a tendency towards external academic locus of control, they think their success or failure is due to fortune or other's actions, and that there is nothing or little they can do to change it. On the contrary, students with a tendency towards internal academic locus of control think their academic success or failure depends on their own actions and personal responsibility. The repercussion on their behaviour is related to how, by taking responsibility of their own academic results, they take control of their actions in order to achieve the learning goals.

In the context of learning supported by computer technology, it should be related to attitudes and behaviours related to the use of such environment. One of the first works linking locus of control with attitudes towards computers was the one conducted by Coovert & Goldstein (1980), which found that people with higher scores for internal locus of control have a more favourable attitude towards the use of computers than those with extrinsic locus of control. Since then, more research has been done exploring this link with similar results.

For instance, Drennan (2005) proposed that internal locus of control was positively related to attitudes towards computers at the beginning of a flexible online course[1], and that better attitudes at the beginning of the course were related to higher satisfaction with the course at the end of it. The results of the study suggest that when students face a less structured learning course and they have an internal locus of control, then they will feel more comfortable - they will have better attitudes - than those with external locus of control, and they will have better results as well. This could be related to the lack of external guidance, and with the resultant demand for self-regulated learning behaviour, making this learning scenario more suitable for students with low dependence on external guidance and proactive learning strategies.

The role of academic locus of control on the continued use of a computer-based course was also investigated by Levy (2007). He found that, on the contrary to what previous studies suggested, locus of control has no role on the decision of dropout of an e-learning course or to continue with it. It was found that lack of satisfaction with the course was the main reason for dropping out. It suggests that the trends observed in

[1] A “flexible online course” involves learners studying at their own pace and time, using the amount of learning materials that they consider as necessary, and requiring instructional support at their own discretion.

previous studies are dynamic and can evolve within the length of the course, and also that locus of control would have an effect on the initial attitudes towards the learning environment, but later on it would be subordinated to process-related effects.

In a later study, Joo and colleagues (2011) explored the relationship between locus of control, user satisfaction, and persistence. They found a direct relationship between intrinsic locus of control and user satisfaction, and between internal locus of control and learner persistence. These findings suggest that those students with a perception of self-control over their academic results and learning-related behaviour report more enjoyment and lower rates of dropout.

In summary, the role of academic locus of control seems to be related to motivation and control behaviour. It has been suggested that people with traits of internal locus of control are more self-aware of the consequences of their own behaviour, and that they can adapt better to learning situations where the responsibility of the learning relays on them. Nonetheless, what appears to be a behavioural tendency has been observed to change over time and give way to other variables to shape learning behaviour. The following studies will try to understand better the relationship between academic locus of control and the attitudes involved in the process of adoption of learning technology.

3.2.2. Learning Style.

Another variable which is going to be explored in the following studies is called "learning style", as it has been proposed to be related to learning media preferences and to learning achievement. Learning style has been defined as "*the complex manner in* *which, and the conditions under which, learners most efficiently and most effectively perceive, process, store and recall what they are attempting to learn"* (James & Blank, 1993, pp. 47–48). In 1979, Keefe complemented this definition by adding that learning styles are relative stable indicators – which comprise cognitive, affective, and psychological behaviours – of how learners perceive, respond to, and interact with a learning environment (Felder & Spurlin, 2005). Even though other definitions may include certain nuances, the two above comprise the most relevant characteristics of learning styles: a complex system of individual characteristics including cognitive, affective and behavioural indicators, which give account of information processing tendencies or preferences while interacting with a learning environment.

The field of learning styles is very complex, due to the large number of variants of its definition, which varies depending of the focus of interest of the authors, and the variables and relationships proposed in their models. For instance, Coffield and his colleagues (2004) identified 71 different instruments to assess learning styles, with substantial differences related to their background theory and with various limitations due to their design, applications, or reduced utilisation – leading to lack of empirical support. They classified five families of learning styles, named:

(i) Constitutionally-based learning styles and preferences, referring to some set of characteristics based on genetics and/or developmentally imposed, which are fixed or difficult to change.

(ii) Cognitive structure, understood as ways of thinking that are deeply embedded in the cognitive system and not susceptible of training or modification.

(iii) Stable personality type, which argues that learning styles are an expression of personality characteristics.

(iv) Flexibly stable learning preferences, an approach based on the idea that learning styles are not fixed patterns of conduct, but preferences for some learning activities and related conducts that can change among learning situations.

(v) Learning approaches and strategies, which follow the statement that learning styles are related to general motivational drivers and behavioural tendencies that can be modified and shaped.

Approaches (i), (ii), and (iii) have failed to probe the genetic or structural foundation of learning styles, so they will not be considered in this research. Approach (v) in some respect is not always considered as learning styles due to their lack of stability among learning situations, so learning approaches will be considered in a separate subsection of this chapter. From the many models available among the flexibly stable learning preferences (iv), the more relevant in the literature are the models proposed by Alison and Hayes, by Kolb, by Honey and Mumford, and by Felder and Silverman. All of them are good and reliable models, but not all their measurement instruments are publicly available, and some of them requires too much time to be included in a set of questionnaires like the one to be used in this research. Considering the previous, it was decided to use the Felder and Silverman Learning Styles Model, which has been widely used, it is openly available for research purposes, and for which there is robust evidence of good psychometric qualities (Felder & Spurlin, 2005; Graf, Viola, & Kinshuk, 2006; Graf, Viola, Leo, & Kinshuk, 2007; Litzinger, Lee, & Wise, 2005;

Litzinger, Lee, Wise, & Felder, 2007; Viola, Graf, & Leo, 2006). The model states that individuals engaged in learning activities will select, from all the external and internal sources of information, those materials that have a better match with their way to utilise information, ignoring the rest (Felder & Silverman, 1988). These information-processing preferences have five dimensions according to how learners perceive the information, the type of information they are dealing with, the organization of the information, how it is processed, and how the students' progress towards the understanding of the information. For each preferred learning style, the authors proposed a corresponding teaching style. They suggest that when learning and teaching styles are aligned, then the student can obtain the best of the learning experience, being more comfortable and engaged and, consequently, improving their learning performance. A summary of the five dimensions of Learning and Teaching Styles, retrieved from Felder & Silverman's original article (1988, p. 675) is reproduced in Table 7. Later, these five dimensions were reduced to four by the authors, by the exclusion of the dimension "Organization".

Dimensions of Learning and teaching Styles			
Preferred learning Style		Corresponding Teaching Style	
Sensory	Perception	Concrete	Content
Intuitive		Abstract	
Visual	Input	Visual	Presentation
Auditory		Verbal	
Inductive	Organization	Inductive	Organization
Deductive		Deductive	
Active	Processing	Active	Student Participation
Reflective		Passive	
Sequential	Understanding	Sequential	Perspective
Global		Global	

Table 7. Dimensions of learning and teaching according to Felder-Silverman's Learning Styles Model.

Researchers have explored the relationship between learning styles, learning-technology preferences, and learning-related behaviour in digital environments. For instance, Sun, Lin and Yu (2008) looked for a relationship between learning styles and academic performance as part of a wider research. They used a different learning styles model (Kolb's model of learning styles) finding no difference between learning styles and academic performance. Similar results were found by Akkoyunlu and Soylu (2008), who found evidence of a relationship between learning style and attitudes towards the virtual learning environment.

A study led by Brown (2006) looked for differences in learning performance between different learning styles while using a virtual learning environment. A group of students was assessed according to Felder-Silverman's model – utilising the Felder-Soloman' Index of Learning Styles – regarding their visual-verbal dimension, and then assigned to a matched or mismatched learning environment. At the end of the course their learning achievement was compared, finding no significant difference between the groups of students.

Saeed, Yang and Sinnappan (2009) conducted a study investigating the relationship between Felder-Silverman's learning styles model and preferences on learning technologies with higher education students. They proposed that learning style would influence the preference for and the use of learning technology, increasing the preference/use when learning style and learning technology characteristics are aligned. They also proposed that the appropriate use of learning technology would have a positive impact on academic performance. The results showed that learning styles were related to learners' preference by specific characteristics of the learning environments, but that students are generally flexible enough to effectively use different formats of digital environments without affecting their overall performance. It was also observed that learning styles did not affect the academic achievement of the participants, with no significant difference between them in the outcome. The authors suggested that most of the learners did not have a distinct predominance of a single learning style – on the contrary, there was a majority of well-balanced profiles –, so they were capable to deploy their own learning strategies regardless the characteristics of the digital environment.

Consistent with previous research, these results lead to the conclusion that students can adapt their information processing strategies to different learning scenarios. This adaptation might be facilitated by the features that different learning systems share, and by the varied media included in them (text, video, images).

Taken together, this body of literature allows us to speculate that learning styles might not be related to academic success, and that they might be related to characteristics of the learning environments that can be self-perceived as matching with the way students prefer to analyse the information. In light of this, in the following study, learning styles will be included to test the hypothesis that they are related to learners' preference for a given learning environment. Preference should be maximised when the learning style and the characteristics of the learning environment are aligned. The relationship between learning styles and learning achievement will be assessed in a forthcoming study, included in the next chapter.

3.2.3. Learning Approaches.

The concept of "learning approach" has been considered as part of the learning style theories, but most of the learning approach researchers claim that there is a fundamental difference between learning style and learning approach. While "learning styles" informs about learners' preferences on information processing, students' learning approaches inform about how they engage with the learning process, comprising motivations and general learning strategies. The first mention of “approach to learning” came from a study made by Marton and Saljo (1976, cited by Biggs, 1990) which explained the differences between two types of students when addressing a text learning task. In the study, it was found that one group of students had the intention of focus on the actual words used by the author, so they reproduced sections of the text. The other group was focused on the meaning, so they were more focused on the concepts included in the text. The correspondence between intention and process was called “approach” to learning.

In his paper from 1990, Biggs described three approaches to learning: surface, deep, and achieving. Later on, in a revised version of his theory, the approaches to learning were reduced to surface and deep. The surface approach to learning has been characterised as driven by extrinsic motivations, avoiding failure but trying not to work too much, and focusing on selected and relevant details. On the other hand, the deep learning approach is driven by intrinsic motivations, aiming to satisfy curiosity about a subject, and trying to maximise understanding even when it involves more effort (Biggs, 1990; Biggs et al., 2001; Kember et al., 2004).

In a study conducted by Gurpinar et al. (2013), deep learning approach was found to be associated to higher levels of satisfaction in problem-based learning, an instructional strategy which makes students self-direct their cognitive and affective resources to solve a given task. Even though this relationship goes beyond the use of learning technology, it is important to consider how the instructional design – learning goals, activities, and materials – can influence the attitudes of the students to engage with a learning setting. It might be that the perception of a virtual learning environment is influenced in a basal level by how individuals became deep-motivated by the instructional design of the learning environment. As Jackson (1998) noted, a learning environment might be evaluated from different perspectives, including easiness of use, efficiency, learner's preferences, attractiveness, and cost-effectiveness. As students can have a deep or surface approach towards the learning program, then their attitudes to the environment that supports it might be influenced by their learning approach.

For instance learning approaches, assessed by Biggs' Study Process Questionnaire (SPQ), were linked to attitudes towards the value of learning technology and to academic achievement (Ellis, Weyers, & Hughes, 2013). In particular, deep learning approach was observed as related to positive perceptions of learning technologies and with better marks. On the other hand, surface approach was observed as related to poorest conceptions on the suitability of learning technology to achieve the learning goals and with lower marks. The authors concluded that those students with predominance of surface profile need to be reinforced externally on the usefulness of the contents and activities of the course in order to engage them more – for instance, highlighting the target of the activity and how it is related to the overall goal.

The following studies will assess the relationship of learning approaches with the adoption parameters tested in Study1, and chapter 4 will assess their relationship with the learning process in general.

3.2.4. Perceived Task-technology Fit

The degree of usefulness of a determined information system is a key aspect at the time of understanding its future usage. This has been demonstrated by Davis' TAM research, where perceived usefulness impresses as the most important predictor of intention of use. Nonetheless, this is not the only way to assess people's perception of the instrumentality of a tool for a given context. The degree of coincidence between the technology features and the user requirements of the system is known as "perceived task-technology fit" (TTF), and it has important implications for the potential utilisation of a virtual learning environment, being linked with usage rates and performance.

An early study conducted by Goodhue & Thompson (1995) found that user evaluation of TTF is related to characteristics of the task and characteristics of the system at the same time, and it is also related to individual performance (in a work context). Another study, from Klopping & McKinney (2004), modified Davis' TAM by adding TTF to it, and considering it as a variable able to explain perceived usefulness and ease of use of an e-commerce platform, resulting in positive valuable inclusion into Davis' model, notwithstanding its effect on intention of use was not assessed.

Task-technology fit has been linked with intention of continued use of a learning system (Larsen, Sørebø, & Sørebø, 2009), having an important influence on individual's satisfaction. Larsen and colleagues found that when users have a positive evaluation of TTF they have higher levels of satisfaction when using it, and they are keener to use the system in the future. Nonetheless, this study assessed the variables only of those who actively and consistently used the system along the semester, and there was no measurement of intention of use or of actual use. As our intention is to find evidence of an eventual link between the initial TTF perception and intention of use, and between initial TTF perception and behavioural planning, this study will not be considered as a demonstration of it, but will give some good insight about the bond between TTF and intention of use.

Yu & Yu (2010) conducted a study combining TTF with the theory of planned behaviour and technology acceptance model, in order to understand people's usage of online learning systems. They stated that technology and individual characteristics might interact with or moderate the relationship between the learning environment and the user perceptions. They did not find a significant relationship between TTF and behavioural intention, but they did find a positive relationship with attitudes towards the system. Similar results were obtained by Lin & Wang (2012) in a study investigating the effect of attitudes and TTF on continued use and acceptance of learning systems. They realised that coherence between the features of the learning system and the goals of the learning instruction improves people's actual use and intention of continued use.

Sometimes the utilisation of a virtual learning environment is not optional and higher rates of use do not imply a better adoption of it. In the same way, when the system has a poor fit between what it does and what it should do, the performance is not going to be improved by its use. Nonetheless, how the potential user evaluates the adequacy of any tool for his/her purposes is going to be fundamental for the decision of using or not using that system.

On the other hand, even though it might be very difficult to have an accurate picture of the relevant characteristics of the users of a learning environment, understanding how some of these might increase the liking for particular setting would be worthy. The selected variables “learning approach” and “learning style” would be related to the match between the learning environment and personal dispositions on how to proceed in a learning situation (learning approach), and between the learning environment and personal preferences in order to access the information and processing it (learning style).

3.3. **Overview of studies 2 and 3.**

The present chapter explores the relationship between learning dispositions, attitudes towards virtual learning environments, and the adoption of them. Two studies were designed for this purpose. Study 2 focuses on the relationship between a cluster of variables assessing academic locus of control and learning approach, and perceived ease of use, perceived usefulness, perceived fit, self-efficacy, and intention of use. In a between-participants design, participants were randomly assigned to two groups to evaluate the suitability of two different learning environments in helping them to complete a learning-related task.

The focus of study 3 is similar, but employs a different methodology. In study 3, participants first complete measures (similar to study 2), then view a video explaining the features of a virtual learning environment, and finally, they complete a questionnaire to evaluate the learning environment. The purpose of using these two methodologies to gain insight into the relationship between learning dispositions and attitudes towards learning environments is to test the independence of learning dispositions from learning environment design in different settings, and the dependence of attitudes from learning environment characteristics and goals.

STUDY 2.

The goal of study 2 is to delineate the relationship between learning approach and academic locus of control with the adoption parameters. In this study, we examine the attitudes towards two different virtual learning environments for the fulfilment of a fictitious learning-related task in a between-participants design. The VLEs are differentiated by their opposite degrees of constraint on the learning-task flow. As well as examining the effects of VLE on the adoption parameters, we also look at the potential effects of the individual difference in learning characteristics discussed above, namely learning approach and academic locus of control, on the attitudes towards the VLE, namely perceived ease of use, perceived usefulness, computer self-efficacy, and perceived fit.

To this end, the **first hypothesis** is that a positive correlation will be observed between academic locus of control and deep learning approach. Our **hypothesis 2** is that an inverse correlation will be observed between academic locus of control and surface learning approach. Based on what has been observed about the effect of the learning environment characteristics and the attitudes towards them, out **third hypothesis** is that there will be significant differences on the scores of perceived ease of use, perceived usefulness, perceived fit, self-efficacy, and intention of use according to the virtual learning environment evaluated. According to the theories about the role of cognitive dispositions on behaviour, our **hypothesis 4** states that academic locus of control will have a positive effect on the attitudinal variables; **hypothesis 5** proposes that deep learning approach will have a positive effect on the attitudinal variables; and **hypothesis 6**, that attitudes will significantly predict intention of use.

3.4. **Method**

3.4.1. Participants

Participants were 228 volunteer students from undergraduate and postgraduate level from a British university, 67.1% of them were female. The age of participants ranged from 17 to 33 with a mean age of 21.35 and a standard deviation of 3.35. All subjects were recruited through an online research participation system, and their participation was also online.

3.4.2. Design and Procedure

This is an online study, in which participants faced a fictional task to be completed by utilising a virtual learning environment. The study can be split into three stages, in order to explain its flow. In the first stage the participants completed a measure of learning approach and academic locus of control. In the second stage, they were randomised to be allocated into either a structured or an unstructured virtual learning environment in which they should have to complete the hypothetical task. The simulated "structured VLE" included specific folders with reading resources and class materials, and everything was ordered in step-by-step program-controlled environment. The "unstructured VLE" was the complete opposite, and it only comprised a web browser, the more flexible tool to find the resources to complete the given task, allowing students to access to different kinds of materials depending of their own interests and preferences, being a completely learner-controlled environment. Finally, the participants reported Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Fit (PF), Computer Self-Efficacy (CSE) and Intention of Use (IOU) associated to the specific VLE they were allocated.

3.4.3. Instruments

A set of questionnaires and scales were selected to assess the variables included in this study. The selected material was adapted when necessary to fit with the research setting.

Perceived Usefulness and Perceived Ease of Use were previously used in Study 1, and described on section 2.4.3.

The rest of the instruments are described below:

Perceived Self-Efficacy: The degree of confidence that students' have on their own ability on using digital learning environments was assessed with a scale utilised by Liaw (2008). It consists in three items scored from 1 (Strongly disagree) to 5 (strongly agree). The score is obtained after adding the items, with a minimum score of 5, indicating low self-confidence, and a maximum of 15, indicating high self-confidence (example item: "I feel confident using the contents of the learning platform").

Perceived Fit: Student's perceptions about the suitability of the learning environment to achieve the task aims were measured by a perceived fit scale extracted from Lin (2012). It comprises seven Likert-type items scored from 1 to 5 according to their degree of agreement between the scale's statement and the student perception (example item: "This learning environment provides good functions to help me complete my learning tasks"). The items were added to obtain a general score.

Intention of Use: The behavioural driver on using the virtual learning environment of the participants was measured by a scale also used by Liaw (2008). It is a three items Likert-type scored from 1 to 5, which are summed to obtain the scale's score with high scores directly indicating a positive behavioural intention (example item: "I would like to use the content of the learning platform to assist my learning").

Academic Locus of Control: The students' perception on the degree of relationship between their academic output and their own or some else's behaviour was assessed with Levy's ALOC instrument (2007). It comprises twelve items on a 5-points Likert-type scale from "Strongly Disagree" (1 point) to "Strongly Agree" (5 points). The total score is obtained by adding the score of each item, ranging from 12 – as an External Academic Locus of Control –, to 60 – as in Internal Academic Locus of Control (example item: "Some of my good grades may simply reflect that these were easier courses than most").

Learning Approach: The set of motivations and strategies that students typically deploy in a learning context were assessed by the R-SPQ-2F (Revised Two-Factor Study Process Questionnaire) developed by Biggs et al. (2001). It is comprised by 20 items clustered in two factors named "Deep" and "Surface" – approach – which are composed by two subscales of 5 items each, regarding the source of motivations (intrinsic or extrinsic) and strategies (narrow target or maximizing meaning). The items use a Likert-type response from 1 ("this item is never or only rarely true of me") to 5 ("this item is always or almost always true of me"). Each participant scores in both factors independently by adding the score of the items included in each dimension, as the author states that every person poses deep and surface characteristics, nonetheless one of the factors can be predominant. The “Deep Approach” can be exemplified by the item “I find that at times studying gives me a feeling of deep personal satisfaction”, and the “Surface Approach” by “I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra”.

3.5. **Procedure**

The study comprised three parts. In the first part, participants completed two questionnaires, one on academic locus of control and another one on learning approach. In the second part, the participants were randomly allocated into two groups, A and B. Both groups had the same hypothetical task, as it follows:

> *“Imagine you are taking a course on "Research Methods". The final assessment consists on comparing two different methods to address a study and to write a report justifying your choice”.*

To address the task, group A was told to use a learning platform that contained all the required material to complete the task – such as papers, lecturer notes and presentations – and a proposed order to access the contents. This environment was named as “Structured” (Figure 6). On the other hand, group B was indicated to complete the task making use of a web browser, with complete freedom to choose the source and amount of information. This setting was called as “Unstructured” (Figure 7). In the third part of the study, the participants had to answer a set of questionnaires about attitudes and behavioural intention. Figure 8 shows the process flow of the study.

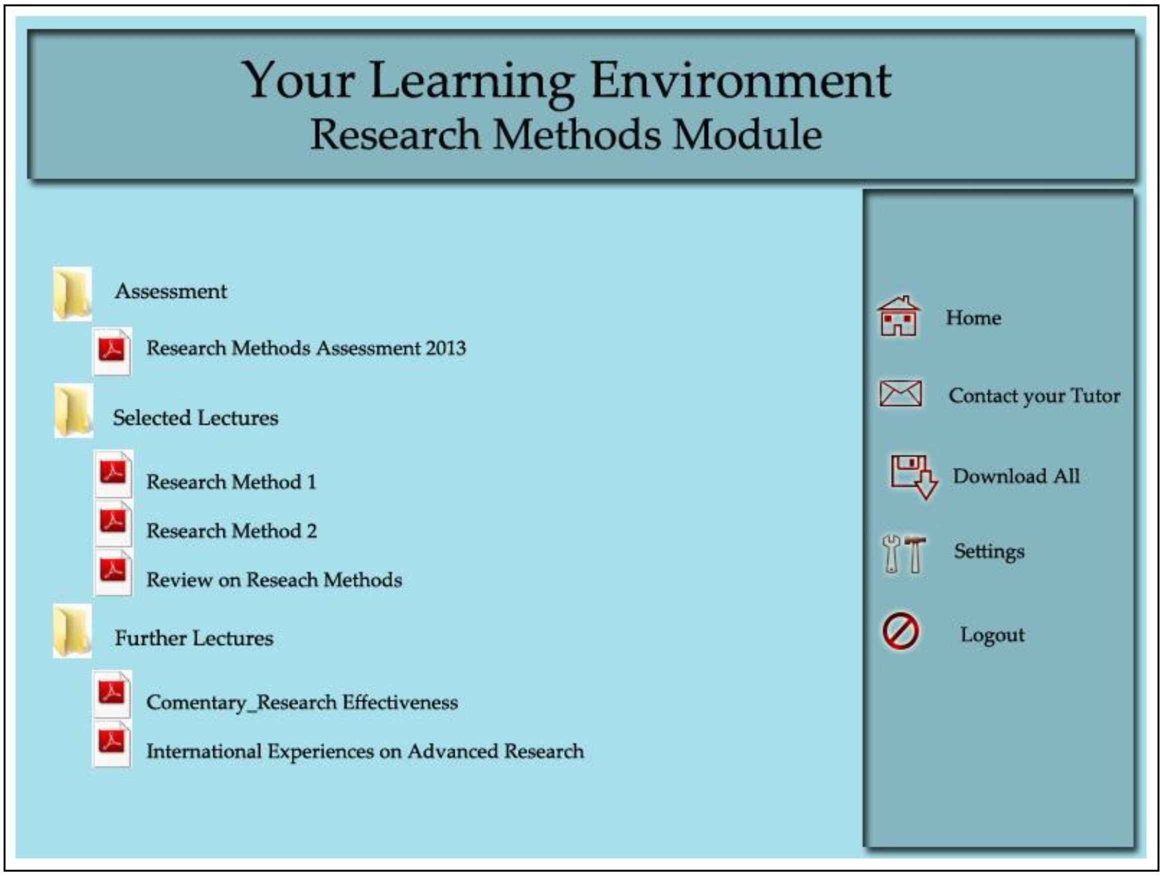

Figure 6. Screenshot of the structured environment.

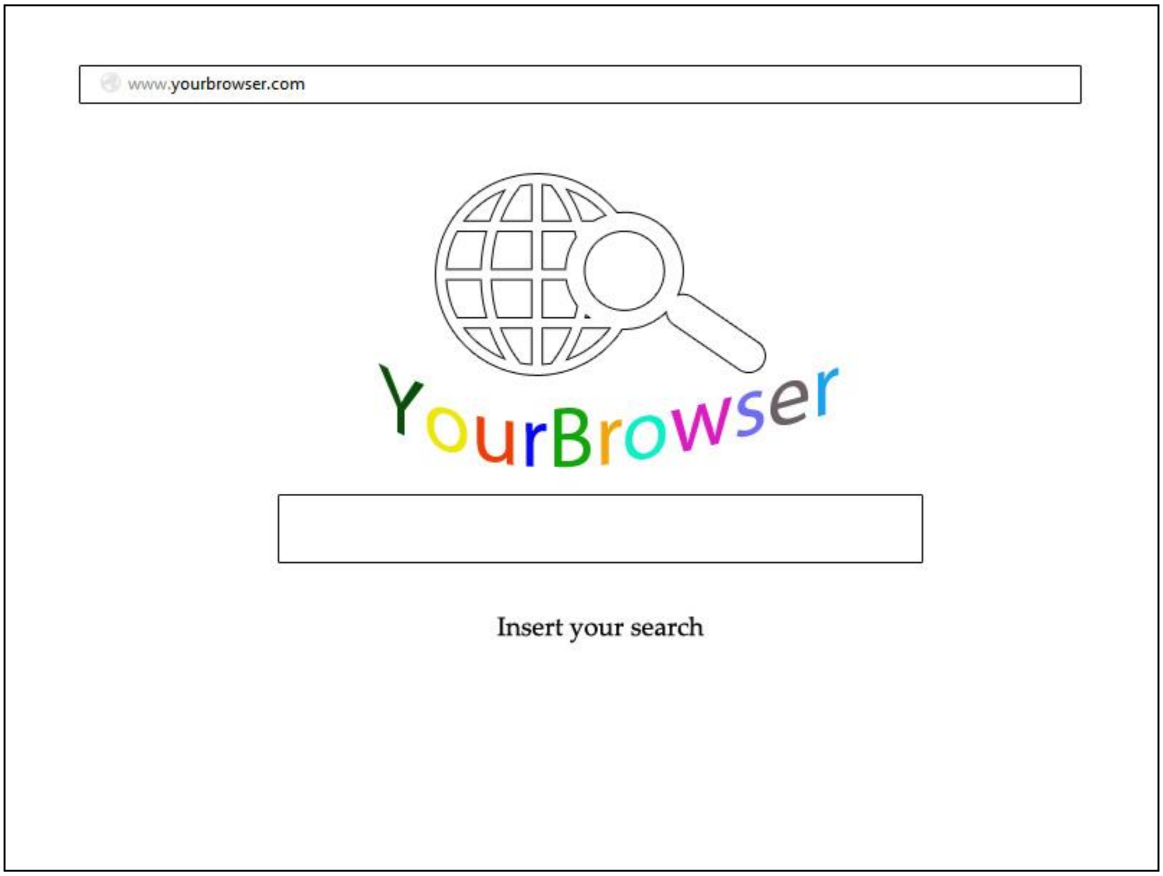

Figure 7. Screenshot of the unstructured environment.

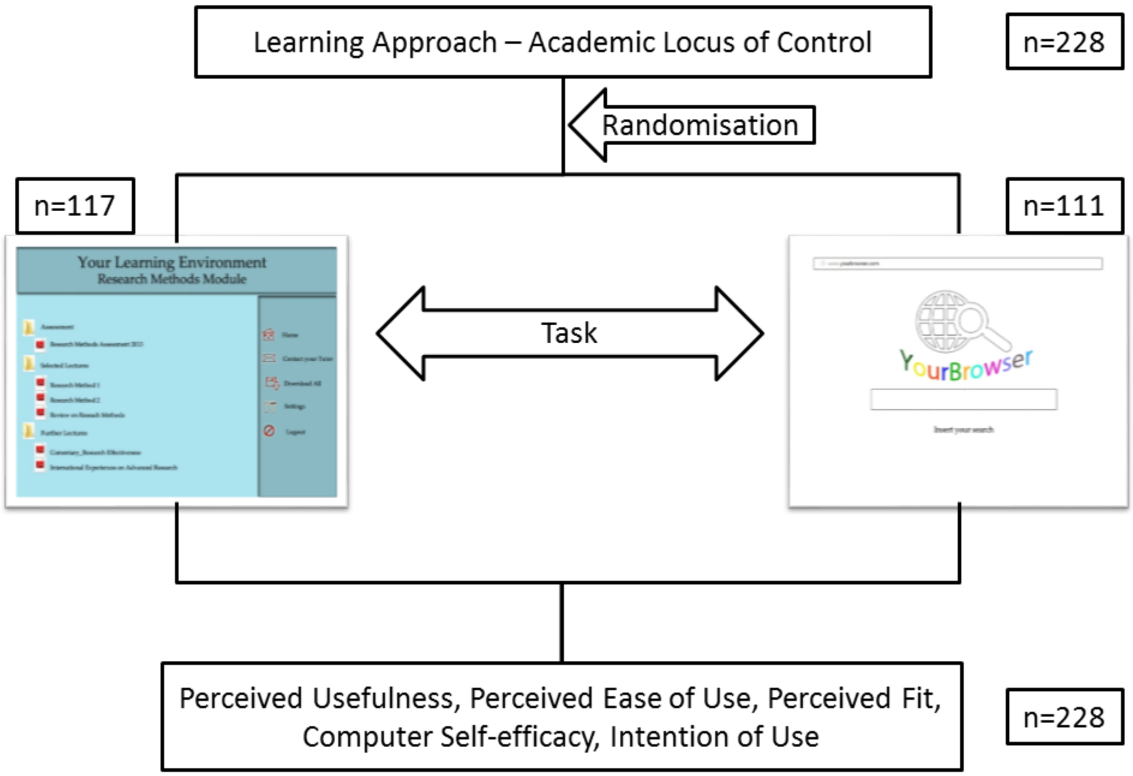

Figure 8. Study 2 Process flow.

3.6. **Results**

The data was analysed using SPSS and AMOS v.22. The psychometric quality of the instruments will be presented in the following section. The analytic strategy and the assessment of the proposed research model will follow.

3.6.1. Scales reliability

The internal consistency of all instruments was assessed by using Cronbach's alpha. The values ranged from 0.70 to 0.90, consistent with has been reported in similar studies. Detailed information about the mean, standard deviation, and internal consistency of all the scales can be found in Table 8.

Table 8. Mean, standard deviation, and internal consistency reliability of the variables included in the model.

Variable	Mean	SD	ICR
Academic Locus of Control	37.86	5.93	0.74
Deep Learning Approach	27.17	6.34	0.80
Surface Learning Approach	32.16	5.87	0.79
Self-efficacy	12.31	2.26	0.89
Perceived Usefulness	12.34	3.16	0.90
Perceived Ease of Use	16.12	2.81	0.88
Perceived Fit	24.46	3.77	0.70
Intention of Use	11.93	1.81	0.74

The psychometric quality of the R-SPQ-2F, which assesses learning approach, was judged at both item-level and structure-level, as it was proposed by Biggs (2001) in his original article presenting the instrument. In this article, the author specifies that learning approach is composed by two independent factors, “Deep” and “Surface” approach with 10 items each. These factors are likewise composed by a dimension called “Motivation” and another one called “Strategy”, each of them represented by a subscale of 5 items (Figure 9).

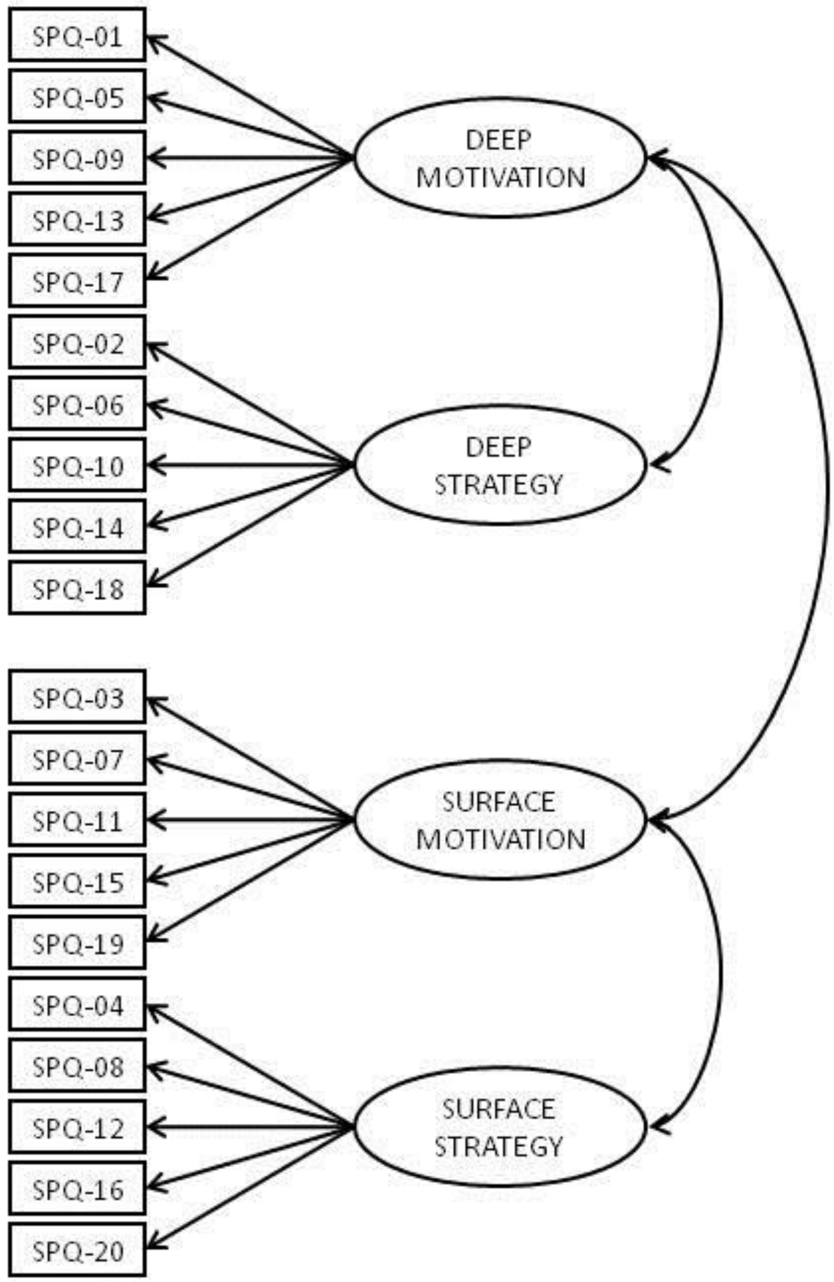

Figure 9. Biggs' R-SPQ-2F (learning approach) ítem-level strucutre

In the current dataset, at item-level a simple Cronbach's Alpha indicates a good reliability of the two-factor model with values of 0.80 for Deep Approach and 0.78 for Surface Approach. Nonetheless, Confirmatory Factor Analysis performed with AMOS v.22 reveals that the two-factor structure does not fit the data very well, obtaining CMIN/DF=2.625, CFI=0.765, and RMSEA=0.085 (More details in Figure 10).

On the other hand, at structure-level, the two dimensions of each factor were assessed considering each dimension as an observed aggregated variable (sum of the items score), as proposed by Biggs (2001). The results show a satisfactory fit to data, with χ^2 (1)=0.125, p=0.723, CMIN/DF=0.125, CFI=1.000, and RMSEA=0.000 (Figure 11).

It can be said that, even when the structure-level analysis can be considered as strong, the item-level analysis shows some flaws. Nonetheless, the psychometric quality of the R-SQP-2F has been assessed using larger samples and consistently finding good fit to data, as it was presented in section 3.2.3. For this reason, the scale and the items are going to be maintained as they are, but recognising that further analyses are needed, especially with larger samples that allow more sophisticated factor analysis.

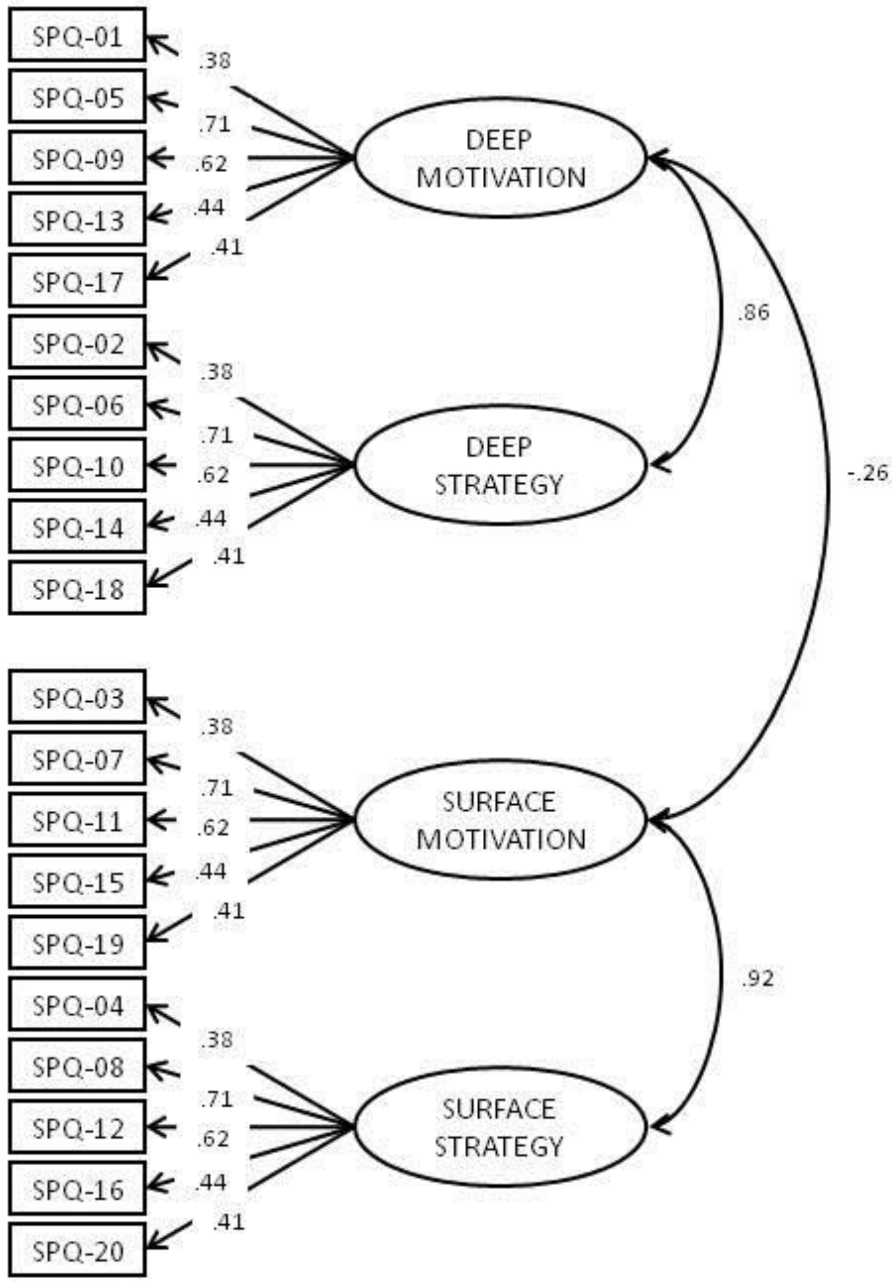

Figure 10. Results of Confirmatory Factor Analysis for Biggs' R-SPQ-2F at item-level.

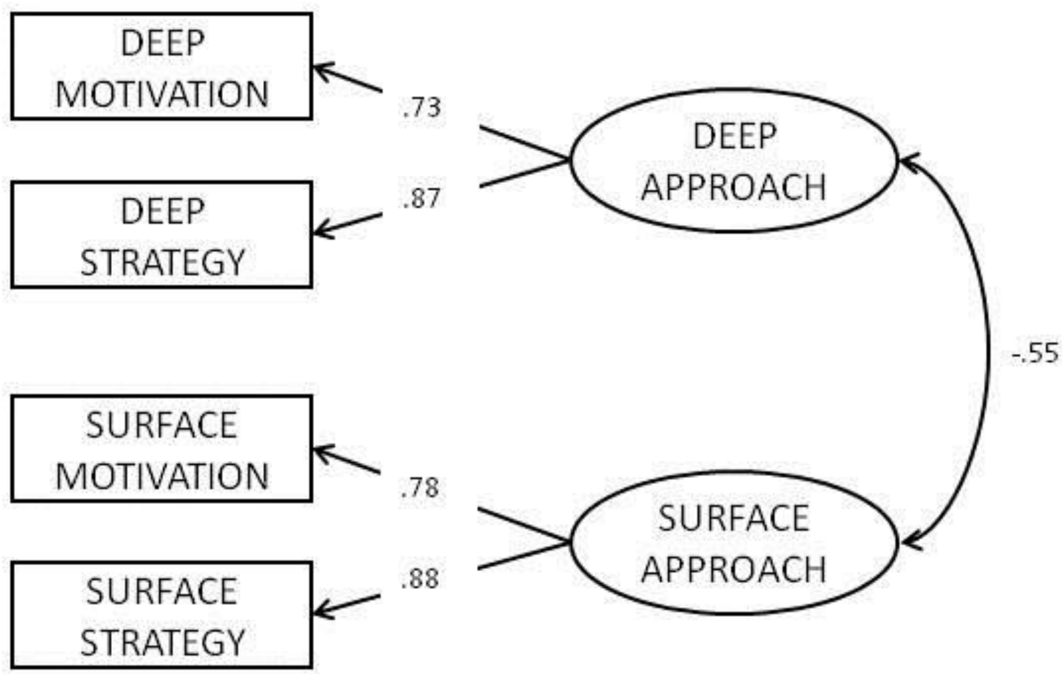

Figure 11. Results of Confirmatory Factor Analysis of Biggs' R-SPQ-2F at structure-level.

3.6.2. Analytic strategy for the research model.

In order to test the proposed hypotheses three analyses were applied. First, Pearson's correlation coefficient was utilised to tests the covariance between the variables; then, an independent sample t-test was performed in order to observe the difference in the participants' scores depending of the learning scenario evaluated. Finally, a path analysis was performed to test the effect of the variables on intention of use.

The relationships between the variables included in the study can be observed in *Table 9*. It shows, as expected i) similar correlations between scenarios for the variables related to cognitive preferences, and ii) higher correlations among the variables in the unstructured scenario.

Table 9. Correlation coefficients of the variables included in the model by learning environment.

Structured Learning Environment							
Observed Variable	1	2	3	4	5	6	7
1. A. Locus of Control	1.00						
2. Surface L. A.	-0.31**	1.00					
3. Deep L.A.	0.34**	-0.51**	1.00				
4. Self-efficacy	0.04	0.03	0.10	1.00			
5. Perceived Usefulness	0.07	0.06	0.06	0.57**	1.00		
6. Perceived Ease of Use	0.17	0.01	0.12	0.54*	0.54**	1.00	
7. Perceived Fit	0.03	-0.28**	-0.05	0.30**	0.57**	0.33**	1.00
8. Intention of Use	0.06	0.08	0.03	0.48*	0.53**	0.50**	0.51**

Unstructured Learning Environment							
Observed Variable	1	2	3	4	5	6	7
1. A. Locus of Control	1.00						
2. Surface L. A.	-0.35**	1.00					
3. Deep L.A.	0.39**	-0.37**	1.00				
4. Self-efficacy	0.09	-0.22*	0.23*	1.00			
5. Perceived Usefulness	0.13	-0.21*	0.23*	0.54**	1.00		
6. Perceived Ease of Use	0.15	-0.17	0.33**	0.66**	0.46**	1.00	
7. Perceived Fit	0.02	-0.09	0.17	0.42**	0.57**	0.43**	1.00
8. Intention of Use	0.06	-0.14	0.21*	0.35**	0.54**	0.55**	0.56**

Note: *p<.05 ; **p<.001

Additionally, it sheds some light on the relationship between learning approach and attitudes towards learning technology, which can be observed in the small but significant correlation between deep approach on the one hand and self-efficacy, perceived usefulness, and perceived ease of use on the other. Surface approach showed no relationship with any variable except by the negative relationship with deep approach. The same thing can be observed about academic locus of control, being related with deep approach and with perceived ease of use.

Regarding the characteristics of the virtual learning environment and the reaction of the learner towards it a number of significant differences can be observed.

Table 10 shows the results of an independent-samples t-test for the difference of the mean scores on the attitudinal scales between learning scenarios and Figure 12 presents this information graphically. All the differences, although discrete, are significant and suggest that the students have a better reception of a learning environment that grants them more freedom, in opposition to a more structured one.

Table 10. Independent-Samples t-test assessing the difference between attitudes towards the learning environments.

Observed Variable	Learning Environment	Mean	Std. Deviation	Std. Error Mean	t	Mean Difference	sig. (2-tailed)
Self-Efficacy	Structured	11.79	2.39	0.22	-3.70	-1.08	0.00
	Unstructured	12.86	1.98	0.19			
Perceived Usefulness	Structured	11.91	1.61	0.15	-3.88	-0.89	0.00
	Unstructured	12.79	1.84	0.18			
Perceived Ease of Use	Structured	15.57	2.60	0.24	-3.07	-1.12	0.00
	Unstructured	16.69	2.91	0.28			
Perceived Fit	Structured	23.67	3.45	0.32	-3.36	-1.64	0.00
	Unstructured	25.31	3.92	0.37			
Intention of Use	Structured	11.38	1.61	0.15	-4.90	-1.12	0.00
	Unstructured	12.50	1.84	0.18			

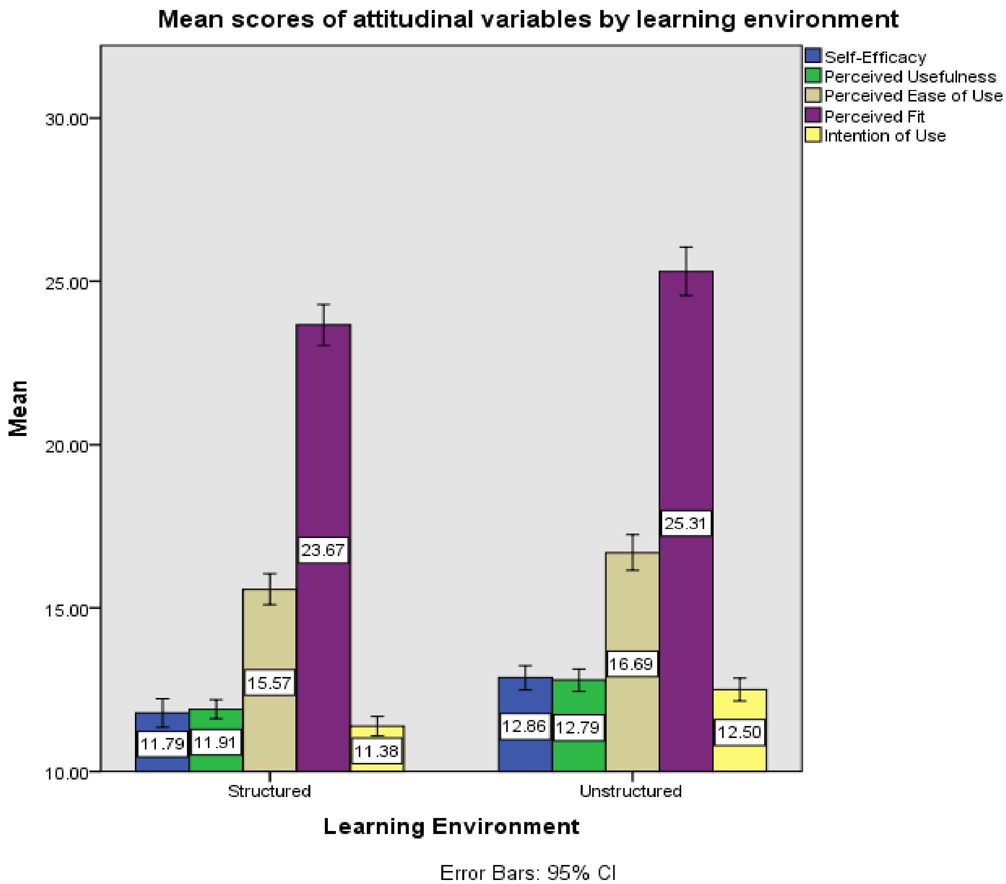

Figure 12. Independent-samples t-test for mean differences.

Finally, a path analysis was performed by using AMOS v.22. The goodness-of-fit of two models were compared to take into account the effect of the learning environment characteristics, the attitudes, and the interaction between attitudes and learning approach on intention of use. Both models are based on Davis' TAM, but modified by adding self-efficacy, perceived fit, and the interaction with deep learning approach. The first model comprises the effect of attitudes towards the learning environment and the type of learning environment the students were assigned (structured or unstructured) on intention of use. The second model includes the effect of deep learning approach while interacting with the attitudes, and how it can predicts intention of use.

The two models are graphically explained by Figure 13

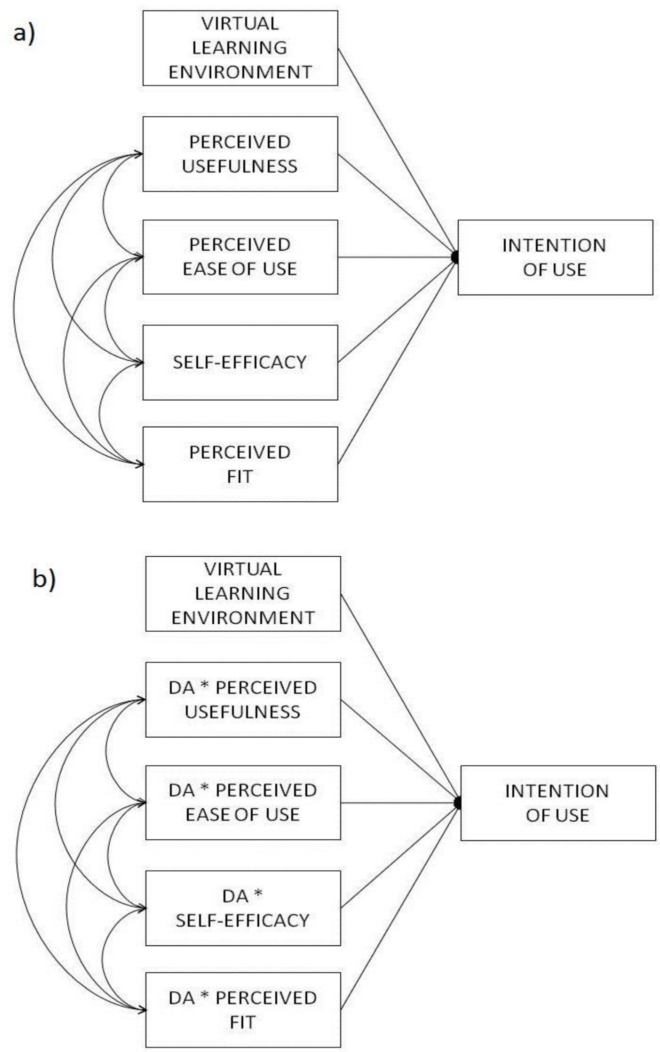

Figure 13. Research models. Model b) includes the interaction of deep learning approach with the attitudes towards technology.

The results showed that the first model (Figure 14) predicts intention of use according to what could be expected by Davis' TAM, with a significant positive effect of perceived fit, perceived ease of use, and perceived usefulness, and a discrete but significant effect of the learning environment. These results are congruent with the relationships observed on the covariance matrix (*Table 9*). Nonetheless, and despite the 46% of explained variance, the fit indexes suggest the model does not fit with the data, $\chi^2(3)=17.696$, $p=.001$, CMIN/DF=5.899, CFI=0.956, RMSEA=0.147. Most of the indexes suggest a bad fit with the data, except CFI.

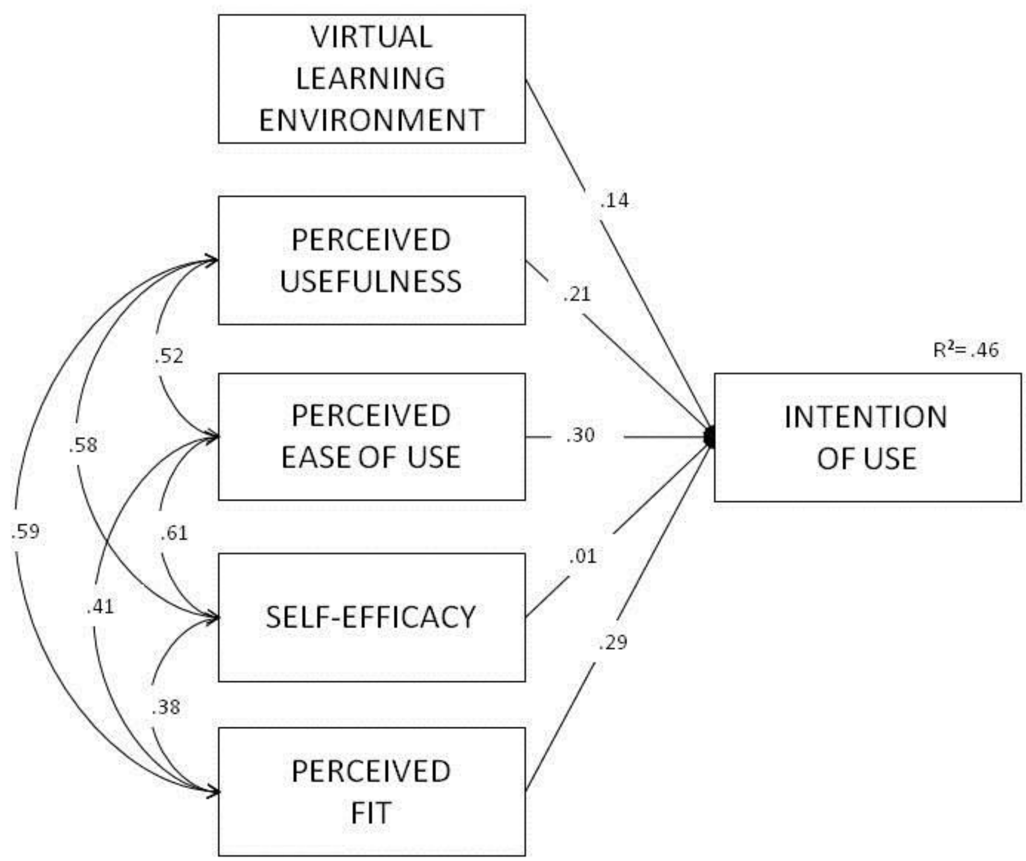

Figure 14. Results of research model a).

The second model includes the interaction of the variable “deep learning approach” with the attitudinal parameters. This modification changes considerably the results, showing a non-significant effect of the attitudinal variables on intention of use, and a stronger effect of the learning environment on the output variable than in the previous model. The fit indexes improve considerably, being $\chi^2(3)=3.285$, $p=0.350$, CMIN/DF=1.095, CFI=0.999, RMSEA=0.020. On the other hand, the explained variance decreases to 12.2%. Figure 15 illustrates these results and the path diagram.

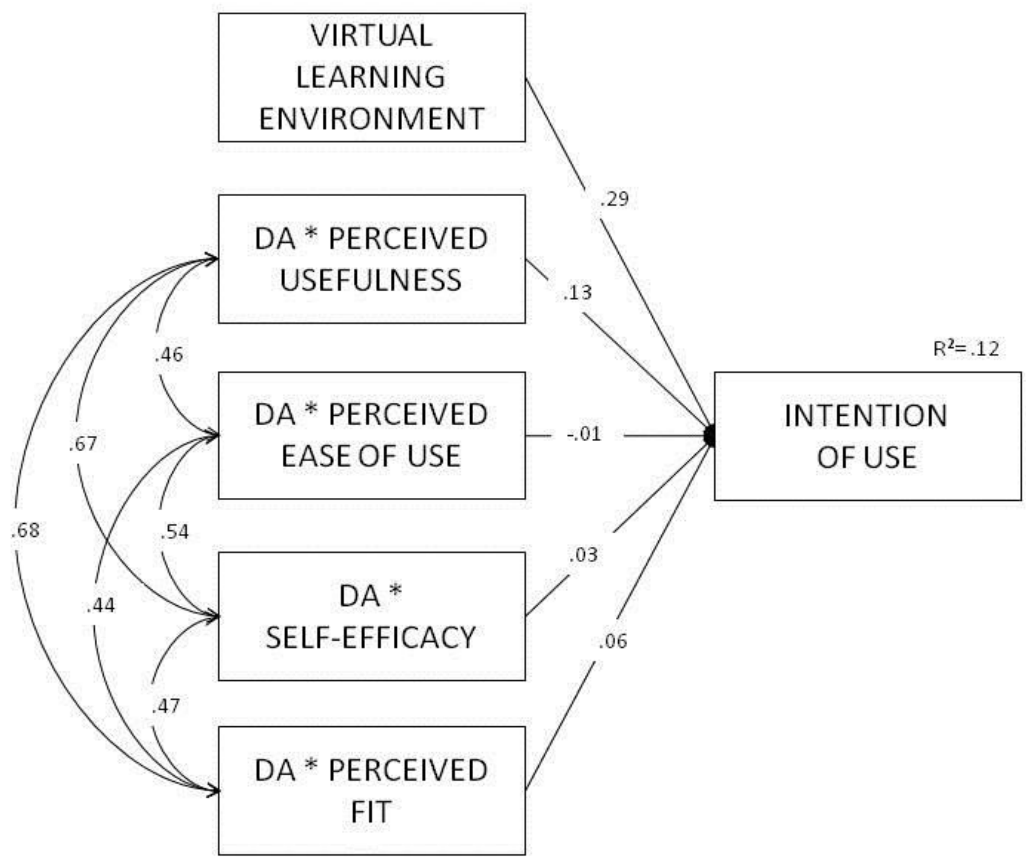

Figure 15. Results of research model b).

The comparison between the models shows that model (a) has a high R^2 but bad goodness-of-fit, and that model (b) has low R^2 and an adequate goodness-of-fit. This suggests that model (a) is more reliable in its projections (high R^2), but that its results might be biased, maybe for the low variability in the scores of the attitudinal scales. When deep learning approach was introduced in model (b) interacting with the rest of the variables, it generated more variability in the scores, therefore the decreasing in the R^2, but a better adjustment with the estimated parameters of the goodness-of-fit, and modifying the strength in the relationship between the independent and the dependent variables. This might be related to the observed inconsistencies between the attitudes-intentions and the actual behaviour. It might be that people tend to respond with some bias the attitudinal scales that makes them have a strong consistency, but when they face the real task their behaviour would be driven by something different. When learning approach, a variable much less affect-dependent than attitudes, was included in the analysis, the variability augmented, increasing the uncertainty of the model, but fitting better with data. It has to be considered in forthcoming studies to observe its relationship with actual use and other process–related variables.

In summary, the results of study 2 support the hypothesis that academic locus of control and deep learning approach are positively related (H1). It can be said that the level of perceived control over the learning process has a positive effect on the attitudes towards the learning environment that support such learning process (H3). Besides, it can be said that attitudes are strong predictors of intention of use (H6). There was found partial support for the hypothesis that deep learning approach has a positive effect on attitudes (H5). The hypothesis that academic locus of control and surface learning approach have an inverse relationship (H2) cannot be supported because the inverse relationship observed between them is not significant. Finally, the hypothesis that deep learning approach has a direct effect on attitudes can be supported only partially, because a direct effect was observed on perceived ease of use and usefulness, and on self-efficacy, but not on perceived fit neither on intention of use.

STUDY 3.

The goal of study 3 is to assess the relationship between individual learning characteristics and the adoption parameters in a different setting, but incorporating learning style as an antecedent of individual preferences. Study 3 builds on study 2 by reassessing the relationship between learning approach and attitudes towards learning technology in order to gather more data to support or reject the findings of study 2. Here, we focus on the relationship between learning approaches, learning styles, and adoption parameters named intention of use and behavioural planning. Subsequent to completing measures of learning approach/style, participants evaluated a media-rich learning environment and stated their estimated usage of it.

This study looks to complement the results of study 2, testing the idea that there will be no relationship between learning approaches and learning styles (**hypothesis 1**). Our **hypothesis 2** is that scores of the attitudinal variables will vary among learning styles. Based on the results of the previous study, it is hypothesised that deep learning approach have a positive effect on the attitudinal variables (**hypothesis 3**). Finally, our **hypothesis**

4 is that attitudes will significantly predict intention of use; and that attitudes will significantly predict behavioural planning (**hypothesis 5**).

3.7. **Method**

3.7.1. Participants

Participants were 115 psychology undergraduate students from a British University. All participants were volunteers recruited through an online research participation system, and then were invited to an experimental session to collect their responses. The mean age was 19 years-old with a standard deviation of 1.96, and the female proportion of the sample was 79.1%. Notwithstanding that females might be seen as over-represented, the correlations between gender and the variables included in the model were non-significant.

3.7.2. Design.

Study 3 was a cross-sectional study. All the information was given by the participants in a single experimental session, and then collected and stored by a computer-based experimental environment. The composition of the sample was not random, because its composition was voluntary and subject to a reward system based on academic credits. The study comprised three parts: i) the collection of data regarding participants' learning approach and learning styles, ii) the presentation of a video showing a rich-media learning environment, and iii) the collection of participants' perceptions about the learning environment keeping in mind that it is the instructional system to complete a mandatory course.

3.7.3. Instruments

Most of the instruments used in this study were described previously. This is the case for R-SPQ-2F (learning approach), perceived usefulness, perceived ease of use, intention of use, behavioural planning, and perceived fit. The only instrument that has not been used before is the Felder-Soloman Index of learning styles (ILS), described below.

Index of Learning Styles: It was developed by Felder and Soloman (n.d.), aiming to assess individual preferences on the four dimensions proposed by Felder-Silverman learning style model. The ILS consists of four bi-dimensional scales composed by eleven items. Each item present a learning-related scenario followed by two alternatives that represent both dimensions of the scale from which the participant have to choose one. Litzinger and colleages (2005) describe the four scales representing the following learning preferences:

Active (learn by doing, prefer groups) or Reflective (learn by thinking, prefer to work alone or with few). Example item:

"I understand something better after I:
a) try it out. (as *active*)
b) think it through. (as *reflective*)"

Sensing (practical, focused on facts) or Intuitive (conceptual, focused on theory). Example item:

"I would rather be considered:
a) realistic. (as sensing)
b) innovative. (as intuitive)"

Visual (preference for visual material) or Verbal (preference by written or spoken information). Example item:

"When I think about what I did yesterday, I am most likely to get
a) a picture. (as visual)
b) words. (as verbal)"

Sequential (tendency to linear thinking) or Global (use of holistic thinking). Example item:

"I tend to
a) understand details of a subject but may be fuzzy about its overall structure. (as sequential)
b) understand the overall structure but may be fuzzy about details. (as global)"

The indicated preference scores as 1 point on the selected scale, and a total score is obtained for all of them. On each dimension, the smaller total is subtracted from the larger, indicating the preferred style and the difference with the opposite, with a minimum of 1 and a maximum of 11. A difference up to three indicates a mild preference, and a difference of seven or more indicates a strong preference for a learning style.

3.8. **Procedure**

Participants had to attend an experimental session lasting 20 to 30 minutes, including an initial introduction to the task and time for participants' questions at the end of the session, when required. After receiving the instructions, the participants were left alone inside the room to complete the task delivered by a computer-based experimental platform.

The study comprised three parts. The first part was an electronic questionnaire comprising the Felder-Soloman Index of Learning Styles and Biggs' Study. In the second part, the participants watched a video presenting a virtual learning environment (http://tinyurl.com/odzuzym). The main characteristics of this VLE is that it allows rich contents such as video, the script of lectures, and visual support materials, in addition to static text and image files. In the third part the participants answered questionnaires regarding their attitudes towards the VLE, and a behavioural projection of the time they would spend using it in order to complete an 8 weeks module required to progress on their plan of studies. The complete task took around 15 minutes to be completed.

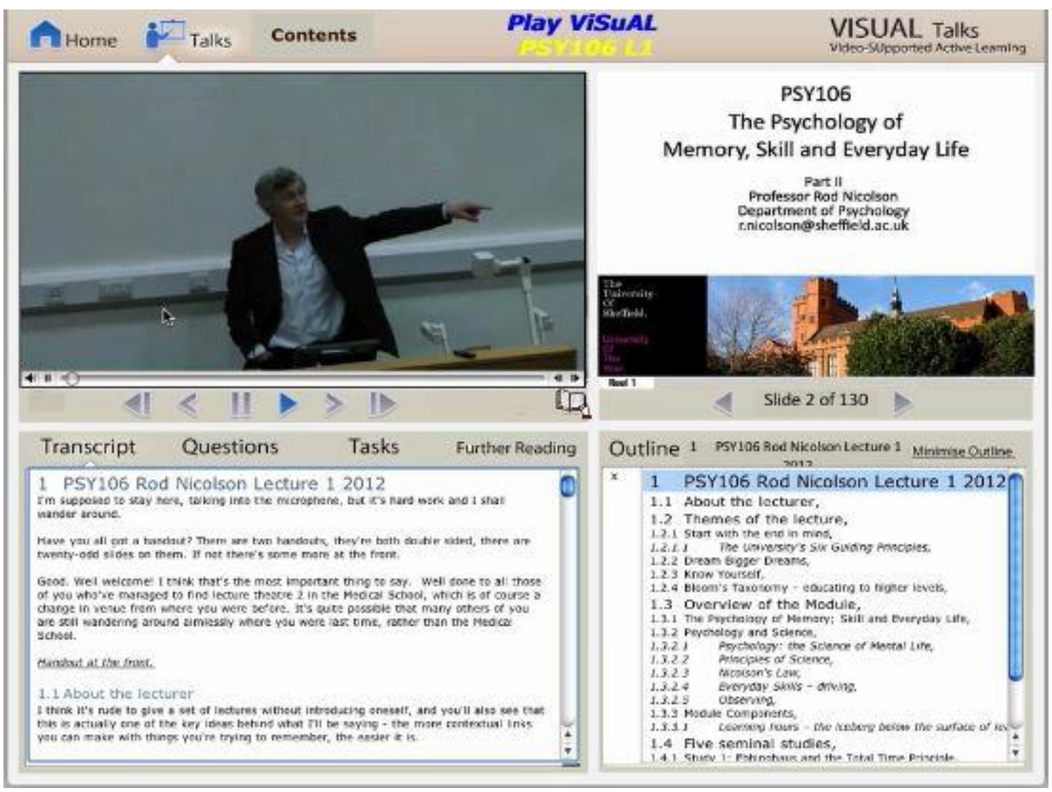

Figure 16. Screenshot of the virtual learning environment used in study 3.

3.9. **Results**

SPSS and AMOS v.22 were utilised to analyse the data. Reliability and factor composition of the instruments will be presented first. The analytic strategy and results of the research model will follow.

3.9.1. Scales reliability

Internal consistency of the attitudinal scales was assessed by using Cronbach's alpha. The values ranged from 0.631 to 0.946, similar to what has been observed in the previous studies of this thesis, and in other similar studies. Detailed information about the scales comprising internal consistency, mean, and standard deviation can be found in Table 1111.

Table 11. Mean, standard deviation, and internal consistency reliability of the variables included in the model.

Observed Variable	Mean	SD	ICR
Deep Learning Approach	33.47	4.99	0.74
Surface Learning Approach	26.03	6.16	0.82
Self-efficacy	11.66	2.48	0.95
Perceived Usefulness	13.06	1.45	0.63
Perceived Ease of Use	16.35	2.56	0.87
Perceived Fit	25.62	3.14	0.63
Intention of Use	12.70	1.94	0.84

Learning Styles			
Active – Reflective	17.31	2.21	0.56
Sensing – Intuitive	15.91	2.63	0.69
Visual – Verbal	16.12	2.48	0.68
Sequential – Global	15.46	1.66	0.14

The psychometric quality of the R-SQP-2F (learning approach) was assessed in the same way than in section 3.6.1. A Confirmatory Factor Analysis was performed in AMOS v.22 according to instrument's author, comprising a two-factor design with a two subscales of 5 items each. The item-level analysis result is congruent with was found in the previous study in this chapter, not achieving the standards to be considered as good (CMIN/DF=1.876, CFI=0.743, RMSEA=0.088). The structure-level analysis offers better results, suggesting a good fit, with $\chi^2(1)=2.584$, $p=0.108$, CMIN/DF=2.584, CFI=0.992, RMSEA=0.118. Finally, Cronbach's alpha for internal consistency shows a good item-test covariance and values of 0.740 for Deep Approach and 0.818 for Surface Approach. The results of both the item-level and the structure-level analysis for R-SPQ-2F are consistent to what was found on the previous study, and can be observed in Figure 17 and Figure 18.

The index of learning styles (ILS) is composed by four bi-dimensional factors, as described previously in section 3.7.3. Being an attitudinal instrument that measures two opposite dimensions in each subscale, an $\alpha=0.5$ is going to be considered as an acceptable indicator of internal reliability, according to Tuckman's criterion (Tuckman & Harper, 2012).

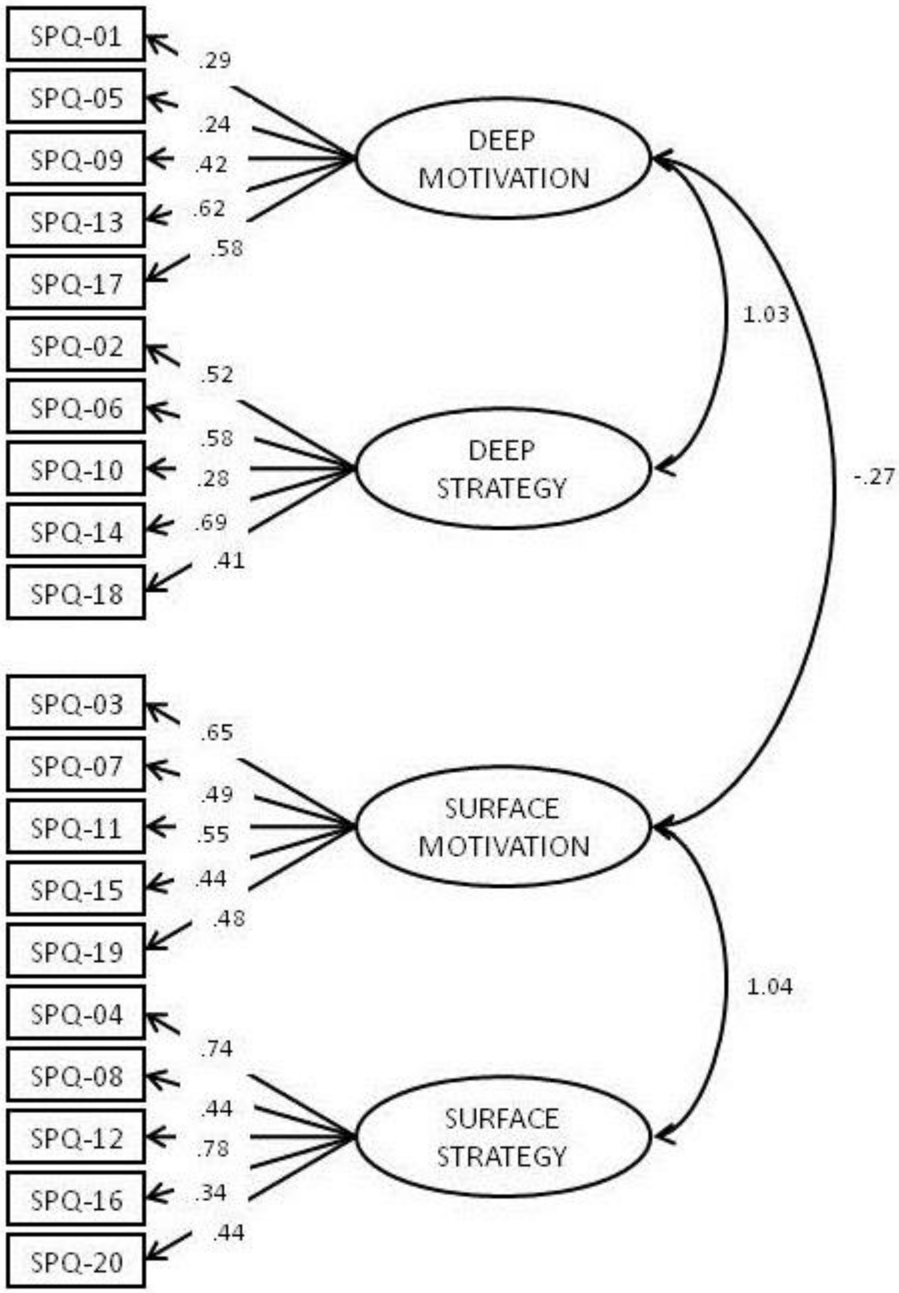

Figure 17. Results of Confirmatory Factor Analysis for Biggs' R-SPQ-2F at item-level.

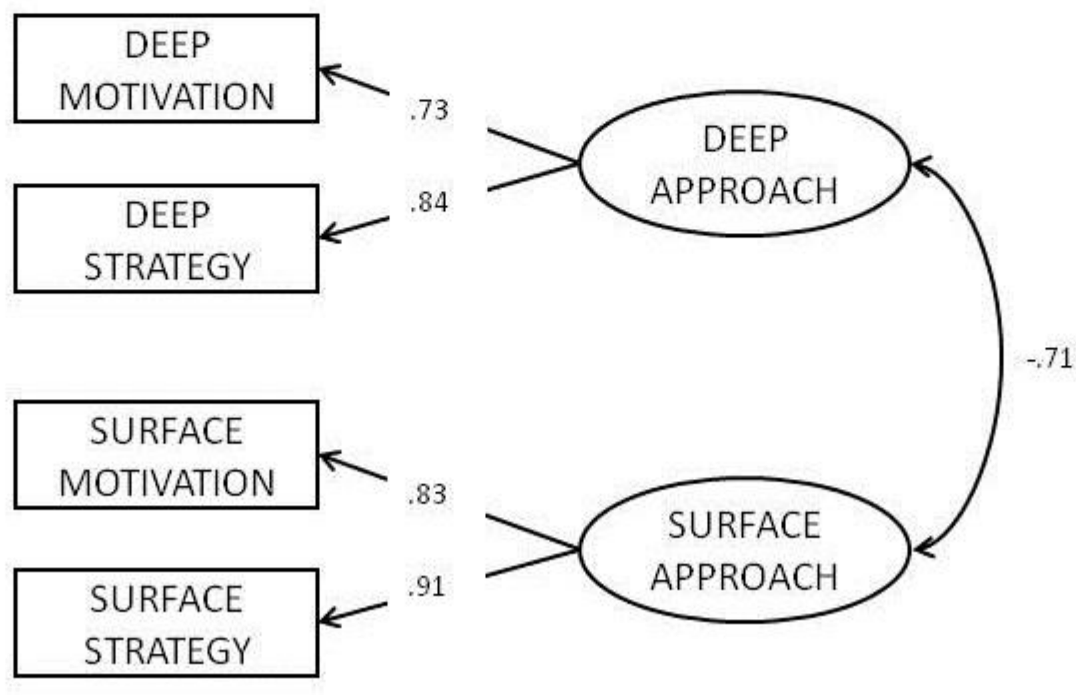

Figure 18. Results of Confirmatory Factor Analysis for Biggs' R-SPQ-2F at structure-level.

The analysis shows that three out of four subscales has acceptable ICR according to the adopted criterion: Active-Reflective=0.557, Sensory-Intuitive=0.669, and Visual-Verbal=0.675. The fourth subscale, Sequential-Global possess a low ICR (0.136). The Inter-Item correlation matrix showed low relationship between the items, and the Item-Total statistics reported poor improvement in case any of the items were deleted. Based on these results it has been decided do not include this subscale in the forthcoming analyses.

3.9.2. Analytic strategy of the research model.

In order to test the proposed relationships, two analyses were performed. First, Pearson's correlations to estimate the covariance between the variables included in the research model. In second place, a path analysis assessed the effect of the variables on intention of use and on behavioural planning.

Table 122 shows the correlation between the learning style dimensions, where the only significant relationship is the one between the Active-Reflective and the Visual-Verbal dimensions. The rest of the scales have a low and non-significant correlation.

Table 12. Correlation between the Index of Learning Styles' dimensions.

	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Active	1.00							
Reflective	-1.00	1.00						
Sensing	-0.14	0.14	1.00					
Intuitive	0.14	-0.14	-1.00	1.00				
Visual	0.30**	-0.30	-0.05	0.05	1.00			
Verbal	-0.30	0.30**	0.05	-0.05	-1.00	1.00		
Sequential	-0.01	0.01	0.34**	-0.34	-0.08	0.08	1.00	
Global	0.01	-0.01	-0.34	0.34**	0.08	-0.08	-1.00	1.00

**p< 0.01 (2-tailed).

Table 133 contains the covariance matrix between learning styles, learning approaches, and the adoption parameters. It only shows poor and non-significant correlations. Finally, Table 144 contains the relationship between learning approach and the adoption parameters, which shows that – consistently with the previous study – learning approach has no relevant relationship with attitudinal parameters, but a significant relationship is observed with both behavioural planning variables. Based on these results, the whole set of learning style dimensions will be excluded of the forthcoming analyses.

Table 13. Correlations matrix between learning styles, learning approaches, and adoption parameters.

Observed Variables	Active	Sensing	Visual	Sequential
Deep Learning Approach	-0.08	-0.02	-0.15	-0.05
Surface Learning Approach	0.09	0.03	0.17	0.03
Perceived Fit	0.02	-0.04	0.09	-0.05
Self-efficacy	-0.06	0.13	0.13	0.06
Perceived Usefulness	0.05	0.05	-0.10	-0.07
Perceived Ease of Use	0.03	0.07	0.16	0.01
Intention of Use	0.00	0.01	0.03	-0.04
Behavioural Planning – Days	-0.04	-0.05	-0.02	-0.05
Behavioural Planning – Hours	-0.04	0.03	-0.04	-0.07

* p<.05 (2-tailed).

Table 14. Correlation matrix between learning approaches and adoption parameters.

Observed Variables	Deep Learning Approach	Surface Learning Approach
Perceived Fit	0.13	-0.05
Self-efficacy	0.25^{**}	-0.13
Perceived Usefulness	0.17	-0.13
Perceived Ease of Use	0.16	-0.08
Intention of Use	0.14	-0.15
Behavioural Planning - Days	0.22^{*}	-0.29
Behavioural Planning - Hours	0.27^{**}	-0.32

** p<.001 (2-tailed) * p<.05 (2-tailed).

Therefore, the main analysis is going to be focused on the effect of learning approach on the attitudes towards technology, the effect of the attitudes on intention of use and behavioural planning, and the interaction between them.

The first analysis shows the effect of learning approach on attitudes, and the effect of attitudes on intention of use. As can be observed on Figure 19 – and as it was observed in study 2 – the effect of surface learning approach is almost null, and the effect of deep learning approach is only significant on self-efficacy and perceived ease of use. In the right side of the figure it can be observed that perceived ease of use and self-efficacy have a small and non-significant effect on intention of use, and that perceived usefulness and perceived fit have a significant and positive load on the output (0.34 and 0.58 respectively). The total variance explained by this model is 49%, similar to what was found on studies 1 and 2. The fit indexes show a poor model fit, $\chi^2(9)=259.486$, $p=.000$, CMIN/DF=28.8, CFI=0.321, RMSEA=0.494.

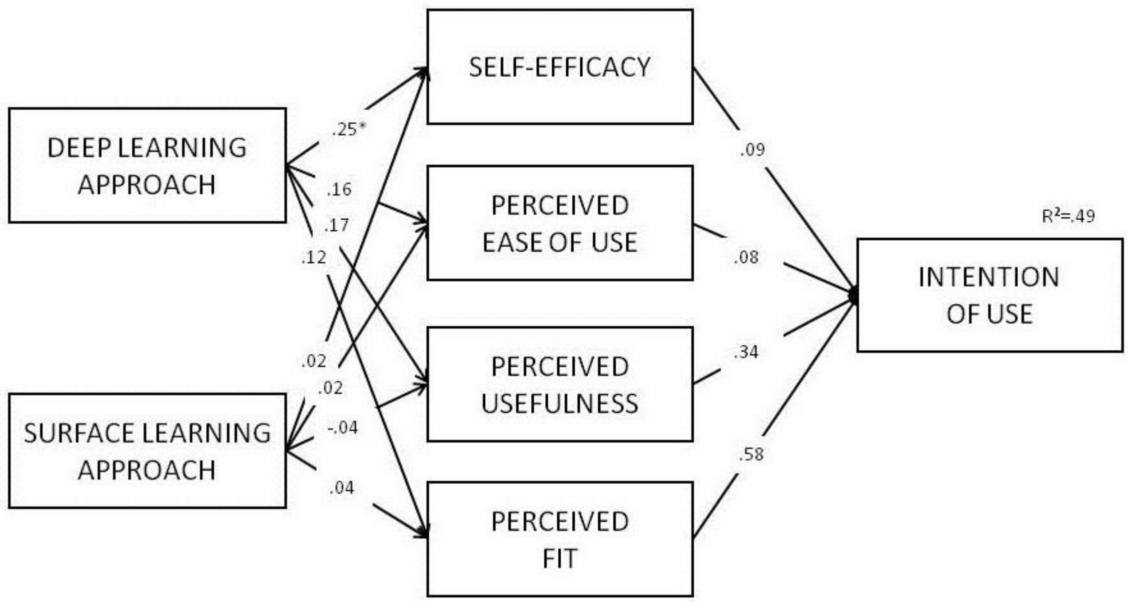

Figure 19. Predictive model for Intention of Use based on attitudes.

When the interaction of deep learning approach with the attitudinal variables was considered as predictor of intention of use (Figure 20), the result varies consistently with the results of study 2: the effect of the attitudes becomes non-significant and all the predictive power is allocated on perceived fit. The fit of the model is poor $\chi^2(6)=492.895$, $p=0.000$, CMIN/DF=82.16, CFI=0.071, RMSEA=0.844, and moreover, the explained variance decreases to 32%.

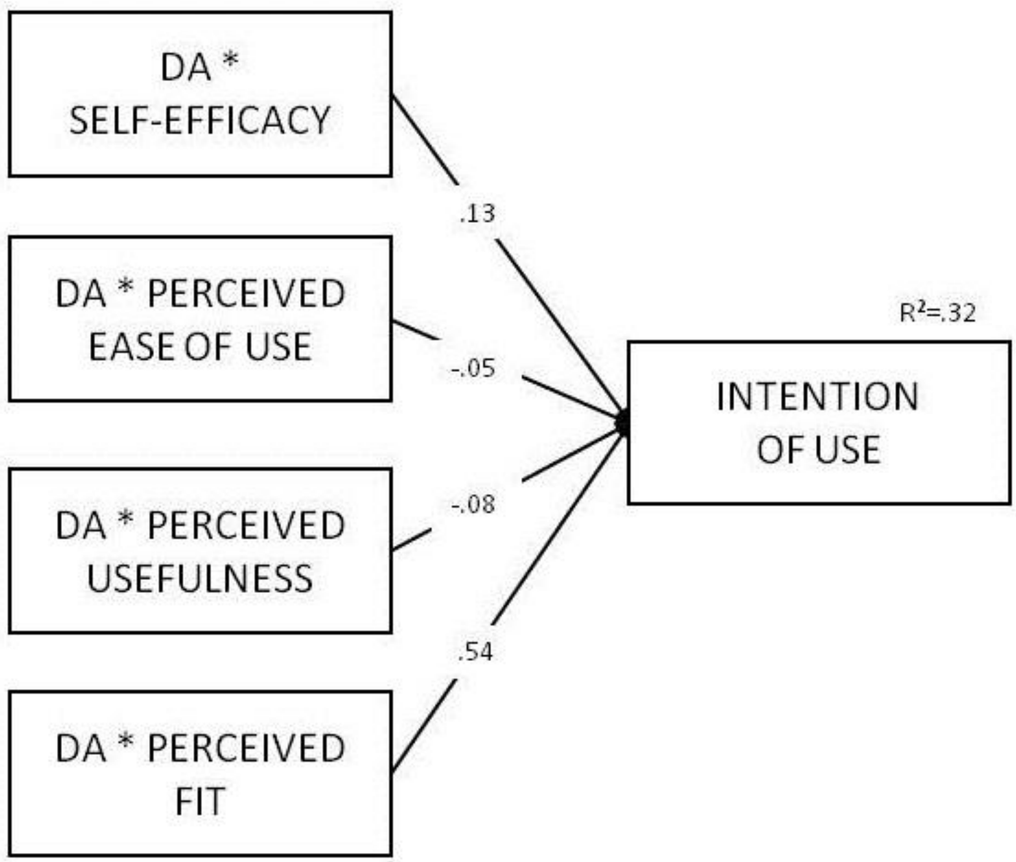

Figure 20. Predictive model for Intention of Use based on the interaction of deep learning style and attitudes.

The second analysis comprises the same structure than the first one but replacing intention of use for the amount of days that students plan to use the learning environment (Figure 21). As previously, the effect of surface learning approach is practically null, and the effect of deep learning approach is significant only on self-efficacy and perceived ease of use. In the right side of the model, only perceived fit is a significant predictor. The model does not have a good fit, $\chi^2(9)=268.024$, $p=0.000$, CMIN/DF=29.8, CFI=0.134

, RMSEA=0.502. The variance explained is 24%, 9% more than what was observed in study 1.

When the interaction between deep learning approach and the attitudes was included as predictor (Figure 22) the results changed. Self-efficacy and perceived fit becomes better predictors and the explained variance increases up to 40%. Nonetheless, it results interesting that self-efficacy possesses a negative load on the output (-0.15), and the model fit decreases, $\chi^2(6)=492.285$, $p=0.000$, CMIN/DF=82.16, CFI=0.050, RMSEA=0.844.

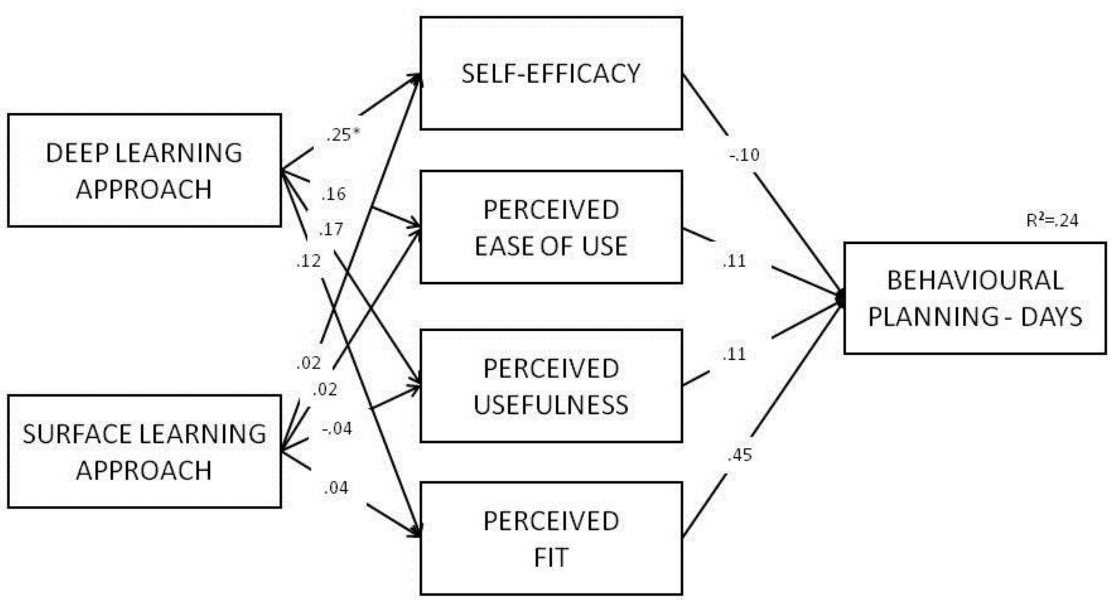

Figure 21. Predictive model for Behavioural Planning (days) based on attitudes.

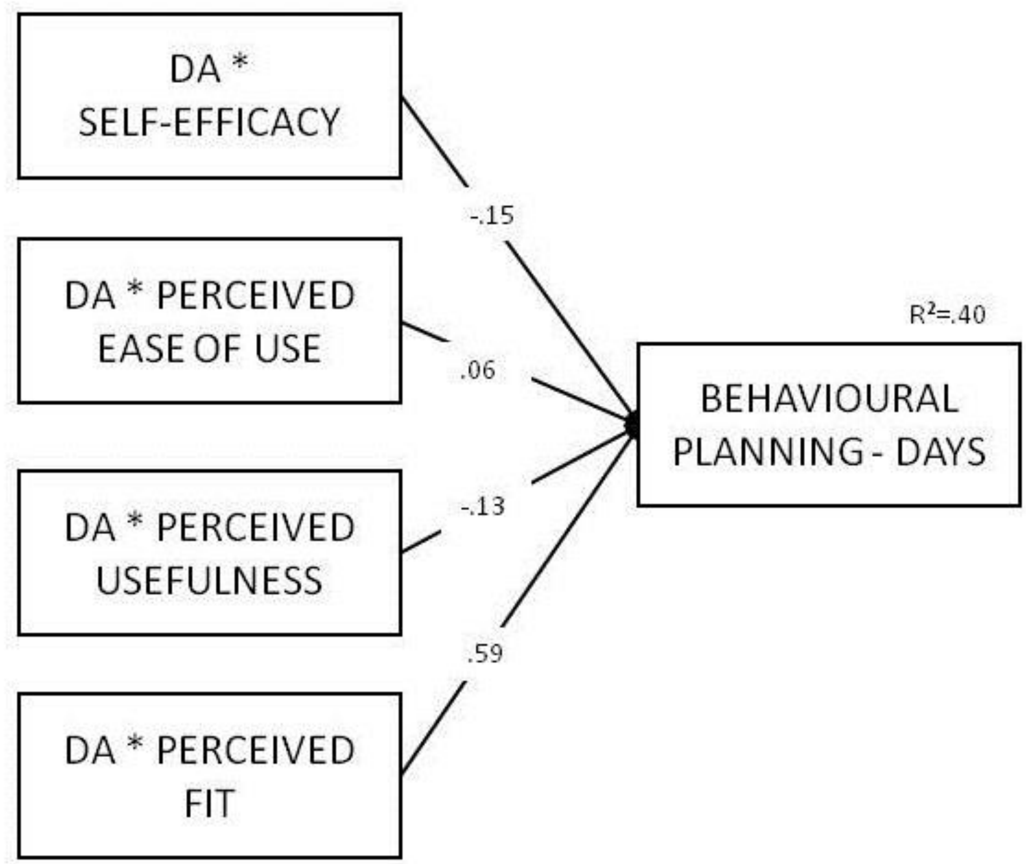

Figure 22. Predictive model for Behavioural Planning (days) based on the interaction of deep learning style and attitudes.

The last analysis followed the same approximation, but this time considering as output variable the amount of hours a week of using of the learning environment attempted by the students (Figure 23). In line with the previous two analyses surface learning approach has a null effect on the attitudinal variables, and the effect of deep learning approach is only significant on self-efficacy and perceived ease of use. Perceived usefulness and perceived fit have a significant and positive effect on the outcome variable

(0.32 and 0.35 respectively). The model fit does not achieve the acceptable threshold $\chi^2(9)=270.679$, $p=0.000$, CMIN/DF=30, CFI=0.148, RMSEA=0.505. The explained variance is 24%. When the interaction of deep learning approach with the attitudinal variables was utilised as predictor variable (Figure 24), once again the results varied. Self-efficacy became a significant negative predictor ($\beta=-0.19$, $p=0.015$), perceived usefulness diminished its b-value from 0.35 to 0.20 remaining significant, and perceived fit increased its power from 0.35 to 0.45. The model fit indicators fall to $\chi^2(6)=288.603$, $p=0.000$, CMIN/DF=96.2, CFI=0.096, RMSEA=0.914, and the explained variance increases just 4%.

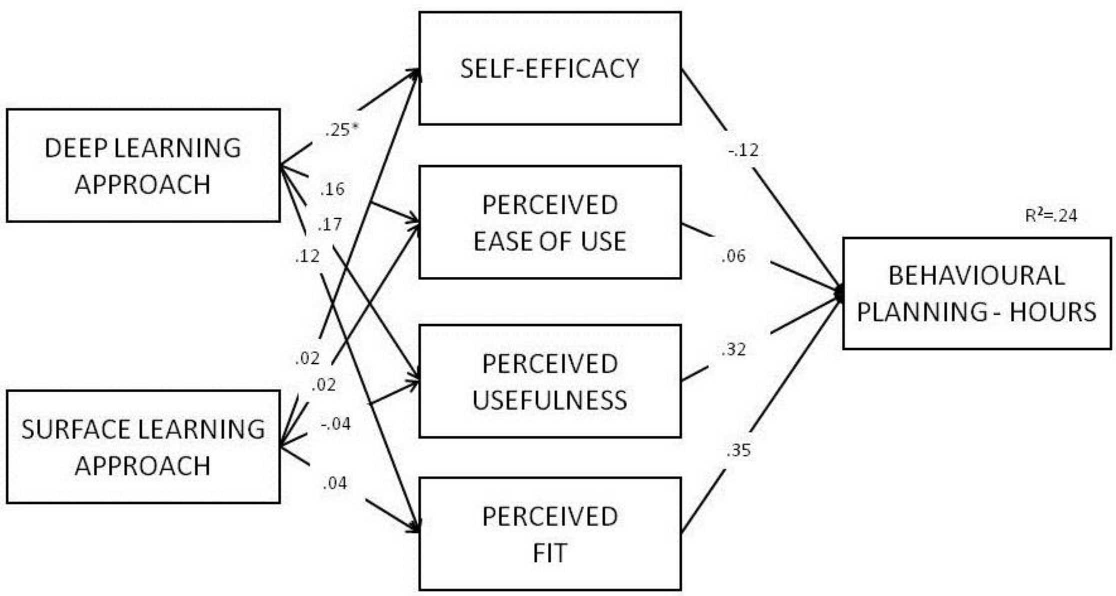

Figure 23. Predictive model for Behavioural Planning (hours) based on attitudes.

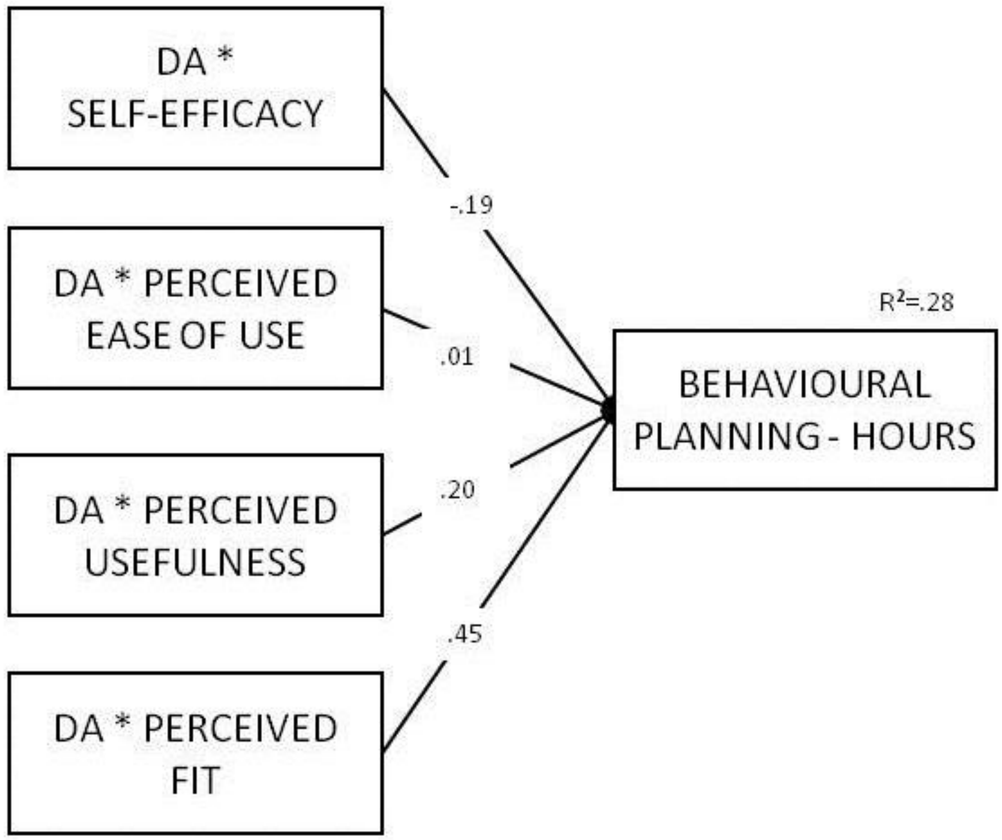

Figure 24. Predictive model for Behavioural Planning (hours) based on the interaction of deep learning style and attitudes.

The results are consistent with what was observed in study 2, but increasing explained variance is at a cost of reduced model fit. Attitudes towards the learning environment, specially perceived fit, are good predictors of intention of use and behavioural planning. Once again the effect of deep learning approach on the attitudinal variables alters their strength as predictors of the dependent variable, affecting at self-efficacy, perceived ease of use, and perceived usefulness, by reducing their effect on the outcome variable. The opposite effect is observed on perceived fit. Additionally, learning styles were unrelated to any variable. Even though this study cannot be considered as conclusive on the relationship between learning styles and adoption of learning technology, because of the null relationship observed its inclusion as part of the model might be reconsidered in future studies.

By way of summary, the hypothesis that learning approaches and learning styles are not related can be supported by the data (H1). In addition, the idea that attitudes are strong predictors of intention of use (H4) and of behavioural planning (H5), is supported, but with some differences related to the specific weight of the predictors in each case. There was partial support for the hypothesis that deep learning approach has a direct effect on attitudes (H3). Finally, the hypothesis that learning styles would have an effect on attitudes (H4) is rejected as a result of the findings.

3.10. **Discussion and implications of the findings**

The two studies comprising this chapter offer some important insights for understanding the adoption of learning environments, and how it is to actual use and the learning process leading to the achievement of learning goals. The general conclusions that rise from this study are: i) Davis' technology adoption model is a very strong and consistent approach to predict intention of using a determined learning environment; ii) some characteristics of the learning environment – specifically an unstructured, student controlled learning environment – leads to better students attitudes, and this effect is independent of the academic locus of control of the student; iii) attitudes work differently in predicting the behavioural component of intention of use (behavioural planning), being observed a strong relationship between perceived usefulness and perceived ease of use with intention of use, and an important association between perceived fit and behavioural planning; iv) learning styles have no effect on adoption of learning technology, and no relationship with learning approach; and v) learning approach interacts with student attitudes by reducing their predictive power on intention of use, but improving it on behavioural planning.

The main conclusions listed above, limitations of the studies, and guidelines for continuing the research project will be discussed below.

3.10.1. Technology adoption model.

As the character of these studies was exploratory, the original adoption model proposed by Davis – which has been noted previously as the reference model for technology adoption – was modified. One of the introduced variables was student's computer self-efficacy, which effect was not as expected. The almost null effect of self-efficacy suggest that how proficient the students think they are was not a relevant variable at the time of evaluating the learning environments. This might be due to at least two reasons: a) the variability between the subjects was too small, or b) when evaluating a learning environment the students are more focused on the environment characteristics than on their computer skills.

The first explanation can be evaluated with some more data analysis. Figures Figure 25 and Figure 26 show the distribution of scores obtained by the participants. The scale has a maximum score of 15 and it can be observed that the percentage of participants obtaining 12 or more was almost 80% in study 2 and almost 65% in study 3. With this concentration of scores, the variability is so small that no relationship can be observed between computer self-efficacy and intention of use.

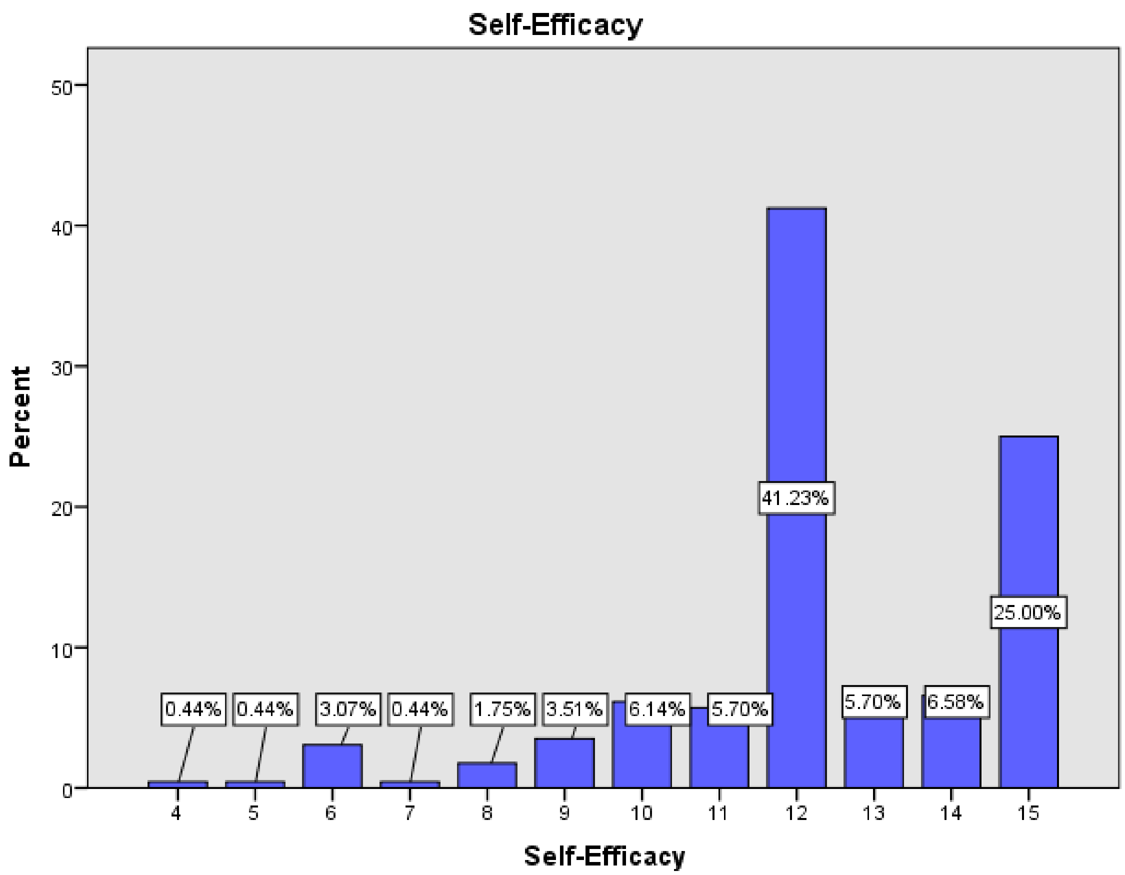

Figure 25. Scores distribution of Computer Self-efficacy in study 2.

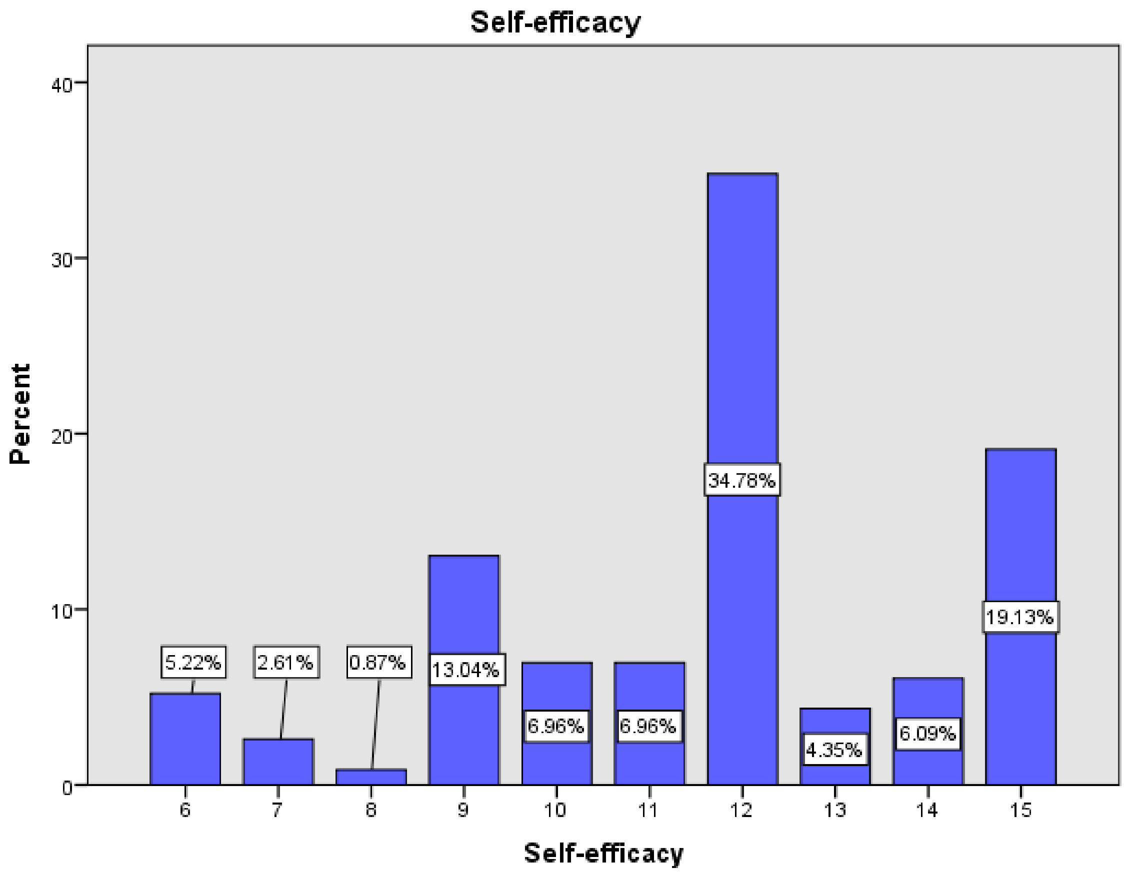

Figure 26.Scores distribution of Computer Self-efficacy in study 3.

Regarding the second explanation, that students may focus more on the environment characteristics than on their computer skills, it is worth considering that the sample was composed by university-level students which use computer technology in a daily basis. Nowadays technology is frequently considered as “user friendly”, which means that is designed to be easy to use. Moreover, for the purposes of these studies the settings chosen were familiar for them. For all of the above, it can be suggested that participants felt confident using the digital environments (which explains the low variability of the scores and their clustering at the high end of the scale) and for that reason their intention of use was determined by variables directly related to the characteristics of the learning environment and to the task.

Following the last idea, it is interesting that the effect of perceived ease of use was not consistent from study 2 (β=0.30 and significant) to study 3 (β=0.08, non-significant). The results might be related to multiple causes, such as sample-related characteristics, sample bias, or a research design that could have not been completely appropriate to give account of the effect of self-efficacy. It is worth considering these results in the design of a future study. The main predictors of intention of use were perceived usefulness and perceived fit. Perceived usefulness was proposed in the original model and has been consistently reported as a direct and significant predictor of intention of use, as it has been observed in all the 3 studies reported so far in this thesis.

On the other hand, perceived fit was introduced as a new variable in the model in order to take into account the perceived match between the environment characteristics (design and features) and the task that has been given, and not the mere evaluation of the usefulness of the environment in general. It can be illustrated as the participant evaluating the digital environment but bearing in mind a specific task to be fulfilled. While it can be suggested that both are measuring the same, the correlation between them is not high enough to consider it (around 0.6). The results of the analysis show that perceived fit was a better predictor than perceived usefulness, and it was better not only predicting intention of use, it was also better at predicting behavioural planning – but this point will be discussed later.

3.10.2. Virtual learning environments characteristics.

Study 2 evaluated the attitudes and preferences of students about two different virtual learning scenarios, which were labelled as “structured” and “unstructured”. The two ideas behind this design were to test the relationship between academic locus of control and the adoption parameters, and to observe the different effects on participants’ adoption parameters under two opposite conditions of control of the learning process by the instructor (reflected in the design of the learning environment).

The results were in some respect different to what was expected, especially because no significant relationship was observed between academic locus of control and the adoption parameters. It was expected that students with low scores in academic locus of control would feel more comfortable in the structured learning environment and thus have higher intention of using it than those with high scores in academic locus of control, and the opposite was expected in the unstructured scenario. Nonetheless, the relationship between academic locus of control and the adoption parameters was non-significant.

3.10.3. Predicting behavioural planning.

One of the most relevant findings from Study 1 was the link between behavioural planning, actual use, and learning achievement. It was sustained that improving the understanding of the variables affecting people’s behavioural planning would help to engage them more in learning activities based on computer technology by improving the planning and design of them. Following this, Study 3 was focused in that goal, including “how many days a week” and “how many hours a week” students planned to use the learning environment in order to achieve the instructional requirements of an e-lecture (a lecture delivered using computer software). It was proposed that perceived usefulness would be a relevant predictor of behavioural planning, as observed in Study1. It was also proposed that the variable “perceived fit” would be another relevant predictor, and that deep learning approach would be directly related with all of them.

The results showed that when asking students to predict their amount of use of the learning environment, self-efficacy, perceived ease of use, and perceived usefulness did not predict their answers. Perceived fit was the only direct and significant predictor of the output variable, explaining an acceptable amount of its variance. When deep learning approach was included in the analysis interacting with the attitudinal variables, the main changes were appreciated on perceived usefulness and perceived fit. Perceived usefulness changed the direction of its effect from positive to negative, and perceived fit increases its magnitude. Moreover, the overall explained variance was importantly enhanced, almost trice what was observed in our first study, showing a positive progression to our main goal.

The second indicator of behavioural planning was the number of hours a week students were planning to use the learning environment. This time perceived usefulness played a more relevant role as predictor along with perceived fit, notwithstanding, when learning approach was introduced interacting with the attitudinal variables their effect changed differently in each case. Self-efficacy became significant, but its effect was inverse, this means that while higher the scores in self-efficacy and deep learning approach, lower the amount of hours projected of work. The effect of perceived usefulness decreased almost a third, and the effect of perceived fit slightly increased.

What may be inferred from these results is that even though deep approach does not have a direct effect on behavioural planning, it affects it in an indirect way by amplifying the variability of attitudes scores according to people's capacity of mobilising their resources towards a learning goal. It is important to note that the largest effect of this interaction between deep learning approach and perceived fit was observed when predicting the number of days, rather than the number of hours, that students planned to use the learning environment. Future research is needed to assess the accuracy of students' abilities to predict their own future behaviour regarding engagement with learning environments.

3.10.4. Learning styles.

This variable did not work as expected. It was introduced in the research model with the goal of assessing its relationship with learning environment preferences. It was assumed that when the learning style of the student match with the characteristics of the learning environment, preference for that learning environment would be high. For instance, the predominance of visual learning style would match with a learning environment rich in visual contents, therefore it would be expected higher scores in intention of use. Nonetheless, as it was reported in section 3.9, none of the learning styles dimensions correlated with any other variable included in the model. In fact, the correlations were very close to zero. Additionally, one of the subscales (Global-Sequential) showed a weak internal consistency (α=0.13). For all of the above it was decided to exclude this variable from the research model.

With the current data it can only be said that no support was found to sustain the idea that learning styles might be involved in the adoption of learning technology process. Nonetheless, its role in the adoption-learning process cannot be discarded yet, not until its relationship with the variables related to actual use and learning achievement is assessed.

3.10.5. Learning approach

As it has been said before, a small relationship was found between learning approach and the adoption parameters. In particular, deep learning approach – characterising those more enthusiastic with learning activities – has a small but significant relationship with some of the attitudinal variables in both structured and unstructured environments. It suggests that those with high scores in deep learning approach have a base level of "positive attitudes" towards technology higher than those with low scores. It is interesting to realise that this effect does not depend of the scores obtained in surface learning approach, supporting the proposition that every person possess an independent amount of these two dispositional dimensions (Biggs et al., 2001; Kember et al., 2004). It implies that the behavioural drive of deep learning approach results more relevant than the one of surface learning approach, therefore being aware of students' learning approach profile might result in relevant considerations about the selected instructional and technological design.

Even though the effect of deep learning approach over the attitudinal variables is small, the most noteworthy effect is when interacting with perceived fit. The interaction between deep learning approach and perceived fit is predictive of intention of use and behavioural planning. The next step will be to observe its relationship with actual use and learning achievement in future research.

3.11. **Limitations**

While the present research has provided much insight into the relationship between learning approach, attitudes and adoption, the two studies that comprise this chapter are not without limitation. Firstly, the sample composition (most of the participants were young undergraduate students) means that some biases could be present as a result of homogeneity. However, when comparing these results with those from study one – a diverse sample of Chilean teachers with average age of 39 years old – it can be noticed that the variables work in similar way. Another bias could be related to computer self-efficacy, given they are accustomed users of computer technology devices and environments which could explain the high scores in this variable.

A second limitation is the sample size. A larger sample size would have enabled a more sophisticated and complex analysis. Indeed, the relatively small sample size may have affected some goodness-of-fit indexes, which was the reason to take them as a reference but not as a cut point to confirm or discard completely any parameter close enough to the suggested cut value. Future research could seek to replicate these models in larger, more diverse samples.

3.12. **Conclusion**

These studies gave valuable information about the proposed paradigm. It was confirmed that Davis' TAM is a strong model to predict people' intention of using learning technology to support their learning, but it not good to predict their behavioural planning in terms of usage rates. The introduced variable Perceived Fit showed to be a significant input to TAM and as a predictor of the behavioural component of adoption. Learning approach has to be considered in future research to better understanding of its role shaping students attitudes and how it could be related to learning engagement and learning achievement. Learning styles were not supported as a component of adoption of learning technology, but their part in the learning process supported by digital environments has to be examined further.

The next step of the research project will be to assess these and other variables in a real learning situation. The research model of the first study will be modified based on the results so far, and the research method will be refined based on the previous experience and limitations.

4. ASSESSING A NEW FRAMEWORK FOR UNDERSTANDING THE LEARNING PROCESS SUPPORTED BY LEARNING TECHNOLOGY.

4.1. **Introduction**

This is the third empirical chapter of the present thesis. Chapter 2 proposed a model to understand the adoption and use of, and the learning achievement with, learning technology. The results suggested that modifications have to be made in order to improve the explicative power the model. Chapter 3 included two studies, one testing variables related to individual characteristics, and the second one testing perceptions about the learning environment characteristics and the task characteristics. The present chapter will assess a modified version of the research model presented in study 1, including those variables tested in studies 2 and 3 – and others from similar studies – to give account of the complete process of learning supported by computer-technology.

The following sections will describe the theoretical foundations and reflections about computer-supported learning, the research questions and hypotheses that guide this study, the method and results, and the discussion including the main findings and their implications.

4.2. Theoretical background

The introduction of computer technology has produced changes to the conventional teaching-learning system, modifying the roles of instructors and learners in ways that are not yet completely understood. The theoretical background presented in the introductory chapter, focused on the interaction between attitudinal and behavioural variables, will be complemented with a different approach, which is centred on the variables related to the learning process in virtual environments instead of those related to the adoption of learning technology. The main reason for the inclusion of this complementary approach has been given by the so far consistent results linking attitudes with adoption of technology, and the need for a theoretical and empirical approach able to take into account the elements comprising the learning process supported by computer technology, and the relationships between them.

The main goal is to understand the reasons for the individual differences in the learning output, which could be due to individual and/or process related variables. The following theory, although centred on the design of computer-based instruction rather than in the learning process itself, is particularly useful for understanding how the interaction of the learner with the VLE produces individual reactions or responses that can reflect how the affective and cognitive resources are being deployed through the learning process. The theory and their elements will be presented, and the variables included in our research model will be linked to them, with the intention of arranging them into a more structured framework.

The theory of effective computer-based instruction for adults

Lowe and Holton (2005) proposed a theoretical framework explaining how adults learn effectively using computer-technology, with the objective of providing an articulated and coherent background to computer-based instruction (CBI) design.

The theory includes variables that have been widely studied but not systematically interrelated, comprising aspects associated with the design of the learning environment and others related to the support required for the learners. Some of these elements are considered as inputs to the CBI instruction, others are considered as process-related variables, and all of them work together to achieve the learning output. Figure 27 explains graphically the model, and the detailed explanation of the elements and relationships that comprise it will follow.

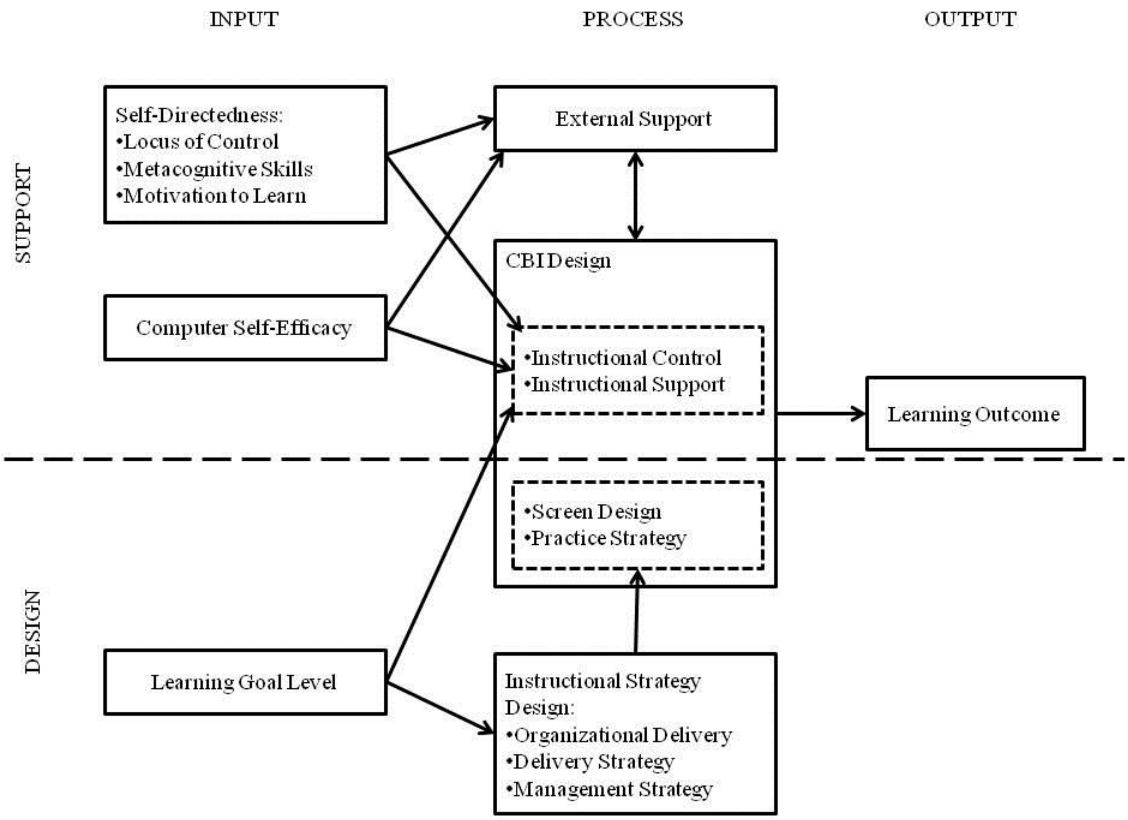

Figure 27. Conceptual model of effective computer-based instruction proposed by Lowe and Holton, 2005.

As can be seen in the figure above, the variables belonging to the Input/Support portion of the model are related to individual characteristics previously reviewed such as locus of control, motivation to learn, and computer self-efficacy. In the case of metacognitive skills, Lowe and Holton define them as skills that facilitate the understanding and regulation of people's cognitive performance, deploying the adequate resource in the right moment, at the same time that the behaviour is self-monitored. This variable might be linked to intrinsic academic locus of control, because the responsibility of monitoring the behaviour is assumed by the learner itself, not waiting for external guidance, and mobilises learners to their own goals.

The Input/Design portion of the model refers to learning goal level, which is related to Bloom’s taxonomy of educational objectives (Krathwohl, 2002). It states that the design of a learning environment has to be aligned with the learning goals proposed in order to offer contents, activities, and strategies according with them. It may be related to people’s perception of task-technology fit, which indicates the perceived coherence between the learning environment and the task or learning to be achieved.

The Process/Design section of the model comprises the instructional strategy design and two aspects of CBI design, namely screen design, and practice strategy. The instructional strategy design refers to the methodology of instruction, which defines the sequence of activities, the materials, and the contents involved in the learning program. The election of an adequate instructional design is central to ensure the quality and pertinence of learning. The practice design is part of the CBI design and refers to the amount of time estimated to be required to accomplish the learning goals. The screen design refers to how the information will be displayed. These aspects have a counterpart on learner’s reactions when interacting with the learning approach in the form of satisfaction with the course, perceived instrumentality, with the deployment of different learning strategies related to individuals’ learning approach, and the amount of time that learners are engaged using the VLE.

The Process/Support parcel of the model is composed of external support and two CBI design-related variables, such as instructional control and instructional support.

Instructional control is related to who is guiding the learning process, the instructor (instructor controlled, structured, less active student) or the learner (active learner, less structured environments, self-directedness is highly required). The instructional support makes reference to how the VLE supports or assists student's learning. It comprises feedback, coaching, glossaries, examples, etc. The features of the VLE contain all these elements as part of it. On the other hand, external support refers to any assistance received by peers, instructors, facilitators, or support staff. The external support might be related to technical support and with the content-related support, according to learners' needs, and must be – to be considered as it is – delivered outside the learning environment and it must aim to help achieving the proposed learning goals. As previous, these variables might be related to learner's satisfaction, actual use, locus of control, and deep learning approach.

As has been stated before, this model allows us to focus on the mechanism that makes people achieve a learning goal, and it does not incorporate the variables that make people use and engage with the digital environment that supports the learning. Nonetheless, it can be seen as a good complement of what has been proposed in studies 1, 2, and 3. Therefore, the complete landscape would incorporate a group of variables that explain the adoption of the learning environment, such as learning approach, academic locus of control, perceived fit, perceived usefulness, and the importance of the course according to the student's criteria. It would incorporate as well a second group of variables affecting the use of the learning environment, such as the previous intentions and behavioural projections, the satisfaction with particular and general aspects of the learning environment, motivational drivers, and the instructional design/strategy implemented. Finally, it is supposed that an individual's cognitive characteristics, actual use, and the level of knowledge/skill on the topic would explain the final learning output. Figure 28 shows graphically the proposed research model.

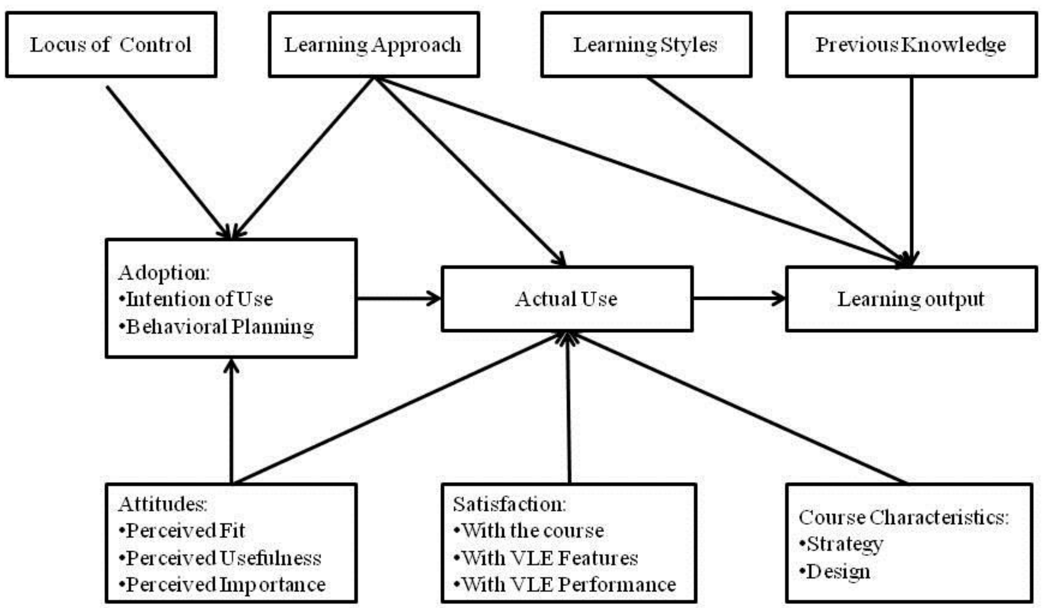

Figure 28. Conceptual research model for study 4.

4.3. **Overview of Study 4**

The aim of the study 4 is to test a novel, integrated, computer-based learning model. The new proposal is composed by variables that can be organised in three interrelated clusters, namely adoption, engagement, and performance. The model will be assessed in a real learning process, utilising intensive longitudinal methodology or repeated measures, in which participants submitted weekly reports since the beginning of an academic module to its end (11 weeks).

The **first hypothesis** is that perceived ease of use and perceived fit will be significant and direct predictors of intention of use, based on the results of studies 1, 2 and 3, and the wide literature on the topic. Guided by results of studies 2 and 3, and by their role as behavioural enhancers, the **hypothesis 2** is that scores in the scales of deep learning approach and academic locus of control will be directly related to higher levels of frequency (days) and intensity (hours) of behavioural planning. According to the results of the previous studies, the **hypothesis 3** is that the accuracy (R-square) of the predictive model for behavioural planning is higher than that for intention of use.

Taking into account the variation over time that all the variables might suffer, and focused specifically on the understanding of the engagement with the learning environment, the **fourth hypothesis** is that time – or the temporal order of the events and activities comprising the course – has a significant effect on actual use. In the same way, it is expected that the mandatory or voluntary condition of the course will be related to higher or lower rates of usage, respectively (**hypothesis 5**). The **hypothesis 6** is that the declared intention of use and behavioural planning will be directly related to actual use, as has been proposed and observed in the literature on the topic, albeit their predictive power over time will be involved in this assessment. It is also expected that positive attitudes towards the VLE will be related to better rates of usage, so the **hypothesis 7** is that the scores in the scales of satisfaction with the course, technical and functional evaluation, perceived fit, and the importance of the course, will be direct and significantly related to usage rates of the VLE. To complete the picture, it is expected that deep learning approach will have a positive effect on actual use (**hypothesis 8**). Also, it is expected that the perceived importance of the module, deep learning approach, and the satisfaction with the VLE will be directly related to the intention of continued use, or future use (**hypothesis 9**).

Regarding the achievement of learning goals, the **hypothesis 10** proposes that learning style and deep learning approach will be directly related to the learning output, due to their role controlling the processing of the information and a proactive behaviour, respectively. **Hypothesis 11** sustains that previous/initial knowledge on the topic will be significantly related to the learning output. Finally, it is expected that attitudinal variables, such as the functional and technical evaluation, perceived fit, and the perceived importance of the module, will have a small but significant effect on the learning output (**hypothesis 12**).

To test these hypotheses a repeated measures design has been selected, and it will be necessary to perform multilevel analysis techniques. The details of this and the description of the sample will be presented in the next section.

4.4. **Method**

4.4.1. Participants.

The sample was composed by 41 students[2] in their first year of BSc in Computer Science in Greece. They were aged from 17 to 28, with a mean age of 19.68, and a standard deviation of 4.6. Regarding gender, 10% of them were females.

The participants were studying the academic module called “Programming Principles and Algorithms”, which is a mandatory unit of their academic program. Even though the module was mandatory, the participation in the study was not. The students were invited to take part in the study during the introductory week of the semester, and their participation, personal information, and answers were anonymised.

4.4.2. Design

In order to answer the research questions guiding the present study the design had to have very specific characteristics. First, in order to assess the learning process from beginning to end, it had to include repeated measures along the course. Repeated measures design is a strong and reliable tool to assess social and personal variables capturing their interrelationship and the effect of time on them (Nezlek, 2012). In this case, it was decided to use a combination of fixed interval assessments in the form of weekly reports,

[2] In a cross-sectional study, a sample n=41 indicates that the maximum number of observations will be 41. In a repeated measures design, several observations can be collected from each participants. In this study, the number of observations was 261.

and contingent assessments to capture information related to specific events, such as lab activities or evaluations. The event contingent assessments were added to the weekly report form when necessary. The objective was to retrieve as much information of the learning process as possible, maintaining the temporal context of it as constitutive part of the process.

Second, it had to be possible to capture both individual and group process-related variables. For this reason, the weekly reports included questions from both dimensions, becoming the present into a multi-level repeated measures study.

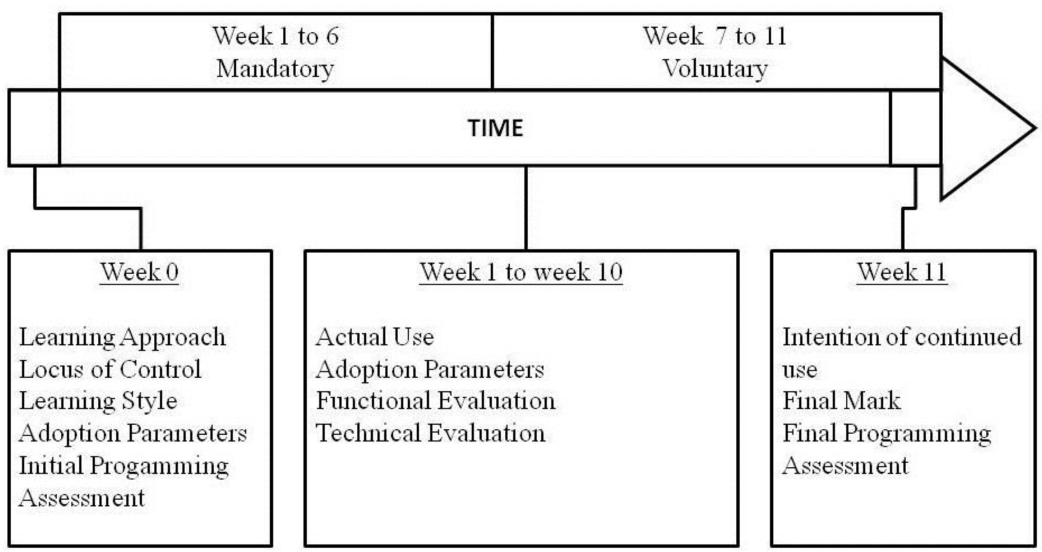

Figure 29. Research model, Study 4.

Another relevant aspect on the design of the study was how the learning achievement would be measured. It was decided to adopt a dual perspective: one focused on the achievement of the learning goals present in the unit's syllabus, which were assessed according to students marks. The second perspective was focused on the development of new knowledge and skills, which is assessed by a programming test specially developed for this purpose, and which was completed at the beginning and at the end of the course. The design of the study is presented in Figure 29.

Finally, as the goal was to assess the learning process in virtual contexts, the election of the virtual learning environment was a critical one. Programming is a hands-on activity, not merely theoretical. For that reason, it was necessary to utilise a learning environment that would allow students not only access to information, but one that would allow them to develop the required skills. The solution was the election of software developed specifically to assist students on developing their programming skills. The description of Mentor, as it is called, and its linkage with programming learning is going to be presented in detail in the following section.

4.4.3. Mentor and the teaching of programming

Probably the hardest achievement for any educator is to make the students to engage with the learning process. In Computer Science one of the most challenging units to teach, and at the same time one of the most important for the discipline, is Introductory Programming. The diversity of students towards their attitude and their knowledge (when they start their studies) regarding programming makes the challenge even greater.

Moreover, globalization in combination with the extensive ability to communicate with the use of technology over the last decades had a significant impact to higher education. The inevitable mixture of students from different educational systems, life experiences and cultures creates a need for teaching strategies that are extremely flexible and employ innovative ideas that will enable a community feeling to emerge. Ignoring students' previous learning styles, educational cultures, and most importantly knowledge and skills inadequacies, results in the formation of minorities. Members of such minorities do not engage, are discouraged, and eventually abandon their studies.

Teaching diverse groups of students requires focusing to the aim and learning objectives of every taught unit and the curriculum in general, and rethinking ways, techniques and tools used to achieve them.

Mentor (http://www.robotseducate.us/) is a tool that simulates a software robot moving in a 2-dimensional tiled world, which was designed aiming to resolve many of the above-mentioned issues. Users of Mentor can program the robot aiming to achieve the required tasks in a specific map or in a group of maps.

Mentor allows the introduction to the programming language from the first lecture and disguising the awkward syntax of the language, and aims to enable any student to experiment and engage early. It also enables the use of understandable problems to solve using storytelling, fairy tales and sci-fi stories. Although not initially expected, this played an extremely important role towards minimizing the effects of either technological or cultural level diversity of students, and enabled the focus to the important computation skills that should be developed in the beginning of such course.

Mentor as an educational tool allows people that are new to the concept of programming a machine, to acquire and develop computational thinking skills, building a sound foundation to learn programming languages (emphasis on Java) and learn how to program machines. The user is able to control a robot (from the generation of Automata. There will be other generations in future releases.) It always has the name Io (a maiden from the Greek mythology) and the user can choose its appearance with several predefined images.

Using the basic features of the program is quite straightforward. The toolbar with the large icons can guide users through it. The map button opens an existing map. The appearance of the robot can be changed by clicking on the button with R2D2 (a popular character from the movie Star Wars) and the robot will then be placed at the appropriate starting point in the map. Then, the behaviour for the robot can be loaded by clicking the battery button, and finally click on the play button to observe the behaviour of the robot in this map. Figure 30 shows the main commands and interface appearance of Mentor.

After observing the behaviour of the robot, the user can see it at the end as a log file. Otherwise, the user can stop observing it by pressing the stop button that stops the execution, where they will be able to see the logging of what it did until that point. All actions above can be accessed through the File menu and keyboard shortcuts. Additionally, the users can enable or disable the toolbar through the Settings menu if they feel it is intrusive, adjust the animation speed of the robot, and set their logging preferences.

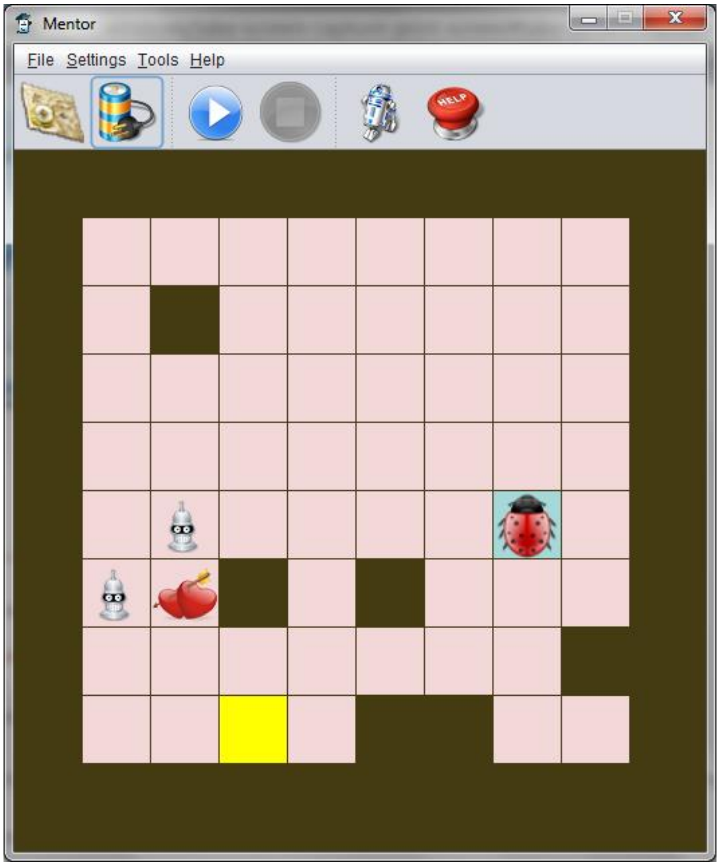

Figure 30. Screen capture showing the tool bar, main action buttons and Mentor's grid.

Behaviour files must have the extension ".handler" and follow specific rules. As an example, let us assume that we want to create a behaviour that makes the robot move 3 steps south, then paint 1 tile in front of it black and then follow with 2 white tiles, all that in the "Empty" map. Therefore, the desired map exists, but not the behaviour required.

The behaviour that is wanted to be created is:

```
robot.south(3);

robot.paintBlack();

robot.forward(1);

robot.paintWhite();

robot.forward(2);

robot.stopPainting();
```

The text typed should look like:

```
public void executeAlgorithm()

{

	robot.south(3);

	robot.paintBlack();

	robot.forward(1);

	robot.paintWhite();

	robot.forward(2);

	robot.stopPainting();

}
```

All that is needed to do then is to save the file with a proper name. If we want to name it My First Behaviour then the full name of the file has to be "MyFirstBehaviour.handler". Then the user can go and open the empty map, locate the folder where the behaviour file is saved and load it. The default directory the program opens is the directory inside the folder of the program named "user". It is a good idea to keep all map and behaviour files there for quick access.

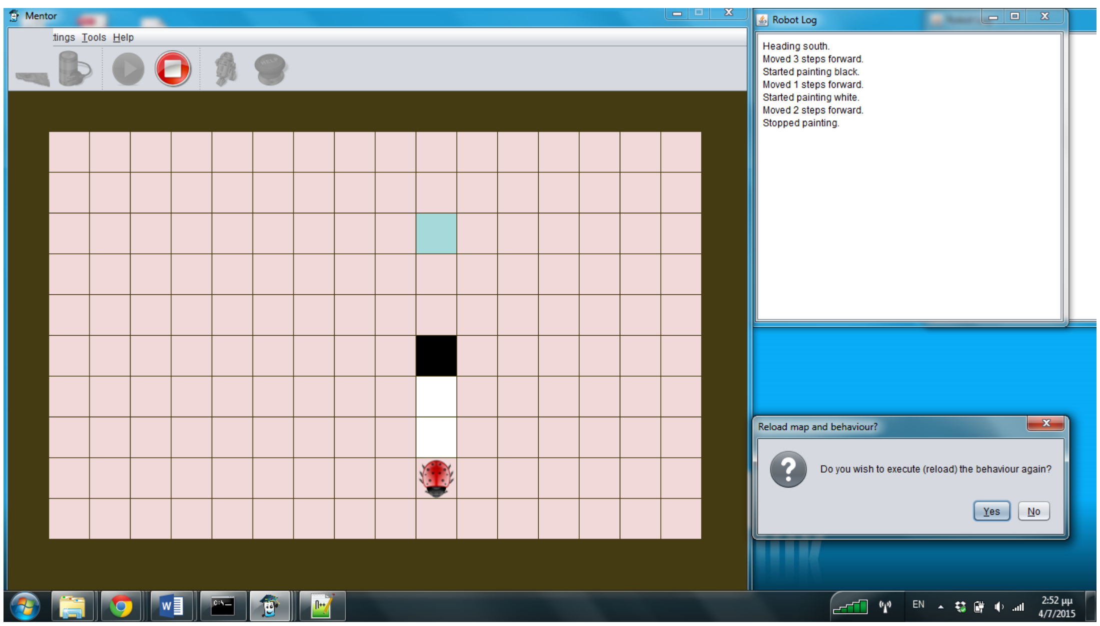

Figure 31. Screen capture showing Mentor's interface while executing a task.

As Mentor aims to assist programming learning it is necessary to compare the features of Mentor as a learning environment with the learning goals expected at the end of the course. Table 155 presents the learning outcomes included in the syllabus of the course and the features of Mentor. This will justify the election of Mentor for the aims of the present research as a suitable learning enviroment to evaluate a real learning process while the involved variables were assessed from the beginning to the end of it.

Table 15. General objective and expected outcomes of the module.

General objective: to introduce the beginning computer science student to: algorithmic thinking; simple problem analysis; structured design; top-down stepwise refinement.
Expected learning outcome
Analyse problems and break them down to smaller individual parts.
Construct appropriate pesudocode as well as flow charts to handle analysed problems.
Implement appropriate algorithmic techniques to solve problems.
Evaluate possible syntactical and/or logical errors in code.
Evaluate results obtained from code.
Identify the various types of variables and implement them in arithmetic expressions and relational operations.
Recognise the cases requiring the use of control structures (if, then, else, switch, etc.) and implement such structures in solving simple problems.
Recognise the cases requiring the use of iterative structures and implement them.
Recognise the type of user-defined methods that needs to be constructed in various cases.
Construct appropriate user-defined methods to handle specific problems.
Understand the importance of testing.

4.4.4. Instruments

The present study comprises a considerable number of variables, which are assessed by instruments that have been presented and explained in previous chapters in their greater number. The table 16 names those instruments and the chapters where their description can be found:

Table 16. List of instruments utilised in the present study and described in previous chapters.

Instrument	Page
Scale for Perceived Usefulness	47
Scale for Perceived Ease of Use	47
Statements for behavioural planning	47
Scale of Intention of use	47 - 83
Perceived Satisfaction with the course	48
Scale for Perceived Fit	82
Computer Self-efficacy	82
Scale of Academic Locus of Control	83
Revised Study Process Questionnaire for Learning approaches	83
Index of Learning Styles	104

The rest of the variables and the instruments that assess them will be explained bellow.

Programming knowledge assessment: To have a measurement of the programming knowledge of the participants at the beginning of the course has been seen as essential in this study. The instrument utilised was developed ad-hoc by Dr. George Eleftherakis, the instructor and designer of the academic unit that serves as context of this study. The instrument comprises a set of questions regarding the self-perception of programming knowledge (example item: “I have at least some basic knowledge about the following programming languages: Java/C/Scala/HTML”) and about actual knowledge on programming (example item: “What is the output of the following program? integer a = 10; while (a <= 10) print(“Hi”) ”; followed by the alternatives: a. I don’t’ know;

b. “Hi” 10 times; c. “Hi” only once; d. It will not print “Hi”; e. “Hi” ; f. something else.).

Both components have a summative score from 0 to 50.

Mentor technical evaluation: An ad-hoc scale developed by Dr. Eleftherakis evaluated the students’ perceptions of the technical quality of Mentor (design, interface, visual aspect). It consists in 10 Likert-type items, anchored from 1 (Strongly disagree) to 5 (Strongly agree) according to the level of agreement with a sentence (example item: “Mentor's graphical user interface is suitable for a learning system”). The general score is obtained by adding the score of each item.

Mentor functional evaluation: Dr. Eleftherakis developed a third scale for the purposes of this study. It assesses students’ perceptions about the suitability of Mentor for helping them to enhance their learning. The scale has 10 Likert-type items, anchored from 1 (Strongly disagree) to 5 (Strongly agree) according to the level of agreement with a sentence (example item: “I think that "Mentor" is a tool that could be used to solve these problems no matter the programming experience of the user.”). The general score is obtained by adding the score of each item.

4.5. **Procedure**

The students were recruited the first week of the semester by the lecturer of the unit.

The first questionnaire was completed in an introductory session, previous to the first class and previous to the presentation of the learning environment. This first questionnaire comprised the instruments to evaluate learning approach, academic locus of control, learning style, and the programming knowledge baseline.

From week 1 to week 6 the students participated in twice weekly sessions as part of the course, one on Wednesday and one on Friday. Every Friday at the end of the session they completed the weekly reports, which included the evaluation of self-efficacy, perceived ease of use, perceived usefulness, perceived fit, and the technical and functional evaluations. On week 1, the report included the scale of intention of use, and the questions about behavioural planning. From week 2 to week 10 the questions about behavioural planning were replaced by the equivalent report of actual use (how many hours/days did you use Mentor to assist you learning in the last week?).

From week 1 to week 6 the use of Mentor was included on the course sessions, so its use should be considered as mandatory, nonetheless its use outside practical sessions was just suggested as a way to enhance learning. Additionally, on week 6 contingent measures were included in the weekly report, such as course instrumentality and satisfaction with the course in order to capture students overall evaluations of the tool in relationship with the learning goals so far.

From week 7 to week 10 the use of Mentor became not mandatory, only suggested. Accordingly, the weekly reports were modified, and the questions that remained were those asking about actual use.

A final questionnaire was delivered at the end of the module, before the beginning of the second semester. The assessment included the instruments related to course satisfaction, perceived ease of use, perceived usefulness, perceived fit, self-efficacy, technical and functional evaluation, and the programming knowledge assessment. The marks of all the participants were retrieved subject to previous explicit authorisation from them.

4.6. **Results**

The data were analysed using SPSS v.22 and MPlus v.7.31. The psychometric quality of the instruments will be presented in the following section. The analytic strategy and the assessment of the research model will continue afterwards, including a brief explanation of the main techniques utilised.

4.6.1. Scales reliability

As it has been stated before, the present study includes repeated measures of several variables. The instruments that have been applied once are those measuring learning approaches, learning styles, academic locus of control, intention of use, overall satisfaction with the course, and perceived instrumentality. The internal consistency of these instruments were assessed by Cronbach’s alpha, and the results are shown below (Table 177):

Table 17. Mean, standard deviation, and internal consistency of the variables included in the model (single application).

Variable	Mean	SD	ICR
Learning Approach - Deep	37.03	4.977	0.780
Learning Approach - Surface	21.35	6.167	0.816
Academic Locus of Control	42.39	7.442	0.866
Intention of Use	11.32	1.681	0.730
Satisfaction with the Course	54.76	3.195	0.850
Perceived Instrumentality	54.63	3.63	0.928
Marking	65.78	13.04	
Initial Knowledge	14.80	13.29	
Final Knowledge	24.48	10.40	
Learning Styles			
Active - Reflective	16.06	2.205	0.525
Sensing - Intuitive	16.06	2.516	0.695
Visual - Verbal	14.16	2.934	0.837
Sequential - Global	16.23	1.534	-0.092

The values observed in Table 17 are consistent with what has been observed in the previous studies. It draws the attention that the sequential-global subscale of learning styles again shows a very poor reliability, therefore it was decided to exclude this parameter from the research model.

Another group of variables were assessed several times through the length of the course. These variables are perceived fit, perceived ease of use, perceived usefulness, computer-self efficacy, and the technical and functional evaluation of Mentor. For these variables, longitudinal reliability was assessed using the coefficient Omega, proposed by Shrout and Lane (2011) to solve the problem of including event related variability to the consistency assessment of scales used in repeated occasions. It considers the consistency of the scale at within-person and at between-person levels, and can be interpreted in the same way than Cronbach's alpha. The results are presented below (*table 18*).

Table 18. Mean, standard deviation and omega coefficient of the variables included in the model, which measured more than once.

Perceived Usefulness				Perceived Fit			
Omega coefficient = 0.72				Omega coefficient = 0.62			
Week	Responses	Mean	SD	Week	Responses	Mean	SD
1	31	12.06	1.29	1	31	25.26	2.57
2	29	12.64	1.89	2	29	26.50	3.46
3	27	12.81	1.39	3	27	26.96	3.85
4	27	12.30	2.22	4	27	26.81	4.14
5	22	12.00	2.81	5	22	26.14	6.18
6	25	12.28	2.30	6	25	28.28	5.04
7	27	12.30	2.07	7	27	27.93	4.22
8	13	12.08	2.63	8	13	27.31	4.25
9	19	12.38	1.55	9	19	26.58	3.58
10	18	12.29	1.55	10	18	26.35	3.49
11	24	12.83	1.63	11	24	26.79	3.59

Computer Self-efficacy				Perceived Ease of Use			
Omega coefficient = 0.72				Omega coefficient = 0.74			
Week	Responses	Mean	SD	Week	Responses	Mean	SD
1	31	12.10	2.10	1	31	16.48	2.19
2	29	12.93	1.51	2	29	16.39	2.27
3	27	12.96	1.91	3	27	16.35	2.19
4	27	12.44	1.65	4	27	16.19	3.37
5	22	12.09	2.84	5	22	15.91	3.62
6	25	12.56	1.94	6	25	16.64	2.63
7	27	12.30	1.86	7	27	16.37	2.22
8	13	12.38	1.98	8	13	16.54	2.44
9	19	12.63	1.59	9	19	12.38	1.55
10	18	12.73	1.53	10	18	12.29	1.55
11	24	13.25	1.73	11	24	16.67	2.33
Mentor - Technical Evaluation				Mentor - Functional Evaluation			
Omega coefficient = 0.72				Omega coefficient = 0.82			
Week	Responses	Mean	SD	Week	Responses	Mean	SD
1	31	39.74	4.23	1	31	39.61	4.43
2	29	41.54	4.48	2	29	41.14	5.11
3	27	40.88	4.49	3	27	41.12	5.05
4	27	40.19	5.71	4	27	39.52	7.19
5	22	39.23	8.43	5	22	38.50	8.86
6	25	41.28	6.09	6	25	41.40	6.50
7	27	39.78	6.38	7	27	40.44	6.51
8	13	41.62	5.84	8	13	41.62	6.80
9	19	40.61	4.77	9	19	40.50	5.18
10	18	40.26	4.57	10	18	40.05	5.17
11	24	39.96	4.83	11	24	40.67	5.28

The omega coefficients of all the scales above are similar to the Cronbach's alpha coefficients obtained in the previous studies for the same scales. Additionally, even though some variability can be observed from week to week, it can be noticed that the variation of these attitudinal parameters is small.

Overall, it can be said that the scales used to assess the research variables present good psychometric quality. The only exception was the sequential-global subscale of the index of learning styles, which has been excluded from the rest of the analyses.

4.6.2. Analytic strategy

The research model designed for Study 4 is longitudinal. In longitudinal designs, data are organised in at least two hierarchical levels, with lower levels nested within a higher one, for instance students nested in schools, and schools nested in cities, and so on. When working with repeated measures, individuals represent the higher level of the structure – in this particular case, level-2 – and time represents the lower level – or level-1. Variables which are measured once, given account of the differences between individuals are aggregated to level-2. On the contrary, variables that were measured several times, giving account of the variation of individual experiences or responses, were considered as part of level-1. This data structure is multilevel, and therefore has to be analysed by multilevel techniques.

Multilevel modelling techniques present two main advantages over other techniques to analyse repeated measures data, such as repeated measures ANOVA. First, missing data is managed in a different way, avoiding listwise deletion. Second, multilevel modelling techniques can discriminate the between-person from the within-person variation in a dependent variable, which is crucial assuming that individuals do not vary at the same rate over time.

Because of these reasons, and considering that it is intended to analyse the structure of the relationships between the variables of the model, it has been decided to utilise Multilevel Structural Equation Modelling (MSEM) to test the research hypotheses of the present study. Being that the quality of the scales was satisfactory, and that the primary intention is to test the factor-level solution of the model instead of an item-level solution, it was decided to utilise the parcelling technique (Little et al., 2002) – as in the previous studies –, which suggests to work with the aggregated scores of the scales. A more detailed explanation of this technique was offered in section 2.6.2.

The results will be presented following the proposed three-cluster organisation of the model. First, the results of the adoption-cluster will be presented, next the engagement-cluster, followed by the effectiveness-cluster.

Cluster 1 – Adoption

The cluster is centred on the understanding of the relationships between the variables involved in the adoption of learning technology. Based on the results and discussions of the previous studies, the proposed model for the adoption of learning technology comprises deep learning approach, surface learning approach, academic locus of control, perceived fit, perceived ease of use, intention of use and behavioural planning. A competitor model which includes Self-efficacy and Perceived Ease of Use – aligned with a more traditional view of TAM – will be tested as well Figure 32. It is important to recall that behavioural planning comprises a frequency component (how many days a week do you plan to use Mentor?) and an intensity component (how many hours a week do you plan to use Mentor?), as it was presented in Study 3.

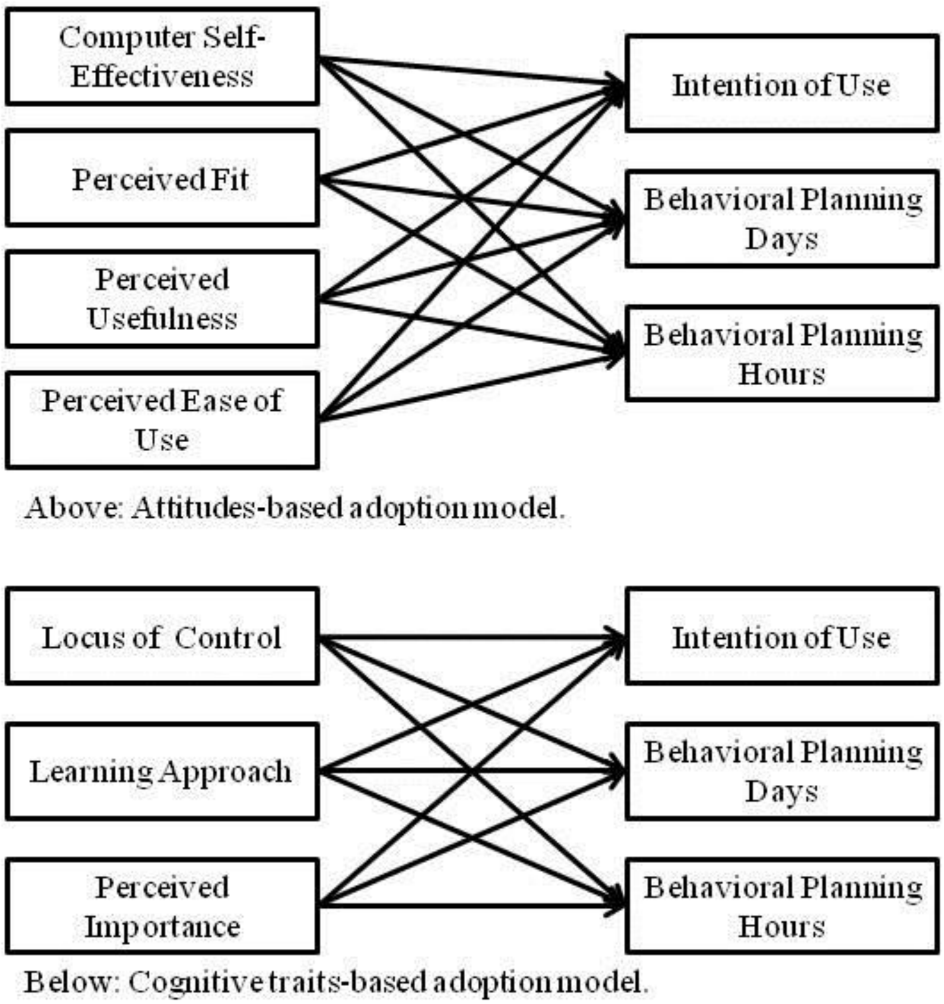

Figure 32. *Adoption research models. Above: model based on attitudes. Below: model based on cognitive traits.*

Table 199 presents the results of three models: A, B, and C. Model A is saturated with variables and relationships between them, as it is a combination of Davis' TAM and the cognitive traits included in studies 2 and 3. The fit indexes appear as good, with $\chi^2(3)=1.909$, $p=0.591$, RMSEA=0.000, CFI=1.000. Nonetheless, most of the analysed paths are non-significant. The R-square values are significant for almost all the dependent variables, excepting intention of use (Self-efficacy: $R^2=0.165$, $p=0.008$; P. Ease of use: $R^2=0.150$, $p=0.030$; P. Fit: $R^2=0.108$, $p=0.031$; P. Usefulness: $R^2=0.172$, $p=0.009$; BP-days: $R^2=0.201$, $p=0.035$; BP-hours: $R^2=0.225$, $p=0.023$; Intention of Use: $R^2=0.294$, $p=0.057$;).

Table 19. Model A. Results of the saturated model.

Model A			
Observed Variable	Estimate β	Est./S.E.	Two-tailed p-value
Self-Effectiveness ON			
Deep Approach	0.175	1.201	0.230
Surface Approach	-0.404	-2.421	0.015
A. Locus of Control	-0.164	-1.072	0.284
Perceived Ease of Use ON			
Deep Approach	0.254	1.510	0.131
Surface Approach	-0.327	-1.788	0.074
A. Locus of Control	0.188	-1.133	0.257
Perceived Fit ON			
Deep Approach	0.116	0.679	0.497
Surface Approach	-0.114	-0.582	0.560

A. Locus of Control	0.152	0.687	0.492
Deep Approach	0.142	0.891	0.373
Surface Approach	-0.269	1.348	0.178
A. Locus of Control	0.066	0.316	0.752
Intention of Use ON			
Self-Effectiveness	-0.266	-2.213	0.027
Perceived Ease of Use	0.030	0.329	0.742
Perceived Fit	0.437	3.132	0.002
Perceived Usefulness	0.278	2.126	0.033
Behavioural Plan-Days ON			
Deep Approach	0.335	1.955	0.051
Surface Approach	0.031	0.114	0.909
A. Locus of Control	0.012	0.033	0.974
Self-Effectiveness	-0.347	-3.770	0.000
Perceived Ease of Use	0.066	0.583	0.560
Perceived Fit	0.259	2.282	0.023
Perceived Usefulness	0.095	0.940	0.347
Behavioural Plan-Hours ON			
Deep Approach	0.142	0.857	0.391
Surface Approach	0.465	1.929	0.054
A. Locus of Control	0.457	2.327	0.020
Self-Efficacy	-0.273	-3.469	0.001
Perceived Ease of Use	0.049	0.565	0.572
Perceived Fit	0.178	1.877	0.060
Perceived Usefulness	0.099	1.216	0.572

R-SQUARE			
Self-Efficacy	0.165	2.640	0.008
Perceived Ease of Use	0.150	2.175	0.030
Perceived Fit	0.108	2.153	0.031
Perceived Usefulness	0.172	2.615	0.009
Intention of Use	0.294	1.902	0.057
Behavioural Planning-Days	0.201	2.122	0.034
Behavioural Planning-Hours	0.225	2.267	0.023

Model B (Table 2020) includes the variables proposed in the research hypotheses, based on what has been observed in the results of the previous studies of this thesis. The fit indexes decreased, but they remain within the acceptable range. These are $\chi^2(5)=6.681$, $p=0.245$, RMSEA=0.036, CFI=0.979. Once again, most of relationships cannot be confirmed, and the R-square values are non-significant for the main research outputs.

Table 20. Model B. Results of the proposed model.

Model B

Observed Variable	Estimate β	Est./S.E.	Two-tailed p-value
Perceived Fit ON			
Deep Approach	0.109	0.669	0.503
Surface Approach	-0.073	-0.498	0.619
A. Locus of Control	0.099	0.720	0.472

Perceived Usefulness ON			
Deep Approach	0.068	0.955	0.340
Surface Approach	-0.091	-1.306	0.192
A. Locus of Control	0.019	0.321	0.748
Intention of Use ON			
Perceived Fit	0.160	2.638	0.008
Perceived Usefulness	0.135	1.167	0.243
Behavioural Plan-Days ON			
Deep Approach	0.118	2.228	0.026
Surface Approach	0.014	0.442	0.658
Perceived Fit	0.075	2.059	0.040
Perceived Usefulness	-0.032	-0.377	0.706
Behavioural Plan-Hours ON			
Deep Approach	0.315	1.753	0.080
Surface Approach	0.196	1.389	0.165
Perceived Fit	0.235	1.635	0.102
Perceived Usefulness	-0.086	-0.417	0.677
R-SQUARE			
Perceived Fit	0.108	2.136	0.033
Perceived Usefulness	0.172	2.586	0.010
Intention of Use	0.260	1.843	0.065
Behavioural Planning-Days	0.144	1.465	0.143
Behavioural Planning-Hours	0.086	1.009	0.313

Finally, model C (in Table 21) is an optimised model. It was built from the results of model B, but with the deletion of some paths, decision based on previous results and theoretical criteria. The fit indexes resulted optimal, $\chi^2(13)=16.402$, $p=0.228$, RMSEA=0.033, CFI=0.958. The main highlight of this result is the central role played by learning approach. Specifically, surface learning approach can be observed as a significant predictor of perceived fit ($\beta= -0.286$, $p<0.000$), and of perceived usefulness ($\beta = -0.403$, $p<0.000$). On the other hand, deep approach and the perceived level of importance of the module are directly related to behavioural planning in its frequency component (deep approach: $\beta=0.493$, $p<0.000$; importance: -0.439, $p=0.004$), and to behavioural planning in its intensity component (deep approach: $\beta=0.307$, $p=0.054$; importance: -0.256, $p=0.020$). Finally, perceived fit is significantly related to intention of use ($\beta=0.471$, $p=0.004$).

Table 21. Model C. Results of the optimised model.

Model C

Observed Variable	Estimate β	Est./S.E.	Two-tailed p-value
Perceived Fit ON			
Surface Approach	-0.286	-3.962	0.000
Perceived Usefulness ON			
Surface Approach	-0.403	-4.882	0.000
Intention of Use ON			
Perceived Fit	0.471	2.880	0.004

Behavioural Plan-Days ON			
Deep Approach	0.493	4.056	0.000
Perceived Importance	-0.439	-2.889	0.004
Behavioural Plan-Hours ON			
Deep Approach	0.307	1.926	0.054
Perceived Importance	-0.256	-2.319	0.020
R-SQUARE			
Perceived Fit	0.082	1.981	0.048
Perceived Usefulness	0.163	2.441	0.015
Intention of Use	0.221	1.440	0.150
Behavioural Planning-Days	0.436	2.198	0.028
Behavioural Planning-Hours	0.160	1.325	0.185

Model C appears as the most consistent model out of the three tested in this section, with optimal goodness-of-fit indexes and coherent relationships between their components. Nonetheless, the R^2 indexes show uneven level of suitability. The prediction of perceived fit has a low but significant R-square (R^2=0.082, p=0.048), as in the case of the prediction of perceived usefulness (R^2=0.163, p=0.015), while the frequency component of behavioural planning shows better results (R^2=0.436, p=0.028). On the other hand, intention of use and the intensity component of behavioural planning show non-significant results (intention: R^2=0.221, p=150; intensity: R^2=0.160, p=0.185).

In summary, it can be said that the attitudinal based perspective on adoption of technology did not find support in this study. On the contrary, data support the perspective proposed by the author that the model based on learning approaches – accompanied by the importance assigned to the course – is better than the model based on attitudes to explain why people adopt learning technology, even making a rough prediction of how much the learning environment will be utilised. The next step is to find out whether that prediction is accurate or not.

Cluster 2 - Engagement

This section aims to understand two general aspects regarding the adoption and effective use of technology: the strength of the link between intention/planning and actual use, and the variables which can affect the use of technology over time. It was included in this cluster, as a secondary but not least important aim, to define which variables influence individuals' decision of future use of the environment. Figure 33 offers a graphic description of the research proposal.

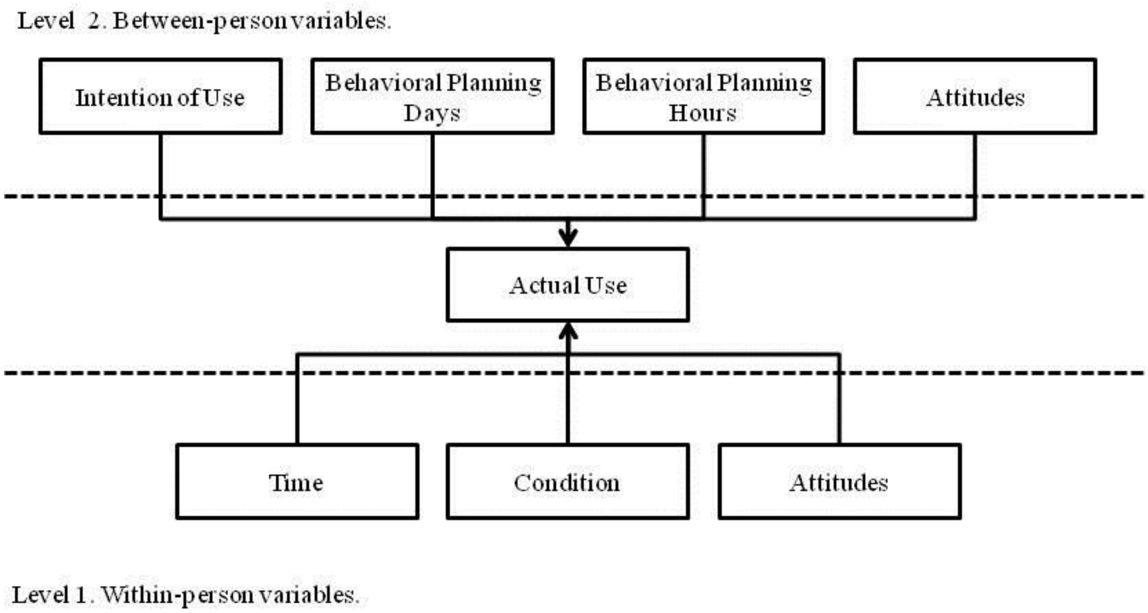

Figure 33. Research model to understand actual use of learning technology.

The first step was to test the relationship between intention/planning and actual use. This analysis considered the output or dependent variables of the cluster 1 (intention of use and behavioural planning) as the input or independent variables for actual use. Actual use was measured over time, turning this analysis into a multilevel structural equation modelling, with time and condition (mandatory/voluntary) as within (level-1) variables. The use of Mentor as learning environment was mandatory the first 6 weeks of the course, so the variable "condition" (mandatory, optional) was introduced to give account of this information at the within-level. Actual use was assessed by self-reports, with the same two components of behavioural planning, frequency (how many days did you use Mentor the last 7 days?) and intensity (how many hours did you use Mentor during the last 7 days?).

The results are displayed in Table 22 and they show at within-level that time and condition are significant predictors of the number of days a week (time: $\beta=0.356$, $p=0.010$; condition: $\beta=0.569$, $p<0.000$), and also of the amount of hours per week Mentor was utilised (time: $\beta=0.442$, $p=0.001$; condition: $\beta=0.609$, $p<0.000$). Nonetheless, the R-square for both indicators was low and barely non-significant (actual use – days: $R^2=0.101$, $p=0.061$; actual use – hours: $R^2=0.102$, $p=0.063$), and the model could not be identified, which means that the number of parameters to be estimated bigger than the number of measured variables, resulting not possible to identify a better solution for the model.

On the other hand, at between-level, either intention of use and behavioural planning-days were good predictors of actual use in its frequency component (intention: $\beta= -0.330$, $p=0.019$; planning (days): $\beta=0.727$, $p=0.000$) and its intensity component (intention: $\beta= -0.485$, $p=0.011$; planning days: $\beta=0.686$, $p=0.031$). The *intensity* component of behavioural planning was non-significant for actual use-days ($\beta=0.110$, $p=0.607$) neither for actual use-hours ($\beta=0.113$, $p=0.590$). Moreover, the R-square indicator for the between-level were high and significant, with actual use-days: $R^2=0.629$, $p=0.008$, and actual use-hours: $R^2=0.665$, $p=0.039$. The fit indexes of the model were good, with RMSEA=0.000 and CFI=1.000.

It was proposed that other variables could affect the use of the learning environment over time, such as the perceived fit with the task, the importance of the course for the learner, the learning approach and style, and the technical and functional features of the tool. In the results displayed in Table 233 the first thing to be noticed is that the model was non-identified due to the large number of variables, therefore it was not possible to obtain fit indexes, standardised estimates, nor R-square values.

Table 22. Results of the simple model for Actual Use.

Observed Variable	Estimate β	Est./S.E.	Two-tailed p-value
WITHIN LEVEL			
Actual Use - Days ON			
Time	0.356	2.559	0.010
Condition	0.569	3.500	0.000
Actual Use - Hours ON			
Time	0.442	3.619	0.001
Condition	0.609	3.782	0.000
BETWEEN LEVEL			
Actual Use - Days ON			
Intention of Use	-0.330	-2.343	0.019
Behavioural Planning - Days	0.727	3.557	0.000
Behavioural Planning - Hours	0.110	0.515	0.607
Actual Use - Hours ON			
Intention of Use	-0.485	-2.534	0.011
Behavioural Planning - Days	0.686	2.159	0.031
Behavioural Planning - Hours	0.133	0.538	0.590
R-SQUARE			
WITHIN LEVEL			
Actual Use - Days	0.101	1.873	0.061
Actual Use - Hours	0.102	1.860	0.063
BETWEEN LEVEL			
Actual Use - Days	0.629	2.661	0.008
Actual Use - Hours	0.665	2.064	0.039

Table 23. Results of the saturated model for Actual Use.

Observed Variable	Estimate	Est./S.E.	Two-tailed p-
WITHIN LEVEL			
Actual Use - Days ON			
Time	0.091	1.296	0.195
Condition	1.046	2.250	0.024
Functional Evaluation	0.111	1.857	0.063
Technical Evaluation	-0.360	-0.663	0.507
Perceived Fit	0.045	0.603	0.546
Actual Use - Hours ON			
Time	0.428	2.532	0.011
Condition	3.263	2.532	0.011
Functional Evaluation	0.179	1.372	0.170
Technical Evaluation	-0.239	-1.691	0.091
Perceived Fit	0.233	1.080	0.280
BETWEEN LEVEL			
Actual Use - Days ON			
Intention of Use	-0.377	-4.341	0.000
Behavioural Planning - Days	0.549	6.804	0.000
Functional Evaluation	-0.226	-3.025	0.002
Technical Evaluation	0.051	0.953	0.341
Perceived Fit	0.366	4.491	0.000
Perceived Importance	-0.901	-4.531	0.000
Deep Learning Approach	0.061	2.397	0.017
Surface Learning Approach	0.022	0.919	0.358
Learning Style - Active	0.065	0.401	0.688
Learning Style - Reflective	-0.065	-0.429	0.668
Learning Style - Visual	-0.038	-0.573	0.567
Learning Style - Verbal	0.038	0.651	0.515

Actual Use - Hours ON			
Intention of Use	-0.835	-3.686	0.000
Behavioural Planning - Days	0.840	3.447	0.001
Functional Evaluation	0.002	0.006	0.995
Technical Evaluation	-0.159	-0.843	0.399
Perceived Fit	0.461	1.236	0.216
Perceived Importance	-1.320	-1.837	0.066
Deep Learning Approach	0.035	0.370	0.711
Surface Learning Approach	0.050	0.665	0.506
Learning Style - Active	0.026	0.082	0.935
Learning Style - Reflective	-0.026	-0.090	0.929
Learning Style - Visual	-0.066	-0.814	0.416
Learning Style - Verbal	0.066	0.737	0.461

NOTE: The estimate values are not standardised.

It was decided to remove some of the non-significant variables from the model, such as learning styles, surface learning approach, technical evaluation and the within indicators for technical evaluation. The new solution (Table 244) is more suitable, and possesses good indicators of fit, $X^2(0)=1.180$, $p=0.000$, RMSEA=0.000, CFI=0.992. At the within-level, it can be observed that the functional evaluation has a significant effect on actual use-days ($\beta=0.262$, $p=0.001$) and actual use-hours ($\beta=0.112$, $p=0.022$). Nonetheless, the R-square values varied little, with actual use-days: $R^2=0.144$, $p=0.020$; and actual use-hours: $R^2=0.065$, $p=0.133$.

On the other hand, at the between-level can be observed some significant effects on actual use-days, such as perceived fit (β=0.364, $p<0.036$), importance of the course (β= -0.614, $p<0.000$), and deep learning approach (β=0.270, $p=0.036$). It can be observed that the effect of the importance of the course is significant on actual use-hours (β= -0.490, $p=0.019$), while the effects of functional evaluation, perceived fit, and deep approach are non-significant. The improvement of the R-square indexes are important as well, with actual use–days: $R^2=0.933$, $p<0.000$, and actual use–hours: $R^2=0.926$, $p<0.000$.

Table 24. Results of the optimised model for Actual Use.

Observed Variable	Estimate	Est./S.E.	Two-tailed p-
WITHIN LEVEL			
Actual Use - Days ON			
Time	0.331	2.857	0.004
Condition	0.475	3.348	0.001
Functional Evaluation	0.262	3.359	0.001
Actual Use - Hours ON			
Time	0.338	2.833	0.005
Condition	0.397	2.511	0.012
Functional Evaluation	0.112	2.285	0.022

BETWEEN LEVEL			
Actual Use - Days ON			
Intention of Use	-0.565	-3.694	0.000
Behavioural Planning - Days	0.794	6.385	0.000
Perceived Fit	0.364	2.098	0.036
Perceived Importance	-0.614	-4.324	0.000
Deep Learning Approach	0.270	2.436	0.036
Actual Use - Hours ON			
Intention of Use	-0.745	-3.694	0.001
Behavioural Planning - Days	0.781	6.385	0.000
Perceived Fit	0.527	1.860	0.063
Perceived Importance	-0.490	-2.341	0.019
Deep Learning Approach	0.037	0.178	0.859
R-SQUARE			
WITHIN LEVEL			
Actual Use - Days	0.144	2.330	0.037
Actual Use - Hours	0.065	1.501	0.133
BETWEEN LEVEL			
Actual Use - Days	0.933	9.329	0.000
Actual Use - Hours	0.926	3.661	0.000

By way of summary, the results indicate that intention of use and behavioural planning (days) are good predictors of actual use. An interesting thing to highlight is that at the between-level, the effect of intention of use is negative, that is, higher levels of intention are related to lower levels of actual use. A similar effect can be observed with functional evaluation, and the attributed importance of the course. The effect of functional evaluation at the within-level is positive, which indicates that despite the variation in mean scores between subjects, the week-to-week fluctuation in use within subjects is actually influenced by the good or bad impression of the features of Mentor. Finally, it can be noticed that deep learning approach has a small but significant effect on actual use, which reaffirms the role of learning approach as a determinant in the base level of the main variables involved in the adoption-engagement with learning technology.

Another aspect to be considered in the process of adoption-engagement with technology is the intention of continuing its use in future. One question was introduced in the last weekly report, which was focused on the intention of keep using Mentor to improve learning. It was proposed that a deep learning approach, perceived fit, and the importance of the subject would be predictors of continued use. The results of the analysis show that deep learning approach and the importance of the module are good predictors of intention of continued use (deep learning approach: β=0.581, p=0.002; importance: -0.536, p=0.003), with good model fit (RMSEA=0.000, CFI=1.000), and R^2=0.416, p=0.025. Once again, the effect of the importance given to the module has an inverse relationship with the intention of continued use, while deep learning approach has a direct and significant effect. When this model is compared with one based on attitudes such as perceived fit, satisfaction with the course, and self-perceived learning – usually utilised to assess computer-based learning effectiveness – the results show that the model based on learning approach is more effective and fits the data better (Table 25).

Table 25. Results of two models (A and B) for Continued Use of VLE.

Observed Variable	Estimate	Est./S.E.	Two-tailed p-
Model A			
Continued Use ON			
Deep Learning Approach	0.581	3.094	0.002
Perceived Importance	-0.536	-3.008	0.003
Perceived Fit	0.203	1.250	0.211
Model B			
Continued Use ON			
Perceived Fit	0.160	0.543	0.587
Satisfaction with the Course	0.010	0.041	0.968
Self-Perceived Learning	0.116	0.396	0.692
R-SQUARE			
Continued Use (A)	0.416	2.249	0.025
Continued Use (B)	0.065	0.586	0.558

Overall, the results of these clusters of variables suggest that learning approach is a useful indicator of people's adoption-engagement with technology. Both learning approach components – deep and surface – are related to different variables depending whether the action is related to the deployment of resources in an specific activity (deep approach) or the assessment of convenient a situation or scenario is (surface approach).

The next section will take the analysis to the final stage of the process, being focused on the determinants of learning performance.

Cluster 3 – Effectiveness

The assessment of the effectiveness of learning technology is not easy, due to different understandings of what the concept implies and how it would have to be measured. As it has been sustained in this thesis, the effectiveness of the learning environment will be associated to the achievement of the learning goals the environment was built for. In this particular case, to the achievement of the expected programming skills stated in the module syllabus. Two different approaches were utilised to attempt this: (a) an instrument focused on measuring the knowledge on programming the students have before they start the course and at the end of the course; and (b) the final mark of each student in the module. The proposed research model is presented in Figure 34.

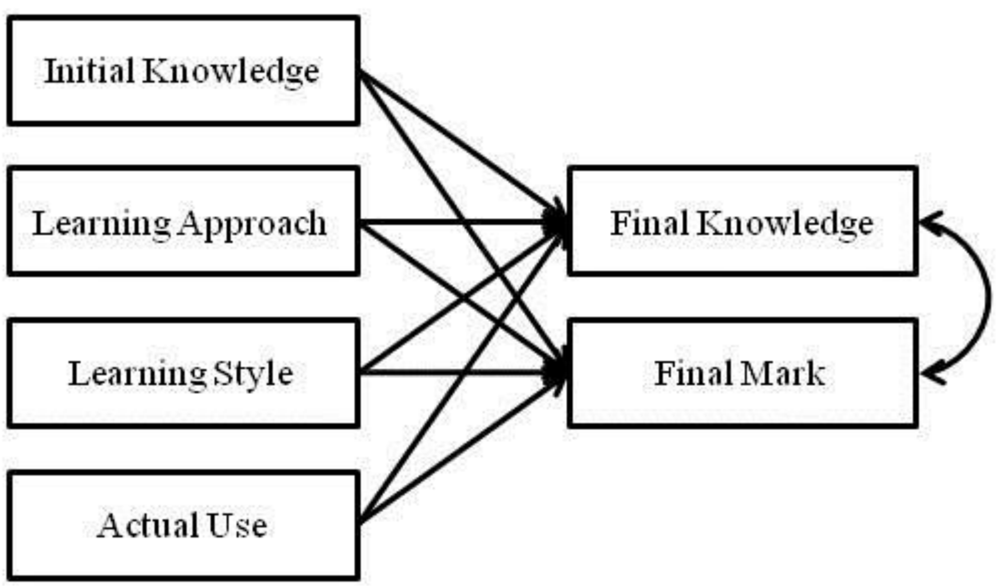

Figure 34. Research model for VLE's effectiveness.

It is hypothesised that students with higher scores in a deep learning approach, sensing and visual learning styles, and actual usage indicators, will have better scores in the final knowledge programming test. The initial evaluation on programming knowledge and the final mark of the students will also be included as predictors.

The results are presented in Table 26. A deep learning approach and sensing learning style are the only significant predictors of knowledge on programming at the end of the course (deep: $\beta=0.339$, $p=0.024$; Sensing: $\beta=-0.494$, $p=0.002$). The resulting R-square indicator should be considered as optimal ($R^2=0.527$, $p<0.000$), nonetheless the non-identification of the model is a problem that have to be addressed.

Table 26. Results of the proposed model for VLE's effectiveness - Knowledge.

Observed Variable	Estimate	Est./S.E.	Two-tailed
Knowledge - Final ON			
Deep Learning Approach	0.339	2.262	0.024
Performance	0.247	1.168	0.243
Actual Use - Days	-0.180	-0.445	0.656
Actual Use - Hours	0.377	0.980	0.327
Knowledge Initial	-0.284	-1.480	0.139
Learning Style - Active	-0.073	-0.278	0.781
Learning Style - Sensing	-0.494	-3.103	0.002
Learning Style - Visual	-0.304	-0.956	0.339
R-SQUARE			
Knowledge Final	0.527	3.799	0.000

In order to solve the nonidentification of the model, it was decided to remove two of the variables with lower estimates and/or worse p-value. The variables removed from the model were actual use – days and learning style – active. Besides, actual use - hours was constrained , because by its theoretical importance for the model it cannot be deleted, and because from all the variables included in the model, the time that students spend in the learning activities could be the easiest to control.

The result (Table 27) follows the same pattern, with deep learning approach, sensing and visual learning approaches as significant predictors of programming knowledge at the end of the course (deep: β=0.301, p=0.013; sensing: β= -0.480, p=0.002; visual: β= -0.378, p=0.046). The R-square value remains almost the same (R^2=0.518, p<0.000), and the fit indexes are good, $\chi^2(1)$=0.021, p=0.884, RMSEA=0.000, CFI=1.000.

Table 27. Results of the optimised model for VLE's effectiveness - Knowledge.

Observed Variable	Estimate	Est./S.E.	Two-tailed p-
Knowledge - Final ON			
Deep Learning Approach	0.301	2.485	0.013
Performance	0.242	1.319	0.187
Actual Use - Hours	0.232	4.847	0.000
Knowledge Initial	-0.262	-1.398	0.162
Learning Style - Sensing	-0.480	-3.158	0.002
Learning Style - Visual	-0.378	-1.992	0.046
R-SQUARE			
Knowledge Final	0.518	3.741	0.000

These results suggest that those students disposed to have a meaningful learning experience and with a preference for intuitive and abstract information processing, tend to have better scores in a programming-related assessment. It supports partially what has been hypothesised, because the direction of the learning styles indicator is opposite to what was expected (that higher scores in sensing and visual scales of learning styles will affect positively the learning outcome), and because the influence of actual use was not significant. It is worth highlighting that the initial and final scores are not related, which can suggest that the progression of the students can be shaped by factors other than the initial knowledge on the topic.

The other way to assess learning effectiveness is by using the final mark as an indicator of learning achievement. It was hypothesised that learning approach, actual use, initial score in the programming assessment, and sensing-visual learning approaches will be predictors of final marking. The results can be observed in Table 28 and they reveal that the only significant predictor is the score in the visual learning style subscale ($\beta=0.416$, $p=0.041$). Overall, this model does not work well according to the R-square index ($R^2=0.349$, $p=0.169$) and the nonidentification of the model.

Table 28. Results of the proposed model for VLE's effectiveness - Performance.

Observed Variable	Estimate	Est./S.E.	Two-tailed p-value
Performance - Final ON			
Deep Learning Approach	-0.188	-1.603	0.109
Actual Use - Days	0.483	1.544	0.123
Actual Use - Hours	-0.430	-1.728	0.084
Knowledge Initial	-0.219	-1.198	0.231
Learning Style - Active	-0.212	-1.145	0.252
Learning Style - Sensing	-0.196	-1.330	0.183
Learning Style - Visual	0.416	2.048	0.041
R-SQUARE			
Knowledge Final	0.349	1.374	0.169

As in the previous analysis, it was decided to remove the variables actual use – days and learning style – active. It was also decided to constrain the variable actual use – hours. The results (see Table 29) did not suffer an important variation, maintaining the visual learning style subscale as the only significant predictor (β=0.334, p=0.041) and a non-significant R-square (R^2= 0.303, p=0.206), while the fit indexes are acceptable, $\chi^2(1)$=0.239, p=0.624, RMSEA0.000, CFI=1.000.

Table 29.Results of the optimised model for VLE's effectiveness - Performance.

Observed Variable	Estimate	Est./S.E.	Two-tailed p-value
Performance - Final ON			
Deep Learning Approach	-0.185	-1.512	0.131
Actual Use - Hours	0.040	2.257	0.024
Knowledge Initial	-0.288	-1.515	0.130
Learning Style - Sensing	-0.220	-1.776	0.076
Learning Style - Visual	0.344	2.045	0.041
R-SQUARE			
Knowledge Final	0.303	1.264	0.206

In summary, these results suggest that the knowledge on programming at the end of the course is related to learning approach and learning styles, partially supporting the hypothesis proposed. Besides, the analyses show that the selected set of variables is not a good predictor of the final mark of the course, rejecting the proposed hypothesis. The implications of this will be discussed in the next section

4.7. **Discussion and implications**

The present study proposed a model that integrates the key elements of the utilisation of learning technology: its adoption, its use, and its effectiveness. These were considered as interrelated process, parts of a complex model that starts with the first approximation to the learning environment and ends with the achievement of the learning goals this environment was focused on. In order to present the results of the analyses in a neat way, they have been grouped into three clusters, named after the three sub-process mentioned above.

The first cluster centres on the adoption of technology, where learning approach plays a fundamental role, confirming what has been observed in Studies 2 and 3. It is important to remember that learning approach has two dimensions. One dimension is called *deep* learning approach and it is associated to behavioural and cognitive drivers that aim to obtain the best results of a learning experience, even though it involves more effort. This is why it makes sense to find that deep learning approach is associated to behavioural planning; involving that higher scores in the deep learning approach scale is associated with people projecting a more frequent and intense use of the learning environment than those with lower scores.

The second dimension is called *surface* learning approach, and it gives account of what can be understood as people's evaluation of *cost-benefit* when they are in a learning situation, so that they can fulfil the requirements to pass or approve the learning module, but with maximising their resource deployment or effort. It was observed that the scores in the surface learning approach scale were negatively associated with those observed in the perceived fit and perceived usefulness scales. This indicates that people with high scores in the surface learning approach scale have a worse valuation of the characteristics of the virtual learning environment, or tend to consider learning technology as less useful to make them succeed straightforward. Nonetheless, such association was low because perceived fit and perceived usefulness scores should be more associated to the actual characteristics of the learning environment.

The proposition that attitudes are good predictors of intention of use found low support in this research model, basically because when variables (such as perceived usefulness and perceived ease of use) were included in the analysis competing with perceived fit and learning approaches, they were non-significant. On the other hand, the declared intention of use towards the learning environment was highly related to perceived fit, but the explained variance was less than that explained for behavioural intention (intention: R^2= 0.221; behavioural planning: R^2=0.436). In other words, the model based on learning approach was more effective than the one based on attitudes.

The inclusion of students' evaluation about the importance of the learning module as a predictor of behavioural planning had a significant effect, but the direction of the relationship is negative – counter intuitively –, which indicates that while more perceived importance of the learning module is *declared*, lower is the projected utilisation of the virtual environment. This result can be explained by two reasons. One is that the question was not an appropriate measurement, and thus it has to be improved or replaced for a more suitable indicator. The other one is that declared attitudes are not a reliable source of information on what people are actually thinking. Perhaps social desirability biased participants' answers on the importance of the module because the instrument comprising that question was delivered within the context of the introduction lecture to the module, with the fresh impression of its lecturer still in their memory. Nonetheless, the responses for behavioural planning were collected in the same questionnaire, and its relationship with actual use is positive and significant. Certainly, this result is striking, but no conclusion can be derived from this sole observation.

The second cluster was focused on the understanding of actual use, and the factors that might influence people's engagement with the learning environment. This is a crucial stage in the computer-based learning process, because utilisation is a necessary condition for learning, as the virtual environment delivers information and stimulates the development of new skills by the interaction with the learner. In the previous stage, three variables were considered as outputs of the adoption model: intention of use, behavioural planning-days, and behavioural planning-hours. The first goal of the proposed research model was to discriminate which of them is the best predictor of actual use. Besides, the proposed model included a temporal setting, assessed by repeated measures week after week for three months. The goal was to understand the individual variation over time of the "actual use" indicator and its associated variables, hence a two-level analysis (within-between person) was adopted.

At the within-level the results showed that time was a significant predictor of actual use, even though its effect is low. It is important to notice that this does not necessarily mean that a longer course will involve higher rates of use. The variable *time* indicates a temporal order, so it is more related to the design of the course and the events associated to it, so it can be said that time should be associated to the temporal order of the events that can enhance usage rather than to an amount of time (days, weeks, months). Concretely, it can be said that time was associated to activities and events – as laboratory activities in week 1-6, or marked assessments in week 6 and 11). Another significant predictor of actual use was the mandatory utilisation of the learning environment. The use of the tool was mandatory from week-1 until week-6, but the amount of hours was not fixed and it depended of each student. Considering these two conditions, it is possible to understand the variation in the actual use of Mentor through the length of the course (Figure 35). For instance, from week-1 to week-6 the average use was considerably higher than the average use from week-7 to week-11. Although, it can be observed a peak on week-6 and another one in week-11, which matches with the date of two assessments related to Mentor-based activities.

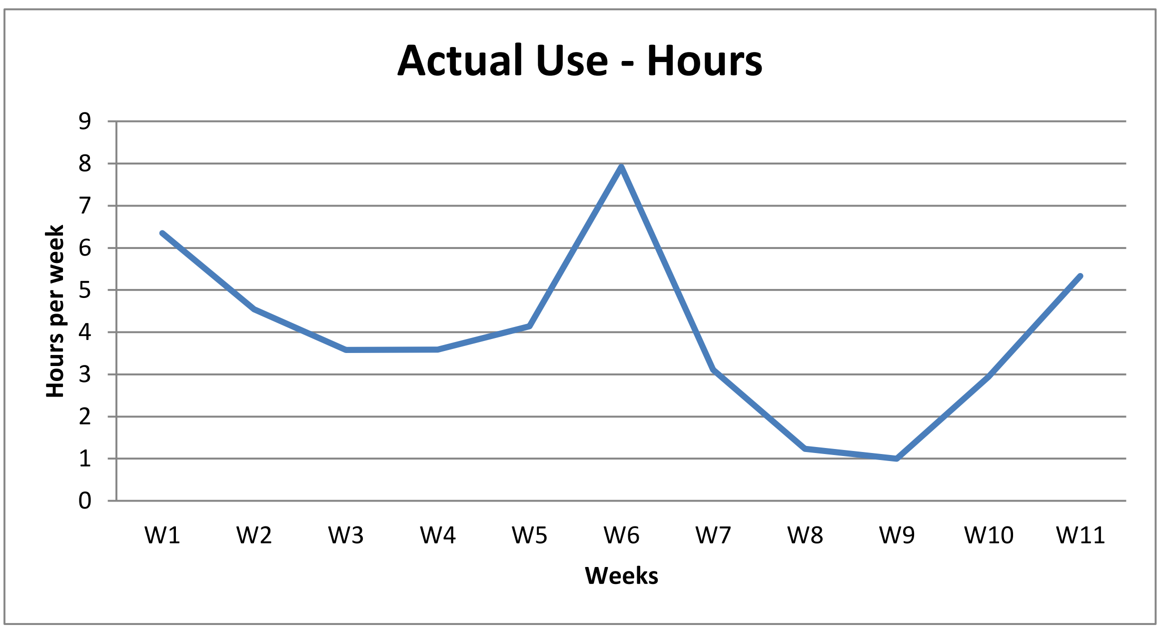

Figure 35. Graphic representation of Mentor actual hours of use (grand mean).

Nonetheless, the variables time and condition (mandatory/voluntary) can explain just a small amount of actual use. The fact that the within-person variation over time is small indicates that the main difference is at the between-person level. In other words, it can be said that each person have a "base level" of actual use and of all the associated variables, which will differentiate them from each other, and that the individual variation over time is smaller than the variation between individuals.

At the between-level, intention of use and behavioural planning-days were the main predictors of both days and hours of actual use. Other variables were associated to actual use as well, such as deep learning approach, perceived fit, the functional evaluation, and the perceived importance of the module. What is remarkable about this is that intention of use, perceived fit, functional evaluation, and the perceived importance of the module are all negatively related to actual use. It is counter-intuitive that the perceived utility of a learning environment, the importance of the contents, and intentions to use it often, would predict low actual use. Two possible explanations exist. Firstly, the instruments may not be reliable, and secondly, a response bias may be responsible for the results. However, in the first case, the psychometric quality of the instruments has been assessed appropriately and it was satisfactory. Besides, most of the instruments have been utilised in other studies successfully. The alternative of biased responses seems more plausible considering the small sample size to which we have access, which makes it more sensible to cultural, effective, or context related biases.

It is possible that the response biases could be related to some personal characteristic that shape the response of the participants in one way, and their behaviour in an opposite one. For instance, considering that behavioural planning has a positive effect on actual use, and that behavioural planning is related to deep learning approach – and moreover, deep learning approach has a small direct effect on actual use – it might be that attitudes give inaccurate information about the real perceptions of the learners about the importance and usefulness of the learning environment. They might be considering other aspects as relevant to shape their behaviour (motivations, long term goals, etc.) and reacting to the attitudinal stimuli in a selective way, e.g., answering the scales too positively, and thus producing the observed negative relationship with actual use. It is hard to clarify the real reason of this bias, but certainly these guesses have to be tested in future studies.

Finally, the learning achievement was assessed utilising two indicators. One indicator was the final score of each student, which was related to the score in the visual learning style subscale. Nonetheless, the explained variance was relatively small and not significant. The other indicator was the score in an assessment of knowledge on programming learning, which was more consistent. The variables explaining the result are deep learning approach and two learning styles: visual-verbal and sensing-intuitive. What these variables are suggesting is that more committed students achieve more academically, and that a combination of visual stimuli with a balanced amount of concrete applications for abstract concepts contributes to better performance in programming learning.

It has to be noticed that the initial knowledge on programming was not a predictor of knowledge at the end of the course nor final mark. This results might be considered as positives, because indicates that all students, despite their initial level of skills in programming can achieve the proposed learning goals with commitment and a learning design that allows them to deploy their learning strategies accordingly.

It has been stated that the main goal of this study was to test a single model that allows us to explain the learning process supported by computer technology from its beginning to its end. This single model was split and then presented using a three-cluster structure, which represents the flow or sequence of its stages. It starts with the adoption of learning technology, followed by the engagement with the learning environment, and finishes with the learning output. The graphical representation can be observed in the figure below.

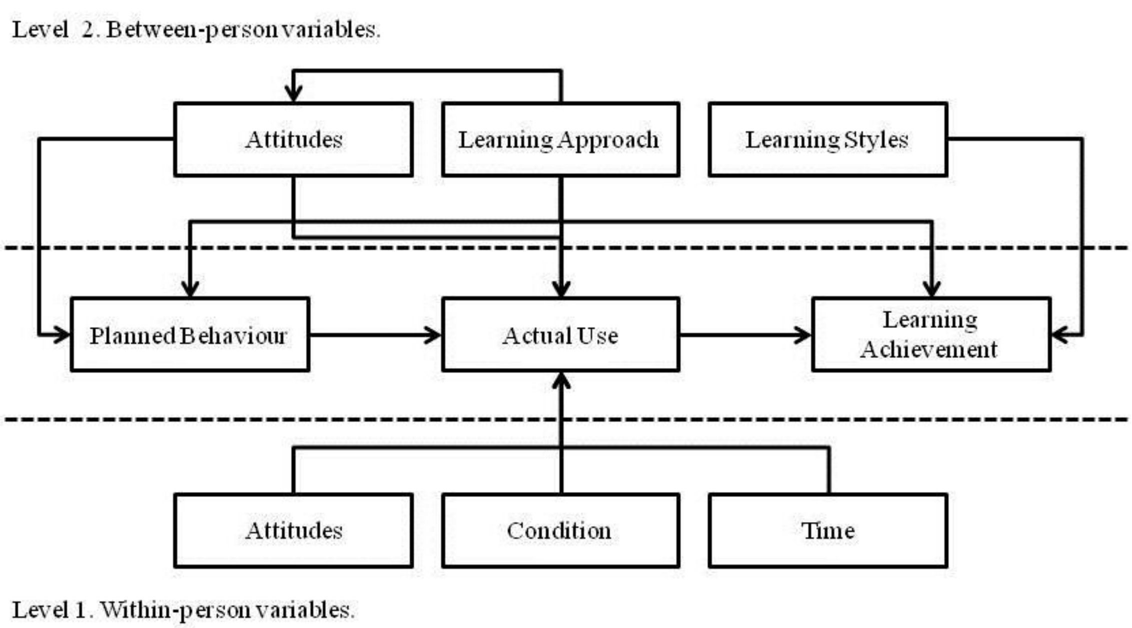

Figure 36. Integrated model of Computer-based Learning.

It can be observed that learning approach intervenes in all the three stages of the process, becoming a central and fundamental element in the design of the learning environment and learning strategy, and the monitoring of the learning process. It seems that learning approach is the machinery that enables the movement of all the process: it promotes the adoption, enhances engagement, and boosts the learning achievement by managing the cognitive resources to processing effectively the information.

The main conclusion of this study is that technology is important, that the features and the attractiveness of the technology supporting learning are important in generating interest and a positive attitude towards its use. However, what is most important is the learner's cognitive and affective resources. If practitioners do not have an accurate understanding of the end user of the learning technology, neither the potential of the technology nor the learner can be maximised.

5. CHAPTER FIVE: GENERAL DISCUSSION

5.1. **A general summary of the research process.**

Four chapters have been presented. The first chapter explained the rationale of the research, arguing that the current approach to understanding how people interact with learning technology is failing to explain the inconsistencies between the adoption process, effective use, and effective achievement of learning goals. The main issues are related to low rates of use and high rates of dropout, which affect the quality of the learning output and put the sustainability of computer-based learning strategies in higher education and life-long learning schemes at risk. A theoretical problem that underlies to this situation is the lack of an integrated model to account of the complete process.

The second chapter proposed a first solution, as a starting point to be refined in subsequent studies. It was based on the mainstream approaches to adoption and effectiveness of computer-based learning. It comprised an adoption solution based on Davis' Technology Acceptance Model (TAM) with the addition of behavioural planning indicators, with a learning achievement solution based on the more utilised and tested variables on the available literature. The model was tested using a two-stage follow up design, in order to capture information at the beginning of the course – measuring the adoption parameters – and at the end of the course – assessing the effectiveness parameters. The results provided insight for future development. For instance, the TAM explained individuals' intention of use, but it was clear that intention of use was not a reliable indicator of actual use, neither was it associated with the variables involved in learning achievement. In turn, learning achievement was not related to the learner perceptions and attitudes towards the course, nor the virtual environment. In fact, the only predictor of learning achievement was actual use, a behavioural indicator that says little about the learning process or the individual characteristics.

On the other hand, behavioural planning was related to actual use, creating a path from adoption to achievement that indicated two things: i) that it was feasible to link both processes while being focused in the learner rather than in the technology; and ii) that an attitudinal based approach was not enough, that other variables should be included in order to improve the explained variance of the model. It opened the door to questioning not only the current theoretical perspective on the subject, but also to realising the need to include more complex designs, in order to capture the dynamic of the learning process.

As a real learning process takes time, it was clear that the model should be refined previously to be tested in a real setting. It was decided to broaden the theoretical perspective, incorporating a group of variables from learning and instructional theory to be included and tested in more simple studies before running a complex study involving more time and human resources.

Chapter 3 addressed that challenge. In two cross-sectional studies, a group of cognitive, affective, and context-dependent indicators were included in our basic model.

The inclusion of cognitive variables was consequence of the understanding that attitudes, which are context dependents and can be distorted by many situational factors, were not enough to understand learning behaviour. Therefore, the attention was placed on behavioural drivers and information processing profiles. Specifically learning approach, academic locus of control, learning styles, and perceived task-technology fit.

Studies 2 and 3 tested the role of these variables on the emergence of intention of use and behavioural planning, and their relationship with the attitudes towards technology. The role of learning styles was not confirmed, which may be due to their nature as information processing profiles rather than a shaper of motivational drivers. However, there was evidence linking learning styles and preference for certain virtual learning environment characteristics. The role of academic locus of control was also not confirmed, but its relationship with learning approach was interesting and thus it would be worth including it in future studies. The main finding was the role of learning approach, being related to intention of use, to behavioural planning, and to attitudes. It seemed that learning approach fixed a base level for subsequent behaviour. Learning approach might therefore underpin the whole process, if its effect could be observed on learning achievement.

With a more clear idea of the complete landscape, the fourth chapter was the final study of this research programme. A valuable input to set all the pieces in a consistent framework came from instructional theory, with Lowe & Holton model for the design of effective computer-based instruction (Lowe & Holton, 2005). Their approach is very similar to what has been proposed in the previous chapters, splitting the process in three parts (Input, Process, Output), and two levels (Design, Support). This model is focused on the technology, while our proposal is focused on the learner (interacting with the technology). Nonetheless, both coincide in the relevance of learner's cognitive profile, the role of technology as a facilitator of the learning process, and the importance of learning achievement as an indicator of success.

With this new perspective, Study 4 was designed to assess all the elements of the model and to capture the dynamic of the learning process in a real setting. The study was 3 months long and involved 41 first-year students enrolled in a Programming module.

The selected design included repeated measures, self-reports, objective assessments, and marking scores. The analysis of the data included multilevel structural equation modelling, among other techniques. The results were interesting and supportive of some of the main hypotheses.

For instance, it was found that individuals' cognitive learning profile is more predictive than their attitudes in explaining their learning behaviour, including both the adoption and actual use of the learning environment. A relationship between learning styles and the learning output was also observed, indicating that it is important to understand how the end user processes information in order to design learning materials that match their cognitive profile. Nonetheless, it was also observed that most of the participants have balanced profiles, which means that they are flexible enough to adapt to different modes of informative media input.

The most remarkable finding was the effect of learning approach on the whole process. In the adoption cluster, surface learning approach affects the attitudes towards technology, while deep learning approach is related to behavioural planning. In the engagement cluster, deep learning approach has a significant effect on actual use and intention of continued use. In the effectiveness cluster, deep learning approach affects the learning output. The deep learning approach subscale appears as fundamental to understanding the computer-based learning process, and to articulate a coherent framework.

These results – while not conclusive – give solid foundations to improve our understanding of the subject, and useful inputs for practitioners. Nonetheless, there are various aspects to be rectified. The following sections will discuss the theoretical and methodological issues of the present research, concluding with practical implications and some ideas for future research.

5.2. **Theoretical limitations.**

The intention of building an integrated framework to understand the learning process in virtual environments born from the need to have one when facing the challenge of improving the engagement with learning technology and the achievement of learning goals. The importance of computer-based instruction is growing in different social and geographical contexts, but there are obstacles to improving its effectiveness. This research solves one of them: how can we design a virtual environment that fits with learners' profiles, enhancing their strengths and overcoming their weaknesses? The first step is to have a clear understanding of the phenomena, but with several approaches doing it, it is hard to reach a consensual approach. Despite the large amount of literature on the subject, concepts are defined in many different ways (for instance, effectiveness), that some variables are measured with different indicators (for instance, actual use), and that depending on the field of expertise, there is an unbalanced focus on the variables studied.

Some results are difficult to explain satisfactorily. For example, the negative effect of intention of use, or from perceived importance of the course, on actual use. This is a counter-intuitive result, because most of the research has found the opposite result. It was proposed that the effect might be due to a response bias, or to a flaw in the instruments. Maybe it is a genuine effect, telling us not to trust in over optimistic self-projections that cannot be accomplished in the medium or long term. Certainly it is necessary to conduct more research to resolve this issue, because even though the effect was observed in studies 1 and 4 consistently supported by data, the comprehension of its rationale must be consistent as well.

Another theoretical issue is the general agreement on which indicators are going to be selected for outcome variables such as effectiveness. This research utilised a dual approach, considering the final mark and the score in a specific test on the subject, as possible indicators of learning effectiveness. Empirically, the score on the test worked better than the final mark, but if we think about what is considered as a valid outcome for the educational institutions, the picture changes. Maybe a serious reflection of our learning indicators is necessary, or maybe other variables must be included in the model that can explain the final mark of the students. It is an open discussion, and one that cannot be solved only based on the results of this research. For the purposes of this study the inclusion of both indicators seemed to be the best alternative, but it has to be taken into account that what can be considered as correct in theory (assessing learning achievement with a test of maximum performance) cannot find a correlate in the instructional design utilised by instructors and institutions.

As can be seen, the findings of this research are not taken as conclusive, since theoretical discussions and decisions must be addressed. Nonetheless, it can be said that a good starting point has been achieved, and that an integrated and coherent framework is closer.

5.3. Methodological limitations.

There is no doubt that methodological issues were a challenge in the current research programme. As it was mentioned above, some variables have been measured and assessed by different indicators, which poses the problem of choosing which of them to use. In some cases, the election was easy, especially if one of the instruments has been used previously with good and reliable results. However, in others, that was not the case. In some cases, the election was based on theoretical criteria, as the utilisation of Felder-Soloman's Index of Learning Styles (It is worth to mentioning that there are more than 70 instruments focused on learning style assessment). Nevertheless, for a couple of variables the strategy was to use a new indicator or to develop a new instrument.

That was the case of behavioural planning, a variable which has been measured in similar ways to intention of use, or with items that theoretically did not fit with the proposed approach. It was decided to ask directly how many days and hours it was planned to use the VLE involved in the study. The alternative of developing a new scale was discussed, but a straightforward question seemed more adequate. The same decision was taken to perceived importance of the course.

A different scenario was faced at the time to assess the satisfaction of the users with the VLE utilised in Study 4. The functional and technical performance of Mentor were very specific, so it was decided to develop a scale to collect students' opinions about it. In the case of programming knowledge, the decision was based in the absence of a consensual instrument. In both cases, the developing of the instruments relied on the designer of Mentor and lecturer of the module, Dr. Eleftherakis. The convenience of this decision can be discussed, but the psychometric quality of the scales was optimal according to our analyses. Definitively it is an issue that can be discussed and improved for future studies, but for the present research seemed as the more suitable solution under these circumstances.

The main methodological issue of the research was the sample size, especially for studies 1 and 4. The difficulty in recruiting participants for these studies was caused by the study design involving multiple time points. In Study 1, the participation only involved two questionnaires with a 5 week interval between the first and the second questionnaire. In total, 168 volunteers took part in the study, but less than 60 completed both questionnaires. Study 4 involved weekly reports over three months. 41 students were enrolled, but around 20 completed more than 9 reports. Besides, 10 of them missed the first questionnaire, which was focused on the learning profile. Even though multilevel techniques can handle a data set with missing values better than others techniques (it is important to highlight that the number of participants is not equal to the number of observations in a repeated measures design), when a complex model is being analysed, sample size is fundamental to support the number of parameters to be estimated. In Study 4, the assessment of learning achievement was particularly complex because of the number of parameters involved and the number of valid observations, which leads to a nonidentification of the model in first instance. To improve the rate of participation was one of the objectives, and different measures were addressed to do it, but unfortunately, the challenge is double: first, to have access to a satisfactory sample; and second, to engage them to participate consistently. In future research, this is an issue to keep in mind.

5.4. **Final reflections.**

The goal of this research was ambitious. The idea of studying the use of learning technology was not new– this had been done for at least two decades. The contribution of the present thesis was to build a theoretical framework able to explain the utilisation of virtual environments to support the learning, describing a complex process of three distinguishable stages (adoption, engagement, and achievement), and identifying its main components (deep learning approach, actual use, perceived fit, course design), which can lead us to attain our highest goal: to enhance the learning process by utilising computer technology. A wide literature review revealed that the perspectives on the study of technology related phenomena had changed little in two decades. The characteristics of the learners of 21st century were discussed in depth, but not included in the research models, nor our instruments updated. It seems that the inertia of the traditional approaches make them available to some modifications, but not to questioning their rationale. For instance, perceived ease of use is included in almost all the models of adoption of technology, in different contexts. Two decades ago it was a fundamental criterion to adopt technology, because the software in those days was less easy to use than todays, and the users were not accustomed to use technology in their daily activities.

Nowadays, a significant percentage of the population in the western countries and developing economies have access to smart phones, laptops, tablets, and internet connection. The software and mobile applications are very easy to use, and most of them share interface features that make people get use to new technologies easily. In this scenario, is not surprising that perceived ease of use was found as a non-significant variable in almost all the analysis of this research. It is just an example, but it shows the need to rethink our understanding on human-technology interaction.

On the other hand, the role of learning profile, especially learning approach, has been set as central for the engagement with learning technology and the achievement of learning goals. It might be a very useful input for designers and practitioners, allowing them to adjust the instructional strategy based on the results of a 20-item test that can be completed in less than 15 minutes. The results of the research suggest that people with high levels of deep learning approach are more self-regulated and engage more easily with the VLE and the learning activities, so the focus should be on those with low levels of deep learning approach. Obtaining a learning approach profile of the course might be useful to have an idea of the proportion of students than might need more attention and reinforcement to engage with the learning activities, or to modify the instructional strategy in case of a high risk of dropouts, and so on.

Future studies have to be focused on answering the questions that remain open, and to solve the problems that could not be fixed in this research. For instance, the role of attitudes and the counter-intuitive results observed in Study 4. If the present results are due to a response bias, then all the results should be verified. But, on the contrary, if the results are associated to attitudes misinforming of the real behavioural projections of the participants, then the attitudinal models applied in the field of adoption and utilisation of learning technology should be reviewed. In Study 4 the variation of the attitudinal indicators was disaggregated into a between and a within component, finding that the situation related fluctuation of these variables was small in comparison to the variation between subjects, which might indicate that the base level of the attitudinal response depends more on personal characteristics than on situation or interactions. Nonetheless, more research is required to clarify this issue.

Three valuable aspects of the current work should be highlighted. Firstly, the main objective of building an integrated framework to understand the learning process in virtual environments was achieved. It is neither definitive nor immutable, but at least set the basis for future improvement. It can explain the process from beginning to end, following a clear path; its elements are linked by theoretical and empirical support; and it comprises elements related to the user, to the VLE, and those that emerge from their interaction.

Secondly, the work has practical implications. Since some elements have been identified as predictors of engagement and achievement, an adequate assessment of those indicators might help practitioners to enhance the potential of the VLE and the potential of the learners, turning the technology into a tool for life improvement, rather than a tool for task fulfilment.

Finally, the research answered some questions, but at the same time, it opened many more, such as the role of certain variables, the improvement of the methodology, potential new uses, or even the application of a similar framework in a different field. As the technology changes, our relationship with it changes as well. Our understanding of these changes must follow the pace in order to both face the challenges that emerge, and to propose new pathways.

"*The important thing is not to stop questioning*"

(Albert Einstein).

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APENDIX

Instruments utilized in the present thesis.

Perceived Fit (Adapted from Lin, 2012)

1. By using "Mentor", it fits well the way I like to improve my learning.
2. By using "Mentor", it fits well the way that I can upgrade the efficiency of my study.
3. "Mentor" provides good assistance to help me complete my learning activities.
4. "Mentor" is compatible with all aspects of my study.
5. By utilizing "Mentor", I can concentrate more on my other studies.
6. For me, using "Mentor" to prepare my study is not efficient.
7. I learn better with "Mentor" than without it.

Perceived Usefulness (Adapted from Davis, 1989)

1. I believe "Mentor" contents are informative.
2. I believe "Mentor" is a useful learning tool.
3. I believe "Mentor" activities are useful.

Perceived Ease of Use (Adapted from Davis, 1989)

1. It would be easy for me to become skillful at using “Mentor".
2. Learning to operate "Mentor" would be easy for me.
3. I would find it easy to get “Mentor" to do what a want it to do.

Intention of Use – study 1 (Adapted from Davis, 1989)

I will try to use the learning platform in as many occasions as possible, within the length of the course.

Intention of Use – studies 2, 3, 4 (Adapted from Liaw, 2008)

1. I intend to use "Mentor" to assist my learning.
2. I intend to use "Mentor" activities to assist my learning.
3. I intend to use "Mentor" as an autonomous learning tool.

Perceived Self-Efficacy (Adapted from Liaw, 2008)

1. I feel confident using "Mentor" system.
2. I feel confident operating "Mentor" functions.
3. I feel confident performing "Mentor" activities.

Satisfaction with the course (Adapted from Johnson et al, 2008)

1. I am satisfied with the clarity with which the class assignments were communicated.
2. I am satisfied with the degree to which the types of instructional techniques that were used to teach the class helped me gain a better understanding of the class material.
3. I am satisfied with the extent to which the instructor made the students feel that they were part of the class and ‘‘belonged’’.
4. I am satisfied with the instructor’s communication skills.
5. I am satisfied with the accessibility of the instructor outside of class.
6. I am satisfied with the present means of material exchange between you and the course instructor.

Self-perceived learning [Course instrumentality] (Adapted from Johnson, 2008)

1. I feel more confident in expressing ideas related to [Information Technology].
2. I improved my ability to critically think about Information Technology.
3. I improved my ability to integrate facts and develop generalizations from the course material.
4. I increased my ability to critically analyze issues.
5. I learned to interrelate the important issues in the course material.
6. I learned to value other points of view.

Academic Locus of Control (Levy, 2007)

1. Some of the times that I have gotten a good grade in a course, it was due to the teacher's easy grading scheme.
2. Sometimes, my success on exams depends on some luck.
3. In my case, the good grades I receive are always the direct results of my efforts.
4. The most important ingredient in getting a good grade is my academic ability.
5. Some of my good grades may simply reflect that these were easier courses than most.
6. I feel that some of my good grades depend, to a considerable extent, on chance factors such as having the right questions show up on an exam.
7. Whenever I receive good grades, it is always because I have studied hard for that course.
8. I feel that my good grades reflect directly on my academic ability.
9. Sometimes, I get good grades only because the course material was easy to learn.
10. Sometimes, I feel that I have to consider myself lucky for good grades I get.
11. I can overcome all obstacles in the path of academic success if I work hard enough.
12. When I get good grades, it is because of my academic competence.

Revised Study Process Questionnaire (J. Biggs et al., 2001)

1. I find that at times studying gives me a feeling of deep personal satisfaction.
2. I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied.
3. My aim is to pass the course while doing as little work as possible.
4. I only study seriously what’s given out in class or in the course outlines.
5. I feel that virtually any topic can be highly interesting once I get into it.
6. I find most new topics interesting and often spend extra time trying to obtain more information about them.
7. I do not find my course very interesting so I keep my work to the minimum.
8. I learn some things by rote, going over and over them until I know them by heart even if I do not understand them.
9. I find that studying academic topics can at times be as exciting as a good novel or movie.
10. I test myself on important topics until I understand them completely.
11. I find I can get by in most assessments by memorising key sections rather than trying to understand them.

12. I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra.
13. I work hard at my studies because I find the material interesting.
14. I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes.
15. I find it is not helpful to study topics in depth. It confuses and wastes time, when all you need is a passing acquaintance with topics.
16. I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined.
17. I come to most classes with questions in mind that I want answering.
18. I make a point of looking at most of the suggested readings that go with the lectures.
19. I see no point in learning material which is not likely to be in the examination.
20. I find the best way to pass examinations is to try to remember answers to likely questions.

Index of Learning Styles (Felder & Soloman, n.d.)

1. I understand something better after I
(a) try it out.
(b) think it through.

2. I would rather be considered
(a) realistic.
(b) innovative.

3. When I think about what I did yesterday, I am most likely to get
(a) a picture.
(b) words.

4. I tend to
(a) understand details of a subject but may be fuzzy about its overall structure.
(b) understand the overall structure but may be fuzzy about details.

5. When I am learning something new, it helps me to
(a) talk about it.
(b) think about it.

6. If I were a teacher, I would rather teach a course
(a) that deals with facts and real life situations.
(b) that deals with ideas and theories.

7. I prefer to get new information in
(a) pictures, diagrams, graphs, or maps.
(b) written directions or verbal information.

8. Once I understand
(a) all the parts, I understand the whole thing.
(b) the whole thing, I see how the parts fit.

9. In a study group working on difficult material, I am more likely to
(a) jump in and contribute ideas.
(b) sit back and listen.

10. I find it easier
(a) to learn facts.
(b) to learn concepts.

11. In a book with lots of pictures and charts, I am likely to
(a) look over the pictures and charts carefully.
(b) focus on the written text.

12. When I solve math problems
(a) I usually work my way to the solutions one step at a time.
(b) I often just see the solutions but then have to struggle to figure out the steps to get to them.

13. In classes I have taken
(a) I have usually gotten to know many of the students.
(b) I have rarely gotten to know many of the students.

14. In reading nonfiction, I prefer
(a) something that teaches me new facts or tells me how to do something.
(b) something that gives me new ideas to think about.

15. I like teachers
(a) who put a lot of diagrams on the board.

(b) who spend a lot of time explaining.

16. When I'm analyzing a story or a novel
(a) I think of the incidents and try to put them together to figure out the themes.
(b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.

17. When I start a homework problem, I am more likely to
(a) start working on the solution immediately.
(b) try to fully understand the problem first.

18. I prefer the idea of
(a) certainty.
(b) theory.

19. I remember best
(a) what I see.
(b) what I hear.

20. It is more important to me that an instructor
(a) lay out the material in clear sequential steps.
(b) give me an overall picture and relate the material to other subjects.

21. I prefer to study
(a) in a study group.
(b) alone.

22. I am more likely to be considered
(a) careful about the details of my work.
(b) creative about how to do my work.

23. When I get directions to a new place, I prefer
(a) a map.
(b) written instructions.

24. I learn
(a) at a fairly regular pace. If I study hard, I'll "get it."
(b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."

25. I would rather first
(a) try things out.
(b) think about how I'm going to do it.

26. When I am reading for enjoyment, I like writers to
(a) clearly say what they mean.
(b) say things in creative, interesting ways.

27. When I see a diagram or sketch in class, I am most likely to remember
(a) the picture.
(b) what the instructor said about it.

28. When considering a body of information, I am more likely to
(a) focus on details and miss the big picture.
(b) try to understand the big picture before getting into the details.

29. I more easily remember
(a) something I have done.
(b) something I have thought a lot about.

30. When I have to perform a task, I prefer to
(a) master one way of doing it.
(b) come up with new ways of doing it.

31. When someone is showing me data, I prefer
(a) charts or graphs.
(b) text summarizing the results.

32. When writing a paper, I am more likely to
(a) work on (think about or write) the beginning of the paper and progress forward.
(b) work on (think about or write) different parts of the paper and then order them.

33. When I have to work on a group project, I first want to
(a) have "group brainstorming" where everyone contributes ideas.
(b) brainstorm individually and then come together as a group to compare ideas.

34. I consider it higher praise to call someone
(a) sensible.
(b) imaginative.

35. When I meet people at a party, I am more likely to remember
(a) what they looked like.
(b) what they said about themselves.

36. When I am learning a new subject, I prefer to
(a) stay focused on that subject, learning as much about it as I can.
(b) try to make connections between that subject and related subjects.

37. I am more likely to be considered
(a) outgoing.
(b) reserved.

38. I prefer courses that emphasize
(a) concrete material (facts, dat(a).
(b) abstract material (concepts, theories).

39. For entertainment, I would rather
(a) watch television.
(b) read a book.

40. Some teachers start their lectures with an outline of what they will cover. Such outlines are
(a) somewhat helpful to me.
(b) very helpful to me.

41. The idea of doing homework in groups, with one grade for the entire group,
(a) appeals to me.
(b) does not appeal to me.

42. When I am doing long calculations,
(a) I tend to repeat all my steps and check my work carefully.
(b) I find checking my work tiresome and have to force myself to do it.

43. I tend to picture places I have been
(a) easily and fairly accurately.
(b) with difficulty and without much detail.

44. When solving problems in a group, I would be more likely to

(a) think of the steps in the solution process.
(b) think of possible consequences or applications of the solution in a wide range of areas.

Knowledge on Programming (Eleftherakis, George)

1. Write the "Hello World" program in any language you prefer
(text)

2. Provide a solution using pseudo-code to the problem "I want to go to school in the morning"
(text)

3. What is the output of the following program?

```
integer a = 10;
if (a >= 10*5)
a = a + 5;
a = a - 5;
print ("a");
```

a. I have no idea
b. 10
c. 5
d. 15
e. something else
f. not sure

4. What is the output of the following program?

```
integer a = 10;
while (a <= 10)
        print("Hi");
```

a. I have no idea

b. It will print “Hi” 10 times

c. It will print “Hi” only once

d. It will never print “Hi”

e. It will infinitely print “Hi”

f. It will do something else

5. What is the output of the following program?

```
integer a = 10;
integer b = 2;
if (b > 2 && a == 10)
        a = 4;
print(a*b);
```

a. I have no idea

b. a*b

c. 20

d. 8

e. Something else

6. What is the output of the following program?

```
integer a = 1;
integer b = 1;
while ( b < 11)
{
        if (b == a && a <= 1)
        {
                a = a*2;
        }
        b = b + 1;
        print( a + " * " + (b - 1) + " = " + a*(b-1));
}
```

a. I have no idea

b. It will print the multiplication table of all 10 first numbers

c. It will print the multiplication table of 1

d. It will print the multiplication table of 2

e. It will print something else

7. What is the result a computer will provide in the following operation?

   1 + 1 = ?

a. I have no idea

b. 2

c. 10

d. 11

e. Something else

f. A computer is not capable to respond to this without further info

Mentor Functional Evaluation (Eleftherakis, George)

1. I think that "Mentor" will allow me to focus to the aim and learning objectives of the unit.
2. I think "Mentor" will bolster my skills.
3. I like that "Mentor" enables visual and immediate output of my efforts.
4. I think "Mentor" is really easy to use with few minutes training.
5. I think "Mentor" has a fun factor.
6. I think "Mentor" will boost my creativity
7. I think "Mentor" will help me to achieve deeper understanding of the fundamentals of computer programming.
8. I think that the problems we have to solve with "Mentor" are easily understandable.
9. I think that "Mentor" is a tool that could be used to solve these problems no matter the programming experience of the user.
10. I think that Mentor allowed the introduction to the programming language in the first lecture and disguised the awkward syntax of the language, enabling me to experiment and engage early.

Mentor Technical Evaluation (Eleftherakis, George)

1. Mentor's graphical user interface is suitable for a learning system.
2. The program directions are clear.
3. Mentor supports interactivity between learners and system by the immediate feedback it provides through its visual output.
4. I have not faced any system errors on Mentor.
5. When I counter an error in the system, I can get immediate feedback my e-mail.
6. When I have errors in my code, Mentor's feedback helps me to identify were they are.
7. Navigation is very easy on Mentor.
8. I can find required information very easily on Mentor.
9. "Help" option is available on the system.
10. Mentor is a good educational tool and improves my learning