# Visualization and Numeracy in Consumer Decision Making

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The candidate confirms that the work submitted is his/her own and that appropriate credit has been given where reference has been made to the work of others.

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# Abstract

This thesis investigates the relationship between the cognitive style of visualization, composed of an Object and a Spatial component, and its effects on numeracy and numerical decision-making contexts. Extant research points to spatial visualization skills aiding numerical performance. However, the findings are not conclusive and only refer to spatial visualization as a skill, not as a cognitive style. The role of object visualization on numerical skills and numerical decision-making contexts has been ignored altogether by previous research. This work aims to fill these gaps in the literature.

Firstly, the relationship between Object and Spatial visualization as parts of a cognitive style was investigated, with all performed studies consistently supporting the idea that these are two independent mental constructs. The study of the relationship between numeracy and visualization revealed that, while higher Object visualization predicts lower scores in a numeracy test (Abbreviated Numeracy Scale, ANS), higher Spatial visualization predicts greater numerical ability in the same test. This result proved to be consistent across all the experiments in this study.

Having established the relationship between the ANS and visualization, this study extended the investigation to other numerical and graphical scenarios which resemble tasks that could be found in natural scenarios. The results showed that spatial visualization predicts better performance in numerical and graphical tasks beyond the ANS.

This thesis then extended the investigation to see whether the biases Peter et al. (2006) and Weller et al. (2012), which were found to be affected by Numeracy, were also similarly affected by visualization, therefore widening the potential impact of visualization on the field of Decision-Making. The results indicated that in a task with a normatively correct answer, spatial visualization predicted better performance, whereas numeracy or object visualization did not have this effect. In the tasks where only judgments of preference or attractiveness were elicited, neither numeracy nor visualization predicted preferences or attractiveness.

Finally, this study investigated whether the cognitive style of visualization had an effect on individuals' weighing information consistent with their cognitive style more heavily. In a task where participants saw information in the form of tables or graphs, accompanied by a human figure, it was found that neither spatial or object visualization preference seemed to influence the weighing of object or spatial information.

Overall, this thesis demonstrates the relationship between numeracy and visualization style, and is the first investigation demonstrating how visualization cognitive style is related to numeracy and how a person's visualization cognitive style affects Decision-Making tasks. The close relationship found between Spatial visualization and Numeracy, with Spatial visualization in some cases predicting results where Numeracy failed to show a differential effect, also opens the door to further consideration of the use and creation of Spatial visualization measures to be used instead of Numeracy scales in the numerical decision-making contexts.

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# Chapter 1

# Introduction

The object of this thesis is to investigate the recently recognized and operationalized cognitive style of Object and Spatial visualization in numerical decision-making contexts. As we will see in the literature review that follows, there are bases to hypothesize a relationship between visualization style and numerical abilities, namely, Spatial visualization being positively related to numerical performance. As will be detailed in the following chapters, previous research (Peters et al., 2006; Weller et al., 2012) has found that an individual's numeracy is a predictor of choices and attractiveness in some numerical decision-making tasks.

Visualization is a factor that may potentially affect decision-making, and identifying such factors and their role in decision-making is important. After all, decisions are made every day. Some of these decisions, such as which sweater to wear, may seem trivial. Others, such as how to invest one's personal savings, gain increased importance in our daily wellbeing. And yet others, such as those in the field of medical decision-making (e.g. which cancer treatment to follow) may determine our chances of survival. Our understanding of the processes affecting judgments and decisions may have a potentially important impact on the lives of ordinary people. An element of particular importance which may influence decision-making is a person's cognitive style. That is, the psychological construct that describes an individual's cognitive functioning, and is a consistent individual measure of how people organize and process information (Ausburn & Ausburn, 1978; Kozhevnikov, 2007; Messick, 1976, 1984). However important an individual's cognitive style might be in determining decision making (Messick, 1976; Kozhevnikov, 2007), the study of individual differences, particularly the study of cognitive styles in the field of Decision-Making, has been largely neglected. As Mohammed & Schwall (2009, p. 249) argue, "*(…) it seems almost commonsensical that individual differences would affect decision-making processes and outcomes. Surprisingly, however, there has been a longstanding reluctance to incorporate individual differences into the study of decision making*."

This thesis will add to the scant body of knowledge on cognitive styles and judgment and decision-making.

## *1.1 Cognitive Styles*

Research on cognitive styles agrees that a cognitive style is an innate and stable individual trait (Messick, 1976; Thornell, 1976; Allinson & Hayes, 1996; Kozhevnikov, 2007) which may inform decision-making in a manner that could predict behaviour more reliably than other types of individual attributes such as skills. Whereas a skill may be modified by training, education, socialization, etc, a cognitive style is a more basic construct, ingrained in the individual. It would be reasonable to assume that a skill changing due to the aforementioned factors of training, exposure, etc, might not be a stable dimension for predicting behavior unrelated to the specific skill. Therefore, while a skill might have the potential to predict a given behavior or decisions at a given time, the underlying psychological construct, being more permanent, has the potential to be more reliable in informing predictions about individuals’ decision-making.

As we will argue hereon, there is scant research on the factors that might modify one´s cognitive style. One of the premises held by researchers in the area of cognitive styles is that a cognitive style is unique to an individual, who possesses a preferred manner in which she acquires, processes, and makes use of information. However, although there is not a coherent body of literature directly addressing the possibility of modifying one´s cognitive style, one could conjecture that a cognitive style is malleable. In fact, some research in the area of learning might suggest that an individual´s approach to acquiring information might evolve with experience (Kolb, 1984).

However, due to the aforementioned lack of research specifically addressing the possibility of cognitive styles being modifiable, for instance through training, it is therefore difficult to take a theoretical stance based on extant research. The very question merits in-depth investigation that would exceed the scope of the current thesis. In fact, uncovering whether there are factors that might change one´s cognitive style could be not only the subject of a thesis, but even an entire line of research worth pursuing.

In the literature review and subsequent chapters we will argue that this research is about one´s cognitive style in the way it is present at the moment of our studies. The current research understands cognitive style as defined in the literature and for the purposes of this research an individual´s cognitive style, one could say, will constitute a picture of an individual´s style at the time of doing this project, at a certain time in the life of participants. The results, thus explain how her cognitive style of visualization may affect numeracy and decision making at this particular point in time.

As we have previously argued, despite the aforementioned lack of thorough research that the study of cognitive styles has suffered in the specific area of Judgment and Decision Making (JDM), the importance of such individual characteristics has been recognized by researchers in other areas. For instance, Kozhevnikov (2007, p. 464) argues that *"In the field of industrial and organizational psychology, cognitive style is considered a fundamental factor determining both individual and organizational behavior (e.g., Streufert & Nogami, 1989;Sadler-Smith & Badger, 1998; Talbot, 1989)".* And, although lacking extensive research in the particular area of JDM, recent arguments acknowledge that personal characteristics, along with environmental and task influences, are some of the elements which affect decision-making (Mohammed & Schwall, 2009). Paralleling an earlier similar argument by Messick (1976), some authors argue that the potential impact of the study of cognitive styles on decision-making stems from the fact that "*cognitive styles serve as high level heuristics in complex processes that are applied spontaneously across situations and form an enduring basis for behaviour*" (Armstrong, Cools & Sadler-Smith, 2011, p.1). Cognitive styles, therefore, form a basis which informs the decision-making process.

As we will see in the continuing literature review, information consistent with a decision-maker's cognitive style has a heavier influence on decisions than information that is not consistent with her cognitive style. The importance of this matching has been recognized in literature in fields such as Marketing, Advertising and Management. As we will later argue, the study of cognitive styles in the context of decision-making processes has not only theoretical implications, but also practical ones. From a theoretical perspective, the study of the impact of cognitive styles in decision-making will contribute to the creation of a body of knowledge that has been largely neglected. From a practical standpoint, predicting behaviour based on cognitive styles and how different types of individuals make judgments and decisions based on information that is consistent with their cognitive style may help create more effective communication strategies in fields such as public communication, marketing and advertising of products, etc.

## *1.2 Visualization Style*

Many of the relevant decisions we make in our everyday life involve the use and interpretation of numbers. As we will see more thoroughly in the following literature review, previous research has found increased spatial visualization abilities to be correlated with a higher ability to deal with numbers (Hegarty and Kozhevnikov, 1999). This finding hints at the possibility that the cognitive style of visualization, particularly its spatial component, might be related to an individual's visualization style.

Despite the potential importance that mental visual imagery can have in numerical decision-making tasks, to the best of our knowledge, the field of JDM has no study investigating the effects of the cognitive style of visualization in decision-making in general and in particular in numerical decision-making scenarios. This lack of research on the cognitive style of visualization in decision-making and numeracy is not surprising, taking into account the novelty of the construct and its recent operationalization.

Although some tests measuring the spatial visualization skills of individuals have existed for a long time, Spatial Visualization was measured as a skill, and therefore was subject to being greatly affected by many external factors to the individual such as training or age. In addition, the object visualization of an individual was not measured using a scale. We argue in this thesis that the limitations of the body of knowledge on the effects of visualization style and numeracy and decision-making are therefore evident, and this work represents a first step towards filling this gap.

The limitation of the absence of a test that could reliably assess an individual's trait of visualization was overcome by Blajenkova, Kozhevnikov & Motes (2006) with the creation of the Object-Spatial Imagery Questionnaire (OSIQ). Until then, instead, visualization was understood as a unitary dimension, part of the Verbalizer-Visualizer dichotomy, and the two components of visualization (Object and Spatial) had not been identified as separate and distinguishable parts of visual imagery. Very recently, the creation of the Object-Spatial Imagery and Verbal Questionnaire (OSIVQ) incorporated the study of the verbal dimension, finding that there was no such dichotomy between verbalization-visualization and that these were three different mental constructs (Blazhenkova & Kozhevnikov, 2009).

The clear definition of the cognitive style of visualization by the OSIQ, later on reaffirmed by the OSIVQ, opens up a new door to investigate whether the two components of visualization do indeed have an effect in numerical decision making contexts; if, as some literature argues (Hegarty and Kozhevnikov, 1999) spatial visualization skills are positively related to numerical performance, and numerical performance affects decision-making tasks

(Peters et al. 2006, Weller et al. 2012) this could mean that spatial visualization may have an effect on numerical decision-making tasks. As for object visualization, however, the relationship between this construct and numeracy is difficult to hypothesize due to the lack of literature for the establishment of a theory from which hypotheses could be derived. These points are precisely what this thesis will investigate. First, the relationship between numeracy and spatial and object visualization style will be investigated and, later, the use of spatial and object visualization style as a variable to account for in decision-making will be validated.

## *1.3 Numeracy*

Numeracy, defined in the literature as an individual's ability to understand basic numerical concepts with the objective of enabling the individual to "*deal comfortably with the fundamental notions of number and chance*" (Paulos, 1988, p. 3) to solve daily life problems has been found to influence the judgment and decision-making of individuals.

In today's data-driven society, individuals are increasingly reliant on numbers to make decisions. From choosing a mobile phone plan, a pension scheme, or simply calculating the tip at a restaurant, the use of numbers to make decisions informs many of our daily activities. Despite the importance of a good mastery of numbers, relatively few people possess sufficient numeracy skills to cope with the ever increasing demands to deal with numerical information in our daily lives (Cohen, 2001; Dieckmann, 2008).

Until 2006, the importance of numeracy in the field of JDM was mostly focused on the importance of numerical abilities in the area of medical decision-making. In a seminal study departing from the tradition of studying numerical decision-making only in a medical context, Peters et al. (2006) set to investigate whether numerical abilities influenced decision-making. A set of four studies showed that having higher numerical abilities translated to reduced attribute framing and in higher numerates being able to draw stronger affective meaning from numbers as well as reporting higher affective precision (clarity of their feelings) when facing numerical decision-making tasks.

A form of presenting numerical information is the use of graphs. To facilitate the understanding of numerical information in daily life tasks, much numerical information is conveyed in this manner (Ratwani, Trafton & Boehm-Davis, 2004; Galesic & Garcia-Retamero, 2011). This way of presenting numerical information demands new cognitive skills. As Ratwani, Trafton & Boehm-Davis (2004, p.1) put it, "I*n order to be able to function in this data rich world, it is imperative that we have the necessary skills to interpret these graphs*". For the correct interpretation of graphs and to draw inferences about the numerical data which they convey, people carry out mental spatial transformations on the data they see before them (Trickett & Trafton, 2004; Trafton & Trickett, 2006).

As we have previously mentioned, and which will be more thoroughly developed in the literature review that follows, a positive relationship between spatial visualization and numeracy can be hypothesized. Preference for spatial visualization predicts higher spatial visualization skills (Blajenkova, Kozhevnikov, and Motes, 2006), which in turn rely on spatial cognition, a key element for graph interpretation (Tricket & Trafton, 2006). This leads to the proposal that visualization cognitive style, particularly its spatial component, might be related both to number and graph processing. However, the importance of this individual trait has not been studied in its relationship with number and graph processing in general, and in judgment and decision making tasks in particular. The chapters outlined in the next section set out to overcome this limitation in the literature.

## *1.4 Organization of next chapters*

In order to analyze the importance of the cognitive style of visualization in numerical processing and in judgment and decision making, this thesis is composed of eight chapters which offer a perspective on the importance of the topic. The literature review will highlight extant research and its limitations, and will address the importance and place of visualization cognitive style in the current research environment. Finally, a series of experiments are designed to understand whether visualization affects numerical understanding, and whether this has an impact on judgment and decision making. The thesis will conclude with a discussion integrating the findings of this research and its overall picture in the field of judgment and decision making.

In the following, Chapter 2 will offer a comprehensive literature review, defining first the concept of cognitive style in general, and how cognitive styles have been shown to affect judgment and decision making, particularly in the fields of Marketing and Advertising, and Management. This review will carry out the definition and specification of the two components of the cognitive style of visualization: Object and Spatial visualization. Chapter 2 will then explain how these two constructs stem from biological bases, and are therefore a potentially strong predictor of numerical and graph understanding and consequently of judgment and decision-making in such settings.

Despite the identification of the object and spatial components of visualization, the relationship between these two constructs is not yet entirely clear. The scant existing research on object and spatial visualization as components of visualization cognitive style presents conflicting arguments. Whereas some authors (Kozhevnikov, Hegarty & Mayer, 2002; Kozhevnikov, Kosslyn & Shephard, 2005) argue that object and spatial visualization are at two ends of a continuum on the dimension of visualization, other research (Chabris et al., 2006; Blazhenkova & Kozhevnikov, 2009) found that such a dichotomous relationship is not warranted. Part of the experimental research of this thesis will be devoted to the study of whether object and spatial visualization are at two opposite ends of the visualization dimension, or whether they are two separate and independent constructs, therefore contributing to the existing literature on the matter.

As it will be later argued in Chapter 2, visualization has the potential to affect numeracy. In particular, spatial visualization skills have been shown to relate to numerical ability. However, as it will be explained in more detail in the literature review section, although some research does indeed find a positive relationship between spatial visualization skills and numerical abilities, such a relationship is not as straightforward as some studies claim, with the scientific evidence for such a relationship being overstated by some authors (e.g. Hegarty and Kozhevnikov, 1999). In any event, whereas it could be argued that there exists a positive relationship between spatial visualization skills and numerical ability, the relationship between visualization as a cognitive style and numerical ability has not been studied.

Because spatial visualization skills and preference for spatial visualization are correlated (Blajenkova, Kozhevnikov, & Motes, 2006; Blazhenkova & Kozhevnikov, 2009), it could be hypothesized that preference for spatial visualization would also be positively correlated with numerical abilities. However, this point has never been investigated. The relationship between preference for object visualization and numerical ability is another point of interest that has not been addressed in the literature. These gaps constitute a further research question that will be addressed in this thesis.

Finally, Chapter 2 will review extant literature on numeracy in general and, in particular, on the importance of numeracy in the field of JDM. As we will see, the study of numeracy in the context of Judgment and Decision Making was originally focused on the area of medical decision making. Only recently did Peters et al. (2006) start the investigation of the effects of numeracy in non-medical decision-making scenarios, showing that higher numeracy is associated with lower framing effects (Levin, Schneider & Gaeth, 1988) and with more precise feelings derived from numerical evaluations.

Chapter 3 will explain the research questions that compose this thesis, providing a motivation to study each of these questions, and the importance that answering each of them has in the body of literature on cognitive styles, judgment and decision making, and numeracy.

The empirical investigation of research questions will start in Chapter 4, which will try to shed light on the relationship between object and spatial visualization, and whether the evidence points to these being two independent constructs or two ends of a continuum along a line of visualization. In addition, Chapter 4 will check for the relationship between object and spatial visualization, and numeracy. As previously stated, whereas there is some indication in the literature that preference for spatial visualization might be positively related to numerical abilities, no studies until now have investigated whether this is the case. In addition, the relationship between preference for object visualization and numeracy is a research question that lacks any previous evidence in the literature.

In Chapter 5 a series of experiments will be created to investigate the value of visualization style with regard to perception of the positivity or negativity of a company's results when they are presented in a tabular format. Following the investigation of the effects of visualization style when appraising tabular information, a second task in Chapter 5 will analyze whether people with differing visualization styles are able to predict the future values in a series of data presented in a tabular format. Continuing with the effects of visualization style on numerical and graphical tasks, Chapter 5 will investigate whether visualization style affects the judgments and appraisal of distorted or undistorted bar graphs. This information will be provided in the form of bar graphs with either the Y-axis truncated or with the Y-axis starting from 0, therefore distorting the graph slope without changing the values of the data on the Y-axis; this manipulation will allow investigation of whether individuals pay more attention to the absolute values of the Y-axis or to the slope presented in the graph depending on their visualization style. The last task in Chapter 5 will investigate whether visualization style affects people's ability to correctly identify the correct graph corresponding to data displayed on a table.

The investigation of the influence of visualization in a series of decision making tasks is undertaken in Chapter 6, where the experiments carried out by Weller et al. (2012) and Peters et al. (2006) are replicated to check for the effect of visualization style on a series of four tasks. Task 1 investigates the effects of visualization style on attribute framing effects (Levin & Gaeth, 1988). In Task 2 this thesis investigates visualization in the context of the paradigm originally developed by Slovic, Monahan & MacGregor (2000) in which people's risk assessments were demonstrated to vary depending on whether they received information presented in a probabilistic (10%) or frequentistic (1 out of 10) format. From here the research will move on to investigate Peters's et al. (2006) third task, based on the paradigm developed by Denes-Raj & Epstein (1994), in which participants are asked whether they would pick a colored jelly bean from a bowl A, containing 1 colored and 9 blank balls, or from a bowl B, containing 9 colored and 91 uncolored jelly beans. Finally, the third task replicated from Peters et al. (2006) and Weller et al. (2012) consists of a paradigm originally designed by Slovic et al. (2004), which found that people value a roulette bet with a small loss as more attractive as opposed to the same bet with no loss of money. In this task, both authors found that high numerates experienced this effect more than low numerates. Chapter 6 will analyze whether visualization affects the aforementioned tasks.

Concluding the experimental part of the thesis, Chapter 7 will check whether the cognitive style of visualization conforms to the assumption held by extant literature affirming that information consistent with one's cognitive style has stronger weight in judgments than information inconsistent with one's cognitive style. To that end, Chapter 7 reports the result of an experiment where participants evaluate the results of a company based on financial data presented in a graph or tabular format, and with (or without) an accompanying businesswoman-looking figure in a positive or negative demeanour in such a manner that she will display an image either consistent or inconsistent with the hedonic valence of the trend depicted by the graph or table. Since the female figure basically constitutes a form of Object information, as a face as a stimulus is rich in details and aesthetical aspects, this will serve to check whether a match between cognitive style and input of information results in heavier weighting of the consistent information.

Finally, the concluding Chapter 8 will put together the findings of this thesis and discuss them in light of extant research, pointing to the unique contributions of this piece of work. In addition the discussion chapter will point to the limitations of the current study as well as suggesting future directions that research in this area could take in the quest for enlarging the body of knowledge in the field of Cognitive Styles and Judgment and Decision Making.

# Part I

# Background

# Chapter 2

# Literature Review

This chapter reviews extant research on the cognitive style of visualization and its potential relationship with numeracy, identifying existing gaps in the literature and proposing a series of research questions not currently addressed.

As we have argued in the prior introduction and we further elaborate in the literature review that follows, visualization is a cognitive style whose definition and operationalization has been only recently developed, therefore leaving a wealth of research questions which can be addressed to help inform the literature in the area of Decision-Making. As we will argue, although visualization as a cognitive style has been well defined, there is conflicting evidence about the interrelationship of its constructs (object and spatial visualization). Our investigations will contribute to this body of knowledge.

As we will also see, object and spatial visualization appear to have biological bases, with the areas in charge of object and spatial visualization processing also being involved in the processing of other information. For instance, extant literature points to spatial visualization ability being positively correlated with mathematical ability, though the extent of such relationship in some occasions may not be completely justified by authors claiming such link and some assertions seem to be overstated and not fully substantiated. As previously pointed in the introduction section, no research has so far investigated the relationship between spatial visualization as a cognitive style and numeracy, with most research having been conducted on the relationship between the skill of spatial visualization and numeracy.

Although the wealth of extant research addressing the relationship between spatial visualization skills and numeracy allows to make predictions about what the relationship with the cognitive style of spatial visualization might be, when it comes to hypothesize the relationship between object visualization and numeracy the situation is not as clear, as there are no prior studies investigating this matter using object visualization either as a skill or as a cognitive style. We will therefore dedicate one of the coming research questions to investigate the relationship between numeracy and spatial and object visualization style.

As we will argue, investigating a cognitive style rather than an ability might be helpful in pinning down the relationship between these constructs and uncovering the relationship between the underlying psychological constructs (instead of abilities). This may provide more information on human behaviour, since the mode of processing information could inform how people might react to information that is consistent or inconsistent with their cognitive style. Therefore, the cognitive style of visualization may be a suitable construct to use in order to make predictions of human behaviour.

If there is indeed a relationship between the cognitive style of visualization and numeracy, there is no reason to think that visualization should not also affect numerical decision-making tasks, as evidence indicates that numeracy does affect decision making. The next sections will investigate empirically whether the assumed relationship between visualization and numeracy does indeed exist and whether visualization style affects decision making tasks.

Finally, we will also address in the literature review the evidence pointing to a given cognitive style determining the evaluation of information, particularly the aforementioned phenomenon of the tendency individuals have to give heavier weight to information consistent with their cognitive style. If that is the case, by presenting conflicting object and spatial information to individuals, we might be able to detect which information they pay attention to depending on the preference for object and spatial visualization, and how this impacts judgment and decision making.

These issues have both academic and practical implications. The study of visualization as a recently operationalized cognitive style, with its division into the object and spatial components, is still in its infancy. From a theoretical standpoint, this thesis will contribute to the academic knowledge on this cognitive style and may inform and guide future research. From a practical perspective, understanding how different numerical information presentation formats (graphs or tables) are understood and acted upon by people with different visualization cognitive styles may help in the crafting of this information more effectively. This would be particularly important, since very often people need to interpret numerical and graphical information and make decisions based on it.

## *2.1 Cognitive Styles*

A Cognitive Style has been defined in the literature as a psychological construct that describes an individual's cognitive functioning and that is a consistent individual measure of how people organize and process information (Kozhevnikov, 2007; Messick, 1984). As Steers (1988) put it, a cognitive style is ‘*the way in which people process and organize information and arrive at judgments or conclusions based on their observations of situations’* (p. 131). Similarly, Ausburn & Ausburn (1978), argue that a cognitive style represents the way in which an individual consistently processes and acquires information. In line with these definitions, Messick (1976) argues that a cognitive style is the set of stable preferences, attitudes and strategies whereby a person processes information, particularly in the tasks of perception and problem solving. In this fashion, a Cognitive Style would constitute a person’s preferred way to acquire and process information. That is, a Cognitive Style reflects “*´How´ rather than ´how well´ we perceive and judge information. It emphasizes individual traits rather than cognitive ability, focusing on ´preferred styles´ as opposed to ´more is better´ psychometric measures such as IQ”* (Hough and Ogilvie, 2005, p. 421).

Consistent with the previous literature, Witkin, Moore, Goodenough, and Cox (1977, p.7) affirm that “*people are likely to be quite stable in their preferred mode of perceiving, even over many years*”. This view is again adopted by Mesick (1984) when defining Cognitive Styles as “*characteristic selfconsistencies in information processing*” (p. 61).

It is apparent from the literature on Cognitive Styles that there is a collective view of a Cognitive Style being stable across time (Allinson & Hayes, 1996; Sadler-Smith, 1998), with authors traditionally assuming the role of individual traits in processing information as an invariable one. This assumption of an individual’s way of processing information being a stable trait permeates through the literature on Cognitive Styles.

Although it is apparent that the stability of a person's cognitive style is not questioned by the literature, the fact that extant research does not question the permanence of an individual´s cognitive style does not mean that the preferred way in which a person processes information could not be modified. In fact, some literature tangential to the area of Cognitive Styles might indirectly question the view of a Cognitive Style being perennial. Particularly, work in the area of Learning Styles by Kolb (1984) has put forth Experiential Learning Theory (ELT, Kolb, 1984). According to ELT, an individual's approach to processing information and acting upon it varies according to experience, and the ensuing learning process is then applied when new situations are encountered. According to ELT, a Concrete Experience of a learner would lead to a process of Reflective Observation, which would conduce to Abstract Conceptualization, from which Active Experimentation would follow. This cycle would repeat every instance an actor finds a novel situation where the cognitive processing of information occurs (see Figure 2.1.1).

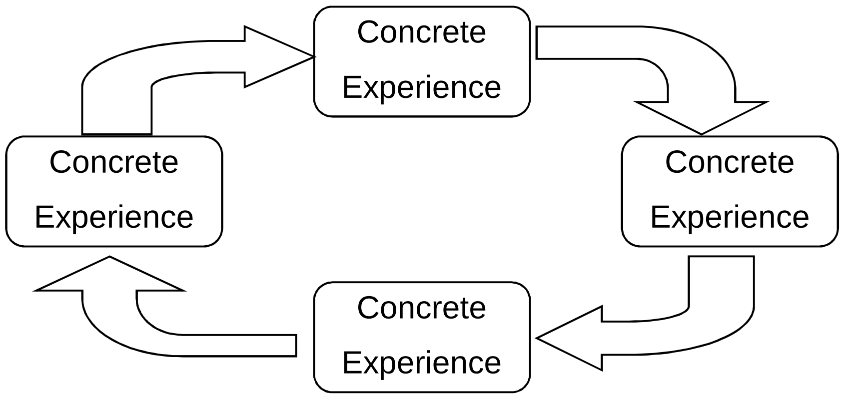



**Figure 2.1.1** Kolb, 1984 Experiential Learning Theory (ELT) model of Learning

Although this process does not indicate that one’s “preferred” way of processing information will definitely be affected, it offers a plausible mechanism whereby the “actual”, if not the “preferred”, way of processing information might evolve according to what has in the past yielded the best outcome. In fact, although Kozhevnikov (2007) concedes that a cognitive style would serve to adopt a strategy to problem solving consistent with one´s cognitive style, a strategy does not need to be permanent and can be modified according to whether it´s a satisfactory one to solve the cognitive problem at hand.

Another plausible mechanism whereby a cognitive style could be modified is through training. For instance, it has been documented that spatial abilities can be improved by training (Uttal et al., 2013). After performing a meta-analysis on 217 studies investigating the effects of training on spatial skills, Uttal et al. (2013) concluded that training does indeed improve spatial skills and that the effects of training are durable. It would be reasonable to think that once a person is trained they will use the newly acquired skills to deal with situations that resemble the trained scenarios.

Despite the aforementioned arguments that point to the possibility of individuals dealing with cognitive tasks according to experience and/or training, to the best of our knowledge the literature has never directly investigated the question of whether a Cognitive Style, that is the “preferred” way in which an individual processes information, is modified through experience or training. Although there are arguments that make it plausible that the “actual”, which might not be the “natural” or “preferred”, way of processing information might be modified by experience, the term Cognitive

Style has been referred to in the literature as a stable one across time within an individual. Maybe Cognitive Style and Cognitive Strategy might be two related concepts, with Cognitive Style giving raise to Cognitive Strategies (Kozhevnikov, 2007), which in turn could be modified through experience (Kolb, 1984) or training (Uttal et al. 2013).

In any event, the purpose of the current thesis is to investigate Cognitive Styles, particularly the Cognitive Style of Visualization, which have been the object of rather extensive research and are well documented in the literature. Venturing to investigate whether Cognitive Styles might (or might not) be modified through training or experience could be the subject of an entire, and one must concede, interesting, different research project, though at this point one can only form conjectures about the matter.

## *2.2 Cognitive Styles and Decision Making*

The importance of a cognitive style in determining decision-making has been recognized by scholars. As Kozhevnikov (2007, p. 464) argues, "*In the field of industrial and organizational psychology, cognitive style is considered a fundamental factor determining both individual and organizational behaviour*". For instance, Blaylock & Rees (1984) found that an individual's cognitive style determines what information she considers important in a decision making scenario. Specifically, in a merger and acquisition simulated scenario, Blaylock & Rees (1984, p. 74) found that when presented with information about such a setting, individuals characterized as having a "feeling" cognitive style (characterized for their reliance on affective process and personalistic evaluations –good/bad,  like/dislike) identified information about the welfare of workers and the community as more useful than individuals with a “thinking” style (characterized by a systematic cause-and-effect analysis and impersonal, true-false, evaluation of information). To illustrate a practical implication of their research, Blaylock & Rees (1984, p. 88) concluded that “*There is no sense providing information to a decision maker whose cognitive make-up is such that he or she will ignore it*.” Although the extant literature does not argue that information inconsistent with one’s cognitive style will be ignored outright, the evidence does point to a clear downplaying of such information by decision makers.

The previous findings are consistent with Hunt, Krzystofiak, Meindl & Yousry (1989), who found that in a simulated decision-making task where participants were shown a situation in which advice was given on payoff strategies in international business deals, experimental subjects consistently chose the advice that matched their cognitive style. In this case, the cognitive styles were Analytic (characterized by attention to detail when gathering information) and Intuitive (characterized by focusing on patterns). Hunt et al. (1989) presented participants with a task where the top management of a company had to decide on the policy about payoffs directed towards obtaining government favours in a South American subsidiary. To decide on such a policy, participants read the counsel of advisors who presented information consistent with either an analytical or an intuitive style. The results indicated that analytic and intuitive types differed in their choice of advice. Specifically, the analytic types were more likely to choose the advice given by the “analytic” advisors, whereas the intuitive types tended to choose the advice given by “intuitive” advisors.

Similarly, Henderson & Nutt (1980) found that in (fictitious) capital expansion projects in hospitals and firms, the cognitive style of participants was decisive in the choice individuals made. Specifically, in the “sensing” category (individuals who prefer detailed, structured, routine, and exact processing of information) people could be further classified as “thinking” (preference for impersonal, pragmatic, logical analysis of information) and “feeling” types (preference for feelings and emotions in evaluating information). According to Henderson & Nutt (1980), the sensing-thinking types, probably perceiving that there were insufficient elements to make a thorough appraisal of the investment scenario (as interpreted by Henderson & Nutt, 1980), were in general more risk averse and inclined to forgo the adoption of new projects. In contrast, those with the feeling style showed the opposite pattern. This constitutes another example of how individuals with different cognitive styles process the same information differently, giving more weight to the parts that are consistent with their cognitive style and ultimately arriving at different decisions.

More recent studies investigating cognitive styles and decision making (Sojka and Giese, 1997; 2006), argue that consumers can be classified into four types depending on their Preference for Affect or Need for Cognition and whether they are high in one of these dimensions, in both, or low in one or both. These types would be Feeling Processors, Thinking Processors, Combination Processors, and Passive Processors (Figure 2.2.1).

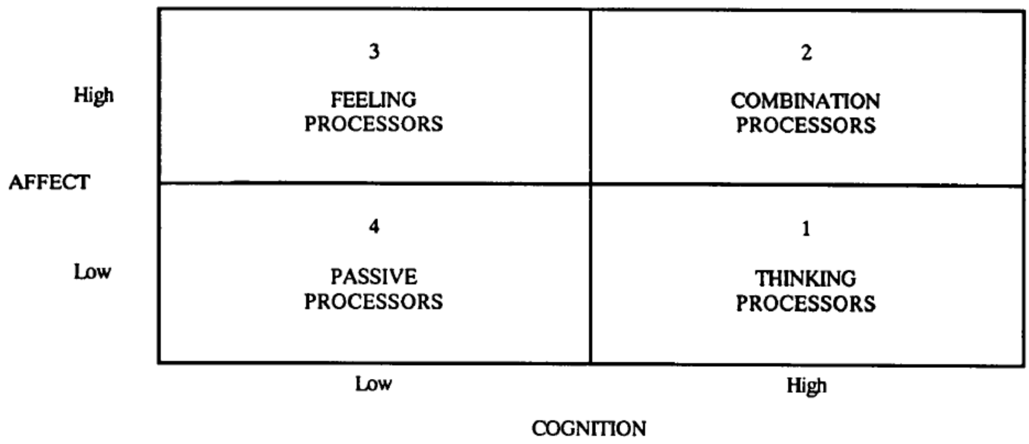



***Figure 2.2.1*** Sojka & Giese (1997) classification of individuals according to their Preference for Affect and Need for Cognition.

A study on the consequences of this classification showed that matching the consumers' cognitive style and product information "generates more positive attitudes towards a brand, purchase intention, and brand choice" (Ruiz & Sicilia, 2004, p. 657).

Consistent with Ruiz & Sicilia's (2004) findings, Thompson & Hamilton (2006, p. 531) affirm that, "*consistency between the type of information provided and the mode of information processing used by the consumer is an important predictor of persuasion*." Further, Thompson & Hamilton (2006) argue that influencing consumers depends on information being easy to process, and this ease of processing is facilitated when there is congruence between an individual's cognitive processing mode and the type of information available. Thompson & Hamilton (2006) tested their proposal, instructing participants to either imagine driving a car from an advert (imagery processing) with only information about the model, or factually checking the characteristics of this car compared to competitors (analytical processing). The authors argued that analytical processing was consistent with performing a comparison between brands, as the task involves a check between informational items, whereas imagery processing was not. They found that matching the type of ad to the style of processing resulted in easier processing and enhanced Attitude to ad, Attitude to brand, and Purchasing Intention.

The effect of cognitive styles on human behavior goes beyond decision making tasks and extends to other domains where cognition plays a role. Taking, for instance, the cognitive activity of learning, Hayes and Allinson (1994, p. 67) affirm that "*There is a widely shared view that people will learn much more effectively when the learning environment matches their cognitive style*." This affirmation is indirectly supported by Billington, Baron-Cohen, & Wheelwright (2007), who argue that individuals who prefer information processing in a systematic manner tend to choose academic careers such as engineering, because the way to solve problems in this discipline requires this systematicity, and individuals high in the dimension of systemizing find these careers both easier and more appealing. In contrast, "empathizing" individuals tend to choose studies in humanities.

As we have seen, cognitive styles have an influence on people's decision making, with people making decisions and judgments weighing information that is consistent with their cognitive style more heavily. The study of cognitive styles can therefore inform our understanding of how people make decisions and make predictions of what information people will evaluate when facing a decision. Although in principle correctly identifying individuals according to their cognitive styles might seem difficult, the use of proxys to identify them (e.g. professional career) could be useful and might allow organisations to craft more effective communications in line with the presumed cognitive style of the audience (e.g. engineers vs. historians). Providing individuals with information consistent with their cognitive style might therefore make more compelling arguments and in turn this would help enhance the impact of communications.

## *2.3 Visualization as a Cognitive Style*

As we have previously argued, decision making is influenced by cognitive style, which is a psychological dimension that consistently represents a person's cognitive functioning process, in particular the way in which she acquires and processes information. There has been a recent interest in research on the cognitive style of visual imagery. Basing their definition on Kosslyn's (1995) work, Hegarty and Kozhevnikov (1999, p. 684), define visual imagery in the following terms: "*Visual imagery refers to the ability to form mental representations of the appearance of objects and to manipulate these representations in the mind*". According to the recent research which we will review below, individuals vary in the degree to which they prefer object or spatial visualization.

One of the cognitive styles investigated from early on in the literature characterized people based on their preference for either verbal or visual information (Paivio, 1990). However, more recent research (Blajenkova et al. 2006; Hegarty & Kozhevnikov, 1999) has fine-tuned that classification and argued that visualization is composed primarily of two components: a spatial and an iconic component. For instance, early work by Kozhevnikov, Hegarty, and Mayer (2002, p. 48), mentions the term visual imagery as referring to "[…] a representation of the visual appearance of an object, such as its shape, size, color, or brightness. Spatial imagery refers to a representation of the spatial relations between parts of an object, the location of objects in space and their movements [...]”. This earlier definition of the two types of imagery likened “visual imagery” to what later the same authors would indistinguishably name “object” or “iconic” visualization. Related literature also defines “object” as pictorial or concrete imagery, and “spatial” as schematic, pattern, or dynamic imagery (see Table A.1., Appendix A for a definition of terms as they appear in the literature). The literature review that follows will use the terms as they appear in the original research cited, although they correspond to “object” and “spatial” visualization as referred to above.

The recent study of visualization preference and the classification of individuals as object and spatial visualizers stems from neuropsychology research, which identifies two types of brain structures which are in charge of processing spatial and iconic information. Kozhevnikov et al. (2002) developed their assumption of two visualization systems starting from biological bases.

According to neuropsychological research, the brain has two different functional and physical pathways which encode object and spatial relations (Haxby et al. 1991; Kosslyn & Koenig, 1992; Ungerleider & Mishkin, 1982). Specifically, as Kozhevnikov et al. (2005, p. 711) argue, “*the object pathway runs from the occipital lobe down to the inferior temporal lobe and has been called the ventral system; this system processes properties of objects, such as shape and color. The spatial relations pathway runs from the occipital lobe up to the posterior parietal lobe and has been called the dorsal system; this system processes object localization and spatial attributes*”.

Further evidence points to the existence of brain structures in charge of processing either pictorial or spatial information. For instance, studies using neuroimaging techniques (Uhl, Goldenberg, Lang, & Lindinger, 1990) found that the parietal lobes are activated when a person visualizes spatial information such as a route on a previously memorized map. In contrast, the temporal lobes are active when a person mentally pictures colors or faces. More neurological evidence from humans and monkeys provides strong support for the involvement of the parietal cortex in the processing of spatial relations, while the temporal cortex is involved in the processing of information related to forms, patterns and objects (Ungerleider and Mishkin, 1982; Jonides & Smith, 1997; Kosslyn & Koenig, 1992; Farah et al., 1988).

However, as Farah et al. (1988) argue, older research in imagery did not account for this new division of imagery into these two sub-components. This lack of specificity in the definition of the mental imagery structures may have led to confusion in the literature. For instance, in a study prior to the development of the cognitive style of visualization and the division of visualization into its object and spatial components, Lean & Clements (1981) did not make a distinction between Object and Spatial visualization. Instead, Lean & Clements (1981) treated visualizers as one single category, and argued that visualizers do not have better spatial ability skills than verbalizers. This failure to take into consideration the two components of visualization might have been what caused a contrast with more recent findings that take into account the differentiation between spatial visualization, object visualization, and verbalization. Specifically, Blazehenkova & Kozhevnikov

(2009) found that preference for verbalization was negatively correlated with spatial visualization, but not with object visualization.

Evidence from research on memory also points to the differentiation between visual spatial and visual iconic brain processes. Memory researchers hypothesize the existence of a Central Executive, which controls the functioning of two systems: the phonological loop (which processes verbal information), and the visuospatial sketchpad (which processes visual and spatial information). According to Baddeley & Lieberman (1980), the visuospatial sketchpad should not be understood as a unitary structure or system in charge of processing only one undifferentiated type of imagery. Instead, Baddeley & Lieberman (1980) argue, the visuospatial sketchpad is composed of two parts in charge of processing, respectively, spatial and pictorial information. This view is consistent with the previously cited literature that identifies two brain structures in charge of processing visual iconic information (faces, colors, forms, etc.) of the type described by Kozhevnikov et al. (2002), and visuospatial information.

In summary, there is enough support from different sources of neuropsychological research that jointly agree on the existence of a subdivision of the visual imagery structures in the brain. The aforementioned sources provide support to a brain structural and functional division in which the parietal lobes would be involved in the processing of visuospatial information, whereas the temporal lobes would be in charge of processing visuoiconic information.

Recent studies on visualization preference are consistent with the previously mentioned structural differences in the brain for the processing of Object and

Spatial visualization. According to Kozhevnikov, Hegarty and Mayer (2002), people vary in how they mentally re-enact information, showing a preference for visuospatial or visuoiconic information processing. Whereas “some individuals may construct vivid, concrete, and detailed images of individual objects in a situation, […] others create images that represent the spatial relations between objects that facilitate the imagination of spatial transformations such as mental rotation” (Kozhevnikov, Hegarty, and Mayer, 2002, p. 48). Kozhevnikov et al. (2002) refer to these different types of visualizers as iconic and spatial types.

In an attempt to elucidate the relationship between the recently developed division of spatial versus object visualizers and the earlier classification of cognitive style as a verbalizer or visualizer, Kozhevnikov et al. (2002) administered a series of spatial ability measures, verbal ability and a modified version of the Visualizer-Verbalizer Cognitive Style Questionnaire (VVCSQ, Richardson, 1977) to 60 college students (see Table B.1., Appendix B for the description of each test). Kozhevnikov et al. (2002) found that, whereas the majority of verbalizers generally performed at an average level in the spatial abilities tests, visualizers (as defined by Richardson, 1977), tended to score either high or low in spatial ability tests, with a minority of them performing at an average level. Suspecting that high and low spatial visualizers would generate different types of mental images, Kozevnikov and colleagues went further and investigated which types of images individuals low and high in spatial visualization mentally pictured. After testing their spatial abilities, Kozhevnikov et al., (2002) gave participants a kinematic graph depicting the motion of an object through time and space (See Figure 2.3.1). The participants were then asked to imagine the real situation depicted by the graph and express their interpretation. To understand the types of mental images participants generated while solving the problem, participants were interviewed and asked to explain their answers.

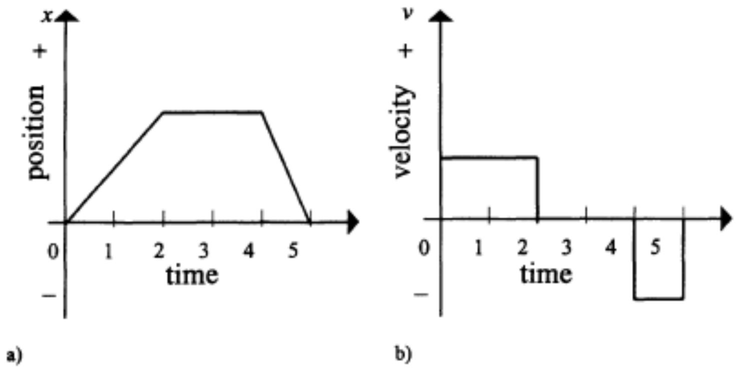



***Figure 2.3.1*** Example of a kinematic graph used by Kozhevnikov et al. (2002)

Kozhevnikov et al. (2002) found that individuals who had scored low and high in a battery of four tests measuring their spatial visualization ability interpreted the graphs in a different manner. While the “iconic” types (low spatial imagery) interpreted the graphs by generating a concrete image, mimicking a real-life scenario while being unable to break the graph down into the different parts showing different intervals, the spatial types (high spatial imagery) made a more schematic representation, breaking the graph into parts. For instance, low-spatial visualizers described the reality of the graphs depicted above as picture-like, linking the shape of the graph to the actual motion of the object, and reporting specific picture-like images of objects such as a “hill, ball, car, elevation, bullet, or table” with statements like “Could it just be elevation or height? And then a hill” (Kozhevnikov, Hegarty and Mayer, 2002, p. 60). In contrast, high-spatial visualizers broke down the graph by intervals and reported the correct situation evoked by the graph, mentioning changes of speed and time without any mention to specific picture-like examples.

As shown in Figure 2.3.2 below, Kozhevnikov, Kosslyn & Shephard (2005) gave participants a graph to interpret and asked them to graphically depict the situation as they imagined it, and as can be seen in Figure 2.3.3 and 2.3.4, the interpretations of object and spatial visualizers differed greatly in the extent to which they mentally visualized the situation. Whereas object visualizers reported a concrete and picture-like image of a situation in great detail (Figure 2.3.3), spatial visualizers depicted the situation with a more part-by-part and schematic analysis (Figure 2.3.4).

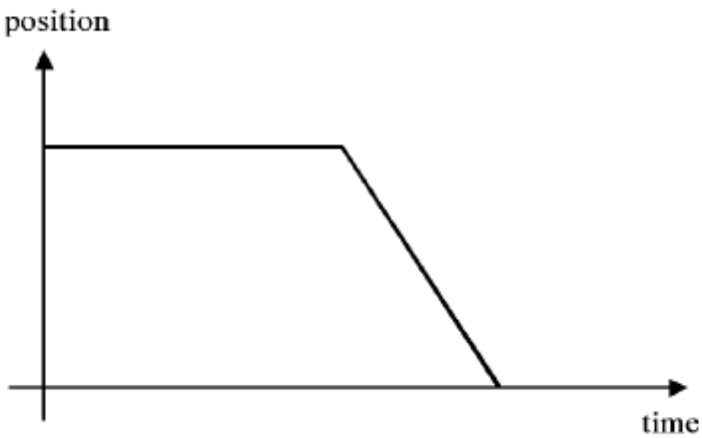



***Figure 2.3.2*** Kozhevnikov, Kosslyn & Shephard (2005) figure given to participants to interpret

Visual artist's response:


***Figure 2.3.3*** Interpretation of Figure 2.3.2 by a visual artist (object visualizer). As we can see, the interpretation is vivid, rich in details (Kozhevnikov, Kosslyn & Shephard, 2005).

Scientist's response:

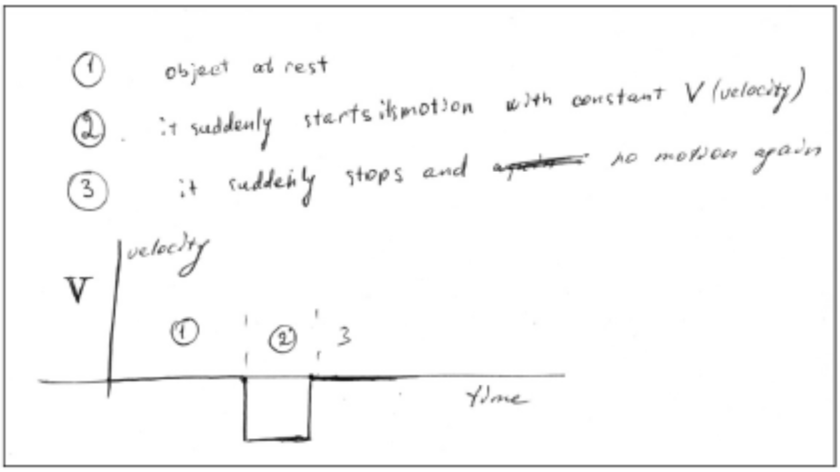



***Figure 2.3.4*** Interpretation of Figure 2.3.2 by a scientist (spatial visualizer). As evidenced by the picture, the interpretation is more broken down into parts and schematic (Kozhevnikov, Kosslyn & Shephard, 2005).

To see the relationship between vividness of imagery and its relationship with cognitive style (see Table B.1., Appendix B for the description of each test), Kozhevnikov, Koslyn, and Shephard (2005) administered the Paper Folding Test (PFT), Ekstrom, French, and Harman (1976), along with the VVCSQ (Richardson, 1977) and the Vividness of Visual Imagery Questionaire (VVIQ) (Marks, 1972), to a group of college students. Interestingly, Kozhevnikov et al. (2005) found that visualizers low in spatial abilities (as based on the PFT), reported a more vivid representation of their mental images (such as colors and shapes), whereas individuals high in spatial abilities did not experience images as vividly. Kozhevnikov et al. (2005) went on to find that, in a test with degraded images where participants had to decipher the faded image, low spatial visualizers outperformed high spatial visualizers both in accuracy and reaction times. In contrast, in a mental rotation task, high spatial visualizers outperformed low spatial visualizers in accuracy and reaction times. These findings led Kozhevnikov and colleagues to put forward the existence of two types of visualizers. One type, the “iconic” or “object” visualizer, would see pictures as a single perceptual unit, rich in details and focused on the shapes and aesthetic aspects of images. In contrast, the other type, “spatial visualizer” would be more apt to manipulate and transform an object’s spatial relations.

Lacking a measurement for visualization to reliably classify individuals according to their visualization cognitive style, Kozhevnikov, Kosslyn, and Shephard (2005) argued that there was a dichotomy, with individuals being “iconic” or “spatial” visualizers. Rather than from a cognitive styles test, this classification stems from spatial ability tests which, as we have argued in section 2.1, can be modified by training. This classification of spatial or iconic individuals at opposite ends of a visualization continuum is a point which, upon the development of the OSIQ and OSIVQ, could be contested, as spatial and iconic (Object) visualization may be independent constructs and there is therefore a possibility of individuals being high or low in each dimension independently.

In short, the aforementioned studies make a clear distinction between object and spatial visualization, and they also show that individuals differ in terms of their ability to deal with a series of spatial or iconic tasks. However, a cognitive style does not refer explicitly to the ability to process a given type of information, but instead to the preference for doing so. Although the existence of two types of individuals processing visual information differently could imply that people do indeed prefer the mode of information with which they are more skilled, no test had been created for visualization styles until Blajenkova, Kozhevnikov, and Motes (2006) developed the OSIQ.

Blajenkova and colleagues argued that the ability to mentally visualize and deal with either spatial or pictorial information could indicate a cognitive style. After designing a 30-item questionnaire with an equal number of statements that questioned participants about their preferences for processing object or spatial information, they administered it to a group of one hundred and forty six college students. Along with the newly designed scale, participants responded to questionnaires testing their spatial ability, as measured by the PFT, the Spatial Imagery Test, and the Vandenberg-Kuse Mental Rotation Test (see Table 5, Appendix B). In addition, participants completed the Degraded Pictures Test as well as the VVIQ to confirm their degree of iconic visualization ability (see Table 5, Appendix B). In short, Blajenkova and colleagues checked the correlation between the ability to deal with a given type of information (spatial or iconic), and the preference for doing so.

The overall results of their studies indicated that the degree of spatial ability was significantly positively correlated with the overall score of spatial visualization preference as measured by the OSIQ, whereas the measures of the tests administered to measure object visualization ability correlated positively with the object visualization preference subscale of the OSIQ. To discard a possible influence of general intelligence on the type of visualization, Blajenkova et al. (2005) included measurements of verbal and non-verbal intelligence and analyzed their correlation with object and spatial sections of the OSIQ, finding no significant correlation to support an effect of general intelligence on visualization preference.

Finally, to test the ecological validity of the scale, Blajenkova and colleagues selected seventy five professionals from fields whose activity was generally more related to either object or spatial visualization. The finding was that scientists (computer scientists, physicists, biologists, engineers, biochemists, a chemist, and a mathematician) showed significantly higher scores in spatial visualization than visual artists (designers and visual artists), who scored higher in object visualization. Although Blajenkova et al. (2006) argued that this provided ecological validity to the scale, the correlational nature of their study does not explain whether scientists choose their careers because they prefer spatial visualization while visual artists prefer iconic visualization, or whether this visualization preference comes after a professional engages in a given career in which using a given type of visualization proves more useful to her job, therefore developing both a skill and preference for that type of visualization (though research in cognitive styles might point to people choosing careers consistent with their cognitive style: Billington, Baron-Cohen & Wheelwright, 2007). In any case, Blajenkova and colleagues' findings provide further evidence of the existence of two types of visualization styles which are also consistent with the findings provided by neuropsychological research.

What Blajenkova et al. (2006) demonstrated is that having an ability to manipulate spatial or iconic information was predictive of the preference for doing so. This is not a minor finding, as it indicates that a cognitive style test can be used as a proxy for performance, and performance and style can be intimately related. It leaves open, however, the question of whether a cognitive style can evolve, much as performance can, with training and/or exposure.

To check the validity of this test in a different country (Italy), the OSIQ was further tested by Vannucci, Cioli, Chiorri, Grazi, & Kozhevnikov (2006), finding results consistent with the original study of Blajenkova and colleagues, thus indicating a significant positive correlation between spatial ability measures and preference for spatial visualization. Similarly, the authors found a significant positive correlation between the object visualization scale of the OSIQ and the VVIQ, which the authors interpret as a positive correlation of two object visualization scales. Supporting a differentiation between spatial and object visualization, the authors did not find the OSIQ measures of spatial visualization to be correlated with the VVIQ, or the object visualization with the Paper Folding Test.

Further studies provide evidence about the existence of two different types of visualization and their probable mutual independence. In a recent study, Chabris, Jerde, Wooley, Gerbasi, Schuld, Bennett, Hackman, and Kosslyn (2006) tested the validity of the OSIQ in a sample of over 3800 individuals, finding results consistent with an independence of spatial and object visualization and of each of these cognitive styles correlating with a corresponding degree of ability in these areas. Specifically, Chabris et al. (2006) found positive significant correlations between preference for spatial visualization and degree of spatial ability, as well as positive significant correlations between preference for object visualization and performance on a difficult task of degraded picture recognition. They also found object and spatial visualization preferences to be significantly negatively correlated, though the correlation ($r=-.05$) was very small and indicated that only .0025% of the variance in one variable is explained by the other. Similar to Blajenkova et al. (2005), Chabris et al. (2006) also found that college students in humanities and individuals with visual arts experience showed a stronger preference for object visualization. They also found spatial visualization to be preferred more by men than by women, by science majors, and by individuals with experience in playing videogames.

In short, the recently reviewed literature points to the existence of two different brain structures and functional processes. The findings regarding the interrelationship of the visualization components are not fully clear, as we have arguments that object and spatial are two opposite visualization styles, with individuals being one type or the other. However, some contrasting evidence points to their being independent, and therefore potentially yielding an individual configuration in which a person could be high in both, one, or none of the dimensions. This apparent controversy leaves an interesting research question to be addressed. Namely, are object and spatial visualization two ends of a continuum line in the visualization dimension, or are they independent constructs, with people being along a continuum line on each of the dimensions? In either case, elucidating this point, as we will further argue, might have implications for human decision-making.

### 2.3.1 Measurement

The new Object-Spatial Imagery and Verbal Questionnaire, developed by Blazehnkova and Kozhevnikov (2009), measures the Object-Spatial-Verbal cognitive style. The OSIVQ, is a self-reported questionnaire stemming from the Object-Spatial imagery questionnaire initially developed by Blajenkova, Kozhevnikov & Motes (2006). To the 30 questions which make up the OSIQ (half of which measure the Object, and half the Spatial dimension), the OSIVQ adds 15 more questions to assess the verbalization dimension. The OSIVQ has been shown to have a clear three-dimension structure when subjected to factor analyses. In regards to construct validity, Blazhenkova & Kozhevnikov (2009, p. 657) demonstrated "*that the new instrument measures the object, spatial and verbal theoretical constructs that it purports to measure. (....) and principal component analysis performed on the OSIVQ items demonstrated that items which were constructed to measure object, spatial or verbal constructs, indeed, loaded on the distinct and coherent factors, supporting the legitimacy of operationalization of our theoretical constructs."* In addition, the constructs were found to show ecological validity, with professionals in the visual arts showing significantly higher object visualization scores than professionals in humanities or scientists. Scientists, on the other hand, had higher spatial visualization scores than professionals in the fields of visual arts or humanities. Finally, both the internal and the test-retest reliability were within the considered acceptable ranges for psychometric imagery.

The difference between the OSIQ, and the OSIVQ is solely the addition of the verbal component, which makes the OSIVQ a test comprising both visualization components and the construct of verbalization, which was a core element previously studied in its relationship with numerical abilities (Lean & Clements, 1981). The verbal dimension will not be investigated in the current thesis for theoretical as well as practical reasons. From a theoretical standpoint, it is the two components of visualization which are a novelty, whereas the construct of verbalization and its relationship with numeracy has long been proposed. This considerably limits the contribution that the study of verbalization and its relationship with numeracy could offer. From a practical perspective, the scope of the current thesis, focusing on visualization style and numeracy and the implications for judgment and decision-making, is in itself no small task. Expanding the thesis from its current scope could prove impractical in terms of both time and resources if one were to attain the depth required in a doctoral thesis. However, although this research is not in principle concerned with the verbalization dimension, having this data available might prove useful in future replications or furthering of the current set of studies.

Because part of the data was collected in Spain, and from a practical perspective administering an English test to this population would not be feasible due to the lack of sufficient foreign language skills, the Spanish version of the OSIVQ was used when gathering data from Spanish speakers. Prior consent from the authors of the Spanish version was sought and granted to use such version of the OSIVQ, (Campos & Perez-Fabello, 2011) which shows the same structure and validity constructs as the original OSIVQ.

In addition, copyright authorization from Rutgers University was sought through their legal department and subsequently granted prior to administering the OSIVQ in its English version, with consent for the use of the Spanish variant also granted by the lead author.

## *2.4 Numeracy and Visualization*

### 2.4.1 Relationship

Obvious individual differences are present when comparing people’s mathematical skills. Some individuals have a cognitive capacity which is more attuned to numbers than others, being predisposed to grasp mathematical concepts in a much easier fashion. But why are some individuals better than others at dealing with mathematical problems in daily life? How can we facilitate the correct understanding of the numerical information that is presented to them? And what types of representations would foster this insight?  We will argue that visualization may play a crucial role in this process.

From her research on visualization type and mathematical ability, Presmeg (1986b, 2006a) suggests that pictorial visualization might be a hindrance whereas pattern and dynamic imagery might be key facilitators of mathematical problem solving, a fundamental basis of numeracy (which is defined as the ability to apply and use mathematical knowledge in daily life problems [Withnall, 1995]). According to Presmeg, pattern imagery (spatial) involves the visualization of relationships and organization of elements of a problem and dynamic imagery would involve the mental spatial manipulation of objects (see Table 2, Appendix A for definitions). These two types of imagery, involving spatial visualization, would enhance mathematical problem solving because of the facility to distinguish relationships and patterns between the different constituent parts of a problem. Pattern imagery visualizers would focus on the spatial location and relationships between component parts of the problem while disregarding aesthetic influences in the process. In contrast, concrete (object) imagers focus on aesthetic elements that are irrelevant to solving the problem at hand. This would be consistent with literature on expertise. According to Chi et al. (1981), who investigated physics problem solving by experts and novices, novices tended to fix their attention more on the literal features of a problem, leading them to more incorrect answers than experts, who would focus more on abstract principles and the relationships between different parts of the problem (which is consistent with the analytical part-by-part type of processes followed by spatial visualizers).

In mathematical tasks, whereas object visualizers (also called pictorial types) would form a very detailed and quality rich mental image of the task at hand, focusing on all of the visual details of the picture such as appearance, shape, color or brightness, spatial visualizers (also called schematic types) would largely focus on the representation and transformation of spatial relations between objects such as "*the spatial relationships between the parts of an* *object and the location of objects in space or their movement*" (Hegarty & Kozhevnikov, 1999; Kozhevnikov et al., 2005; as cited by van Garderen, 2006, p. 497), but omit details that do not provide information relating to the spatial qualities of the object.

Similar to visualization style, which as we argued has biological bases, mathematical processing also has biological roots and develops from early infancy. Researchers in the area of development and mathematics learning (Steffe, von Glasersfeld, Richards, & Cobb, 1983) agree that the infant develops math ability by associating a physical item to a mental representation. Mathematical evolution seems to start with a basic idea of tying physical concepts to a mathematical representation. Mathematics, initially tied to the empirical idea of quantity (Mitchelmore and White, 2004), evolved to represent ever more complex problems whose physical representation is not evident. In child development we find support for this idea, with children being unable to count numbers that go beyond what they can see at the beginning of their mathematical development (Piaget & Inhelder, 1966). Rather, mathematical concepts like counting are based on what is perceived by the infant. It is only after they internally associate the physical reality with a mental representation that children can go beyond what is visible to the senses and handle a symbolic mental representation of a reality. This representation, research argues (e.g., Ho 2009; 2010), is driven by a process of mental visualization, which supposedly helps in the process of numerical problem solving. According to Ho (2009; 2010), visualization in mathematics helps to understand problems and the elements of the problem in relation to each other. Visualization also helps in the simplification of a problem and identifying a way to solve it. In addition, visualization would help connect the problem at hand with the repertoire of previous problems that are incorporated in the knowledge base of the decision maker. One more way in which visualization helps in the solution of mathematical problems is by allowing a person to eliminate the need for computation in problems which may have an easier visual solution, and later allowing the solution to be checked for reasonableness by comparing it with a corresponding mental image (e.g., solving “mixture” problems by first mentally picturing the mixing of liquids and buckets, then numerically calculating the results and further imagining the result as a mental image).

Earlier research on visualization, however, has found conflicting results about the beneficial role of visualization in mathematical performance. For instance, some researchers have argued that the use of visualization techniques (though at that time they did not use the currently identified types of visualization –object vs. spatial) in problem solving is negatively correlated with accuracy (Presmeg, 1999). In particular, Lean & Clements (1981) argue that “verbalizers”, or individuals who show a preference for verbal logical information over visual information, outperform “visualizers” “on both mathematical and spatial ability tests (Lean & Clements, 1981, p. 684).

In contrast, other authors claim that visualization and mathematical ability are positively correlated, finding further supporting evidence about the use of visualization processes when dealing with mathematics. For instance, Montague, Bos & Doucette (1991), found that students classified as high- or average-performers in mathematics used some sort of visual technique in mathematical problem solving, whereas students with learning disabilities did not make use of visualization when solving mathematical problems. Although the use of students with learning disabilities as a comparison might be criticized because such a group might have different brain or learning impairments, some authors offer additional indications of a positive relationship between spatial visualization mathematical ability.

More evidence of this type about the differential performance in mathematics of users of either spatial or object visualization comes from Van Garderen & Montague (2003), who found that schematic visualization (which they defined as images representing “*the spatial relationships among the problem parts and included spatial transformations*”, p. 247) was used in 76% of the cases where a problem was correctly solved. In contrast, students used object representation in 70% of the problems incorrectly solved. The problems used by Van Garderen & Montague (2003) could all be solved by drawing the information in a schematic graph, which would easily provide the solution. However, participants who used pictorial rather than schematic visualization in the problem solving process did not arrive at the correct solution as often as those using schematic representations. At first sight these studies imply that visualization is important for mathematical problem solving. However, these results must be interpreted with caution; although the Van Garderen & Montague (2003) study did find that pictorial representations in mathematical problem solving were used more prevalently in incorrectly solved problems, and schematic representations in correctly solved problems, they did not analyze their results taking as the subject measure the participant. Instead, they analyzed the correctness or incorrectness of the solved problem. That is, the results were not analyzed taking every student and checking whether they had used a pictorial or a schematic representation. Instead, the unit of analysis was the problem to be solved and the method used. Since one's mental images to solve the problem might not be exactly those expressed in writing (e.g. poor drawing skills),  Van Garderen & Montague's (2003) study needs to be considered with the aforementioned qualification.

In relation to the claims some studies make about the positive relationship between spatial visualization and mathematical performance, there seems to be an over-generalization of the positive relationship between spatial visualization and mathematical performance. For instance, Hegarty and Kozhevnikov (1999, p. 648) affirm that "*There is a significant relationship between spatial ability and achievement in mathematics (e.g., Battista, 1990)*". Despite the claim that Battista (1990) found a significant relationship between spatial ability and achievement in mathematics, the nature of this relationship is not explained. When examining Battista's (1990) study, it seems that the possible relationship between spatial visualization and mathematics is geometry, which, although being a component of mathematics, could be considered more a subset of the area. Specifically, what Battista (1990) investigated in his studies is achievement in geometry tasks, in particular (Battista, 1990, p. 49):

"*1. General. How do spatial visualization, logical reasoning, and the discrepancy between them affect performance in geometry? The effects of these variables on both achievement in geometry and specific processes used in geometric problem solving were investigated.*

*2. Gender differences. What is the nature of gender differences in geometry performance? That is, do males and females differ in achievement or problem solving processes, or both?*

*3. Teacher effects. Are the processes students use in geometric problem solving affected by instruction?*"

Battista (1990) found that males outperformed females in spatial visualization skills and geometry problem solving, and also found that in the two classes participating in the study, females performed better when the teacher gave them the freedom to decide on the use or not use of spatial visualization techniques in geometrical problem solving than when they were required to use spatial visualization. Battista (1990) explained this interaction by arguing that females being forced to use visualization techniques might develop extra stress that prevented them from correctly solving the problems, whereas the males, with a higher level of spatial ability did not experience this stress and performed equally when the use of spatial visualization was enforced by the teacher than when the use of spatial visualization was only recommended.

A second paper that Hegarty and Kozhevnikov (1999) cite as providing evidence of a relationship between spatial visualization and mathematical ability is that by Sherman (1979). However, when this article is considered in detail, the affirmation that Sherman found the aforementioned relationship between spatial visualization and mathematical ability is not conclusive. Sherman (1979) investigated the predictive power of several variables (one of them spatial visualization) on mathematical achievement. Pupils' spatial ability was tested using the Spatial Relations Test of the Differential Aptitude Test (Bennett, Seashore, & Ivesman, 1973). In addition, pupils' mathematical problem solving ability was examined using a test with 26 mathematical word problems (Stafford, 1965) and mathematics marks recorded in 10th, 11th and 12th grade. Sherman (1979) used the Spatial Ability score (as well as other independent variables) to predict mathematics scores of 9th grade pupils in 10th, 11th and 12th grades. In addition, female mathematical word problem solving abilities were tested in 12th grade. In summary, Sherman tested whether spatial visualization ability in 9th grade predicted mathematics marks in future years (10th, 11th, and 12th grade). The results were not as straightforward as Hegarty and Kozhevnikov (1999) suggest in their paper. In fact, Sherman (1979) only found that spatial visualization measures could significantly predict math marks in 10th grade, and only for females. When both males and females were put together in the analysis, the predictive significance was again significant, maybe due to the statistical effect being driven by the females. In 11th grade, the regression coefficient of Spatial Visualization as a predictor of math ability was insignificant for both males and females, and in 12th grade, the authors only tested females. In 12th grade, the regression analysis of visualization scores predicting grade performance for females also became insignificant, though it was significant as a predictor of problem solving ability.

The previous results, which use spatial visualization ability as a predictor of mathematical achievement based on grade performance, are indicative of the relationship between spatial visualization and mathematical ability, though they must be taken with caution, since the predicted variable (grade achievement) could also be influenced by other factors (teaching style, course schedule, etc.). In addition, most of the results (male in 10th grade, all participants in 11th grade) did not show a statistical significance of spatial visualization ability as a predictor of grades in mathematics. In short, although Hegarty and Kozhevnikov's claim (1999) that Sherman's study (1979) provided evidence for a positive effect of spatial ability on mathematical achievement, such affirmation must be understood in the context of all the previously stated limitations.

A study that did find a positive relationship between spatial visualization ability and mathematical problem solving was that by Hegarty and Kozhevnikov (1999). In their study investigating mathematical problem solving of sixth-grade pupils, Hegarty & Kozhevnikov (1999) found results that were later paralleled by Van Garderen & Montague (2003), who found that when solving mathematical word problems which could be easily solved by visual methods, those who used schematic visualization in their problem solving (i.e. drawing a graph), consistently outperformed those who drew less schematic images (i.e. picture-like images). In their study, Hegarty & Kozhevnikov (1999) gave participants a series of mathematical problems that could be all solved by visual methods, finding that students who solved problems using spatial imagery (as evidenced by their drawings when solving the problem and their explanations when interviewed) correctly solved more problems than students who used object imagery in their problem solving process. With regard to Hegarty & Kozhevnikov's (1999) study, though the authors did analyze the subjects' strategies for arriving at a solution to mathematical problems and did find a higher use of schematic representations and mental processes (as evidenced by participants' drawings and interviews), the results do not straightforwardly imply that visualization cognitive style (as defined by the

OSIQ or OSIVQ) was associated with mathematical problem solving. In fact, at the time of Hegarty and Kozhevnikov's (1999) study, no test of visualization as a cognitive style existed, since the OSIQ, which reliably assesses an individual's level of object and spatial visualization, was only developed in 2006 by Blajenkova and colleagues. However, the fact that students preferred to use either pictorial or schematic images could be an indication of their cognitive style.

Despite the previously reviewed literature where it is implied that mathematical and spatial ability are positively correlated, and that the former might be influenced by the latter, the claims of such an influence must be interpreted having in mind the limitations of each study we have pointed. However, there are some studies that have found more convincing evidence of, if not a causal link between spatial ability on mathematical performance, at least a positive common root of these variables. For instance, Fennema and Sherman (1977) found a positive correlation between spatial visualization ability, as measured by the Space Relations Test of the Differential Aptitude Test (Bennett et al., 1973), and mathematics achievement in $9^{th}$ - $12^{th}$ grade as measured by the Test of Academic Progress (Scannell, 1972), which tests mathematical achievement in mathematical subjects typically covered in $9^{th}$ – $12^{th}$ grade.

### 2.4.2 Neural Mechanisms

As supported by the literature on numeracy, even infants have a rudimentary "number sense". As Dehaene (2001) affirms, humans are biologically endowed with the neurological make up to process and use numbers and an innate capacity "*for elementary number processing is found early on in human* *development, prior to schooling or even to the development of language skills*" (Dehaene, Piazza, Pinel & Cohen, 2003. p.487).

The existence of neuronal bases for mathematical processing is further supported in the literature. For instance, research on Developmental Dyscalculia (a learning impairment which impedes the normal acquisition of basic mathematical abilities), has found that this impairment is associated with a disorganization in terms of length, depth and sulcal geometry of the intraparietal sulcus (Molko, Cachia, Riviere, Mangin, Bruandet, Le Bihan, Cohen, & Dehaene, 2003). This finding is later supported by Price, Holloway, Rasanen, Vesterinen & Ansari (2007), who found that the intraparietal sulcus (IPS) is key in the development of dyscalculia in 4 year olds. This specific brain region, the IPS, is also involved in numerical operations in adults and responds similarly to numerical stimuli in infants without numerical training as in adults, pointing to the fact that humans are endowed from an early age with the neuronal bases that are in charge of numerical processing (Cantlon, Brannon, Carter & Pelphrey, 2006).

The previous arguments are consistent with Houde & Tzourio-Mazoyer (2003), who affirm that there are brain areas, in particular the bilateral parietofrontal network, which aid in arithmetic computation. Interestingly, the parietal lobes are also involved in spatial visualization (Kozhevnikov et al., 2005). Not surprisingly, because the areas of spatial visualization and mathematical computation are related, Houdé & Tzourio-Mazoyer, (2003, p. 5) found "*strong evidence for the involvement of visuospatial representations in exact computations that require complex operations*". Recent evidence reinforces all of the above, pointing to "*a tight relationship between mental* *rotation proficiency and white matter organization near the anterior part of the intraparietal sulcus*" (Wolbers, Schoell & Buchel, 2006, p. 1450). Specifically, high level proficiency in a spatial mental rotation task was positively correlated with fractional anisotropy (FA) values, indicating increased efficiency in information transfer within white matter (FA values describe the degree of diffusion of a substance, in which higher levels –from 0 to 1– indicate a focused diffusion, or better information transfer, and lower levels an unfocused, or spread diffusion which is an indicator of low efficiency in information transfer).

In short, a wealth of literature supports the existence of common neural mechanisms that underpin the functioning of mathematics and spatial visualization. This evidence might point to the previously hypothesized positive relationship between numeracy and spatial visualization. Different from spatial visualization, however, to the best of our knowledge object visualization is not related to the numerical or spatial neurological structures previously studied. The lack of studies investigating the relationship between numeracy and visualization style (both Object and Spatial), leave an important gap in the literature that this thesis will seek to address. This piece of research will be the first step towards investigating this relationship using non-invasive methods (questionnaires), a first step which could warrant further studies using neuroimaging techniques (though these exceed the scope and resources of this study).

## *2.5 Visualization and Mathematics, Limitations and Gaps*

The previous findings of the implied relationship between type of visualization and mathematical performance only offer a hypothesized process whereby a given visualization style might affect mathematical ability. However, no studies have investigated this proposition in depth. This lack of a clearer link might be due to the fact that the test to identify people's visualization cognitive style, the OSIQ, was only developed in 2006. Most other previous literature did not check for visualization as a cognitive style and its effects on mathematics, but instead used Spatial Visualization as a learned ability, not as an individual trait.

Ability can be influenced by training methods, hours of training, ability of the trainer, etc., and in particular spatial visualization abilities have been shown to improve with training (Moses, 1980; Uttal et al., 2013). Although, tests of spatial ability test the dexterity of people in this domain, cognitive styles differ from skills and are assessed with different tests to elucidate the way one acquires and processes information. In fact, most studies classify the types of visualizers according to their use of, instead of their preference for, visualization. For instance, Presmeg (1986) investigates students' "*use of imagery in their solution of problems from the high school mathematics syllabus*" (p. 297), and further defines a visual image as "*a mental scheme depicting visual or spatial information*" (p. 297). Although the use of external imaginal representations might be a good proxy of a cognitive style, it might also be that one might have a preference for a given type of information, but not show a high level of ability. Thus, it is conceivable that the studies on visualization and mathematical performance referred to before, claiming a relationship between mathematical ability and visualization based on participants showing external imagery representations, might give us only a partial picture when it comes to assess the true mental bases of mathematical ability. In contrast, personality tests are resistant to change over time and faking (Hogan, Barret & Hogan, 2007), making them a more stable measure over time than a skill test.

One further caveat of the studies of visualization and mathematical performance is that they were mostly performed using school-grade pupils, and never adult populations. From a practical perspective, this is an important limitation for the field of Judgment and Decision Making and potentially other fields such as Consumer Behavior, since the populations investigated do not have the purchasing capacity of more adult populations. Even when they do perform everyday purchases, schoolchildren's purchasing choices (what they buy) as well as purchasing decision processes (why they buy it), may be different from more adult populations. This limitation leaves an important gap to fill: how are preferences for visualization and mathematical ability related in a population of individuals who are more mature, educated, and with higher income? How does the external representation of numerical information such as graphs affect decisions made by the different types of visualizers?

## *2.6 Numeracy*

### 2.6.1 Background

To better deal with a situation in which a cognitive evaluation of the numerical information at hand is necessary, an individual's numeracy might play an important role. Indeed, Peters et al. (2006) recently found that numeracy affects decision-making.

Every day we are, as consumers, bombarded with publicity on TV, billboards, mailing, e-mailing, etc. Most of this information to which we are subjected comes through the eyes, and it is typical as a consumer to see pamphlets or brochures depicting numerical information about the characteristics or costs of a product or service (i.e. financial products, retirement plans, etc.). As Dieckman (2008, p.3) argues, referring specifically to numerical information, "*Ever increasing amounts of information are made available to the public, with the expectation that consumers will use this information for decision making."*, making the case that a basic understanding of numbers is fundamental for our lives as consumers of products and information.

The importance of numeracy in decision-making processes was only recently acknowledged. Specifically, medical decision-making has been the area in which most of the research on numeracy and decision-making has been conducted (See Table 2.6.1.2 at the end of the current section 2.6.1 for a summary). For instance, a few studies in the field of medical risk perception have taken into account the influence of numeracy in patients' perceptions of risk. For example, Schwartz et al., (1997, p. 968) asked participants in a study to answer the following question: "*Out of 1000 women just like you, how many* *will die from breast cancer without and with mammography?*" (Table 2.6.1.1), and subsequently presented them with one of four versions of information regarding risk reduction by mammography:

**Table 2.6.1.1**
*Different formats of numerical risk reduction presented to participants and correctness of responses (Schwartz et al. (1997)*

| Group | Version | Correct Responses (% of respondents) |
|---|---|---|
| 1 | 33% reduction, in 12 out of 1000 | 17 % |
| 2 | 33% reduction | 10 % |
| 3 | 4 in 12 reduction from 12 in 1000 | 33 % |
| 4 | 4 in 1000 reduction | 7% |

Unsurprisingly, higher numeracy was positively correlated with the correct estimation of the difference between the risk of dying from breast cancer without and with mammography screening. In addition, providing the baseline information significantly ($P < 0.001$) improved decisions in the absolute risk reduction condition (groups 3 & 4), but not in the relative risk reduction group (Schwartz et al., 1997).

Further evidence that numeracy is positively correlated with better choices in a consumer setting is provided by Peters, Dieckmann, Dixon, Hibbard and Mertz (2007), who provided individuals with information regarding the quality and characteristics of hospitals (i.e. number of registered nurses per 100 patients, etc.), finding numeracy to be positively correlated with the selection of hospitals of better quality (quality being evidenced by objective parameters such as numbers of nurses per patient, existence of key equipment, or abidance with guidelines in dealing with medical conditions such as heart attacks and pneumonia).

Similarly, Hamm, Bard, and Scheid (2003) found that high numeracy was positively correlated with the understanding of medical information. Specifically, they provided individuals with objective information about prostate cancer screening methods and their reliability, finding that high numerates understood the information better than low numerates, as evidenced by their correctly answering questions about the error possibilities of the different pre-screening methods. It also seems that high and low numerates have a preferred mode of receiving information (numerical or non-numerical). Precisely, Gurmankin, Baron, and Armstrong (2004a), found that low numerates expressed higher preference to receive verbal (non-numerical) risk information as well as to trust in this information than high numerates.

Outside of the purely medical decision making area, Peters and colleagues (Peters et al., 2006) pioneered research in numeracy and decision making, finding that high numerates are less influenced by the framing of information, that is by how information is presented, and draw more precise feelings from numbers. In their study, participants were asked to rate the quality of work of other students based on the percentage of correct and incorrect responses on a test. They found that low numerates showed the expected framing effect, giving higher ratings when they received information on the percentage of correct responses (positive frame) than when presented with information on the percentage of incorrect responses (negative frame). High numerates, on the other hand, did not change their ratings significantly despite the frame manipulation. In a second experiment, participants were asked to evaluate the risk of a mental patient hurting somebody upon discharge based on the profile of a patient at a mental institution and the past history of recidivism of similar patients. When presented with frequentistic information (i.e.10 out of 100 patients), low numerates reported a significantly higher risk than when presented with probabilistic information (i.e. 10%). High numerates, however, did not change their assessment of risk based on the different format of the presentation of information. In another study, participants were asked to draw a colored ball from either a bowl containing 1 colored and 9 white balls, which represents a 10% chance of success, or a bowl containing 9 colored balls out of 100, representing a 9% chance (Denes-Raj & Epstein, 1994). Low numerates made more suboptimal choices and were significantly more likely to choose the latter – 9% of colored balls - than high numerates.

In the final task, and contrary to their initial hypothesis, Peters et al. (2006) demonstrated that high numeracy could also be associated with worse evaluations of a numerical situation. Specifically, Peters et al. (2006) found that when asked to evaluate the attractiveness of a bet either having 7/36 probabilities of winning $9 and 29/36 probabilities of winning $0 or a different bet (between-subjects study) with the same characteristics but with the $ 0 substituted by a $.05 loss, the differences in attractiveness between the two conditions for two low numerate groups were insignificant. In contrast, between the high numerate groups, the bet with a loss was ranked as more attractive than the bet without the loss. The authors explained this by the fact that the loss bet puts the value of the $9 prize into perspective, which allowed the high numerates to affectively map the situation of the bet more precisely.

In contrast, low numerates were not able to efficiently perform different affective mapping between the two bets.

Continuing their research on Numeracy and Decision Making, Peters & Levin, (2008) investigated the interplay of Numeracy and Risky-Choice Framing Effects, discovering that while high-numerates' choices in a series of typical Risky-Choice Framing problems were accounted for by the attractiveness attributed to each of the two choices in a problem, for low numerates this was not the case, and they responded according to the expected risky-choice framing effect. Peters & Levin (2008) interpreted these findings as "*consistent with an increased tendency of the highly numerate to integrate complex numeric information in the construction of their preferences and a tendency for the less numerate to respond more superficially to non-numeric sources of information*" (p. 435).

The heavier reliance on numbers by the high numerates as compared to the low numerates was also demonstrated by Peters et al., (2009). In a study investigating how high and low numeracy individuals differed in their use of numerical information or their affective state when evaluating the quality of hospitals given a series of numerical quality indicators, Peters et al. (2009) found that whereas the low numerates were affected more in their evaluations of the quality of hospitals based on their mood (more positive mood was associated with higher ratings of hospital quality), individuals high in numeracy did not show this effect, and were driven more by the numerical information presented to them. Curiously, however, when evaluating hospitals from purely numerical data based on the survival rates given in percentages (93%, 96%, or 99% survival), and without evaluative categories indicating where a given percentage fell: poor, fair, good, or excellent, the high numerates evaluated hospitals of higher quality worse than hospitals of lower quality (quality of hospitals was a between-subjects condition, with individuals evaluating either one type of hospital or the other, not both). As this was contrary to Peters et al's. (2006) predictions, they post-hoc hypothesized that the 93% might have evoked survival rates in the 80% range, making the 93% look good. In contrast, the 99% would be compared to 100% and this would make the evaluation of quality seem lower. Peters et al. (2009) argued that this would only be the case for the high numerates, as they try to search for numerical meaning more than the low numerates. The post-hoc explanation given by Peters et al. (2009), however, is a hypothesis and venturing why this effect happens might only be speculation. What they did show is that the heavier reliance on numbers by the high numerates did not always lead to objectively better judgments.

Concurrent with the findings of Peters et al. (2009) that high numerates rely more heavily on numbers than low numerates when making judgments, Dickman, Slovic & Peters (2009) also found that when evaluating forecasts of an event happening in the future, high numeracy individuals tended to rely on given numerical probabilities of the event happening, whereas low numeracy individuals relied more on narrative evidence. Since the experimental scenarios were hypothetical, the question of whether numeracy helps in forecasting accuracy in this context remained unanswered.

One more recent study investigating how individuals differing in numeracy were susceptible to the framing of information found that numeracy did have an effect on the judgments of risk depending on how the information was presented to individuals. Specifically, Peters, Hart & Fraenkel (2011) found that when individuals were asked to rate their judgments of the risks of side effects, presenting the information in a probabilistic (10%) or frequentistic (10 out of 100) format affected high and low numerates differently. While high numerates given information in the frequency format did not differ in their ratings of risk from the high numerates given the information in the percentage format, the low numerates did show a difference. The group of low numerates receiving the risk information in a frequentistic format reported higher ratings of risk judgments than the low numerate group receiving the information in the percentage format.

The potential real-life implications of the format of information presentation to individuals differing in numeracy was studied by Dickert et al. (2011), who found that when individuals "*were asked to imagine that they could contribute to a humanitarian aid organization with the aim of reducing hunger in Africa among poor children in danger of starvation. Their donation would always go to one child out of a group of 100 children; however, in the frequency condition the target child was presented as "one out of 100", whereas in the probability condition it was presented as "one percent out of 100*"" (p. 640). Similar to Peters, Hart & Fraenkel (2011), Dickert et al (2011) demonstrated how the presentation of the information in frequency or percentage formats elicited different responses from individuals depending on their numeracy abilities. In particular, higher numerates provided with the percentage format did not differ in their donation amount from other higher numerates receiving the information in the frequency format. In contrast, the lower numerates provided with the frequency format signalled a willingness to donate significantly more than the group of lower numerates receiving the information in the percentage format. In addition, regardless of the format of information presentation, low numerates had more clear and coherent images of the victim than the high numerates, something which the authors interpret as the higher numerates processing information in a more abstract manner. In addition, Dickert et al. (2011) investigated the “identifiable victim effect” (Kogut & Ritov, 2005a), which dictates that when asked to give a donation to a charitable cause involving victims, individuals signal a willingness to donate a higher amount to one single identifiable victim than to a group of victims. Dickert et al. (2011) found that this effect was indeed present in the group of low numerate individuals, but not in the high numerates.

Some other recent research (Okamoto et al., 2012) has again found that the framing of information affects individuals differently depending on their numeric ability. Specifically, Okamoto et al., (2012) conducted a study in which they asked participants to rate the riskiness of a surgical operation (*1= not risky, 2= slightly risky, 3= risky, 4= very risky)* and presented subjects with the survival rate (“*991 in 1000 people survive this surgery*” or “*9 in 1000 die from this surgery*”).The authors presented both the negative and the positively framed questions, separated by 12 unrelated questions, and measured the extent of the framing effect by calculating the difference between the scores of the answers given to the two different frames. Consistent with previous findings of numeracy affecting individuals high and low in numeracy differently, Okamoto et al. (2012) found that the extent of the framing effect was higher among the group of low numerates than that of the high numerates.

Some areas outside of the realm of the more traditional field of Decision Making have investigated the effects of different numerical abilities on people’s perceptions. For instance, Kahan et al. (2012) investigated the perceptions of the severity of risks associated with climate change and several variables, one of which was numeracy, finding that numeracy was inversely correlated to perception of the risks associated with climate change, with higher numeracy predicting lower perceptions of risk. The author proposed that a higher level of technical (and numerical) understanding would lead to a higher estimation of the risks, whereas lower technical (and numerical) understanding would lead to the underestimation of risks due to the lack of capacity to evaluate the scientific data regarding the phenomenon of climate change. In fact, Kahan et al. (2012) proposed that higher science comprehension, measured by science-literacy, and numeracy would predict higher risk scores due to better understanding of the situation. The findings, however, were opposite to the authors’ predictions, with individuals higher in science literacy and in numeracy reporting lower risks of climate change. It could be hypothesized that they evaluate numerical information in greater depth, as Peters et al. (2006; 2009) suggest, engaging in a more cognitive evaluation (System 2). In contrast, lower numeracy individuals might evaluate the situation from a more visceral perspective (System 1), thereby enhancing the risk evaluations. However, no clear explanation has been proposed to justify this finding.

Research in the areas of finance and consumer decision-making has (although only tangentially) considered numeracy as a trait that may moderate people's decisions. For instance, numeracy has been recognized to be positively correlated with wealth, education, and investment in riskier forms of assets such as shares (Banks & Oldfield, 2007). In addition, low numerate and literate consumers tend to show a predilection for familiar shopping environments and tend to use information about prices as absolute measures, rather than ratios of quantity/price. In addition, low numerate consumers were found to be less able to understand nutritional labels in food products (Rothman, Housam, Weiss, Davis, Gregory, Gebretsadik, Shintani & Elasy, 2006).

**Table 2.6.1.2**
*Summary of findings on Numeracy and Decision-Making*

| Study | Domain | Findings |
|---|---|---|
| Black, Nease & Tosteson, 1995 | Medical Risk Perception | • Low numerate woman overestimated the risk of dying from breast cancer |
| Schwartz, Woloshin, Black, & Welch, 1997 | Medical Risk Perception | • Numeracy correlated with accurate estimates of breast cancer risk regardless of the information presentation format |
| Hamm, Bard, and Scheid, 2003 | Medical Risk Perception | • Numeracy positively correlated with accuracy of estimation of probabilities for prostate cancer screening |
| Gurmankin, Baron, & Armsrong, 2004 | Medical Risk Perception | • Low numeracy associated with more reliance on verbal info given by physicians than on written numerical info |
| Viswanathan, Rosa & Harris, 2005 | Consumer Decision-Making | • Numeracy/Literacy associated with more reliance on pictographic information<br>• Numeracy/Literacy associated with consumer's loyalty<br>• Numeracy/Literacy associated with choice for simplicity of adverts |
| Peters, Västfjäll, Slovic, Mertz, Mazzocco, & Dickert, 2006 | Numeracy and Decision-Making | • High numerates show less attribute framing<br>• High numerates draw more precise affect from numerical info |
| Rothman, Housam, Weiss, Davis, Gregory, Gebretsadik, Shintani & Elasy, 2006 | Consumer Perception | • Low numerate consumers less able to understand nutritional food labels |
| Banks & Oldfield, 2007 | Financial Decision-Making | • Numeracy associated with investment in riskier assets |

**Table 2.6.1.2, cont.**

*Summary of findings on Numeracy and Decision Making*

| Study | Domain | Findings |
|---|---|---|
| Peters, Dieckmann, Dixon, Hibbard & Mertz, 2007 | Medical Perception and Decision-Making | ● Numeracy positively correlated with election of hospitals of better quality<br>● Numeracy positively correlated with accurate expectations of a cancer treatment's benefits |
| Peters & Levin, 2008 | General Decision-Making Theory | ● Low numerates evaluate risky-choice framing effect holistically. High numeracy base their decision on the attractiveness of each separate option |
| Peters, Dieckmann, Västfjäll, Mertz, Slovic, & Hibbard, 2009 | Medical Perception and Decision-Making | ● Low numerates affected by their mood in their judgments of quality hospitals. High numerates derive judgments more from numbers, though arrive at worse judgments. |
| Dickman, Slovic, & Peters, 2009 | General Decision-Making Theory | ● When evaluating the probability of forecasts in a hypothetical scenario, high numerates focus on numbers, whereas low numerates focus on narrative. |
| Peters, Hart, & Fraenkel, 2011 | General Decision-Making Theory | ● Low numerates affected by framing of information (percentage vs. frequencies),high numerates unaffected |
| Dickert, Kleber, Peters, & Slovic, 2011 | General Decision-Making Theory | ● High numerates signal equal intention to donate to a victim regardless of frame (percentage vs. frequency). Low numerates donated more in the frequency format<br>● Low numerates reported stronger & more coherent images of the victim than high numerates<br>● “Identifiable victim effect” only present for low, but not for high numerates |
| Kahan, Peters, Wittlin, Slovic, Ouellette, Braman, & Mandel, 2012 | Climate Change Perception | ● Numeracy was inversely correlated to perception of the risks associated to climate change, with higher numeracy predicting lower perceptions of risk. |
| Okamoto, Kyotoku, Sawada, Clowney, Watanabe, Dan & Kawamoto, 2012 | Medical Decision-Making | ● Numeracy inversely correlated to strength of framing effects in evaluating the risk of a surgery (negative vs. positive framing of death/survival rates of surgery) |

### 2.6.2 Measurement of Numeracy

Several researchers in the domain of Decision-Making have developed scales to measure numeracy (see Table 2.6.2.1 at the end of this section and Appendix C detailing the various scales). In the general domain of education, and more specifically mathematics, educational institutions regularly design tests to check the learning of mathematics. Virtually every mathematics teacher at a school or university will have their own test to check for learning. However, these tests are normally geared towards very specific populations (normally grade-specific) comprising a defined set of mathematical concepts (fractions, square roots, etc.). Researchers in the area of decision-making have generally departed from such tests, one of the reasons being that such tests would be difficult or time consuming to administer during experiments.

Several shorter tests have been designed for specific use in research on Decision Making. One of the first numeracy scales used in the field of decision-making was developed by Black et al. (1995). Later, Schwartz, Woloshin, & Welch (1997) developed a numeracy scale adding more items to the original Black et al. test. More recently, a widely used numeracy scale was developed by Lipkus et al. (2001), including eleven items among which there are three questions from Schwartz et al's. (1997) scale. In an attempt to refine the Lipkus et al. (2001) scale to avoid ceiling effects, Peters et al. (2007) included four items of increased difficulty to obtain a broader distribution of numeracy scores.

Numeracy, in addition to its objective measurement, has also been assessed through self-reporting. Fagerlin et al. (2007) developed a scale that allowed for faster administration of numeracy tests by having participants in their study report their beliefs about their mathematical skills. This subjective numeracy scale was found to correlate well with objective numeracy measures, while allowing for faster and less burdensome administration (Dickman, 2008). Following Dickman´s (2008) review on numeracy scales in the field of Decision Making, a review checking each of the scales mentioned shows that researchers in the field of decision making have, in many cases, determined participants´ numeracy using very crude measures which might compromise the concept of “numeracy”, affecting the results claimed. For instance, Black et al. (1995) determined whether people are numerate or not by asking participants how many times, out of 1000 tosses, a coin is expected to land heads or tails.

The Lipkus et al (2001) scale has been used as a basis for later studies in Numeracy and Decision Making (e.g. Peters et al. 2006) and was the subject of further development (Peters et al., 2007), creating the Decision Research Expanded Numeracy Scale (DRENS). The DRENS included additional items to the Lipkus scale to widen the range of numeracy scores and avoid ceiling effects from having only 11 relatively easy items.

The use of the Lipkus numeracy test was in some cases criticized because of its lack of ideal statistical properties, in particular the difficulty to distinguish between a wide range of numeracy levels. For instance, Okamoto et al. (2012) used the Lipkus scale, though they reported a very strong ceiling effect. This ceiling effect is particularly strong in countries such as Japan, a country which consistently ranks above average in mathematical achievement in international education surveys such as the PISA report. With numeracy tests which are already negatively skewed in populations scoring average on mathematical achievement international surveys (such as the USA), the use of such tests in higher mathematical achieving populations might not capture the effects of numeracy on Decision-Making or other tasks. Researchers have dealt with this problem by transforming scores. For instance, Dickert et al. (2011) used the DRENS scale but used winsorization and log transformation of the numeracy scores to make them statistically usable. Furthermore, Cokely et al. (2012) argue that the Lipkus scale "*is not hard enough to adequately differentiate among the higher-performing, highly educated individuals who are often studied*", with a pronounced negative skew that approached the measurement ceiling (p. 27).

The problems of ceiling effects with the previously reviewed numeracy scales were such that recently authors have tried to come up with different numeracy scales that, being more statistically sound, could capture the effects numeracy would have on different decision-making tasks. One example of such a recent development is the Berlin Numeracy Test (BNT henceforth) by Cokely et al. (2012), which was composed of four questions (see Appendix C) through which participant's levels of numeracy are assessed. The BNT was tested in 15 different countries, with populations diverging in their level of education, age, and other demographic characteristics, and showed high test-retest reliability and good convergent validity with other tests measuring numeracy, intelligence, and working memory. In addition, this test is reportedly easy to administer and quicker to complete than the more widely used Lipkus scale. Due to the recent establishment of this test at the time of administering the experimental tasks contained in the current study, and the fact that the BNT had not been tested in decision making tasks previously checked by Peters et al. (2006) and Weller et al. (2012), and the obvious practical limitations (e.g. time limitations) that administering an array of different tests would imply, the BNT was not included in this experimental setting.

A test that offers very solid statistical properties and which predicts individuals' judgments and decisions in decision-making tasks in the same manner as those included in the seminal paper on Numeracy and Decision-Making by Peters et al. (2006) is the newly developed ANS, by Weller et al. (2012). The ANS was developed using existing numeracy scales. Specifically in the development of the ANS, Weller et al. (2012) started from the Decision Research Numeracy Scale, the 15-item scale developed by Peters et al. (2007), and added the three items from the Cognitive Reflection Test (CRT henceforth, Frederick, 2005). Afterwards, Weller et al. (2012) carried out a Rasch analysis from the original 15 items from the DRENS (which in itself is an amalgam of other numeracy tests) plus the three CRT questions, and selected a combination of 8 items which measured numeracy in a statistically sound manner, avoiding both the prevalent ceiling effect of extant numeracy scales, and the floor effect of the CRT. The resulting scale, composed of 6 items from the DRENS, plus two of the CRT questions, was tested in a very diverse pool of subjects of varying age and educational attainment levels, resulting in a test with high predictive, convergent and construct validity.

As shown in Figure 2.6.2.1, the ANS resulted in a nearly perfectly normal distribution shape of the numeracy scores in the tested population, something which was not present in any of the previously used numeracy measures.

Despite the inclusion of two CRT items, which were originally created to measure the different psychological construct of Cognitive Reflection, Weller et al. (2012) demonstrated, using two Confirmatory Factor Analyses (CFA), that the CRT and the other numeracy items used in the ANS were indeed the same factor. In addition Weller et al. (2012) replication of the three tasks from Peters et al's. (2006) Numeracy and Decision Making original study was satisfactory, reproducing the original results.

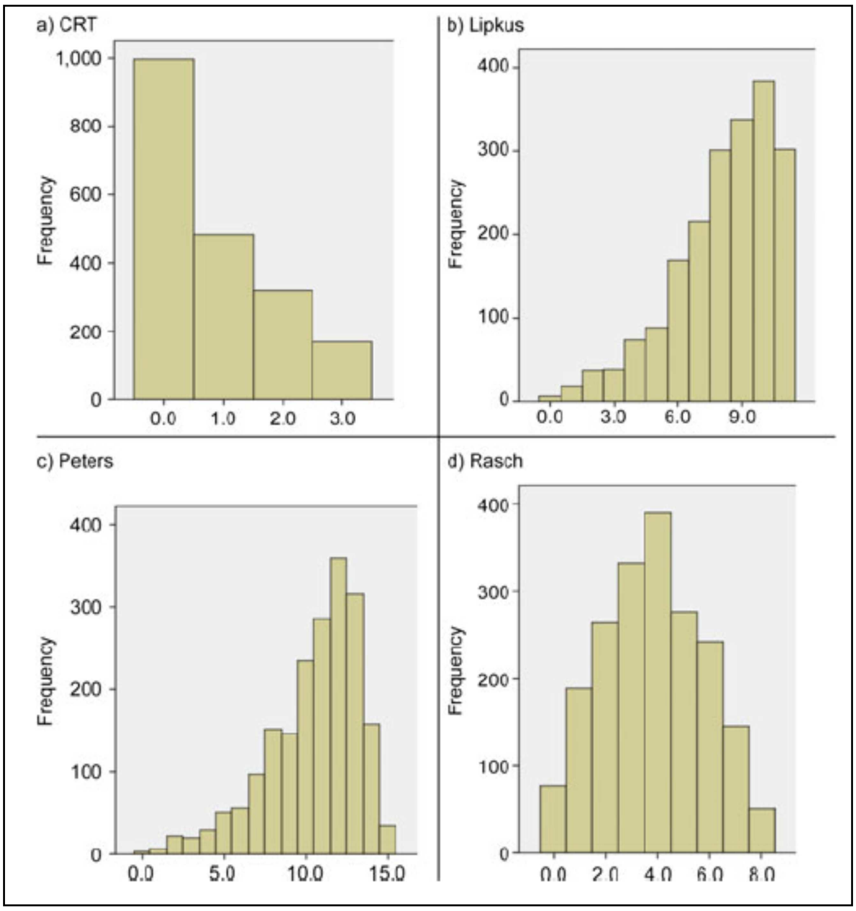



***Figure 2.6.2.1*** From Weller et al. 2012, comparison of the ANS to other numeracy and CRT tests (A= CRT, B= Lipkus, C= DRENS, D= ANS)

Throughout this thesis, numeracy will be determined using the newly developed ANS, as it is the numeracy scale that, having sound statistical properties, has also replicated previous results in the field of Numeracy and

Decision-Making, therefore offering a benchmark to which the results of this research can be compared. Despite the recent publication of the ANS (Weller et al. 2012), access to the scale for research purposes before formal publication was granted by the authors in 2010.

**Table 2.6.2.1**

*Different numeracy tests used in studies investigating Numeracy and Decision Making*

| Study | Scale Used |
|---|---|
| Black, Nease & Tosteson, 1995 | Black Scale, 1 item |
| Schwartz, Woloshin, Black, & Welch, 1997 | Schwartz scale, 3 items |
| Hamm, Bard, and Scheid, 2003 | Lipkus, 11 items |
| Gurmankin, Baron, & Armsrong, 2004 | Gurmankin scale, 9-item test adapted from Lipkus |
| Viswanathan, Rosa & Harris, 2005 | Standardized American Math tests |
| Peters, Västfjäll, Slovic, Mertz, Mazzocco, & Dickert, 2006 | Lipkus, 11 items |
| Rothman, Housam, Weiss, Davis, Gregory, Gebretsadik, Shintani & Elasy, 2006 | Wide Range Achievement Test, third edition (WRAT-3). |
| Banks & Oldfield, 2007 | Subset of math questions contained in the 2002 wave of the English Longitudinal Study of Ageing (ELSA) |
| Peters, Dieckmann, Dixon, Hibbard & Mertz, 2007 | Decision Res. Expanded Num. Scale (DRENS), 15 items |
| Peters & Levin, 2008 | Lipkus, 11 items |
| Peters, Dieckmann, Västfjäll, Mertz, Slovic, & Hibbard, 2009 | DRENS, 15 items |
| Dickman, Slovic, & Peters, 2009 | DRENS, 15 items |
| Peters, Hart, & Fraenkel, 2011 | Scale composed of Lipkus + 2 CRT items (item 1 & 3) |
| Dickert, Kleber, Peters, & Slovic, 2011 | DRENS, 15 items |
| Kahan, Peters, Wittlin, Slovic, Ouellette, Braman, & Mandel, 2012 | DRENS, (minus question 12), plus CRT1 & CRT3 |
| Okamoto, Kyotoku, Sawada, Clowney, Watanabe, Dan & Kawamoto, 2012 | Schwartz Scale, 3 items<br>Lipkus Scale, 11 items |

## *2.7 Conclusion*

This chapter has provided a review of existing literature in three key areas of research which are related and are the subjects of investigation that will be examined in this thesis: visualization as a cognitive style, numeracy, and decision-making.

As Chapter 2 argues, a cognitive style is an individual trait identifying the preferred mode of information processing of an individual. Cognitive styles, being stable and ingrained in an individual's functioning, serve as bases for the prediction of behaviour. However, we have seen that the area of cognitive styles in judgment and decision-making has been lacking sufficient attention in the literature. Similarly, numeracy, the second area of interest in this research, has not been the focus of mainstream research on decision-making. Although some studies have investigated numeracy in decision-making contexts, most studies have been devoted to the specific sub-field of medical decision-making.

As we have argued, the cognitive style of visualization consists of a spatial and an object component. Research indicates that spatial visualization may be related to numeracy. Specifically, neurobiological studies demonstrate that spatial visualization and number processing share a common brain area. This may indicate an existing relationship between numeracy and spatial visualization. Unlike spatial visualization, however, object visualization is processed in a different brain area independent from the areas in charge of numerical and spatial processing. As we have argued, this separation could result in Object and Spatial being two independent constructs which, rather than being at opposite ends of a continuum as previously argued, might be uncorrelated. This could result in visualization types being high or low in each dimension independently. However, this point has not been sufficiently addressed in the literature, giving rise to one of the research questions that will be investigated in this thesis. In regards to the relationship between object visualization and numeracy, to our knowledge this point has never been investigated. Since object visualization and numerical abilities are processed in different brain areas, it could be the case that numeracy may not be predicted by this component of visualization.

The understanding of the cognitive style of visualization and its relationship with numeracy could be important in understanding the core processes that drive the decisions of individuals with differing numerical abilities. As demonstrated by Peters et al. (2006), numeracy does affect numerical decision-making tasks. Hence, if visualization style, particularly spatial visualization, is related to numeracy, it might be the case that visualization might also predict decision-making. However, the study of visualization as a cognitive style is in its infancy, and the study of visualization and its relation with numeracy in general, and numerical decision-making in particular, have never been the subject of scientific enquiry.

Extant literature mentioned in the current chapter indicates that visualization style, particularly the spatial component, might have a relationship with numeracy. We also showed that there is ample evidence in the literature about the phenomenon that numeracy affects decision making. Thus, we propose that visualization might affect decision making similarly than spatial visualization. In this thesis we do not investigate per se  a mediating or moderating effect of Numeracy on Decision Making. That is, does visualization affect decision making because of a mediating or moderating effect of numeracy? For such a mediation analysis and hypotheses to be developed, we should postulate that Visualization (X) has a causal relationship over Numeracy (M) and it´s that way that Decision Making (Y) is affected (Hayes, 2013). To study moderating effects, visualization and numeracy should be orthogonal or at least, not act as we hypothesize, that is one as a proxy for the other. In our study, rather than uncovering the mechanism whereby visualization is related to numeracy, we will take a more basic step and we start by researching whether such a relationship exists, and, if this relationship indeed exists, the effects of visualization on Decision Making parallel those of Numeracy.

The chapters that follow intend to address the aforementioned gaps in the literature

# Chapter 3

# Research Questions

This chapter identifies the research questions that will be the subject of investigation in this thesis. A total of six research questions on the relationship of visualization style and numeracy in judgment and decision-making tasks are proposed along with the respective motivation for each of them. In this chapter we will argue the importance of each of these questions in the context of extant research, and how they fill existing gaps in the literature in the field of Cognitive Styles in Judgment and Decision-Making.

## *3.1 Research Question 1: Object and Spatial Visualization, Relationship*

*Are the components of visualization style (object and spatial visualization) two independent cognitive style constructs as could be implied by the neurological evidence, or are they two separate ends of the visualization continuum line?*

As we have seen in sections 2.3 and 2.3.1 previously, there is an unresolved question in the literature about the independence of the Object and Spatial visualization constructs. Kozhevnikov, Hegarty and Mayer (2002) theorize that spatial and object (which they call “iconic”) visualizers are two different groups and that individuals are either one type or the other. After the administration of spatial ability tests and the verbalizer-visualizer test of cognitive style, these authors put forth the idea of the dichotomous nature of Object and Spatial visualization. As more profoundly elaborated in Section 2.3 of the current thesis, Kozhevnikov, Kosslyn & Shephard (2005) further argue for the existence of two groups of visualizers, Spatial and Iconic (Object), which they argue are mutually exclusive.

These studies, however, were not testing the cognitive style of visualization per se. Instead, the study by Kozhevnikov et al (2002) used a visualizer-verbalizer cognitive style test. As we have previously seen in the literature review, the visualization dimension is composed of two sub-components (object and spatial visualization), and this cognitive style can be reliably assessed by both the OSIQ and the later OSIVQ. At the time of the Kozhevnikov et al. (2002) study, these tests did not exist and the research on Object and Spatial visualization as a cognitive style was only beginning. The later study by Kozhevnikov et al (2005) used the construct of spatial ability instead of the construct of spatial visualization style. Although spatial ability and spatial visualization style are positively related, ability and cognitive style are not the same construct, and this might have caused Kozhevnikov et al. (2005) to make claims which could only later be substantiated with the development of the OSIQ and OSIVQ. These tests reliably assess the object and spatial visualization preferences of an individual as a cognitive style, which is stable across time (Messick, 1976; Thornell, 1976; Allinson & hayes, 1996; Kozhevnikov, 2007), whereas a skill, particularly spatial visualization, has been demonstrated to improve with training (Moses, 1980). This reasoning argues for a cognitive style being theoretically a more solid predictor of judgments than a skill, which is malleable and dependent on training, exposure, etc. (however, to our knowledge there is not relevant literature comparing the predicting capability of a skill vs. a cognitive style).

As elaborated on Section 2.4.2, neurobiological evidence points to the existence of two independent brain structures processing object and Spatial imagery (Uhl et al. 1990; Ungerleider and Mishkin, 1982; Jonides & Smith, 1997; Kosslyn & Koenig, 1992; Farah et al., 1988). In principle, the existence of these two brain structures does not necessarily imply that Kozhevnikov et al (2002;2005) were wrong in classifying individuals as either Object or Spatial visualizers. Instead, the neurological evidence would make it plausible to believe that these two visualization modes would be independent, as they rely on two different brain areas, and therefore they might not be a unitary concept located at two opposite ends of the construct of visualization.

The independence of Object and Spatial visualization is supported by studies using visualization as a cognitive style. Chabris et al. (2006) found Object and Spatial visualization to be virtually uncorrelated (r= -0.05), though this correlation was statistically significant, maybe due to the large sample size (n= 3800). In the development of the OSIVQ, Blazhenkova & Kozhevnikov (2009) also found a similar negative correlation between Object and Spatial visualization style (r= -0.03, n= 128), though in this case, unlike Chabris et al. (2006) who found a weak though statistically significant correlation, this small correlation was not statistically significant.

As we have argued, the previously cited research points to the possibility that the cognitive style of visualization is composed of object and spatial visualization, and that these might be independent. However, the evidence is not conclusive and more studies investigating this relationship could contribute to clarifying this independence of constructs. Research Question 1 aims to further investigate the replication of the non-significant (Blazhenkova & Kozhevnikov, 2009) or significant but very weak negative correlation (Chabris et al. 2006) to provide more solid evidence using, in our case, an adult student sample. The results should shed light on whether Object and Spatial visualization style are indeed related, or independent.

## *3.2 Research Question 2: Visualization and Numeracy, Relationship*

What is the relationship between visualization cognitive style (Object and Spatial visualization) and numeracy?

The literature review previously conducted in the area of neurobiology showed that humans are innately endowed with a sense of numeracy from early on in their lives (Dehaene, 2003) and that they develop brain structures in charge of this functioning, specifically the IPS (Cantlon, Brannon, Carter & Pelphrey, 2006). The same parietal regions in charge of numerical computation, in particular the IPS, are also used in spatial visualization (Molko, Cachia, Riviere, Mangin, Bruandet, Le Bihan, Cohen, & Dehaene, 2003).

Another line of research using visualization and numerical performance tests has conducted studies investigating spatial visualization skills and numerical ability. Some studies have found a positive relationship between these two constructs (Hegarty and Kozhevnikov, 1999). However, as we have previously reviewed in Section 2.4, stronger evidence needs to be gathered to be able to clarify the relationship between spatial visualization and mathematical ability.

In terms of spatial visualization as a cognitive style, no study has been conducted investigating the relationship between Object and Spatial visualization and numeracy. The evidence points to a potential positive relationship between Spatial visualization and numeracy, since a common brain area seems to be involved in Spatial visualization and numerical processing. In contrast to Spatial visualization and number processing, which takes place in the parietal lobes, Object visualization is supported by a different brain area. As explained in detail in Section 2.4, the processing of object information such as colors, pictures and face recognition is supported by the temporal cortex (Uhl, Goldenberg, Lang, & Lindinger, 1990). The lack of literature addressing the potential relationship between Object visualization and numeracy, as well as the evidence pointing to different neuronal systems in charge of mathematical and object information, makes it difficult to hypothesize whether there is a relationship between numeracy and object visualization or, if there is a relationship, in which direction this would be.

The scant evidence existing about the relationship between spatial visualization as a cognitive style and numeracy makes this an interesting question to investigate from the perspective of filling a gap in the literature. Similarly, the lack of studies taking into consideration object visualization and numeracy make this an area where a contribution might be welcome, as the clarification of such a relationship could drive future research on the implications of the cognitive style of visualization in numerical decision-making tasks.

The study of the relationship between visualization style and numeracy will be divided into two parts described hereunder. The first part will concern the study of the relationship between visualization style (Object and Spatial) and a numeracy scale (ANS). Since numeracy has been shown to predict differences in decision-making tasks, it is important to establish the relationship with the OSIVQ, as the relationship between the two tests could indicate potential predictions from visualization style in decision-making tasks. The second part will study visualization style in numerical tasks beyond the scope of numeracy tests. In particular, two tasks will investigate numerical abilities and visualization style (1) in a more business-like scenario, and (2) in a scenario involving graph interpretation.

To analyze this research question addressing the relationship between visualization style and numeracy, the Abbreviated Numeracy Scale (Weller et al. 2012) will be used. As it was previously argued, this scale incorporates the previously developed scales (see Appendix C for an overview of the scales), reducing the number of items while avoiding the prevalent ceiling effects. The ANS has sound statistical properties, capturing the construct of numeracy as demonstrated by factor analyses, and has been confirmed to predict decision-making tasks, in particular, replicating the findings of Peters et al. (2006). Understanding the relationship between numeracy and object and spatial visualization could inform future research and predictions on how visualization styles affect decision-making. As previously argued, research on decision-making has largely neglected the particular importance of individual traits. We will contribute to the body of knowledge on decision-making by bringing to the fore the cognitive style of visualization, thereby filling a gap in the knowledge of the role of individual traits in decision-making.

### *3.3 Research Question 3: Visualization and Trend Extrapolation and Recognition*

This question extends RQ2 by investigating the relationship between spatial visualization and numeracy in numerical tasks beyond numeracy tests. Although a numerical test such as the ANS alone might be enough to capture differences in numerical ability by different visualization styles, some of the questions included in the ANS test were originally designed for the use in Medical Decision-Making studies (though recently Peters et al., [2006; 2007] extended its use to other non-medical Decision-Making tasks). Although the ANS has been shown to be a test with solid statistical properties which is robust in capturing the numeracy of individuals, it is nevertheless a test measuring a skill, which is by definition a malleable individual trait. We will go beyond investigating the relationship between visualization style and the existing ANS and broaden the scope of numerical-related tasks by designing a set of two scenarios which require (1) numerical ability, and (2) graph mental representation for their correct resolution.

In the first of these tasks, individuals will be given tabular information describing the history of profits of two companies, and asked to report which company will have higher profits in the year that follows, provided the trend continues. This task is intended to check whether visualization style results in individuals being able to identify a trend given by the data (which if correctly mentally depicted would solve the problem) and predict the next point in the series.

To investigate whether visualization style affects the mental depiction of numerical data, the second task presents individuals with a table containing data and asks participants to identify, from a series of four graphs, which one represents the tabular information. The capacity to transform numerical data into a shape pattern may be influenced by visualization style, as high spatial visualization might allow individuals to draw a mental image from the presented data, resulting in the correct identification of the pattern depicted by the tabular data. This task will investigate whether this is the case.

These two tasks could be particularly effective in capturing the relationship between numerical ability and visualization. Mentally visualizing the trend described by the numerical data should lead to a correct answer, resulting in expansion of the range of tasks which visualization style can predict beyond the scope of existing numeracy tests. The two previous tasks are such that for their correct resolution, mentally picturing the numerical information offered should result in better performance.

These tasks, for which mentally picturing information might yield more correct results, will complement the investigation of the relationship between numerical abilities and visualization styles.

## *3.4 Research Question 4: Visualization Replicating Numeracy and Decision Making Study*

This research question will replicate the decision-making tasks included in Weller et al (2012) in their development of the ANS, using visualization (object and spatial) as the variables of interest. Weller et al. (2012) used three tasks replicating the results found by Peters et al. (2006) in their seminal paper on numeracy and decision-making.

As we have previously argued in Section 2.6 as part of the literature review, Peters et al. (2006) found that higher numeracy was associated with experiencing less attribute framing effects, that low (but not high) numerates differed in their risk perception depending on whether information was presented in a frequentistic or in a probabilistic format, and that high numerates tended to make suboptimal choices when asked to choose between options that appeared more appealing. In addition, Peters et al. (2006) found that when evaluating bets, high numerates found objectively better bets more attractive than low numerates (see Section 2.6).

Peters and colleagues interpreted the findings of their first and second study by attributing to the high numerates a higher capacity "*to retrieve and use appropriate numerical principles and transform numbers presented in one frame to a different frame*" (p. 412). The findings of the second and third study, according to Peters et al. (2006) were consistent with their "*hypothesis that the highly numerate tend to draw more affective meaning from probabilities and numerical comparisons than the less numerate do*." (p. 412).

Though Peters et al. (2006) used the Lipkus numeracy scale in their studies, Weller et al. (2012) investigated three of the studies (Bowl task, Bets task, and Student framing task), finding that the ANS predicted the results much in the same manner as the Lipkus scale used originally by Peters et al. (2006).

Research Question 4 will investigate whether visualization style has an impact on the three decision-making tasks common to Peters et al. (2006) and later replicated by Weller et al. (2012).

## *3.5 Research Question 5*

We shall now begin investigating the practical implications of visualization style. Research Question 5 investigates the potential influence of visualization style in scenarios that could occur in daily life. Does visualization style influence the perception of numerical information presented in a distorted graphical format (bar graphs)? Having investigated in RQ3 the ability to extrapolate a trend from tabular information, RQ 5 will now investigate whether different visualizers differ in their perceptions of how good the financial situation of a company is when the numerical information is presented in tabular format.

### 3.5.1 Research Question 5A: Graph Distortion

Graphs are a method of conveying numerical information in a visual format, and as shown Section 1.3, *"(...) the ability to understand graphically presented information is essential in everyday life: graphs are ubiquitous in newspapers and magazines, on television, and on the Internet*" (Galesic & Garcia-Retamero, 2011, p. 444). Some people are more able than others to interpret graphs and accurately extract objective information from these information displays. The accuracy of graph interpretation can be in some cases negatively influenced by the manipulation of graphs or, as Beattie & Jones (2008) call it: "graph infidelity". One type of graph infidelity is graph distortion, which happens when the X-axis on a bar chart or line graph starts at Y≠ 0, thereby modifying the slope. Research in the area of financial reporting (Steinbart, 1989; Beattie and Jones, 2000a,b; Frownfelter-Lohrke and Fulkerson, 2001) found graph distortion to be widespread in US company annual reports. Recent research (Pennington & Tuttle, 2009) has found that financial information presented in the format of bar graphs was interpreted differently depending on whether the graphs were distorted or undistorted. Specifically, bar graphs representing an ascending trend whose Y-axis was truncated (therefore giving the impression of a more positive slope) generated more positive impressions than undistorted graphs (Pennington & Tuttle, 2009). This has potential practical implications and, as Pennington & Tuttle (2009, p. 25) indicated, "*The resulting data interpretation errors lead to more positive judgments and investment decisions than would otherwise be warranted.*"

Research Question 5A will investigate whether visualization style has an impact on the likelihood that graph distortion will affect an individual. Since bar graphs are a form of spatial depiction of numerical information, we would expect high spatial visualization to be a predictor of a lower graph-distortion effect.

### 3.5.2 Research Question 5B: Tabular Information

Tables are another format in which numerical information is often presented. Research Question 5B will investigate whether visualization style affects the positivity or negativity of judgments of data when these are presented in tabular format. To the best of our knowledge no research has investigated individuals' judgments of positivity or negativity of a financial scenario described by numerical information presented in a tabular format. This lack of research extends to the potential impact that visualization style might have on these types of evaluations.

The lack of research in this area makes this question particularly relevant, although the existing lack of theoretical development makes establishing predictions on the impact that visualization style will have on such a task an open empirical question. However, high spatial visualization could make the mental translation from the numbers on the table to visualizing the slope easier. This would translate into higher spatial visualization generating ratings with more variance than low spatial visualization, as the evaluations provided by individuals with higher spatial visualization might reflect their judgment more faithfully owing to the fact that they might be surer of their interpretation due to their higher level of spatial cognition. This should give more extreme ratings and higher variance. In contrast, the low spatial visualizers might give more conservative ratings. It is, however, more difficult to make a prediction of how the mental translation from numbers to a slope would be affected by the degree of object visualization of individuals, due to the lack of evidence in the literature. The current research question will therefore help inform this gap in the literature.

By presenting individuals with financial information in a tabular format displaying a series of yearly profits of a company and asking their impressions about the positivity or negativity of results, we expect to elucidate whether visualization style has an impact in such an evaluation.

## *3.6 Research Question 6*

As we have previously reviewed, the matching of information with the cognitive style of individuals has important implications in decision-making. Specifically, matching cognitive style and stimuli results in people paying attention to information consistent with their cognitive style (Blaylock & Rees, 1984; Hunt et al., 1989), a more positive attitude towards ads and brands and more purchase intention (Ruiz & Sicilia, 2004). This argument leads us to hypothesize that visualization style might determine the type of stimuli that are more heavily weighted when processing information and therefore affect the decisions made depending on the visualization style of individuals. This is precisely what this research question will investigate.

How does visualization style affect individuals' decisions and judgments when appraising a numerical scenario to which non-numerical visual stimuli are added?

The investigation of this question could have practical as well as theoretical implications. As we have previously argued, the availability (and need to make use of) numerical information in various presentation formats (tables, graphs) is prevalent. It is common to see published material where numerical information is presented along with other non-numerical stimuli or information to enhance or create an impression. For instance, faces of happy or sad people are often found along with numerical information, and a simple web search for pension plans or investment funds will yield an array of websites containing numerical information from which one has to make an evaluation, printed along with non-numerical information such as smiling retirees, families merrily strolling on a field etc. (for an example, see Figure 3.6.1).

**The Power of $100 a Month**

| Rate of Return | | Number of Years | | | | |
|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 |
| 5% | 6,801 | 15,528 | 26,729 | 41,103 | 59,551 | 83,226 |
| 6% | 6,977 | 16,388 | 29,082 | 46,204 | 69,299 | 100,452 |
| 7% | 7,159 | 17,308 | 31,696 | 52,093 | 81,007 | 121,997 |
| 8% | 7,348 | 18,295 | 34,604 | 58,902 | 95,103 | 149,036 |
| 9% | 7,542 | 19,351 | 37,841 | 66,789 | 112,112 | 183,074 |
| 10% | 7,744 | 20,484 | 41,447 | 75,937 | 132,683 | 226,049 |

**Retirement Considerations At A Glance**

When you would like to retire may be very different from when you can afford to retire. Here are factors that come into play to realistically determine a retirement age:

Life Expectancy: Americans are living longer. When Social Security was created, the average life expectancy past retirement age was 5-10 years. Today it's 20-25 years. Anticipate needing income for a minimum of 20 years if you retire at age 67.

Sources of Income: Pension plans and Social Security are the key sources of retirement income for most Americans. Be sure to take into account the need for other sources of income such as IRAs, investments and a second career.

***Figure 3.6.1*** Example of a website using a profusion of people's images along with financial information (http://www.taxwiseadvisor.com/planning-retirement-income-2/happy-retirement/)

These images, combined with the accompanying financial information could (and indeed their creators would expect) have an effect on judgment and decision making. Investigating how such information is appraised depending on visualization style may help in determining the effectiveness of such visual stimuli for different visualization styles.

The existence of numerical information printed along with human faces and figures on brochures, websites, etc. will, according to the literature, result in different brain areas being activated for the processing of the different visuals. Specifically, as we have seen in Section 2.3 before, the processing of Object information such as faces and human figures will take place in the Object pathway, also called the ventral system and the neural structures processing object information are also in charge of processing visual information on faces. It could thus be hypothesized that a face might constitute an “object” stimulus. In principle, faces are processed in the same temporal area which was previously argued to be part of object visualization structures. In addition, a face is rich in details, a characteristic of object visualization. This argument, which in principle is consistent with the brain structure and visualization processes previously reviewed, could nevertheless be stronger if there was a body of literature classifying and clearly defining what “object” and “spatial” stimuli are. It might be possible to obtain indirect evidence of a face being an “object” stimulus if, as previously reviewed, cognitive style determines what information people consider when making decisions. By creating a scenario showing a face displaying a given emotion (positive or negative), and matching it with numerical information, it might be possible to detect how people appraise the whole situation and investigate whether visualization plays a role.

As the previously reviewed literature makes explicit, object and spatial information are processed by different brain areas. To better investigate the impact of visualization style on decision-making when seeing object (faces) and spatial (graphs) information in a numerical context, we will create a series of scenarios where numerical information is matched with either spatial (graphs) or object (human figures with a positive or negative demeanor) information. Research Question 6A will investigate scenarios with tabular numerical information accompanied by an Object stimulus (a face), whereas Research Question 6B will investigate scenarios with numerical information presented in a spatial format (bar graphs) spatial numerical information (bar graphs) accompanied by a face. This design allows verification of whether faces have a different effect depending on the numerical information format (tables vs. graphs) for different types of visualizers.

### 3.6.1 Research Question 6A: Numerical information and face

This research question will investigate whether individuals' judgement of a company's results based on financial information given in tabular format differs depending on whether the tabular information is accompanied by a positive or negative looking human figure. If numerical ability and spatial visualization are positively correlated, we would expect the ratings to remain stable regardless of whether a happy or serious human figure is presented with the table. If a face indeed constitutes a stimulus which informs object visualization, high object visualization could drive attractiveness ratings depending on whether the face is positive or negative looking.

### 3.6.2 Research Question 6B: Spatial information and face

This research question will investigate whether individuals judge graphical financial information about a company as more attractive when shown profits in the form of bar graphs independent of an accompanying cheerful or serious face. In such a scenario, we would expect ratings to remain stable regardless of whether a happy or sad face is presented with the graphical information about the company. If a face indeed constitutes a stimulus which informs object visualization, high object visualization should drive attractiveness ratings depending on whether the face is positive or negative.

### 3.7 Summary of Research Questions

As shown in Figure 3.7.1, this research has three major components: Decision-Making, Numeracy, and Visualization (composed of Object and Spatial).

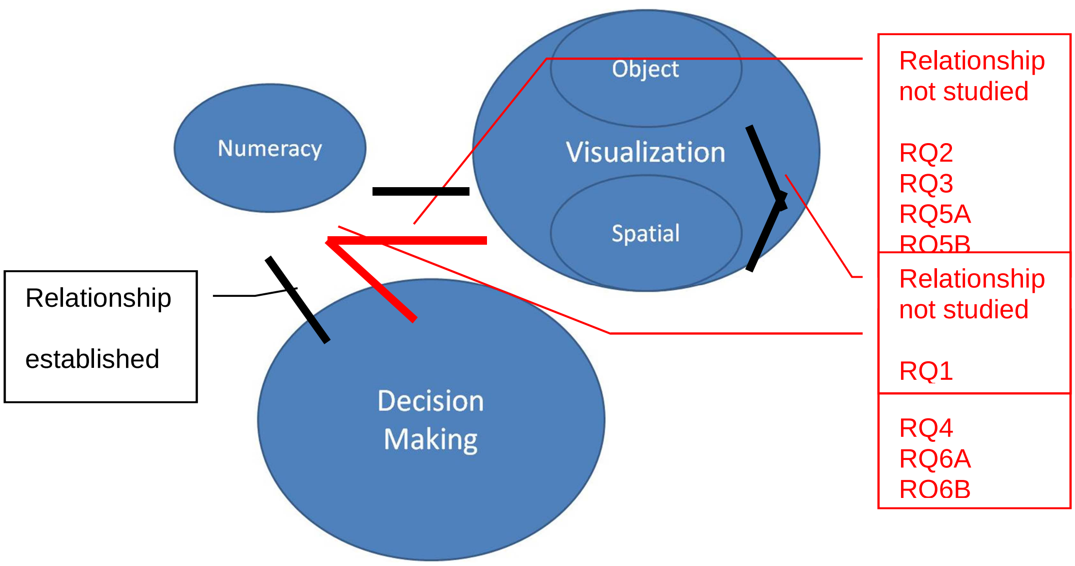



***Figure 3.7.1*** Fit of this research into the existing literature. In red, the focus of this thesis.

As we have argued, the field of Decision-Making has, save for the exceptions noted in the current literature review and the work of Stanovich & West (2000), largely neglected the study of individual differences. Similarly, the relationship between Decision-Making and Numeracy has been the subject of recent attention, though the research in this particular realm is just beginning, therefore leaving much scope for investigation. In addition to contributing to the development of the two aforementioned areas where research is still underdeveloped, this thesis brings to the fore a unique individual trait, Visualization.

# Part II

# EXPERIMENTAL WORK

# Chapter 4

# Relationship between Object, Spatial Visualization, and Numeracy

This Chapter will investigate whether object and spatial visualization are indeed two different constructs or are opposites on a continuum of visualization style. As we have previously argued, evidence from the OSIQ and OSIVQ point to Object and Spatial visualization being two constructs at opposite ends of a continuum (Kozhevnikov, Hegarty & Mayer, 2002; Kozhevnikov, Kosslyn & Shephard, 2005). However, some research (Chabris et al., 2006; Blazhenkova & Kozhevnikov, 2009) argues that object and spatial visualization are independent and uncorrelated constructs. In addition, this question will investigate the relationship between visualization style and numeracy.

These questions are important since the two types of visualization may not be mutually exclusive, and therefore the spectrum of visualization style would expand from two categories (object or spatial) to four different categories depending on an individual’s preference for object (high or low) and spatial (high or low) visualization. Although the OSIQ and OSIVQ authors did not argue for a classification of individuals into categories depending on their composites of object and spatial visualization, it has been shown that a cognitive style composed of two dimensions can form a 2 x 2 matrix. For instance, Sojka & Giese (1997) classified individuals into a four-cell matrix depending on whether people were high or low in the Thinking or Feeling dimensions. The practical importance of such a classification into a matrix was shown by Ruiz & Sicilia (2004), who demonstrated that the presentation of information consistent with an individual's cognitive style generated higher attitude towards the ad and purchasing intention.

Elucidating the types of visualizers and their numeracy is important for making predictions of how visualizers differing in their degree of object and spatial visualization would respond in different decision-making situations where numerical processing is involved.

## *4.1 Method*

### 4.1.1 Instruments

The ANS and OSIVQ were administered, in this order, as part of a package containing other experimental tasks presented to participants in several courses at a major UK university. The materials were administered in the form of a paper questionnaire which participants answered during class time. The experimenter remained present during the administration of the questionnaire to ensure that participants answered only their own questionnaires and were not influenced by other participants or by the use of calculators or other external aid. The few instances of calculator usage detected concerned less than 10 subjects in the total sample of the current thesis. In all cases, to avoid the risk of data contamination, the questionnaires were discarded. The experimenter collected the questionnaires once completed and de-briefed those participants who inquired about the research being conducted.

### 4.1.2 Participants

The sample was purposefully selected to provide a wide variability of numeracy and visualization scores. To this end, participants were selected from the Faculty of Engineering, the Faculty of Literature and Arts, and the Business School. This was intended to widen the range of both visualization and numeracy scores so the relationship between visualization and numeracy could be detected.

A total of 241 participants (116 Business, 88 Engineering, 37 Literature & Arts) took part in the data collection. Due to the fact that this data was intended to lay the fundamental groundwork for the further development of the thesis, there were stringent criteria to make sure the data were reliable and absent of noise (e.g. participants giving random answers, etc.). Thus, questionnaires were eliminated whenever a participant missed any of the 30 visualization questions on the OSIVQ, failed to complete the numeracy scale, or turned in questionnaires suggesting that the subject had not taken the task seriously (e.g. systematically ticking the same column in the answers). The decision to eliminate cases where a participant missed a question in the Object or Spatial part of the OSIVQ (15 questions each), was based on the need to ensure that the data received truly reflected the answers of participants who had full attention devoted to the completion of the tasks. Although statistical techniques to deal with missing responses are available (Schafer & Graham, 2002), due to the fact that the sample size was sufficiently large, the researcher and thesis supervisors opted for the safest option to safeguard data quality. In addition, all cases where participants gave an indication that they might not be actively trying to solve the numeracy questions (e.g. leaving more than 3 answers blank in the numeracy test) were set aside and the experimenters discussed each individual case to look for indications of possible lack of necessary commitment from the participant. To judge whether a case was to be rejected, the experimenters looked at the pattern of completion of the numeracy tasks in conjunction with the other tasks in the experiment. Whenever missing more than 3 responses in the numeracy questionnaire was combined with missing other items in the experimental packet, the student was removed. This rule was applied on a case by case basis, and every incidence of discarding a subject due to doubts about data validity (e.g. a participant ticking a string of answers in a column on the OSIVQ, or with missing items in the numeracy scale) was discussed with the supervisors to ensure quality of the data. These stringent criteria reduced the pool to the resulting sample which, as shown in table 4.1.2.1, comprised 144 participants. Although a rejection rate of 40% like the current case may seem high, the necessity to receive data of quality demanded the application of strict selection criteria, which was deemed particularly important at this point of doing such fundamental research. Thus, avoiding noise in the data was prioritized.

**Table 4.1.2.1**
*Participants' demographics for Research Question 1 & 2: Relationship among visualization constructs, and their relationship with numeracy*

| **Descriptive Statistics, Demographics** | | | | |
|---|---|---|---|---|
| Major | Number of participants (N) | Age Range | Mean (M) | St. Deviation (SD) |
| Business | 50 (38 female) | 17-23 | 18.48 | .95 |
| Engineering | 62 (14 female) | 18-42 | 20.48 | 3.6 |
| Arts & Literature | 32 (24 female) | 18-24 | 19.53 | 1.7 |
| Total | 144 (76 female) | 17-42 | 19.57 | 2.67 |

## *4.2 Results*

### 4.2.1 Preliminary checks

We first analyzed the OSIVQ dimensions to check whether the sample under investigation followed the same pattern as the original OSIVQ. In a repeated-measures ANOVA with the object, spatial and verbal scores as within- and gender as between-subjects factors, Blazhenkova & Kozhevnikov (2009) found a significant effect of gender, a significant effect between the three components of the OSIVQ, and an interaction between gender and OSIVQ. In addition they found that females had higher object scores than males, but males had higher scores in spatial visualization than females. They found no significant differences in Verbal scores between males and females.

Paralleling the original OSIVQ results, a repeated-measures ANOVA with gender as a between- and the three OSIVQ dimensions as within-subjects factors, indicated a main effect of gender ($F[1,133]=3.77$, $p=.05$), a significant difference between the three OSIVQ dimensions ($F[2,266]=24.54$, $p<.001$), and an interaction between gender and OSIVQ ($F[2,266]=18.18$, $p<.001$).

Consistent with Blazhenkova & Kozhevnikov (2009), in the OSIVQ scales, which range from 1 to 5, females ($M=3.53$, $SD=.53$) had significantly higher scores than males ($M=3.29$, $SD=.48$) in object visualization, whereas in Spatial visualization males ($M=3.21$, $SD=.60$) achieved higher scores than females ($M=2.65$, $SD=.65$) (see Table 4.2.1.1 for overall means). Replicating the OSIVQ, this sample showed the differences between males and females in the verbal dimension to be statistically insignificant (Table 4.2.1.2).

**Table 4.2.1.1**

*Table of means Numeracy, Object, Spatial and Verbal*

**Descriptive Statistics**

| | Major | Gender | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| | | Female | 5.37 | 1.52 | 35 |
| | Business | Male | 5.27 | 1.68 | 11 |
| | | Total | 5.35 | 1.54 | 46 |
| | | Female | 5.14 | 1.83 | 14 |
| Numeracy | Engineering | Male | 6.42 | 1.31 | 43 |
| | | Total | 6.10 | 1.54 | 57 |
| | | Female | 5.08 | 1.139 | 24 |
| | Arts & Literature | Male | 6.13 | 1.46 | 8 |
| | | Total | 5.34 | 1.29 | 32 |
| | | Female | 3.56 | .45 | 35 |
| | Business | Male | 3.41 | .50 | 11 |
| | | Total | 3.53 | .46 | 46 |
| | | Female | 3.28 | .60 | 14 |
| Object | Engineering | Male | 3.20 | .48 | 43 |
| | | Total | 3.22 | .51 | 57 |
| | | Female | 3.67 | .56 | 24 |
| | Arts & Literature | Male | 3.58 | .42 | 8 |
| | | Total | 3.65 | .52 | 32 |
| | | Female | 2.57 | .60 | 35 |
| | Business | Male | 2.84 | .41 | 11 |
| | | Total | 2.63 | .57 | 46 |
| | | Female | 3.27 | .61 | 14 |
| Spatial | Engineering | Male | 3.43 | .52 | 43 |
| | | Total | 3.39 | .54 | 57 |
| | | Female | 2.37 | .53 | 24 |
| | Arts & Literature | Male | 2.56 | .41 | 8 |
| | | Total | 2.42 | .50 | 32 |
| | | Female | 3.10 | .49 | 35 |
| | Business | Male | 3.08 | .55 | 11 |
| | | Total | 3.09 | .50 | 46 |
| | | Female | 3.01 | .67 | 14 |
| Verbal | Engineering | Male | 3.17 | .59 | 43 |
| | | Total | 3.13 | .61 | 57 |
| | | Female | 3.46 | .41 | 24 |
| | Arts & Literature | Male | 3.58 | .61 | 8 |
| | | Total | 3.49 | .46 | 32 |

**Table 4.2.1.2**

*OSIVQ, Table of Means for Object, Spatial and Verbal Scores by Gender*

| Descriptive Statistics | | | | | |
|---|---|---|---|---|---|
| | Gender | Mean | Std. Deviation | N | T-test Female vs. Male Groups |
| Object | Female | 3.53 | .53 | 76 | t(142)= 2.89, p=.004 |
| | Male | 3.29 | .48 | 68 | |
| | Total | 3.42 | .52 | 144 | |
| Spatial | Female | 2.65 | .65 | 76 | t(142)= -5.41, p<.001 |
| | Male | 3.21 | .60 | 68 | |
| | Total | 2.91 | .68 | 144 | |
| Verbal | Female | 3.20 | .53 | 73 | t(133)= .95, p=.95 |
| | Male | 3.21 | .60 | 62 | |
| | Total | 3.20 | .56 | 135* | |

* Actual number lower than 144, as there were an extra 9 participants missing at least one verbalization answer in the verbalization part of the OSIVQ

The pattern of score distributions of the three scales follows the same pattern that Blazhenkova & Kozhevnikov (2009) reported in the OSIVQ; object visualization scores are the highest and Spatial the lowest, while the verbal scores fell in between object and spatial visualization (Figure 4.2.1.1)

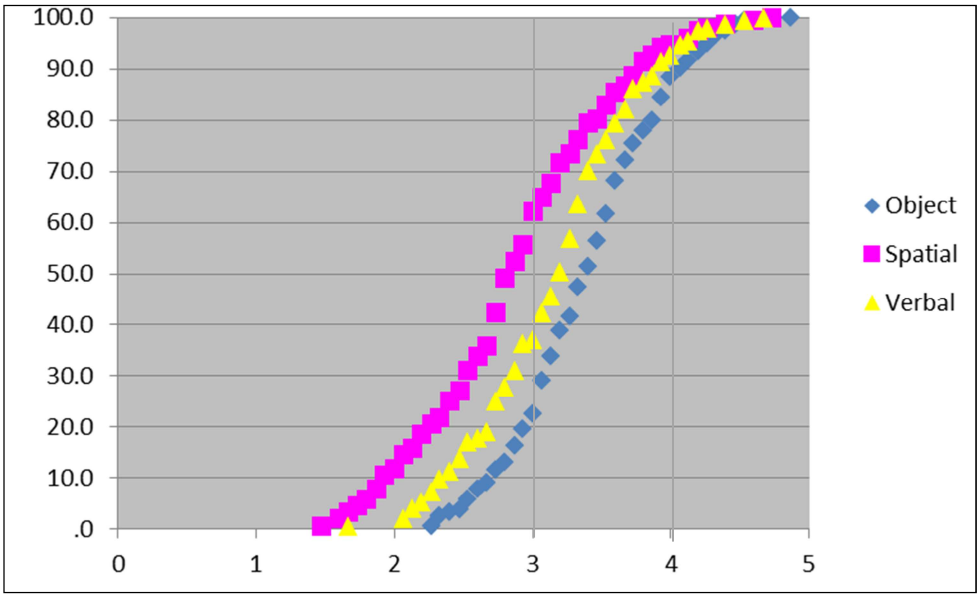



***Figure 4.2.1.1*** Cumulative frequency graph: OSIVQ scores transformation to percentiles (Y= % of cases, X= OSIVQ score). For instance, a score of 3 in the Object scale indicates roughly 21% of the participants scored below this mark.

The distribution of numeracy scores reveals a bimodal distribution (Figure 4.2.1.2) in contrast to the highly skewed distribution of numeracy scores of the Lipkus reported by Peters et al. (2006) in their research on numeracy and decision making. This distribution of scores found by Peters made it necessary to dichotomize this variable into high and low groups when investigating the effects of numeracy in decision-making tasks. The ANS in this sample does show a more spread distribution, therefore differentiating levels of numeracy.

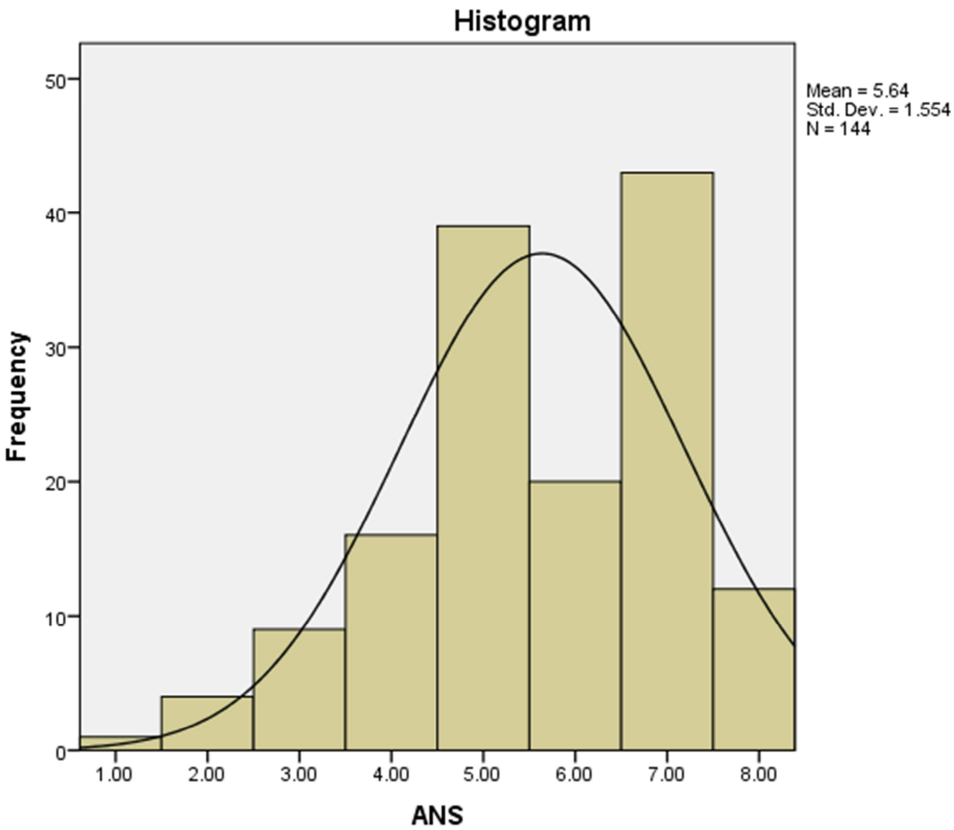



***Figure 4.2.1.2*** Distribution of Numeracy scores

### 4.2.2 General Correlations

A correlation analysis including the OSIVQ components and Numeracy (ANS) scores was run to provide a general idea of the relationships between these variables. The correlation indicated that object visualization is significantly negatively correlated with Numeracy (r[144]=-.27, p=.001). In contrast, spatial visualization follows the opposite pattern of object visualization, being significantly positively correlated with numeracy (r[144]=.33, p<.001). Providing a further argument for the exclusion of the verbal component of the OSIVQ as an area of focus of this thesis, we can see in Table 4.2.2.1 that verbalization is not correlated with numeracy (r[135]= -.002, p=.98).

**Table 4.2.2.1**

*Table of correlations Numeracy, Object and Spatial visualization*

**Correlations**

| | | Numeracy | Object | Spatial | Verbal |
|---|---|---|---|---|---|
| Numeracy | Pearson Correlation | 1 | -.27** | .33** | -.00 |
| | Sig. (2-tailed) | | .00 | .00 | .98 |
| | N | 144 | 144 | 144 | 135 |
| Object | Pearson Correlation | -.266** | 1 | -.07 | .13 |
| | Sig. (2-tailed) | .001 | | .39 | .13 |
| | N | 144 | 144 | 144 | 135 |
| Spatial | Pearson Correlation | .327** | -.07 | 1 | -.19* |
| | Sig. (2-tailed) | .000 | .39 | | .03 |
| | N | 144 | 144 | 144 | 135 |
| Verbal | Pearson Correlation | -.002 | .13 | -.19* | 1 |
| | Sig. (2-tailed) | .980 | .13 | .03 | |
| | N | 135 | 135 | 135 | 135 |

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

### 4.2.3 Predictive value of Object and Spatial visualization

We ran a regression model with numeracy as the dependent variable to check whether the relationships between visualization style and numeracy still persist when running controls for gender and major (the subject of study of an individual). As independent variables we used the visualization preference scores (object and spatial), gender (0= female, 1= male) and a dummy variable representing whether participants were an Engineering major or not (Non-engineering=0, Engineering=1), as majoring in Engineering proved to affect the degree of spatial and object visualization as well as numeracy ability.

To assess the ideal number of levels in the dummy variable defining major in the regression, two separate ANOVAs were run to respectively check for differences in object and spatial visualization scores among the three majors. Both ANOVAs had major as the IV (Business, Arts & Letters, Engineering). Table 4.2.3.1 displays the post-hoc analysis of the ANOVA with object visualization as the DV, showing that the group of Engineering students differed significantly from the Business and Arts groups (which did not differ amongst themselves), whereas the ANOVA checking for differences in spatial visualization among the three majors revealed that, again, the group of Engineers was the one differing significantly from both the Arts & Literature and the Business groups. Specifically, Engineering participants had higher scores in Spatial visualization than either Business or Language/Arts participants (who did not differ amongst themselves). With regard to object visualization, the pattern was the opposite, with Engineering students having lower scores than either Business or Language/Arts participants (who did not differ amongst themselves).

**Table 4.2.3.1**

*Scheffe Post-hoc tests checking for differences in object and spatial visualization among different majors*

**Post-Hoc Analyses, Differences between Majors**

Dependent Variable: ObjectScore

| DummyMajor | DummyMajor | Mean Difference | Std. Error | Sig. | 95% Confidence Interval Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|
| Engineering | Business | -.28* | .093 | .011 | -.51 | -.05 |
| | Arts & Literature | -.42* | .11 | .001 | -.69 | -.16 |
| Business | Arts & Literature | -.14 | .11 | .444 | -.41 | .13 |

Dependent Variable: SpatialScore

| DummyMajor | DummyMajor | Mean Difference | Std. Error | Sig. | 95% Confidence Interval Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|
| Engineering | Business | .75* | .10 | .000 | .50 | 1.01 |
| | Arts & Literature | .97* | .12 | .000 | .68 | 1.26 |
| Business | Arts & Literature | .22 | .12 | .211 | -.086 | .52 |

The regression model performed predicting Numeracy scores from object, spatial visualization, major, and gender was statistically significant, $F(4,139)=7.94$, $p<.001$ (Table 4.2.3.2) showing that once the effects of gender and an engineering major are accounted for, both preference for object and preference for spatial visualization significantly predicts numeracy scores.

**Table 4.2.3.2**

*Regression Model for Visualization Predicting Numeracy*

**Model Summary**

| | | | | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|
| R | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
| ,43[a] | ,19 | ,16 | 1,42 | ,19 | 7,94 | 4 | 139 | ,000 |

a. Predictors: (Constant), Engineering, ObjectScore, Gender, SpatialScore

As shown on Table 4.2.3.3, higher object visualization predicts lower numeracy scores (p=.003), while higher spatial visualization predicts higher numeracy scores (p=.001). Once visualization is taken into consideration, Gender and Engineering do not seem to have a statistically significant power in predicting numeracy and the tests for collinearity are no cause for concern, with all values well below the customary cut-off point for concern of 10 (Cohen et al. 2003).

**Table 4.2.3.3**
*Visualization and control variables predicting numeracy*

**Coefficients[a]**

| Model | Unstandardized Coefficients | | Standardized Coefficients | | | 95,0% Confidence Interval for B | | Correlations | | | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | t | Sig. | Lower Bound | Upper Bound | Zero-order | Partial | Part | Tolerance | VIF |
| (Constant) | 6,01 | ,98 | | 6,13 | ,000 | 4,07 | 7,94 | | | | | |
| ObjectScore | -,76 | ,25 | -,25 | -3,06 | ,003 | -1,25 | -,27 | -,27 | -,25 | -,234 | ,859 | 1,164 |
| SpatialScore | ,76 | ,23 | ,33 | 3,36 | ,001 | ,31 | 1,20 | ,33 | ,27 | ,257 | ,597 | 1,675 |
| Gender | ,48 | ,28 | ,15 | 1,68 | ,095 | -,084 | 1,04 | ,28 | ,14 | ,129 | ,702 | 1,425 |
| Engineering | -,45 | ,34 | -,15 | -1,33 | ,187 | -1,13 | ,22 | ,22 | -,11 | -,101 | ,490 | 2,040 |

a. Dependent Variable: ANS

The previous analyses demonstrate that visualization is related to numeracy. Specifically, whereas object visualization is a negative predictor of numeracy scores, spatial visualization is a positive predictor. In addition, the results speak for an independence of the constructs of object and spatial visualization. In the current sample, object and spatial visualization were insignificantly correlated (r[144]=-.072, p=.389).

Thus, this minor correlation, which is below the .10 mark customarily considered negligible (Cohen, 1988) between these constructs (r=-.07), points to these visualization constructs being independent of each other. The plot of object against spatial scores forms a rather clustered blob, as would be expected if these constructs were indeed independent of each other as neurobiological data and these results suggest.

As shown in Figure 4.2.3.1, a plot graphing the scores of object against spatial visualization does not show any linear relationship among these constructs, as it would be expected if object and spatial visualization were at two opposite ends of a continuum line.

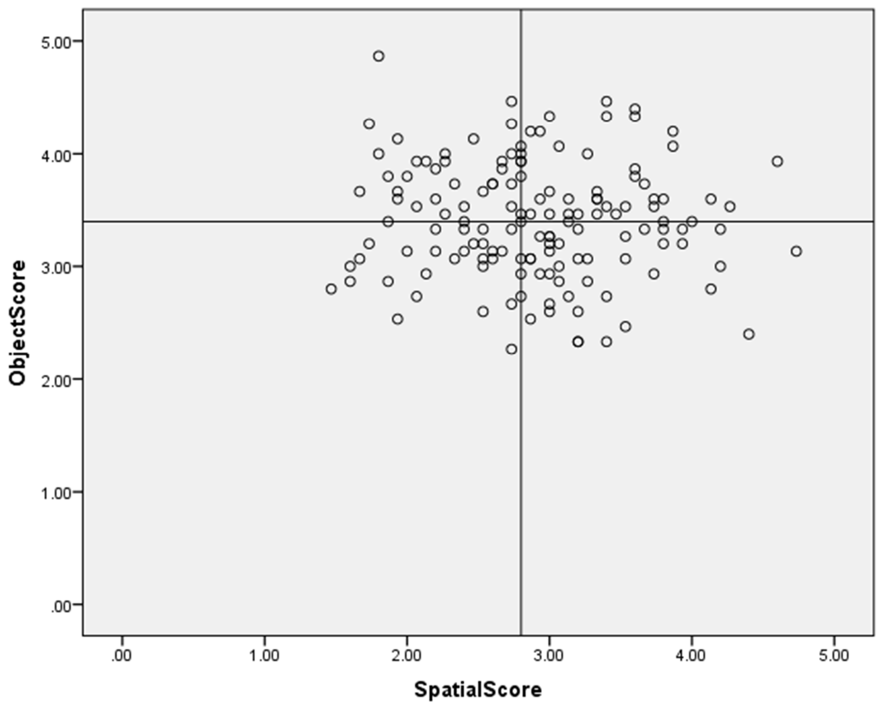



***Figure 4.2.3.1*** Plot of Object against Spatial scores

## 4.2.4 Visualization Matrix

The previous findings indicate that object and spatial visualization are independent constructs, and visualization preference seems to confirm the anatomical and functional differences between the two systems reported in the literature (Mellet, et al., 2002; Gazzaniga, 2004, Thierry & Price, 2006). This means that, instead of falling at opposite ends of a continuum line, individuals can have independent continuous values in the two visualization dimensions.

Because of this independence of scores, individuals could therefore, have a higher or lower preference for each type of visualization independent of the other, creating a two by two matrix depending on whether they have high or low object or spatial visualization. The creation of a classification matrix from an individual's cognitive style depending on their high/low status for each dimension has proved useful in investigating consumers' judgments and decisions (Ruiz & Sicilia, 2004). The classification of individuals according to their combination of visualization preference might also allow predictions to be made about judgments and decisions. It is therefore interesting to check whether classifying individuals in such a matrix would yield consistent results with the aforementioned correlation and regression analyses. If that was the case, the categorization of individuals according to their visualization preferences might predict behaviour in further tasks.

To create a matrix of low/high, spatial/object visualizers, we performed a median split on object and on spatial visualization scores and created groups of low and high in each dimension.

We named the groups generated by median split as follows:

- Object Visualizers: High Object, Low Spatial (+ Object, - Spatial)
- Undefined: Low Object, Low Spatial (- Object, - Spatial)
- ObjectSpatial: High Object, High Spatial (+ Object, + Spatial)
- Spatial: Low Object, High Spatial (- Object, + Spatial).

The median of object visualization was 3.40, whereas the median of spatial visualization was 2.80 on a scale from 0 to 5.

To see how the visualization style matrix classification related to Numeracy, a one-way ANOVA was performed with Numeracy as the dependent variable, and Visualization Type as the independent variable.

The results of the previously reported correlation and regression analyses hint at the possibility that a particular type of visualization links to a particular level of numeracy score. Specifically, object visualization may link to lower Numeracy whereas spatial visualization may link with higher Numeracy scores, whereas the Undefined and ObjectSpatial groups may be in between.

As shown on Table 4.2.4.1, the ANOVA performed on Numeracy scores yielded Visualizer Type a significant factor ($F[3,140]= 7.23$, $p< .001$) and shows how the groups of Object ($M= 5.08$, $SD= 1.62$) and Spatial ($M= 6.54$, $SD= 1.41$) visualizers are at the lowest and highest extremes of numeracy performance respectively, whereas the ObjectSpatial and Undefined groups are at the center (Figure 4.2.4.2 and Table 4.2.4.2) . A post-hoc analysis revealed the Spatial group differs from all other groups, but the other three groups do not differ among themselves (see Table 4.2.4.3). It seems then, that it is high spatial visualization when combined with low object visualization which makes a difference in increasing numerical abilities. The finding that object visualization predicts numeracy in the opposite direction from spatial visualization is a significant novelty, as no previous body of theory has suggested what the effect of object visualization on numeracy could be. The fact that spatial visualization is positively correlated and object visualization is negatively correlated with numeracy matches the finding that the group of Spatial visualizers is the group with the highest numeracy of all four groups.

**Table 4.2.4.1**
*ANOVA model for Numeracy of different visualizers*

Tests of Between-Subjects Effects

Dependent Variable: ANS

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 46.32[a] | 3 | 15.44 | 7.23 | .000 |
| Intercept | 4522.41 | 1 | 4522.40 | 2118.21 | .000 |
| VisualizerType | 46.32 | 3 | 15.44 | 7.23 | .000 |
| Error | 298.90 | 140 | 2.14 | | |
| Total | 4924.00 | 144 | | | |
| Corrected Total | 345.22 | 143 | | | |

a. R Squared = .134 (Adjusted R Squared = .116)

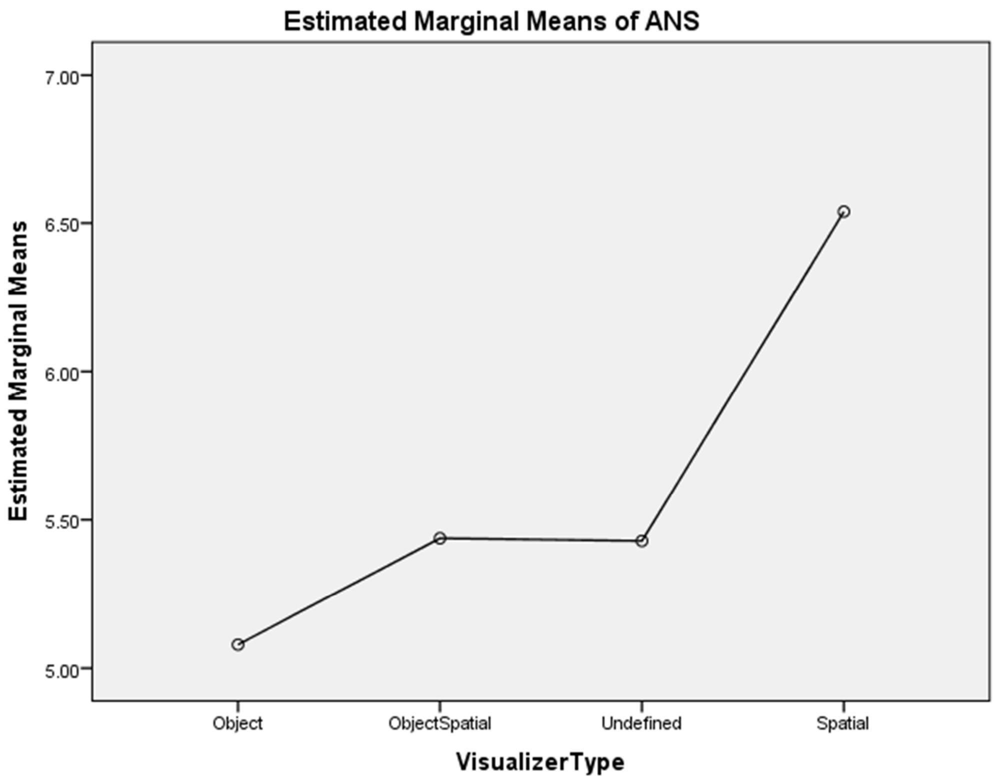



***Figure 4.2.4.2*** Numeracy of different visualizer groups

**Table 4.2.4.2**

*Table of means, visualizer types and numeracy*

**Descriptive Statistics**

Dependent Variable: ANS

| VisualizerType | Mean | Std. Deviation | N |
|---|---|---|---|
| Object | 5.08 | 1.62 | 38 |
| ObjectSpatial | 5.44 | 1.70 | 32 |
| Undefined | 5.43 | 1.04 | 35 |
| Spatial | 6.54 | 1.41 | 39 |
| Total | 5.64 | 1.55 | 144 |

**Table 4.2.4.3**

*ANOVA post-hoc analyses for different visualizer groups*

**Multiple Comparisons**

Dependent Variable: ANS

Post-hoc test: Scheffe

| Vis. Type | Visualizer Type | Mean Difference | Std. Error | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| Object | ObjectSpatial | -.36 | .35 | .790 | -1.35 | .63 |
| | Undefined | -.35 | .34 | .791 | -1.32 | .61 |
| | Spatial | -1.46* | .33 | .000 | -2.40 | -.52 |
| ObjectSpatial | Object | .36 | .35 | .790 | -.63 | 1.35 |
| | Undefined | .01 | .36 | 1.000 | -1.00 | 1.02 |
| | Spatial | -1.10* | .35 | .022 | -2.09 | -.11 |
| Undefined | Object | .35 | .34 | .791 | -.62 | 1.32 |
| | ObjectSpatial | -.01 | .36 | 1.000 | -1.02 | 1.00 |
| | Spatial | -1.11* | .34 | .016 | -2.07 | -.15 |
| Spatial | Object | 1.46* | .33 | .000 | .52 | 2.40 |
| | ObjectSpatial | 1.10* | .35 | .022 | .11 | 2.09 |
| | Undefined | 1.11* | .34 | .016 | .15 | 2.07 |

This pattern is also obvious and might be more parsimonious when the data is analysed dichotomizing Spatial and Object visualization into high and low and running a 2x2 ANOVA with the factors being Spatial (High / Low) and Object (High / Low). As shown in Table 4.2.4.4, the model shows that both Object and Spatial visualization are significant factors, specifically, for Object

Visualization F(1,140)= 8,82, *p=.004* and for Spatial Visualization F(1,140)= 9,04, *p=.003.*

**Table 4.2.4.4**

*ANOVA 2 x 2 Object and Spatial (High / Low)*

**Tests of Between-Subjects Effects**

Dependent Variable: ANS

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared | Observed Power[b] |
|---|---|---|---|---|---|---|---|
| Corrected Model | 46,32[a] | 3 | 15,44 | 7,23 | ,000 | ,13 | ,98 |
| Intercept | 4522,41 | 1 | 4522,41 | 2118,21 | ,000 | ,94 | 1,00 |
| ObjectScoreCategorical | 18,83 | 1 | 18,83 | 8,82 | ,004 | ,06 | ,84 |
| SpatialScoreCategorical | 19,29 | 1 | 19,29 | 9,04 | ,003 | ,06 | ,85 |
| ObjectScoreCategorical * SpatialScoreCategorical | 5,05 | 1 | 5,05 | 2,37 | ,126 | ,02 | ,33 |
| Error | 298,90 | 140 | 2,14 | | | | |
| Total | 4924,00 | 144 | | | | | |
| Corrected Total | 345,22 | 143 | | | | | |

a. R Squared = ,134 (Adjusted R Squared = ,116)

b. Computed using alpha = ,05

As shown on Figure 4.2.4.3, the Object and Spatial visualizers' numeracy mirrors each other. High Object visualizers score lowest in numeracy, and low Object visualizers score higher. With Spatial visualizers the pattern is the opposite, with higher Spatial visualizers scoring higher than low Spatial visualizers.

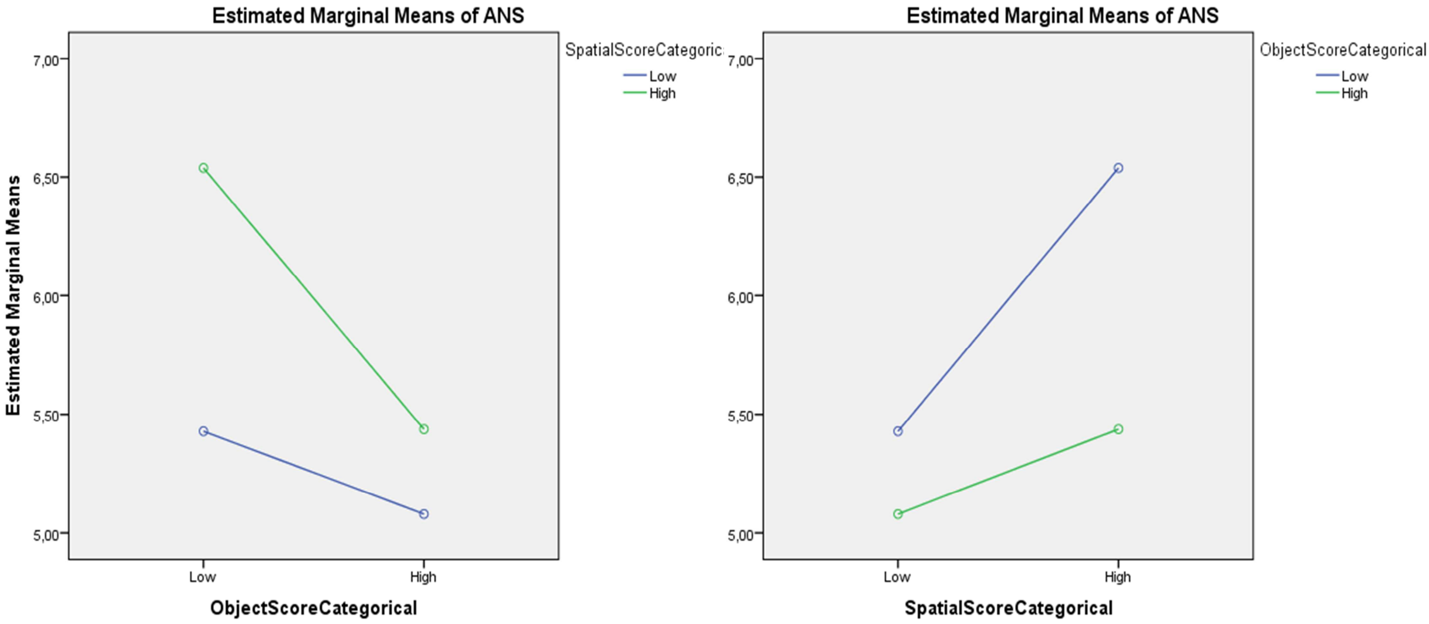



***Figure 4.2.4.3*** Object and Spatial Visualizers Numeracy (2x2 ANOVA)

## *4.3 Discussion*

The above analyses provided answers to the research questions investigated in this Chapter. Specifically, regarding the research question on the independence of the constructs of Object and Spatial visualization, the findings indicated an independence of the constructs composing visualization style. The reported results are not consistent with the research indicating that object and spatial visualization are one continuous dimension (Kozhevnikov, Hegarty & Mayer, 2002; Kozhevnikov, Kosslyn & Shephard, 2005). Instead, our findings are consistent with extant literature on object and spatial visualization style in that object visualization and spatial visualization are two independent constructs (Blajenkova, Kozhevnikov, & Motes, 2006; Kozhevnikov, Kosslyn, & Shephard, 2005), and that individuals have a visualization style that is a composite of these two dimensions. The confirmation of this point has practical and theoretical implications, since the understanding of the classification of individuals according to their cognitive style could yield predictions about their behaviour. For instance, a study on the consequences of this classification showed that matching consumers' cognitive style (in this particular case being a "feeling" or "thinking" processor) and product information "*generates more positive attitudes towards a brand, purchase intention, and brand choice*" (Ruiz & Sicilia, 2004, p. 657). Although the groups in this thesis are based on a different cognitive style than those investigated by Ruiz & Sicilia (2004), the finding that individuals can be also classified in groups according to their visualization style is the first step towards opening a door for further research on the behaviour of the different groups of visualizers in various areas, in particular the area of Decision-Making. In the specific case of visualization preference, Blazhenkova & Kozhevnikov (2009) showed how different professions tend to show differences in their visualization preference (e.g. engineers higher in spatial and lower in object visualization). Taking profession as a proxy for visualization style, marketers could draft advertising for their products in a different manner depending on the end consumer. We have, thus, found support to the view that Object and Spatial visualization are not mutually exclusive and do not fall at opposite ends of a continuum line but are, rather, independent dimensions.

Regarding the research question investigating whether the visualization components could predict numeracy, it was demonstrated that numeracy is predicted in a different manner by the two types of visualization preference, with the combination of high spatial with low object visualization resulting in greater numeracy. Considering the visualization constructs independently, whereas higher preference for spatial visualization predicts higher numeracy scores, higher preference for object visualization predicts lower Numeracy. However, an individual has a visualization style composed of both object and spatial visualization. The analyses of numeracy scores per type of visualizer revealed that each individual construct (object or spatial visualization) alone is not sufficient to produce significant results in numerical ability. It is the particular combination of high spatial with low object visualization (the group called “Spatial” visualizers) that showed significantly higher scores in numeracy than the other groups, which among themselves did not differ.

In addition to the practical implications, the above findings also have theoretical importance, as understanding the predictive value of object and spatial visualization in a range of numerical tasks could have importance in guiding future research.  For the first time it has been demonstrated how the cognitive style of visualization can predict numeracy, an ability which has been demonstrated to affect decision-making. The fact that numeracy can be predicted by visualization is of vital importance for the field of Decision-Making. In particular, the findings reported in the literature in the field of numeracy (for a review, see Dieckmann, 2008), may be informed by visualization style. Peters et al. (2006) reported a range of decision-making tasks in which the level of numeracy of the decision-makers drove decisions in different ways. For instance, one of Peters et al. (2006) finding is that low numerates are more prone to attribute framing effects. It might be the case that visualization is a more ingrained individual characteristic and more permanent over time and therefore could serve as a predictor of attribute framing effects or other decision-making tasks in which numeracy has been demonstrated to play a role.

Cognitive style being a stable trait reflecting the innate way of processing information by an individual rather than a learned ability (which can be influenced by training, culture, etc.), numerous decision-making tasks could now be investigated with regard to the cognitive style of visualization preference rather than numeracy, although a word of caution is in order: some tasks, especially those for whose resolution specific training is needed (e.g. Bayes theorem) may still not be predicted by a cognitive style, be it visualization or otherwise. Notwithstanding that limitation, however, visualization could be a more faithful predictor in general than Numeracy, which can be affected by training or previous exposure to numerical tasks. Being a cognitive style, visualization is an innate characteristic in an individual, and therefore less susceptible to training or exposure

This thesis will continue to investigate whether visualization style does indeed predict the outcome of decision-making tasks that were in the past demonstrated to be affected by numeracy.

# Chapter 5

# Visualization Influences on Judgments from Numerical Information Presentation

This Chapter will investigate how the format of numerical information presentation can alter the judgments, decisions and accuracy of individuals depending on their visualization preference. This research question is composed of four tasks which will investigate how individuals differing in visualization style judge numerical information, and the correctness of some of these appraisals.

In addition, in this Chapter will build on and replicate Research Question 1 with this sample; that is, whether Object and Spatial visualization are two independent cognitive style constructs or they are antagonists, with each of the dimensions at opposite ends of a continuum line. In addition such replication with the current sample will also be extended to Research Question 2, which tests the relationship between Object, Spatial visualization, and Numeracy.

After the replication of RQ1 and RQ2, this Chapter will present 4 tasks. The first task will analyze whether different visualization styles perceive information presented to them in a tabular format more positively or more negatively. It might be the case that differences in visualization style may drive people’s perception of information in a tabular format. Specifically, the mental depiction of tabular information could be different depending on the extent to which an individual prefers object and spatial mental imagery when seeing numerical information in a tabular format. Precisely, as we have seen previously in 4.2.3 in this thesis, lower object visualization combined with high spatial visualization results in higher numeracy. It could be that, when evaluating numerical information in the form of a table, low-object/high-spatial visualization individuals (spatial visualizers) are able to form a stronger affective evaluation about how well the company is performing. As Peters et al. (2006) suggested, higher numerates draw more affect from numbers, and as we argue in Chapter 5, low-object/high-spatial visualization is a predictor of higher numeracy scores. Therefore, the group of Spatial visualizers might make a more precise appraisal of the numerical information from a table, and this would result in more extreme ratings (more positive in the positive trend, and more negative in the negative trend).

The second task will investigate whether people can project a trend beyond a series given in a tabular format. This task will test whether visualization preference has an impact on how well participants are able to guess trends in data and make predictions about the next data point when presented with tabular information on the profits of two companies. This forecasting task will yield information as to how visualization preference affects people’s ability in a simple yet important task: forecasting performance of a company compared with a competitor. This ability is of particular importance to individuals making investment decisions, comparing financial information, etc.

The third task will investigate whether graph manipulation affects perceptions of positivity or negativity of a financial situation. Presenting financial information to people based on distorted bar graphs (e.g. bars with a truncated y-axis) has shown to cause a more positive (in positive trend graphs) or more negative (in negative trend graphs) impression on people, whilst retaining the same objective information (Arunachalam & Steinbart, 2002). Both from a theoretical and from a practical perspective, it is interesting to investigate whether this effect is influenced by visualization preference, since "*the choice of how to present quantitative data in graphs depends on both the characteristics of the readers and of the data*" Arunachalam, Pei & Stanbart (2002, p. 183). It may well be that visualization preference is a trait that might influence the perception of graphs. Since graphs demand spatial cognitive skills, it could be the case that high spatial visualizers might detect the graph manipulation and therefore provide less extreme ratings (less negative and less positive in the negative and positive frame respectively).

Finally, the fourth task tests whether visualization preference affects the correct matching of tabular information with a specific graph. This task will show whether differences in visualization preference make a difference when translating information from a tabular to a graph format. Identifying trends from a tabular format may be important for people evaluating and making decisions regarding, for instance, financial information.

## *5.1 Participants*

Participants were recruited from the University of Granada, Faculty of Economics and Business Administration and voluntarily participated in the data collection during class time. A total of 284 participants with valid data participated in this study (157 females), aged 19.18 on average (SD=2.6, Min= 17, Max=47) took part in the experiment, which was administered in the form of a paper-and-pencil questionnaire to groups varying in size from 40 to 60 individuals who were distributed in the classroom in a manner that did not allow participants to share their thoughts or answers. In addition, the experimenter remained in the classroom to address points of clarification and ensure that the data was not contaminated by individuals sharing their answers.

## *5.2 Replication of Object-Spatial Visualization Relationship*

To further validate the observed relationship between Object and Spatial Visualization and their relationship with Numeracy, section 5.2 will perform a correlation analysis between the OSIVQ components and Numeracy (ANS) as well as a regression model to predict numeracy from the different components of visualization.

### 5.2.1 Correlation Analysis

A correlation analysis including the OSIVQ components and Numeracy (ANS) scores was run to replicate the findings from section 4.2.2 which found object visualization being negatively correlated with numeracy and spatial visualization following the opposite pattern, with a positive correlation between spatial visualization and numeracy.

As shown in Table 5.2.1.1, the correlational analysis confirms the findings from Chapter 4. Specifically, object visualization is significantly negatively correlated with Numeracy, $r(283) = -.13$, $p = .03$. Confirming the results of Chapter 4, spatial visualization follows the opposite pattern of object visualization in its relationship with numeracy and we find a significantly positive correlation between numeracy and spatial visualization, r(283)= .23, p<.001. In addition, the current correlation analysis points to an independence of the constructs of Object and Spatial visualization which are virtually uncorrelated, r(283)= ,05, p=,44.

**Table 5.2.1.1**
*Correlation Analysis Between Numeracy and Visualization*

| | | Object Score | Spatial Score |
|---|---|---|---|
| Numeracy (ANS) | Pearson Correlation | -,13* | ,23** |
| | Sig. (2-tailed) | ,034 | ,000 |
| | N | 283 | 283 |
| Spatial Score | Pearson Correlation | ,05 | |
| | Sig. (2-tailed) | ,441 | |
| | N | 283 | |

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

## 5.2.2 Predictive Value of Visualization on Numeracy

A regression model was run with numeracy as the dependent variable to check for the replication of the finding reported on Chapter 4 that higher object visualization predicts lower numeracy while increased spatial visualization predicts higher numeracy. To this end, similar to the prior analysis in Chapter 4, we run a regression to predict numeracy scores from object and spatial visualization scores while controlling for the effect of gender. Unlike Chapter 4, Major was not necessary to be included in this recession, as students all belonged to the Business Administration department, and no engineers or history majors were present in the survey.

The aforementioned regression model predicting numeracy scores from object and spatial visualization while controlling for gender was statistically significant, F(3,282)= 15,19, p<.001 (Table 5.2.2.1).

**Table 5.2.2.1**
*Regression Model Predicting Numeracy from Object and Spatial Visualization*

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 115,12 | 3 | 38,37 | 15,19 | ,000[b] |
| | Residual | 704,96 | 279 | 2,53 | | |
| | Total | 820,08 | 282 | | | |

| R | R Square | Adjusted R Square | Std. Error of Estimate |
|---|---|---|---|
| ,475 | ,140 | ,131 | 1,59 |

a. Dependent Variable: ANS

b. Predictors: (Constant), SpatialScore, ObjectScore, Gender

As shown on Table 5.2.2.2, higher spatial visualization predicts higher numeracy scores (p=.004), while higher object visualization predicts lower numeracy scores (p=.065). Collinearity statistics show that the model is robust and there are no grounds for concern as the multicollinearity values are all well below the customary point of concern of 10 (Cohen et al., 2003). The significance level of object visualization is marginal, closely approaching the .05 level. The predictive directionality of object visualization is, however, consistent with the prior results reported in Chapter 4.

**Table 5.2.2.2**
*Regression Coefficients and Collinearity Results for Regression Predicting Numeracy from Object and Spatial Visualization*

| | | Unstandardized Coefficients | | Standardized Coefficients | | | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| Model | | B | Std. Error | Beta | t | Sig. | Tolerance | VIF |
| 1 | (Constant) | 3,702 | ,710 | | 5,213 | ,000 | | |
| | Gender | ,943 | ,198 | ,275 | 4,775 | ,000 | ,926 | 1,080 |
| | ObjectScore | -,312 | ,169 | -,104 | -1,850 | ,065 | ,983 | 1,018 |
| | SpatialScore | ,468 | ,163 | ,164 | 2,865 | ,004 | ,935 | 1,069 |

a. Dependent Variable: ANS

The analysis to perform in Chapter 6, with a further batch of participants might be clarifying in checking whether the current marginal significance level is recurrent and therefore a cause for concern about the hypothesized relationship between visualization and numeracy.

## *5.3 Task 1*

### 5.3.1 Design

Participants saw a table displaying the yearly profits of a company, from 2004 to 2011 in thousands of Euro. The table started with 2800 and finished with 4200 (or vice versa in the negative trend condition), with the points in between being approximately evenly separated (Figure 5.3.1.1, Appendix D for full view of task).

| Year | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|
| Profits (€ 000) | *2800* | *3010* | *3150* | *3430* | *3570* | *3850* | *3990* | *4200* |

***Figure 5.3.1.1*** Table participants saw in Task 1 (positive trend)

Participants were informed that this data showed the performance of a company based on net profits and that no more information was available to them. On the same page they were asked, with regard to that information, how they would rate the results of the company by circling a number from 0 (very bad) to 10 (very good).

Half of the participants received information from year 2004 to 2011 showing a positive trend, and the other half received the same information, but with the order of profits reversed, in such a manner that one condition showed a positive trend, and the other condition a negative trend.

In addition to this task, participants completed the numeracy and OSIVQ tests.

### 5.3.2 Results

An independent-samples t-test indicated that the trend manipulation did indeed have an effect, and that participants in the positive trend condition provided considerably higher ratings ($M=7.23$, $SD=1.7$) than in the negative trend condition ($M=3.70$, $SD=2.17$), $t(263)=-15.31$, $p<.0001$.

A regression analysis with the evaluation ratings as the DV and Trend, Object, Spatial and the interactions Trend x Object and Trend x Spatial revealed a statistically significant model, $F(5,277)= 47.5$, $p<.0001$. In this model, only Trend proved statistically significant, with the positive trend predicting higher evaluation ratings than the negative trend. To verify that the effect of Trend was not masking an effect of either object or spatial visualization, a regression model for each trend (Positive/Negative), was run with object and spatial visualization as predictors. Both models were statistically insignificant and neither object nor spatial visualization significantly predicted evaluations of the company based on the table. In addition, different regression models which were run for object and spatial visualization (checking for trend) did not show that these individual traits affected ratings.

We dichotomized the object and spatial scores into high and low and ran these in a 2x2x2 ANOVA (Trend x Object categorical x Spatial categorical). This ANOVA revealed the significant main effect of Trend and the interaction of Spatial by Trend, $F(1,275)= 4.02$, $p=.046$ (Table 5.3.2.1).

Comparing the scores of the low and high spatial visualizers in the positive trend does not reveal a significant difference. The same is true for this comparison in the negative trend. However, as Figure 5.3.2.1 depicts, a pattern emerges showing how the ratings of High spatial visualizers were less extreme (less negative in the negative trend, and less positive in the positive trend) than those given by Low spatial visualizers (see Table 5.3.2.2 for means).

**Table 5.3.2.1**

*ANOVA, Task 1 Interaction Trend x Spatial*

**Tests of Between-Subjects Effects**

Dependent Variable: T1Table

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 911.21[a] | 7 | 130.17 | 34.65 | .000 |
| Intercept | 8275.01 | 1 | 8275.01 | 2202.33 | .000 |
| T1TableTrend | 867.26 | 1 | 867.26 | 230.81 | .000 |
| ObjectScoreCategorical | 3.80 | 1 | 3.80 | 1.01 | .316 |
| SpatialScoreCategorical | 1.43 | 1 | 1.43 | .380 | .538 |
| Trend * ObjectCategorical | .18 | 1 | .18 | .049 | .825 |
| Trend * SpatialCategorical | 15.11 | 1 | 15.11 | 4.02 | .046 |
| ObjectCategorical * SpatialCategorical | 3.29 | 1 | 3.29 | .88 | .350 |
| T1TableTrend * ObjectCategorical * SpatialCategorical | .70 | 1 | .70 | .19 | .666 |
| Error | 1033.28 | 275 | 3.76 | | |
| Total | 10412.00 | 283 | | | |
| Corrected Total | 1944.50 | 282 | | | |

a. R Squared = .469 (Adjusted R Squared = .455)

**Table 5.3.2.2**

*Table of Means, Task 1 Interaction Trend x Spatial*

| T1TableTrend * SpatialScoreCategorical | | | | | |
|---|---|---|---|---|---|
| Dependent Variable: T1Table | | | | | |
| T1TableTrend | SpatialScoreCategorical | Mean | Std. Error | 95% Confidence Interval | |
| | | | | Lower Bound | Upper Bound |
| Negative Trend | Low | 3.38 | .24 | 2.92 | 3.85 |
| | High | 3.99 | .23 | 3.54 | 4.44 |
| Positive Trend | Low | 7.38 | .22 | 6.95 | 7.81 |
| | High | 7.06 | .25 | 6.57 | 7.55 |

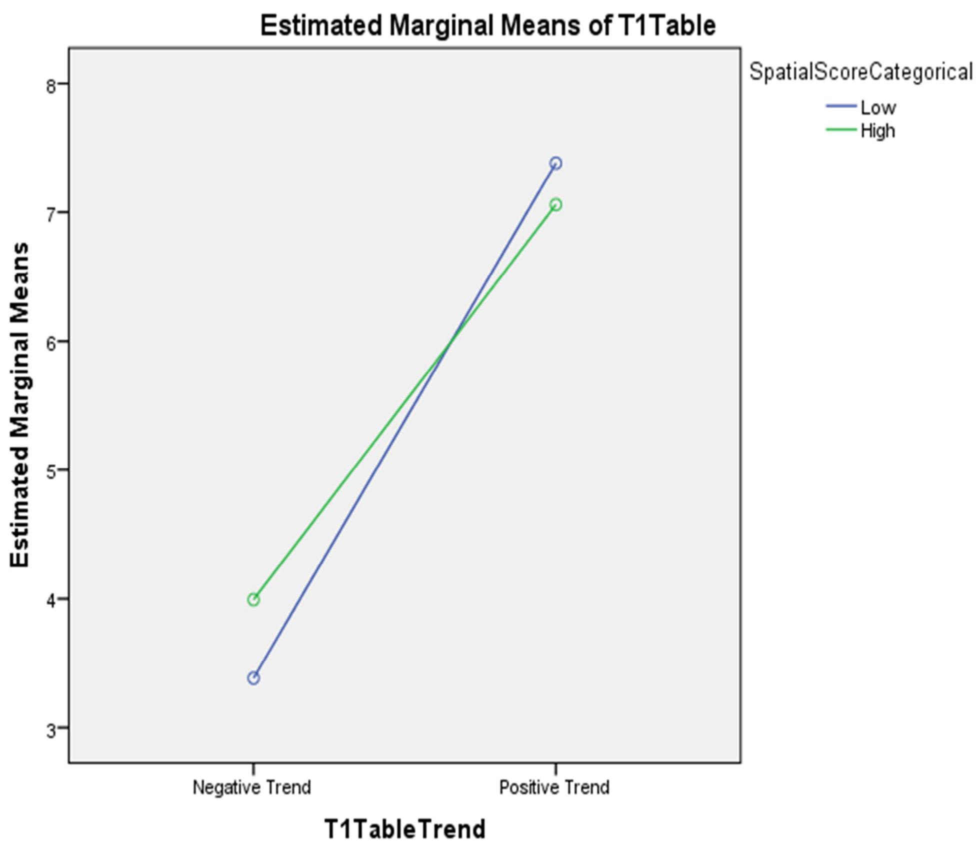



***Figure 5.3.2.1*** Interaction Trend x Spatial categorical

We then tested to see whether the four different types of visualizers would give different evaluations of the same tabular information. For this, we ran a 2 x 4 factorial ANOVA with the factors of Table Trend (Positive/Negative) and Visualizer Type (Object/Spatial/ObjectSpatial/Undefined).This ANOVA revealed only the expected main effect of Trend, $F(1,275) = 230{,}81$, $p < .001$. To ascertain whether the effect of Trend might be masking some statistical effect of Visualizer Type, we ran two separate ANOVAs (one for each trend) to check for differences between the four groups of visualizers. Both ANOVAs failed to reveal any significant difference between the groups of visualizers.

### 5.3.3 Discussion

The results show that the experimental manipulation of trend worked as intended, generating higher ratings in the positive trend and lower ratings in the negative trend. However, analyses of Numeracy and Visualization style offered different results.

Whereas Numeracy did not show an effect when treated as a continuous variable in a regression predicting the ratings of the table, when it was dichotomized into high and low, an ANOVA showed how the high numerates gave overall higher ratings to the company irrespective of the trend.

The case of visualization showed that treating object and spatial visualization as continuous variables did not result in any different predictions of ratings. However, the results indicated that when object and spatial visualization were dichotomized into high and low and run in an ANOVA model along with Trend, an interaction between spatial visualization and trend emerged. This interaction showed how the high spatial visualizers gave less extreme ratings than the low spatial visualizers.

This result may be consistent with low spatial visualizers detecting the trend, for which a low level of reflection on the data is needed, and might act accordingly giving the positive trend higher ratings and the negative trend lower ratings than the high spatial visualizers. The high spatial visualizers, in contrast, might consider the specific numbers in more depth and try to guess an angle for the slope. Although they could tell that the trend was negative or positive, hence their giving higher ratings in the positive than in the negative trend, high spatial visualizers may give more conservative ratings than the low numerates because although high spatial visualizers do understand the trend, they may try to mentally picture the slope in their minds and from the data given this would not be possible. In contrast, the low spatial visualizers might not engage in this type of spatial cognition task and would just label the trend as positive or negative, giving ratings according to only this factor, and neglecting the element of how tilted the slope is.

We further analyzed whether different visualizer types would give different evaluations of the company in the light of tabular information, though these analyses yielded no significant differences among the different groups.

In short, the results show that only high numeracy influences the ratings given to tabular information in the current context. In particular, high numerates give higher ratings in a tabular context than low numerates. This is a finding for which in principle there is no obvious explanation. If, as Peters et al. (2006) suggest, high numerates draw more affect from numbers and numerical comparisons, this enhanced affect should elicit stronger evaluations. That is, we should see that, compared to the low numerates, high numerates should give higher ratings in the positive trend and more negative ratings in the negative trend than the low numerates. In contrast, what we found is that, compared to the low numerates, the high numerates tend to give higher ratings when information is presented to them in a tabular format.

The results are not inconsistent with the idea that high spatial visualizers might engage in deeper spatial cognition processing to determine the tilt of the slope, and as this element is not clear they give more conservative ratings when evaluating the results of a company from a table.

This finding could have both theoretical and practical implications. From a theoretical perspective, it could be important to consider in further research the fact that individuals' preference for spatial visualization might have implications on their evaluation of numerical scenarios. If, as the results indicate, high spatial visualizers are more conservative in their rating of a numerical scenario of this sort, research in areas pertaining to numeracy should account for the spatial visualization factor in their analyses of data and interpretation of results. From a practical point of view, having a high or low level of spatial visualization is a factor that might also shape the responses of individuals to surveys, financial decisions, etc. Organizations involved in collecting such quantitative data should also account for such differences in visualization style. For instance, information about a given retirement plan presented to a group of engineers (who tend to be high in preference for spatial visualization) might not be appropriate for a group of historians.

## *5.4 Task 2*

### 5.4.1 Design

As shown in Figure 5.4.1.1 (Appendix E for full page task), participants see a table displaying the profits of two companies, A and B, displaying each the same trend (either both positive or both negative). Trend was a between-subjects condition. The profits are presented from year 2004 to 2011 and participants are asked to forecast which company will have higher profits in the year following the series by circling either Company A or Company B.

| **Year** | | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
|---|---|---|---|---|---|---|---|---|---|
| **Profits (€ 000)** | **Company A** | *1498* | *1872* | *2527* | *3672* | *4677* | *8286* | *16325* | *32969* |
| | **Company B** | *1500* | *6250* | *10302* | *16290* | *20995* | *26240* | *32306* | *36200* |

**Figure 5.4.1.1** Task 2 stimulus

Responses were recorded and coded as incorrect (0) or correct (1) depending on whether participants correctly reported which of the two companies would have higher profits in the year following the series if the trend was to continue. Conditions across subjects are Positive Trend or Negative Trend. The order of presentation of the companies was counterbalanced. A binary logistic regression predicting correctness of responses from the order of presentation of companies showed the order of presentation had no effect.

In addition to this task, participants completed the numeracy and OSIVQ tests.

### 5.4.2 Results

We ran a logistic regression with Correctness (0= incorrect, 1 correct) as the DV and numeracy and trend as the IVs. The model proved significant, chi square = 13.87, $p<.001$ with df= 2 and higher numeracy proved to be predictive of a greater likelihood of providing correct answers to the question ($p<.001$) while Trend did not have an effect.

Analyzing the effects of visualization, a logistic regression model with Correctness (0= incorrect, 1 correct) as the DV, and Trend, Object and Spatial as the IVs did not prove to be statistically significant, chi square=5.56, $p=.135$, with degrees of freedom 3. However, looking at the predicting variables, we can see (Table 5.4.2.1 and Table 5.4.2.2) that higher scores in spatial visualization are statistically significant as a predictor of correct responses ($p=.03$).

**Table 5.4.2.1**
*Coefficients table, logistic regression predicting correct responses from Numeracy*

| Model for Numeracy | | | | | | |
|---|---|---|---|---|---|---|
| | B | S.E. | Wald | df | Sig. | Exp(B) |
| Trend | -,11 | ,30 | ,14 | 1 | ,708 | ,90 |
| ANS | ,32 | ,090 | 13,11 | 1 | ,000 | 1,38 |
| Constant | -,02 | ,39 | ,00 | 1 | ,953 | ,98 |
| -2 Log Likelihood | Cox & Snell R Square | | Nagelkerke R Square | | | |
| 282,20 | ,48 | | ,07 | | | |
| % Correct Predicted Null Model | | | % Correct Predicted Full Model | | | |
| 77,9 | | | 76,8 | | | |

a. Variable(s) entered in step 1: T2ForecastATrend, ANS.

**Table 5.4.2.2**
Coefficients table, logistic regression predicting correct responses from Visualization

**Model for Visualization**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| Trend | -,03 | ,29 | ,010 | 1 | ,921 | ,97 |
| ObjectScore | -,28 | ,26 | 1,13 | 1 | ,287 | ,76 |
| SpatialScore | ,53 | ,25 | 4,52 | 1 | ,034 | 1,70 |
| Constant | ,72 | 1,11 | ,43 | 1 | ,514 | 2,06 |

| -2 Log Likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|
| 290,16 | ,02 | ,03 |

| % Correct Predicted Null Model | % Correct Predicted Full Model |
|---|---|
| 77,9 | 77,9 |

a. Variable(s) entered in step 1: ObjectScore, SpatialScore.

Taken together, these results indicate that numeracy and spatial visualization are statistically similar in their prediction of correct responses, and as the logs odd ratios reveal (ExpB column on Tables 5.4.2.1), spatial score (B=,53) is a stronger predictor of correct responses than numeracy (B=,32).

## *5.5 Task 3*

### 5.5.1 Design

In this task, participants were asked to evaluate the results of a company based on a bar graph displaying the profits of a company for six years, like in the previous tasks. The years were in this case 2003 to 2010 rather than 2004-11 to avoid participants assuming automatically that the data was the same as in the previous task. As shown in Appendix F, participants saw only a positive or negative graph trend, either with a truncated Y-axis (Figure 5.5.1.1) which made the slope look steeper, or with a Y-axis starting at 0

(Figure 5.5.1.2). The experimental manipulation is the graph distortion achieved by truncating the Y-axis. In the undistorted condition, the X axis is set at Y=0, whereas in the distorted condition the X axis starts on Y=375. In this manner the slope described by the bars is steeper in the distorted graph than in the undistorted graph.

Participants were told that the graph showed the financial results of a company in the form of annual net profits. Subsequently, participants were asked to rate the company's results based on the information given from 0 (Very bad) to 10 (Very good). According to the previously reviewed literature, graph distortion should magnify ratings in such a manner that a distorted graph in the positive trend should generate higher ratings than an undistorted graph. In the negative trend, the distortion should also magnify ratings of negativity, with the distorted graph generating lower ratings than the undistorted graph.

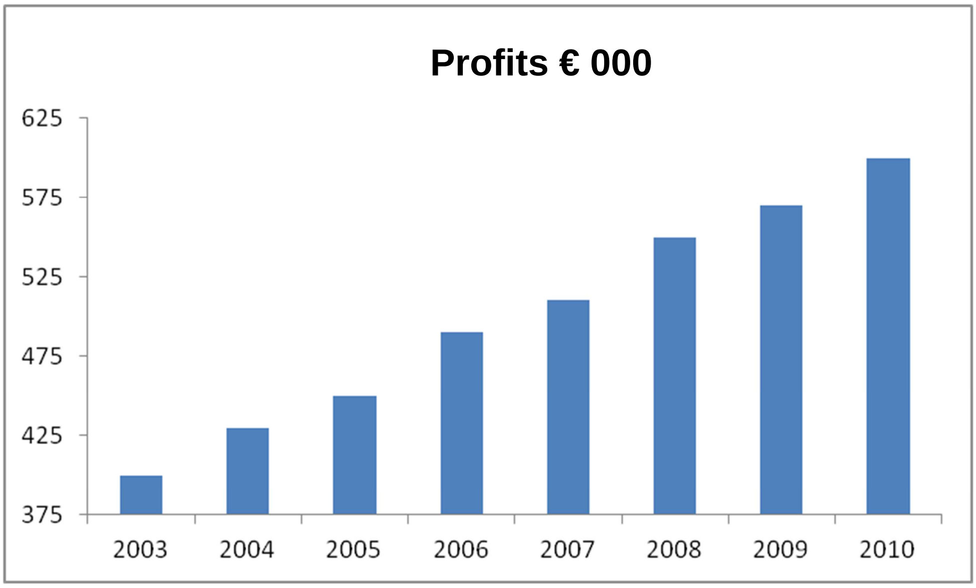



***Figure 5.5.1.1*** Task 3, distorted graph

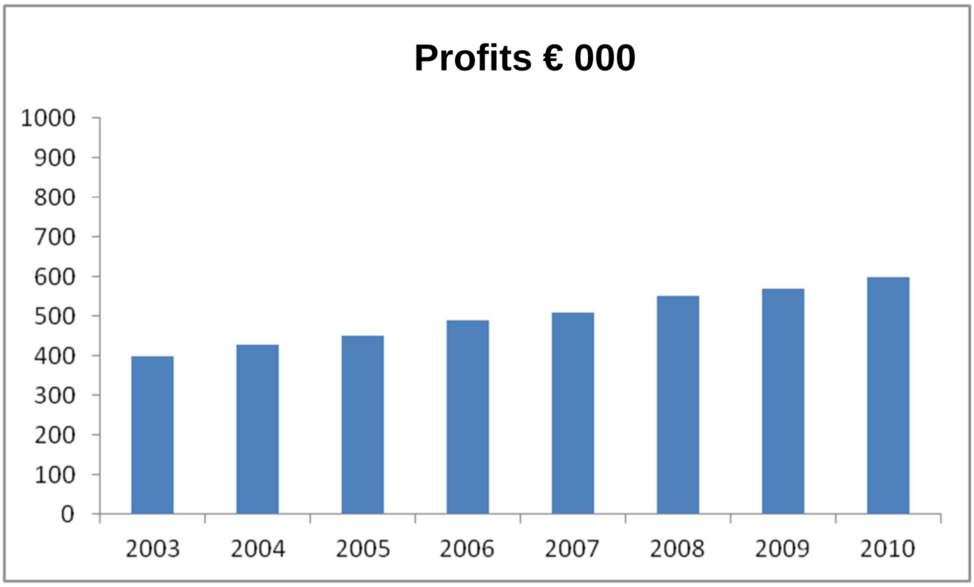



***Figure 5.5.1.2*** Task 3, undistorted graph

The model was a 2x2 experimental design where participants saw a graph which was either Distorted or Not Distorted, and either in a Positive or Negative trend. The IV is the evaluation of results provided by students on a likert scale (0: Very bad – 10: Very Good).

### 5.5.2 Results

Checking first for numeracy effects, for each of the trends we ran a linear regression model predicting evaluation ratings from Graph Distortion (undistorted=0, distorted=1), numeracy, and the interaction numeracy/Distortion. The regression model run on the negative trend was statistically significant ($F[3,137]=10,95$, $p<.001$, (Table 5.5.2.1 for statistical significance of models, and Table 5.5.2.2 for regression coefficients).

**Table 5.5.2.1**

*Regression models Numeracy, statistical significance*

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Negative Trend | Regression | 119,96 | 3 | 39,99 | 10,95 | ,000[a] |
| | Residual | 500,47 | 137 | 3,65 | | |
| | Total | 620,43 | 140 | | | |
| R | R Square | Adjusted R Square | | Std. Error of Estimate | | |
| ,44 | ,19 | ,18 | | 1,91 | | |
| Positive Trend | Regression | 65,95 | 3 | 21,98 | 10,01 | ,000[a] |
| | Residual | 303,02 | 138 | 2,20 | | |
| | Total | 368,97 | 141 | | | |
| R | R Square | Adjusted R Square | | Std. Error of Estimate | | |
| ,42 | ,18 | ,16 | | 1,48 | | |

b. Dependent Variable: T3DistortionA

Similarly, the model for the positive trend proved to be statistically significant (F[3,138]=10,01, p<.001). The results in the positive and in the negative trend both indicate that numeracy or the interaction of numeracy with distortion have no effects on ratings.

**Table 5.5.2.2**

*Coefficients table, Numeracy regressions*

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| Negative Trend | (Constant) | 4,40 | ,71 | | 6,21 | ,000 |
| | T3GraphDistortion | -2,31 | ,98 | -,55 | -2,36 | ,020 |
| | ANS | ,12 | ,150 | ,09 | ,78 | ,439 |
| | T3ANSbyDistortion | ,12 | ,20 | ,15 | ,60 | ,549 |
| Positive Trend | (Constant) | 6,13 | ,44 | | 13,91 | ,000 |
| | T3GraphDistortion | 1,26 | ,64 | ,39 | 1,97 | ,051 |
| | ANS | ,07 | ,09 | ,08 | ,76 | ,448 |
| | T3ANSbyDistortion | ,019 | ,14 | ,03 | ,13 | ,894 |

a. Dependent Variable: T3Distortion

As shown in Table 5.5.2.3 distortion does, however, exacerbate the ratings, with distorted graphs in the negative trend predicting lower scores than undistorted graphs. In the positive trend the effect is mirrored and a distorted graph predicts increased scores than an undistorted graph.

**Table 5.5.2.3**

*Means, Trend by Distortion*

**Descriptive Statistics**

Dependent Variable: T3DistortionA

| Numeracy | Distortion | Trend | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Total | Undistorted | Descending Trend | 4.92 | 1.90 | 72 |
| | | Ascending Trend | 6.43 | 1.77 | 69 |
| | | Total | 5.66 | 1.99 | 141 |
| | Distorted | Descending Trend | 3.17 | 1.94 | 69 |
| | | Ascending Trend | 7.77 | 1.14 | 73 |
| | | Total | 5.54 | 2.79 | 142 |
| | Total | Descending Trend | 4.06 | 2.11 | 141 |
| | | Ascending Trend | 7.12 | 1.62 | 142 |
| | | Total | 5.60 | 2.42 | 283 |

We investigated next whether graph distortion affected individuals differently according to their visualization style. To this end, we ran a linear regression model for each trend predicting the ratings given to the company. These regression models had the following predictors: Distortion (undistorted/distorted), Object, Spatial, and the interactions Distortion by Object, Distortion by Spatial. As shown in Table 5.5.2.4, both the negative and the positive trend models were statistically significant predicting the company ratings.

**Table 5.5.2.4**

*Regression models Visualization, statistical significance*

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Negative Trend | Regression | 116,35 | 5 | 23,27 | 6,23 | ,000[a] |
| | Residual | 504,07 | 135 | 3,73 | | |
| | Total | 620,43 | 140 | | | |
| R | R Square | Adjusted R Square | | Std. Error of Estimate | | |
| ,43 | ,19 | ,16 | | 1,93 | | |
| Positive Trend | Regression | 68,75 | 5 | 13,75 | 6,23 | ,000[a] |
| | Residual | 300,22 | 136 | 2,21 | | |
| | Total | 368,97 | 141 | | | |
| R | R Square | Adjusted R Square | | Std. Error of Estimate | | |
| ,43 | ,19 | ,16 | | 1,49 | | |

a. Predictors: (Constant), T3InteractionDistortiondbySpatial, ObjectScore, SpatialScore, T3InteractionDistortiondbyObject, T3GraphDistortion

b. Dependent Variable: T3DistortionA

None of the regression coefficients for the predictors and interactions entered in the model showed to significantly predict the ratings. This was true for both the positive and the negative trend. However, as shown in Table 5.5.2.5, once the interaction terms were removed from the model, distortion became a significant predictor as in the previous model with numeracy.

In summary, these results indicate that the experimental manipulations of Graph Distortion and Trend did work as expected. However, none of the explanatory variables included in the statistical models (numeracy, Object or Spatial visualization) proved to counteract the graph distortion manipulation.

**Table 5.5.2.5**

*Regression models Visualization, statistical significance*

**Coefficients**[a]

| | | Full Model, with Interactions | | Reduced model without interactions | |
|---|---|---|---|---|---|
| | | t | Sig. | t | Sig. |
| Negative Trend | (Constant) | 3,51 | ,001 | 4,22 | ,000 |
| | Graph Distortion | -1,42 | ,158 | -5,27 | ,000 |
| | Object Score | -,57 | ,572 | -,71 | ,482 |
| | Spatial Score | -,34 | ,738 | ,82 | ,412 |
| | Distortion x Object Interact. | -,11 | ,916 | | |
| | Distortion x Spatial Interact. | 1,21 | ,229 | | |
| | | T | Sig. | T | Sig. |
| Positive Trend | (Constant) | 5,30 | ,000 | 7,52 | ,000 |
| | Graph Distortion | ,49 | ,624 | 5,26 | ,000 |
| | Object Score | -1,21 | ,229 | -,83 | ,410 |
| | Spatial Score | ,12 | ,908 | -,72 | ,472 |
| | Distortion x Object Interact. | ,87 | ,384 | | |
| | Distortion x Spatial Interact. | -,81 | ,422 | | |

This task demonstrated that neither numeracy nor visualization had an impact on the influence of graph distortion. This might be caused by the fact that, when interpreting a bar graph, readers mentally draw a line linking the tops of the different bars so as to obtain a perception of change (Hollands and Spence, 1992). Because individuals would be paying more attention to the slope than to the actual numerical information displayed on the Y-axis, they do not make use of numerical calculations to obtain an impression. To check this explanation, we conducted a pilot test with business students where participants saw either a graph with the Y-axis labels from 0 to 1000, or from 375 to 625, keeping in both cases the same bar graphs (Figures 5.5.2.1 & 5.5.2.2).

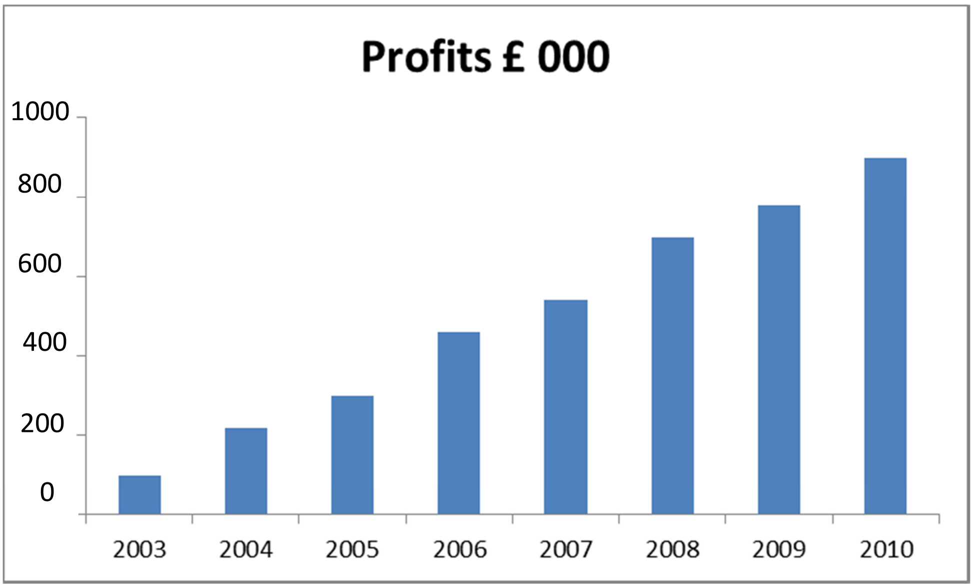



***Figure 5.5.2.1*** Figure testing whether Y-axis or slope affected ratings, axis 375-625

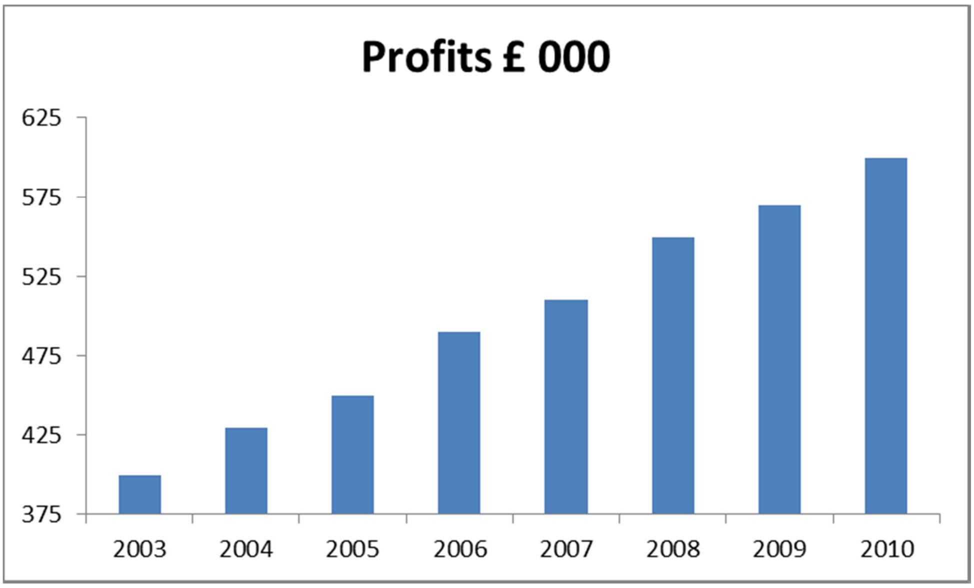



***Figure 5.5.2.2*** Figure testing whether Y-axis or slope affect ratings, axis 0-625

When asked to evaluate a company based on profits shown in such a type of graph, changing the values of the Y-axis (and maintaining the size, and therefore slope, of the bar graphs), participants did not provide significantly different ratings. This is a strong indication that it is the slope, rather than the labelling of the Y-axis, that individuals were paying attention to, hence the similarity in results, despite the change in the actual labelling of the Y-axis.

## *5.6 Task 4*

### 5.6.1 Design

As shown in Figure 5.6.1.1 and with more detail in Appendix G, in this task participants had to identify which of four graphs that were presented to them corresponded to a table provided with data.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *145* | *350* | *545* | *752* | *950* | *1148* | *1353* | *1500* | *1702* | *1899* | *2100* |

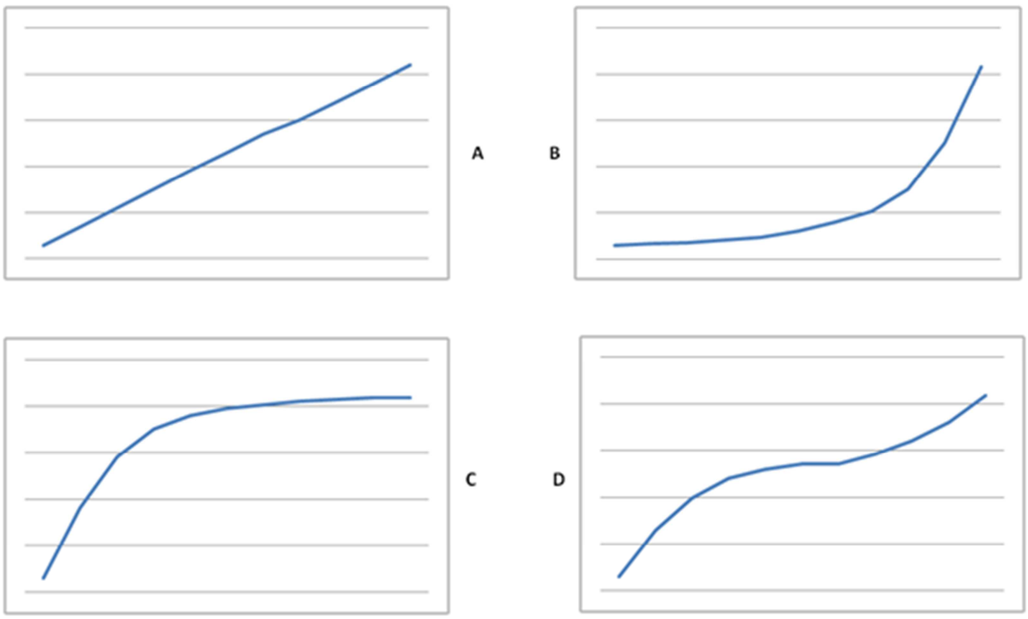



***Figure 5.6.1.1*** Task 4 Table and Graphs

The data in the task displayed either a linear or an exponential trend. The task was repeated on the following page with a different data table, from which participants again had to choose which of the four graphs represented the trend. In one of the tables, the data represented a linear (exponential) trend, and on the next page the described trend was exponential (linear) in such a manner that each participant responded to a table with a linear and an exponential trend (within-subjects condition). The trend was either positive or negative (between-subjects).

The number of correct answers (0, 1, or 2) was computed and used as the DV in the analyses.

### 5.6.2 Results

Because of the relatively reduced range of the DV scale, we performed an ordinal regression model with the number of correct responses (0, 1, or 2). As shown in Table 5.6.2.1, the ordinal model was statistically significant, and as shown in Table 5.6.2.2, Numeracy was a statistically significant predictor of a higher number of correct responses ($p<.001$).

**Table 5.6.2.1**

*Task 4 ordinal regression model significance for Numeracy as a predictor*

**Model Fitting Information**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| Intercept Only | 88.50 | | | |
| Final | 58.91 | 29.58 | 1 | .000 |

Link function: Probit.

**Table 5.6.2.2**

*Task 4, ordinal regression parameter estimates for Numeracy as a predictor*

**Parameter Estimates**

| | | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|---|
| Threshold | [T4andT5Correct = .00] | -.45 | .20 | 5.14 | 1 | .023 | -.83 | -.06 |
| | [T4andT5Correct = 1.00] | 1.02 | .20 | 25.62 | 1 | .000 | .62 | 1.41 |
| Location | ANS | .23 | .04 | 28.83 | 1 | .000 | .14 | .31 |

Link function: Probit.

To investigate the effect of object and spatial visualization, we ran an ordinal regression model with the DV as the number of correct answers (0,1,2) and the predictor variables as object and spatial visualization. This model was statistically significant (Table 5.6.2.3), and showed that spatial visualization was a significant predictor of a higher number of correct responses (Table 5.6.2.4).

Taken together, these results show that when identifying graphs from a given table, numeracy and spatial visualization are both predictors of correct answers.

**Table 5.6.2.3**

*Task 4 ordinal regression model significance for Visualization as a predictor*

**Model Fitting Information**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| Intercept Only | 496.28 | | | |
| Final | 485.96 | 10.31 | 2 | .006 |

Link function: Probit.

**Table 5.6.2.4**

*Task 4, ordinal regression parameter estimates for Visualization as a predictor*

**Parameter Estimates**

| | | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|---|
| Threshold | [T4andT5Correct = .00] | -.90 | .52 | 2.94 | 1 | .087 | -1.93 | .130 |
| | [T4andT5Correct = 1.00] | .50 | .52 | .93 | 1 | .336 | -.52 | 1.53 |
| Location | ObjectScore | -.15 | .12 | 1.54 | 1 | .215 | -.39 | .09 |
| | SpatialScore | .35 | .12 | 8.82 | 1 | .003 | .12 | .58 |

Link function: Probit.

## *5.7 Discussion*

Prior to the four experimental tasks in the current Chapter, we run a replication analysis to check for the relationship between visualization and numeracy. Our results showed consistency with the findings from the original investigation in Chapter 4. Increased spatial visualization predicts higher numeracy scores, while object visualization goes in the opposite direction with higher scores in this dimension predicting (marginally significantly) lower numeracy. The discussion of these findings will be further elaborated in the final discussion, Chapter 8, where we will comment on the replication of the relationship between numeracy and visualization for all collected sets of data in the current thesis.

In Task 1 participants evaluated the performance of a company based on tabular information. Despite the argument that higher numeracy might result in individuals having a more precise feeling of the positivity or negativity of the situation given the numerical information, this was not found to be the case.

Numeracy did not influence whether participants showed magnified ratings (higher in the positive condition, and lower in the negative condition). Peters et al. (2006) argued that high numerates draw more affect from numbers. In the context of Task 1, this ability of high numerates to draw more affect from numbers did not translate into high and low numerates judging the situation of a company differently when given numerical information in tabular format.

When assessing whether visualization had an effect on the ratings, we found that neither object nor spatial visualization could predict different evaluation ratings. Despite the plausible argument that high spatial visualization might result in individuals being able to translate the data from the table into a slope, thus seeing the trend clearly, the analysis of ratings from Task 1 did not support such an interpretation.

In Task 1 we have seen how the experimental manipulation of having a positive or a negative trend worked in the intended manner, with higher ratings in the positive and lower in the negative slope. However, neither numeracy nor visualization made a difference in predicting different ratings. The fact that no differences in ratings were found depending on numeracy or visualization could have been due to the fact that the trend depicted by the data might have been obvious to all participants regardless of their level of numeracy or visualization preference. In any event, the results of Task 1 indicate that presenting tabular information depicting a clear upward or downward trend does not affect in a different manner individuals depending on their numeracy or visualization preference.

Task 2 investigated whether numeracy and visualization preference could predict a participant’s accuracy in answering which of two companies (A or B) would have higher profits based on their respective history of profits in the form of a table, if both trends were to continue.

The results indicated that higher numeracy was associated with a higher likelihood of reporting a correct answer. Similarly, higher spatial visualization was associated with a higher probability of finding the correct answer. As we demonstrated in Chapter 4, the combination of lower object and higher spatial visualization predicted higher numeracy. In Task 2 we saw that higher spatial visualization alone was enough to predict correct answers. Thus, going beyond the context of a numeracy test, the findings in this Task 2 suggest that when extrapolating beyond the scope of a numeracy questionnaire, spatial visualization alone is capable of predicting correct answers. As well as requiring participants to make a numerical calculation of the trend, this second task presented the information on the companies in such a way that, an initial and intuitive answer had to be suppressed in order to find the correct answer. The table presenting information was designed in such a manner that the company which ultimately would have higher results in the next year after the series was consistently showing worse results than the other company. This was the case because the ultimately worse performing company had a steady linear progression, whereas the ultimately better performing company showed a logarithmic trend (“L” shaped in the negative trend and “┘” in the positive trend).

In the final task, where individuals had to identify which of a series of graphs corresponded to a given table of data, it was demonstrated that higher numeracy and higher spatial visualization predicted a higher number of correct responses. This is the second task in this series where an exercise involving numerical mental transformation resulted in spatial visualization being a similar predictor of performance to numeracy.

Taken together, these results could be interpreted as showing that spatial visualization is equivalent to numeracy as a predictor variable in numerical performance tasks. As shown in Task 1, different numerical abilities or visualization style do not affect the interpretation of how good or bad a piece of financial information is. This implies that when evaluating the numerical content of a table, individuals varying in their degree of numeracy or visualization are not affected differently. However, in numerical tasks where calculations must be made, numeracy and visualization act similarly. This reasoning follows on from the observation that in Task 2 and 4, where an objective correct answer had to be provided (we will call these “performance” tasks), spatial visualization provided results consistent with numeracy as a variable predicting higher performance. It was only in the “non-performance” (we will call these “evaluation” tasks) that numeracy or spatial visualization were not shown to predict results in a consistent manner.

# Chapter 6

# Visualization and Numeracy in Decision-Making Tasks

This Chapter will investigate whether visualization has an impact on a series of numerical decision-making tasks previously investigated by Peters et al. (2006) and Weller et al. (2012). These authors reported that the numeracy of individuals impacted decision-making. Having previously established the relationship between visualization and numeracy in Research Question 1, we will now replicate the effect of numeracy in tasks used by Peters et al. (2006) and Weller et al. (2012).

In addition, this Chapter will build on and replicate Research Question 1 with this sample; that is, whether Object and Spatial visualization are two independent cognitive style constructs or they are antagonists, with each of the dimensions at opposite ends of a continuum line. In addition such replication with the current sample will also be extended to Research Question 2, which tests the relationship between Object, Spatial visualization, and Numeracy.

As discussed in Chapter 4, there is a relationship between visualization and numeracy. In particular, higher spatial visualization predicts higher scores in numeracy while higher object visualization predicts lower numeracy. On an individual level, a person has a visualization style composed of object and spatial visualization, and when classifying individuals as high or low in each dimension, the resulting matrix of four types of visualizers shows that the combination of low object and high spatial visualization results in higher numeracy compared to other visualizers, which do not differ amongst themselves. Demonstrating the relationship between numeracy and visualization preference was a novelty and might help to make predictions about the roles of visualization style in decision-making in numerical tasks. This is the point which this chapter will investigate: whether visualization has an influence on a set of decision-making tasks where numeracy has been demonstrated to play a role.

Literature in the area of Numeracy and Decision Making has demonstrated that the level of numeracy of individuals affects how people respond to decision-making tasks. Peters et al. (2006) started with the investigation of the effects of Numeracy on Decision-Making. Peters et al. (2006) used as their numeracy measure the Lipkus 11-item scale, a scale that has been criticized (Cokely et al., 2012; Weller et al. 2012; Okamoto et al, 2012) because of its ceiling effect, with the inability to create a range of scores when the population under investigation was highly educated. To overcome this limitation, Weller et al. (2012) created the Abbreviated Numeracy Scale, a scale composed of 8 items that was considerably better than the Lipkus 11-item scale at determining numeracy abilities across a varied range of populations. In the development of the ANS, Weller et al. (2012) tested the predictive validity of the new numeracy scale by analyzing three of the four tasks studied by Peters et al. (2006). In the remainder of this chapter we will investigate the predictive validity of visualization style in the three tasks common to Weller et al. (2012) and Peters et al. (2006).

In what follows, we will describe the three tasks common to Weller et al. (2012) and Peters et al. (2006) where they found that Numeracy predicts

Decision-Making. The fourth and final task of the current Chapter comes from Peters et al. (2006) study on Numeracy and Decision Making. This fourth task was not included in the replication Weller et al. (2012) did of the original Peters et al. (2006) paper.

The first task common to Weller et al. (2012) and Peters et al. (2006) was the “Framing task”. Both studies found that attribute framing effects are moderated by numeracy, with low numeracy being associated with higher framing effects than high numeracy. In particular, using an attribute-framing task (Levin, Schneider & Gaeth, 1998), Weller et al. (2012) and Peters et al. (2006) found that when presented with information about performance of students on a given course, participants displayed different patterns of attribute framing depending on their numeracy. Specifically, in a between-subjects study (framing: positive/negative), the high numerates in the positive frame did not differ in their ratings from the high numerates in the negative frame. The low numeracy groups, however, gave different performance ratings to the students depending on whether they saw the negative scores (negative frame) or the (equivalent) positive scores (positive frame). Peters et al. (2006) concluded that the ability to make numerical calculations allowed the high numerates to see the equivalent format, whereas the low numerates, not being able to perform the calculation, displayed the typical framing effect to a greater extent. Weller et al. (2012), having replicated the same effects of numeracy on framing originally found by Peters et al. (2006), suggest as a plausible explanation for this effect that “the less numerate decision-makers focus on non-numeric sources of information when constructing preferences” such as the literal wording instead of the numerical values presented. In the first task of this Chapter we will replicate Peters et al. (2006) and Weller et al. (2012) Framing Task.

The second task will investigate the replication of Weller et al. (2012) and Peters et al. (2006) findings in the “Ratio Bias Task”, where they found that high numerates tended to make objectively better choices than low numerates when presented with numerical information. Specifically, using a paradigm developed by Denes-Raj & Epstein (1994) where participants see the image of two bowls with, respectively 100 or 10 jelly beans (the first bowl containing 9 colored beans and the second bowl, one), and they are asked to decide which bowl they would choose from if they were to blindly draw one single colored bean. Peters et al. (2006) and Weller et al. (2012) found high numeracy to be associated with choosing from the objectively better bowl (10% colored beans) instead of from the objectively worse one (9% colored beans).

The final task in common between Weller et al. (2012) and Peters et al. (2006) is the current third task, which will investigate whether visualization affects the “Bets Task” in the manner Weller et al. (2012) and Peters et al. (2006) found it to be affected by numeracy. In this task, the authors used a paradigm developed by Slovic et al. (2004), in which it was demonstrated that high numeracy might sometimes lead to worse decisions. In between-subject studies, when evaluating a gamble either with 29/36 probabilities of winning €9 and 7/36 of losing  €0, or the same gamble but the winning/losing amounts are, respectively, €9 win or 5 cents loss, high numerates tended to value the gamble with a loss higher than the gamble without the loss. However, the low numerates did not show this difference regardless of the gamble they evaluated.

The last of the tasks in the current Chapter investigates whether there is a replication of Numeracy affecting ratings of risk when individuals are presented frequentistic or probabilistic information. We will also study whether Object or Spatial visualization affect ratings of risk in such a scenario. The particular scenario in Peters et al. (2006) study was one where participants had to evaluate the risk of a mental patient committing an act of violence upon discharge from a mental institution. The information was presented in a probabilistic (%) or frequentistic (1 out of X) format, and the original study found low numeracy to be correlated with higher ratings of risk.

To summarize, this chapter investigates whether visualization style can predict the results found by Weller et al. (2012) and Peters et al. (2006) in their numeracy and decision-making research. To this end, the tasks described above were presented in a package which also included the OSIVQ and numeracy tests. The order of the tasks was either presented in the order of the original Peters experiment, or reversed to check whether presentation order had an effect on results. Order was not found to have an effect on the tasks described above.

## *6.1 Participants*

Participants were recruited from the University of Granada, Faculty of Economics and Business Administration and voluntarily participated in the data collection during class time. There were 159 participants (95 females), with an average age of 19.87 (SD=3.33, Min= 18, Max=47), and the materials were presented in the form of a paper-and-pencil questionnaire to groups of 20 to 45 students at a time. To avoid contamination of answers, participants were distributed in the classroom in a manner that did not allow them to share their thoughts or answers. In addition, the experimenter remained in the classroom to monitor behavior, collect the materials and brief participants should they want it.

## *6.2 Replication of Object-Spatial Visualization Relationship*

Similar to the analyses carried out in Chapter 5 to further validate the observed relationship between Object and Spatial Visualization and their relationship with Numeracy, section 6.2 will perform a correlation analysis between the OSIVQ components and Numeracy (ANS) as well as a regression model to predict numeracy from the different components of visualization.

### 6.2.1 Correlation Analysis

A correlation analysis including the OSIVQ components and Numeracy (ANS) scores was run to verify the solidity of the findings from section 4.2.2, later replicated in section 5.2, which found object visualization being negatively correlated with numeracy and spatial visualization following the opposite pattern, with a positive correlation between spatial visualization and numeracy.

As shown in Table 6.2.1.1, the correlational analysis confirms the findings from Chapter 4 and 5. Specifically, object visualization is significantly negatively correlated with Numeracy, $r(159)= -.20$, $p= .01$. Confirming the results of Chapter 4, spatial visualization follows the opposite pattern of object visualization in its relationship with numeracy and we find a significantly positive correlation between numeracy and spatial visualization, r(159)= .21, p= .01. Following the pattern found in previous replications, the Object and Spatial visualization dimensions are virtually uncorrelated, r(159)= ,10, p=.21.

**Table 6.2.1.1**

*Correlation Analysis Between Numeracy and Visualization*

| | | Object Score | Spatial Score |
|---|---|---|---|
| Numeracy (ANS) | Pearson Correlation | -,20* | ,21** |
| | Sig. (2-tailed) | ,011 | ,010 |
| | N | 159 | 159 |
| SpatialScore | Pearson Correlation | ,10 | - |
| | Sig. (2-tailed) | ,21 | - |
| | N | 159 | |

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

### 6.2.2 Predictive Value of Visualization on Numeracy

A regression model was run with numeracy as the dependent variable to check for the replication of the finding reported on Chapter 4 and later replicated in Chapter 5 that higher object visualization predicts lower numeracy while increased spatial visualization predicts higher numeracy. To this end, similar to the prior analysis in Chapter 4 and 5, we run a regression to predict numeracy scores from object and spatial visualization scores controlling for the effect of gender. Similar to Chapter 5, and unlike Chapter 4, Major was not necessary to be included in this recession, as al students belonged to the Business Administration department, and no engineers or history majors were present in the survey.

The aforementioned regression model predicting numeracy scores from object and spatial visualization while controlling for gender was statistically significant, F(3,157)= 11,76, p<.001 (Table 6.2.2.1).

**Table 6.2.2.1**

*Regression Model Predicting Numeracy from Object and Spatial Visualization*

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| | Regression | 71,23 | 3 | 23,74 | 11,76 | ,000[b] |
| 1 | Residual | 310,92 | 154 | 2.02 | | |
| | Total | 382,15 | 157 | | | |

| R | R Square | Adjusted R Square | Std. Error of Estimate |
|---|---|---|---|
| ,33 | ,11 | ,09 | 1,46 |

a. Dependent Variable: ANS

b. Predictors: (Constant), SpatialScore, ObjectScore, Gender

As shown on Table 6.2.2.2, higher spatial visualization predicts higher numeracy scores (p=.033), while higher object visualization predicts lower numeracy scores (p=.018). Tests of Collinearity statistics were performed also in this analysis and showed the trend expressed in Chapter 4 and 5 of no existence of grounds for concern as the values of multicollinearity statistics are all well below the customary point of concern of 10 (Cohen et al., 2003).

**Table 6.2.2.2**

*Regression Coefficients and Collinearity Results for Regression Predicting Numeracy from Object and Spatial Visualization*

| | | Unstandardized Coefficients | | Standardized Coefficients | | | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| Model | | B | Std. Error | Beta | t | Sig. | Tolerance | VIF |
| 1 | (Constant) | 4,48 | ,89 | | 5,01 | ,000 | | |
| | Gender | 1,00 | ,24 | ,32 | 4,20 | ,000 | ,93 | 1,07 |
| | ObjectScore | -,51 | ,21 | -,18 | -2,38 | ,018 | ,97 | 1,03 |
| | SpatialScore | ,453 | ,211 | ,161 | 2,15 | ,033 | ,94 | 1,07 |

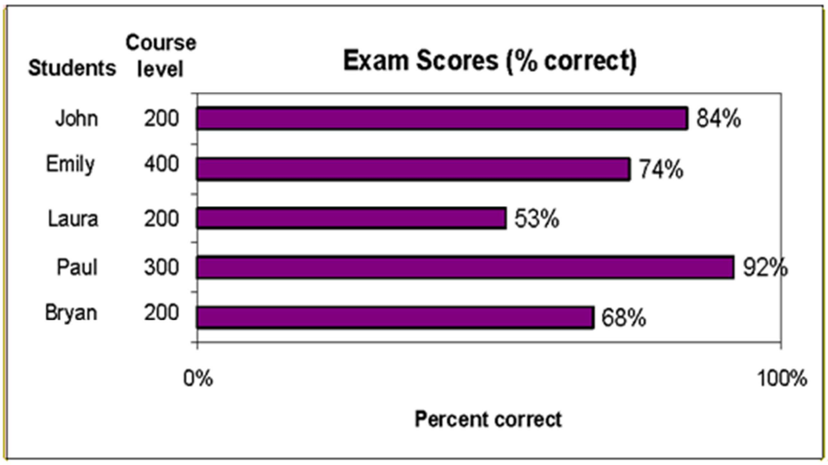
a. Dependent Variable: ANS

## *6.3 Task 1: Attribute Framing and Visualization*

### 6.3.1 Design

This task investigates the extent to which attribute framing (Levin, Schneider & Gaeth, 1988) modifies people's perceptions. Participants received a questionnaire showing the scores of five university students in their 2$^{nd}$, 3$^{rd}$, or 4$^{th}$ year. The scores were presented in the form of bar graphs and showed their scores on one course (See Figure 6.3.1.1) and were presented either as a percentage of correct answers (positive frame) or incorrect answers (negative frame) on the course (between-subjects condition).

Under the image of the bar graphs with scores and scoring information, participants were asked to mark the performance of each of the students from -3 (very bad) to (+3 very good). The task was a Spanish version identical to that used by Peters et al. 2006.




*Please rate the performance of each student by circling* ***one*** *number on* ***each*** *line below.*

| | | Very poor | | | Neither poor nor good | | | Very good |
|---|---|---|---|---|---|---|---|---|
| 1. | John | –3 | –2 | –1 | 0 | +1 | +2 | +3 |
| 2. | Emily | –3 | –2 | –1 | 0 | +1 | +2 | +3 |
| 3. | Laura | –3 | –2 | –1 | 0 | +1 | +2 | +3 |
| 4. | Paul | –3 | –2 | –1 | 0 | +1 | +2 | +3 |
| 5. | Bryan | –3 | –2 | –1 | 0 | +1 | +2 | +3 |

***Figure 6.3.1.1*** Task 1 stimuli and scoring

### 6.3.2 Results

Peters et al. (2006) found a main effect of frame, with scores in the positive frame eliciting higher ratings than scores in the negative frame. In addition, using as their numeracy measurement the dichotomized (high/low) Lipkus 11-item scale, they found an interaction between Frame and Numeracy. This interaction caused scores to be more extreme (higher in the positive and lower in the negative frame) in the group of low numerates than in the high numerates, which they interpreted as the high numerates being less affected by the frame manipulation than the low numerates.

To investigate Peters et al.'s (2006) replication using numeracy, the numeracy of the current sample from the ANS was median-split into high and low numeracy. Following the method of the original study, Numeracy and Frame were used as a between-subjects factor in a Repeated-Measures ANOVA, with the ratings of the five students as the within-subjects factor.

Using a dichotomized numeracy measure did not replicate the findings from Peters et al (2006). The analysis with Frame and Numeracy as between-subjects factors revealed only a main effect of Frame, ($F[1,121]=82.57$, $p<.001$), Table 6.3.2.1.

**Table 6.3.2.1**

*Framing Task, Repeated-Measures ANOVA Model for Numeracy*

**Tests of Between-Subjects Effects**

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Observed Power |
|---|---|---|---|---|---|---|
| Intercept | 617.73 | 1 | 617.73 | 225.58 | .000 | |
| Frame | 226.11 | 1 | 226.11 | 82.57 | .000 | 1,00 |
| Numeracy | 2.80 | 1 | 2.80 | 1.02 | .314 | ,17 |
| Frame x Numeracy Inter. | 5.80 | 1 | 5.80 | 2.12 | .148 | ,30 |
| Error | 331.35 | 121 | 2.74 | | | |

As shown in Table 6.3.2.2, scores in the positive frame were significantly higher than in the negative frame for both the high and low numerates. This indicates that the manipulation check worked as intended and the positive frame elicited higher ratings than the negative frame, and we can also see how the difference between the positive and the negative frame is higher within the low numeracy groups (1,426) than within the High numeracy groups

(1,032). Further analyses will determine whether this difference is statistically significant.

**Table 6.3.2.2**

*Task 1: Attribute Framing Experiment, Descriptive statistics*

**PetersStudentFrame * ANSDichotomous**

Measurement: MEASUREMENT_1

| Frame | Numeracy | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| Negative | Low Numeracy | .23 | .13 | -.01 | .48 |
| | High Numeracy | .57 | .15 | .28 | .86 |
| Positive | Low Numeracy | 1.66 | .12 | 1.43 | 1.89 |
| | High Numeracy | 1.60 | .15 | 1.31 | 1.89 |

As we have seen, using ANS dichotomized into high and low, the interaction of Frame x Numeracy is not significant. This might have been due to the fact that we used a median-split dichotomization and the consequent loss of statistical power, which as reported in Table 6.3.2.1, it stands at 0,171, a number which is below the 0,80 considered statistically desirable (Cohen, 1988). However, Weller et al. (2006) used mean-deviated numeracy scores to predict the ratings of the five students averaged and used this average as the DV. We will investigate next whether using the mean-deviated numeracy measure with the averaged student scores yields different results. To this end, we followed the Weller et al. (2012) procedure and regressed the average ratings of students on Frame (0=Negative, 1=Positive), and the Frame x Numeracy (mean deviated scores) interaction.

Even when the method of analysis was changed to replicate Weller et al. (2012), the results only yielded the same effect of Frame as above, which in this model was a significant predictor ($p<.001$, positive frame predicted higher scores than the negative frame) of scores in much the same manner as using a repeated-measures analysis with dichotomization of numeracy into high and low.

Finally, we analyzed whether framing was affected by visualization. Another Repeated-Measures Analysis of Variance (ANOVA) with the five scores given to each student as the DV, and Frame and Object Categorical and Spatial Categorical (High/Low) as the between subjects factors, revealed a significant effect of Frame (F[1,119] = 85,99, p<.001, Table 6.3.2.3) consistent with the previously reported analyses (higher scores in the positive than in the negative frame, Table 6.3.2.4). However, no main effect or interactions between frame with object or spatial visualization were found.

**Table 6.3.2.3**

*Task 1: Repeated-Measures ANOVA for Attribute Framing Experiment, Frame x Object x Spatial visualization*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared | Observed Power[a] |
|---|---|---|---|---|---|---|---|
| Intercept | 624,93 | 1 | 624,93 | 220,97 | ,000 | ,65 | 1,00 |
| PetersStudentFrame | 243,19 | 1 | 243,19 | 85,99 | ,000 | ,42 | 1,00 |
| ObjectScoreCategorical | ,39 | 1 | ,39 | ,14 | ,711 | ,001 | ,07 |
| SpatialScoreCategorical | 1,46 | 1 | 1,46 | ,52 | ,474 | ,004 | ,11 |
| PetersStudentFrame * ObjectScoreCategorical | ,29 | 1 | ,29 | ,10 | ,750 | ,001 | ,06 |
| PetersStudentFrame * SpatialScoreCategorical | 1,14 | 1 | 1,14 | ,40 | ,527 | ,003 | ,10 |
| Error | 336,55 | 119 | 2,83 | | | | |

a. Computed using alpha = ,05

**Table 6.3.2.4**

*Task 1: Table of means for high and low Spatial and Object visualizers depending on Frame in the Attribute Framing task*

| Object Visualizers Scores | | | | | |
|---|---|---|---|---|---|
| Frame | Visualization Level | Mean | Std. Error | 95% Confidence Interval | |
| | | | | Lower Bound | Upper Bound |
| Negative | Low | ,42 | ,14 | ,15 | ,70 |
| | High | ,33 | ,14 | ,06 | ,61 |
| Positive | Low | 1,64 | ,14 | 1,35 | 1,92 |
| | High | 1,64 | ,13 | 1,38 | 1,89 |
| Spatial Visualizers Scores | | | | | |
| Negative | Low | ,29 | ,13 | ,02 | ,55 |
| | High | ,47 | ,14 | ,19 | ,76 |
| Positive | Low | 1,63 | ,13 | 1,39 | 1,88 |
| | High | 1,64 | ,15 | 1,35 | 1,93 |

The previous analyses therefore do not replicate the results of Peters et al. (2006) or Weller et al. (2012) in which framing was weaker for the high numeracy than the low numeracy groups. The analyses of Visualization are consistent with those of Numeracy, failing to detect a differential effect depending on visualization style. As we have seen in previous chapters, there is a relationship between Numeracy and object and spatial visualization, such that we could hypothesize that spatial visualization predicts Decision-Making in the same way as Numeracy. As no effect of numeracy or visualization was found in the current task, it cannot be argued that numeracy behaves differently or similarly to object or spatial visualization in this particular context.

## *6.4 Task 2: Ratio Bias Task*

### 6.4.1 Design

This task, translated into Spanish due to the location of data collection, was identical to that used by Weller et al. (2012) and Peters et al. (2006), and is based on the task originally developed by Denes-Raj and Epstein (1994). In this task, participants answered the following scenario:

"*Below one bowl has 100 jellybeans, and the other has 10 jellybeans. You will be asked to choose one bowl and indicate the strength of your preference by circling one number on the scale below the bowls. Please imagine that once you have selected a bowl, it will be placed behind a screen, the experimenter will mix up the jellybeans randomly, and then you will reach around the screen (without looking at the bowl) and select a bean.*

*Imagine that if you selected a colored bean, you would WIN $5. Would you prefer to pick from bowl A or bowl B?* "

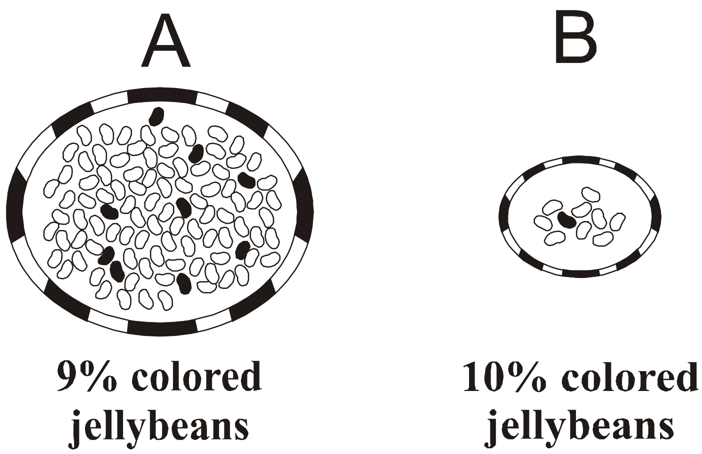



***Figure 6.4.1.1*** Task 3 image of bowls participants see in Task 2, Chapter 6 (from Peters et al., 2006)

After seeing the picture of the jelly beans' bowls, participants were then asked to mark their preference on the scale depicted in Figure 6.4.1.2 below

| Bowl A | 6 | 5 | 4 | 3 | 2 | 1 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | Bowl B |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Strong preference for A | | | Slight preference for A | | | | Slight preference for B | | | Strong preference for B | | | |

***Figure 6.4.1.2*** Task 2 scale (from Peters et al., 2006)

### 6.4.2 Results

Both Weller et al. (2012) and Peters et al. (2006) found that low numeracy was associated with fewer optimal choices.

Specifically, Weller et al. (2012) found that "*more numerate participants had a stronger preference for the objectively better bowl*". Although in the paper Weller et al. (2012) do not refer to the specifics of the analyses, only reporting the previous statement and a regression value, we can infer that Weller et al. (2012) used a regression to predict the preference for each bowl, using the ratings on the scale above as the predicted variable and Numeracy as the predictor. In the case of Peters et al. (2006), using a chi-square analysis, the preference for Bowl A or B was used as a categorical DV, and numeracy was also used as a categorical variable, with the numeracy scale divided into high and low. We will try both methodologies, using categorical as well as continuous variables to check for the replication with numeracy (ANS) and visualization (object and spatial), so as to shed light on the possible differences.

We coded answers from -6 to -1 as "Bowl A" (suboptimal choice) and 1 to 6 as "Bowl B" (optimal choice), with people who marked 0 excluded, as they did not indicate a preference for a specific bowl. We run a chi-square with Numeracy (ANS high/low numeracy) and Bowl Choice (A suboptimal / B optimal).

The results do not replicate Peters et al. (2006) findings that the high numerates chose the optimal bowl more often than the low numerates. As shown, on Table 6.4.2.1, High and Low numerates showed the same pattern of both choosing the objectively better bowl.

As shown on Table 6.4.2.2, the Chi-square reveal that high and low numerates did not differ in their choice of bowl. Therefore, using ANS as the numeracy measure, Peters et al. (2006) are not replicated.

**Table 6.4.2.1**

*Task 2, High and Low numerates choices. Choice of Bowl * ANSDichotomous Crosstabulation*

| | | | ANSDichotomous | | Total |
|---|---|---|---|---|---|
| | | | Low Numeracy | High Numeracy | |
| Choice | Bowl A (Suboptimal) | Count | $27_a$ | $18_a$ | 45 |
| | | Expected Count | 25.5 | 19.5 | 45.0 |
| | Bowl B (Optimal) | Count | $58_a$ | $47_a$ | 105 |
| | | Expected Count | 59.5 | 45.5 | 105.0 |
| Total | | Count | 85 | 65 | 150 |
| | | Expected Count | 85.0 | 65.0 | 150.0 |

Each subscript letter denotes a subset of ANSDichotomous categories whose column proportions do not differ significantly from each other at the .05 level.

**Table 6.4.2.2**
*Task 2, High and Low numerates choices*

**Chi-Square Tests**

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | .29[a] | 1 | .59 | | |
| Continuity Correction[b] | .13 | 1 | .72 | | |
| Likelihood Ratio | .29 | 1 | .59 | | |
| Fisher's Exact Test | | | | .72 | .36 |
| Linear-by-Linear Association | .29 | 1 | .59 | | |
| N of Valid Cases | 150 | | | | |

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 19.50.

b. Computed only for a 2x2 table

Although Peters used a Chi-square with Bowl A or Bowl B and High/Low numeracy as the factors, using numeracy as a continuous independent variable may offer more variance, and this could allow detection of statistical differences that a dichotomous measure might not detect. This regression analysis was indeed what Weller et al. (2012) presumably did. To replicate the finding that high numeracy predicts better performance in the current task, participants' scores for Bowl A and B were recorded as shown in Figure 6.4.2.1, from -6 (Bowl A) to +6 (Bowl B) and used as the DV in a regression model with numeracy as the predictor variable.

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bowl A | -6 | -5 | -4 | -3 | -2 | -1 | 0 | +1 | +2 | +3 | +4 | +5 | +6 | Bowl B |
| | Strong preference for A | | | Slight preference for A | | | | Slight preference for B | | | Strong preference for B | | | |

***Figure 6.4.2.1*** Task 2, coding of ratings for Bowl A and Bowl B

However, even using numeracy as an independent variable (IV) and bowl (DV) ratings as continuous variables in a regression model, numeracy was not found to predict choices and could not significantly predict preference based on the ratings, $F(1,150)=.87$, $p=.352$.

We checked next whether visualization predicts the choice of the optimal bowl. To this end, we ran a logistic regression, with the choice of Bowl as the dependent variable (Bowl A= 0, Bowl B=1), and object and spatial visualization as the predictor variables. The overall regression model was statistically significant (ChiSquare=8.29, with df=2, $p=.016$). As shown in Table 6.4.2.3, of the two visualization dimensions, higher spatial visualization was associated with a higher likelihood of choosing the optimal Bowl ($p=.008$). In contrast to spatial visualization, object visualization does not seem to predict a choice of Bowl above chance ($p=.383$).

**Table 6.4.2.3**

*Bowl Task, logistic regression, visualization predicting choice of optimal bowl*

| Variables in the Equation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | B | S.E. | Wald | df | Sig. | Exp(B) |
| Step 1[a] | ObjectScore | -.32 | .37 | .76 | 1 | .383 | .73 |
| | SpatialScore | .93 | .35 | 7.13 | 1 | .008 | 2.53 |
| | Constant | -.58 | 1.52 | .15 | 1 | .701 | .56 |

| -2 Log Likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|
| 174,96 | ,05 | ,08 |

| % Correct Predicted Null Model | % Correct Predicted Full Model |
|---|---|
| 70 | 73,3 |

a. Variable(s) entered on step 1: ObjectScore, SpatialScore.

The effect of spatial visualization in predicting a higher tendency to choose from the optimal bowl was also evident in a linear regression model using the ratings of preference for each bowl (Figure 6.4.2.1) as the DV, $F(2,148)=3.97$, $p=.021$. As shown in Table 6.4.2.4, spatial visualization predicts higher scores, indicating a higher preference for the optimal, Bowl B. Object visualization does not predict a choice of bowl in a statistically significant manner.

In summary, the results reported in this section did not show a replication of Peter's findings that numeracy predicted the choice of the best bowl. Similarly, Weller et al. (2012) findings that high numerates would tend to favor the better bowl were not replicated.

In contrast, we found that higher spatial visualization scores significantly predict better choices and higher preference for the better bowl. Object visualization, however, did not show a statistically significant effect in predicting the choice of bowl or a higher preference for one. In summary, in this particular task, spatial visualization seemed to be a more reliable predictor of better choices than numeracy.

**Table 6.4.2.4**

*Task 2, linear regression, visualization predicting ratings of optimal bowl*

**Coefficients**[a]

| Model | | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | t | Sig. |
| 1 | (Constant) | .21 | 2.68 | | .08 | .937 |
| | ObjectScore | -.82 | .65 | -.10 | -1.25 | .212 |
| | SpatialScore | 1.58 | .60 | .21 | 2.63 | .009 |

| R | R Square | Adjusted R Square | Std. Error of Estimate |
|---|---|---|---|
| ,23 | ,05 | ,04 | 4,17 |

a. Dependent Variable: PetersBeans

## *6.5 Task 3: Bets Task*

### 6.5.1 Design

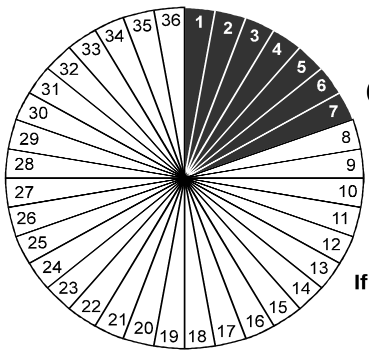
We finally analyzed the last of the Weller et at. (2012) and Peters et al. (2006) tasks included in their studies. In this task, based on an original design by Slovic et al. (2004), participants are shown a roulette wheel divided into 36 equally sized numbered slices, with the slices from 1 to 7 colored in black and the rest in white. Participants were subsequently asked to evaluate a bet where in one condition they had 7/36 chances of winning €9 and 29/36 of losing €0. In the second experimental condition, a different set of participants saw the same probabilistic information, but the bet either wins €9 or loses €0.05 (Figure 6.5.1.1).

Next, please rate how attractive the prospect of playing the following bet is to you.

7/36 to win $9.00

29/36 to lose 5¢

This means that there are 7 chances out of 36 that you will win the bet and receive $9.00 and 29 chances out of 36 that you will lose 5¢




**(We would like you to mentally) Visualize a roulette wheel on the left with 36 numbers along the circumference. If a ball lands on any of the 7 numbers between 1 and 7 inclusive, you win $9.00. If it lands on 8–36, you lose 5¢.**

**Please indicate your opinion of this bet's attractiveness by circling one number on the rating scale below. There is no right or wrong answer, we are interested only in your opinion about the attractiveness of playing this bet.**

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

| Not at all an attractive bet | Moderately attractive bet | Extremely attractive bet |
|---|---|---|

***Figure 6.5.1.1*** Original Bet Task by Peters et al. (2006) & Weller et al. (2012)

### 6.5.2 Results

The common finding of Weller et al. (2012) and Peters et al. (2006) in this task was that the group of high numerates evaluating the bet with a small loss tended to value the bet more highly than the group of high numerates evaluating the bet without the loss. In contrast the low numerates showed no differences in valuing the bet with the loss from the low numerates evaluating the bet without the loss. Figure 6.5.2.1, reproduced from Peters et al (2006) illustrates the previously described pattern.

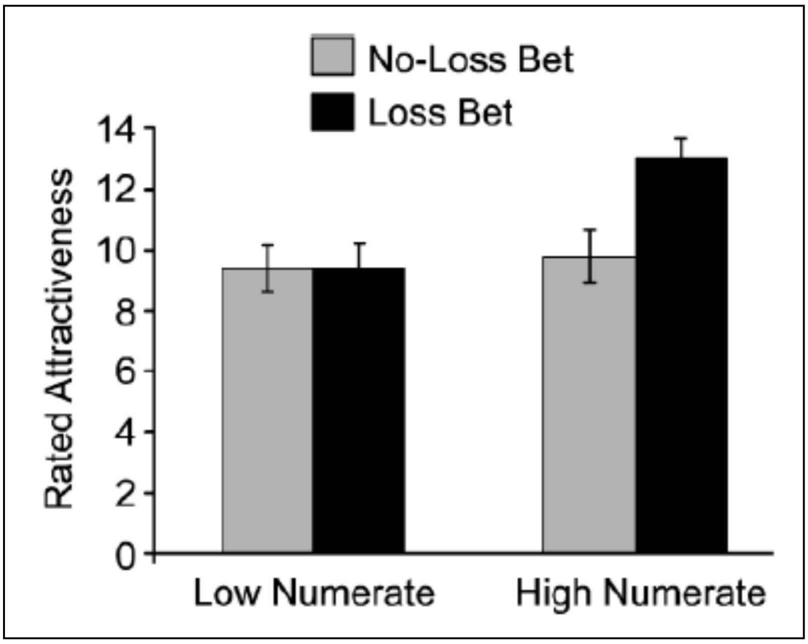



***Figure 6.5.2.1*** Peters et al. (2006) Bet task evaluations

We first checked for the replication of the high and low numerates differing in their evaluations of the bet. Unlike Peters's original results, we did not find that high and low numerates differed in their evaluation of the attractiveness of the bet depending on whether or not there was a small loss. As Table 6.4.2.1 shows, a 2 x 2 factorial ANOVA, with type of bet (loss/no-loss) and numeracy (ANS high/low) shows the main effects of type of bet ($F[1,143]=26.46$, $p<.001$), and Numeracy ($F[1,127]=4.18$, $p=.043$).

**Table 6.5.2.1**
Bet Task, Numeracy x Frame ANOVA

**Tests of Between-Subjects Effects**

Dependent Variable: PetersBetA

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 674.27[a] | 3 | 224.76 | 9.23 | .000 |
| Intercept | 12391.31 | 1 | 12391.31 | 508.74 | .000 |
| PetersBetFrame | 590.76 | 1 | 590.76 | 24.25 | .000 |
| ANSDichotomous | 101.75 | 1 | 101.75 | 4.18 | .043 |
| PetersBetFrame * ANSDichotomous | 10.10 | 1 | 10.10 | .42 | .521 |
| Error | 3093.34 | 127 | 24.36 | | |
| Total | 16392.00 | 131 | | | |
| Corrected Total | 3767.60 | 130 | | | |

The ANOVA model revealed scores to be higher in the bet with a loss than in the bet without a loss (for means, see Table 6.5.2.2) regardless of numerical ability. This pattern of results is illustrated in Figure 6.5.2.1, and Table 6.5.2.2 below.

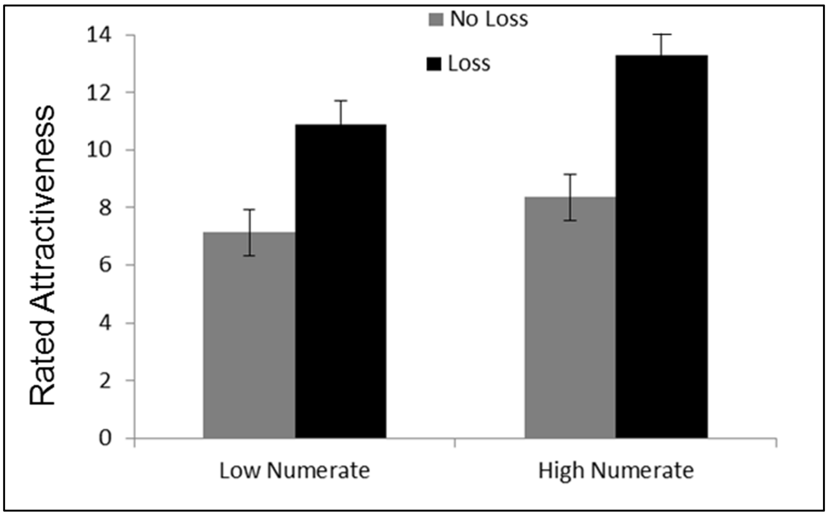



***Figure 6.5.2.1*** Task 3, bet evaluations by numeracy category

**Table 6.5.2.2**
Bet task, table of means

| PetersBetFrame * ANSDichotomous | | | | | |
|---|---|---|---|---|---|
| Dependent Variable: PetersBetA | | | | | |
| PetersBetFrame | ANSDichotomous | Mean | Std. Error | 95% Confidence Interval | |
| | | | | Lower Bound | Upper Bound |
| No Loss | Low Numeracy | 7.14 | .82 | 5.51 | 8.77 |
| | High Numeracy | 8.37 | .95 | 6.49 | 10.25 |
| Loss | Low Numeracy | 10.91 | .76 | 9.40 | 12.41 |
| | High Numeracy | 13.27 | .97 | 11.35 | 15.19 |

Similarly to Weller et al. (2012), we found that high numerates evaluated the bets as more attractive than low numerates. This result is in a certain way similar to that reported in Task 1, Research Question 2 in Chapter 5 which found that higher numeracy individuals give higher ratings of performance to a company regardless of the trend of results displayed in a table. Although these two instances do not constitute a wealth of studies from which to generalize, it could be that high numeracy affects attractiveness/positivity ratings in such a way that high numerates provide higher ratings when evaluating numerical information.

We delved further into the analysis to detect whether the absence of interaction between Numeracy and Frame was caused by the use of ANS as a dichotomous variable instead of a continuous one. To this end, we used ANS as a continuous variable in a regression predicting attractiveness ratings from Numeracy (ANS), Frame (Loss/No Loss) and the interaction. This regression was also run using the mean-deviated ANS scores as the numeracy measure. However, both regressions confirmed the previous analysis showing that Numeracy, in this case, did not predict the attractiveness ratings differently depending on whether the bet was presented with a loss or without a loss.

In short, the previous analysis failed to replicate the interaction originally found by Peters et al. (2006) and later on by Weller et al. (2012) in which low and high numerates gave different evaluations of the bet depending on whether it was in the loss or no-loss condition. Instead, it appears to be a general effect of type of bet driving attractiveness ratings, with the bet with a small loss receiving higher attractiveness ratings and high numerates giving higher ratings of attractiveness than low numerates. Contrary to what Peters et al. (2006) and later Weller et al. (2012) found, the pattern of Low and High numerates is very similar.

**Table 6.5.2.2**
Bet task, table of means

**PetersBetFrame * ANSDichotomous**

Dependent Variable: PetersBetA

| PetersBetFrame | ANSDichotomous | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| No Loss | Low Numeracy | 7.14 | .82 | 5.51 | 8.77 |
| | High Numeracy | 8.37 | .95 | 6.49 | 10.25 |
| Loss | Low Numeracy | 10.91 | .76 | 9.40 | 12.41 |
| | High Numeracy | 13.27 | .97 | 11.35 | 15.19 |

We analyzed next whether visualization had an effect on attractiveness ratings in this experimental setting. To this end, we ran a regression with Frame, Object, Spatial, and the interactions of Frame with Object and Frame with Spatial visualization. This regression was statistically significant $F(5,125)=6.67$, $p<.0001$, and showed how increased spatial scores significantly predicted (p=.05) higher scores in the DV. However, this regression (Table 6.5.2.3) did not show an interaction with either of the visualization dimensions and frame.

**Table 6.5.2.3**

*Effect of visualization on bet ratings*

**Coefficients[a]**

| Model | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | .12 | 5.32 | | .02 | .982 |
| PetersBetFrame | .63 | 7.18 | .06 | .09 | .931 |
| ObjectScore | .44 | 1.08 | .05 | .41 | .681 |
| SpatialScore | 2.20 | 1.11 | .30 | 1.98 | .050 |
| FramebyObjectInteraction | 1.21 | 1.62 | .39 | .75 | .456 |
| FramebySpatialtInteraction | -.20 | 1.56 | -.05 | -.13 | .899 |

| R | R Square | Adjusted R Square | Std. Error of Estimate |
|---|---|---|---|
| ,46 | ,21 | ,18 | 4,88 |

a. Dependent Variable: PetersBetA

To investigate whether the absence of a linear relationship between the terms resulted in a failure to record a statistical effect, we dichotomized spatial and object visualization into high and low and ran two separate ANOVAs, one with object and the next with spatial visualization, both of them including Frame as the second factor.

The ANOVAs did not provide further insight and confirmed the results of the regression model: object visualization did not have an effect as part of the interaction or as a lone factor, whereas spatial visualization was significant as a factor, $F(1,132)=5.82$, $p=.017$, with no interaction of spatial and frame found. As shown in Table 6.5.2.4, high spatial visualizers gave higher attractiveness ratings across conditions (M=10.78, SD=.63) than low spatial visualizers (M=8.74, SD=.56).

**Table 6.5.2.4**
Spatial visualization and bet ratings

**Descriptive Statistics**

Dependent Variable: PetersBetA

| PetersBetFrame | SpatialScoreCategorical | Mean | Std. Deviation | N |
|---|---|---|---|---|
| No Loss | Low | 6.09 | 3.48 | 35 |
| | High | 9.07 | 5.38 | 30 |
| | Total | 7.46 | 4.67 | 65 |
| Loss | Low | 11.39 | 5.42 | 41 |
| | High | 12.50 | 5.08 | 30 |
| | Total | 11.86 | 5.27 | 71 |
| Total | Low | 8.95 | 5.31 | 76 |
| | High | 10.78 | 5.47 | 60 |
| | Total | 9.76 | 5.44 | 136 |

In summary, the above results failed to replicate the interaction of Loss x Numeracy previously reported by Weller et al. (2012) and Peters et al. (2006) whereby high numerates rated a bet with a small loss as more attractive than a bet without a loss whilst the low numerates did not show any differences across the frame. Similarly to numeracy, neither object nor spatial visualization was shown to affect prediction of different attractiveness scores depending on the Loss condition.

Interestingly, however, we found that high Numeracy acted much in the same manner as high spatial visualization in that an increase in either of these variables predicted higher attractiveness scores given to the bets.

## *6.6 Task 4: Risk presentation format and Visualization*

Weller et al. (2006) replicated three Decision-Making tasks from Peters et al. (2006). However, the original study by Peters et al had one extra task that was not investigated by Weller et al. (2012) in their development of the ANS. The task Weller et al. (2012) did not investigate in their study, the “Mental Patient Task” was also found to be influenced by numeracy in Peters et al. (2006). It is not clear why this is the case, but Weller et al. (2012) did not replicate this task. We will still investigate this task and see whether visualization and numeracy (ANS) predict differences in the framing of probabilistic or frequentistic information.

Peters et al. (2006) found that presenting risk information about the probabilities of recidivism of a specific mental patient about to be discharged affected high and low numerates in a different manner depending on whether the information was presented in a probabilistic (10%) or frequentistic (1 out of 10) format. Specifically, information presented to high numerates either in the frequentistic or probabilistic frame did not cause significantly different ratings between groups. However, low numerates who were presented with information in a frequentistic frame gave higher ratings of risk than low numerates presented information in a probabilistic frame. These results are not trivial, since the framing of information has been shown to be widely used in scenarios that affect our own survival such as presenting medical risk information in terms of survival or death rate. As Edwards et al. (2001) argue, health professionals routinely provide risk and other health information to patients it with the goal of “*increasing uptake of screening, such as* *mammography, or modifying behaviour, such as smoking cessation*" (p. 62). The framing of information in this context is widely used by practitioners (for a review, see Edwards et al. 2001), and understanding the different causes or processes whereby framing effects occur would therefore be important, not only from the theoretical point of view of the advancement and understanding of psychological processes, but also from a practical one, as it would inform best practices in informing patients about their risk and health options.

### 6.6.1 Design

Peters et al. (2006) administered this task based on a paradigm initially developed by Slovic, Monahan & MacGregor (2000). This task was originally developed to investigate whether people make different risk assessments when risk information is given to them in a frequentistic (e.g. 1 in 10) or in a probabilistic frame (e.g. 10%). This condition was manipulated between subjects, with participants receiving either the frequentistic or the probabilistic framed information.

The specific wording of the task, based on Slovic, Monahan & MacGregor, (2000) was as follows:

"*A patient — Mr. James Jones — has been evaluated for discharge from a local mental health facility where he has been treated for the past several weeks. A psychologist has done a state-of-the-art assessment of Mr. Jones. Among the conclusions reached in the psychologist's assessment is the following:*

*Of every 100 patients similar to Mr. Jones, 10% are estimated to commit an act of violence to others during the first several months after discharge.*

*Imagine you were working as a supervisor at a mental health facility and received the psychologist's report about Mr. Jones."*

Following this passage, participants were asked a series of questions, including the question analyzed by Peters et al. (2006): "Would you describe Mr. Jones as being at low risk, medium risk, or high risk of harming someone other than himself during the first several months following discharge?" (1 low risk to 6 high risk).

### 6.6.2 Results

The order of presentation of this task in relation to the other tasks in the experimental package was significant. Specifically, scores of risk in the probability format were significantly lower when the task was presented as the second task in the package, immediately following the "Student Framing" task, than when it was presented third in the sequence (after the "Gamble" and the "Jelly Beans" tasks). Thus, a covariate indicating order was included in the analyses to account for this effect. There is no apparent explanation as to why this order effect might have occurred.

Using the Lipkus dichotomized scale, Peters et al. (2006) found an interaction between Frame and Numeracy. Whereas high numerates did not show differences in ratings between the probabilistic and the frequentistic formats, the low numerates gave higher risk ratings in the frequentistic than in the probabilistic format (Figure 6.6.2.1).

We ran a Factorial ANCOVA with Frame and Numeracy (ANS dichotomous) as the factors, including the order covariate. In contrast to Peters, we did not find any significant main effects or an interaction between Frame and

Numeracy. Running the same model without order effect as a covariate also yielded no significant main effect or interaction (Table 6.6.2.1).

**Table 6.6.2.1**

Task 4, Numeracy x Frame ANCOVA

**Tests of Between-Subjects Effects**

Dependent Variable: PetersPatientA

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 8.94[a] | 4 | 2.23 | 1.30 | .274 |
| Intercept | 570.81 | 1 | 570.81 | 331.66 | .000 |
| OrderEffects | 1.78 | 1 | 1.78 | 1.04 | .311 |
| PetersPatientFrame | 2.85 | 1 | 2.85 | 1.66 | .200 |
| ANSDichotomous | 2.89 | 1 | 2.89 | 1.68 | .197 |
| PetersPatientFrame * ANSDichotomous | .46 | 1 | .46 | .27 | .607 |
| Error | 215.13 | 125 | 1.72 | | |
| Total | 1461.00 | 130 | | | |
| Corrected Total | 224.07 | 129 | | | |

a. R Squared = .040 (Adjusted R Squared = .009)

As depicted on Figure 6.6.2.2 (Table 6.6.2.2 for means), the high and low numerate follow the same pattern, but it is visually salient that the difference of ratings between high and low numerates in the different frames are not as high and those found by Peters et al. (2006) in their original study.

**Table 6.6.2.2**

Patient task, table of means from current study (Frame x Numeracy)

| ANSDichotomous | PetersPatientFrame | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| Low Numeracy | Frequencies | 3,19 | ,22 | 2,76 | 3,63 |
| | Percentages | 2,76 | ,20 | 2,36 | 3,16 |
| High Numeracy | Frequencies | 3,37 | ,25 | 2,87 | 3,87 |
| | Percentages | 3,16 | ,26 | 2,64 | 3,68 |

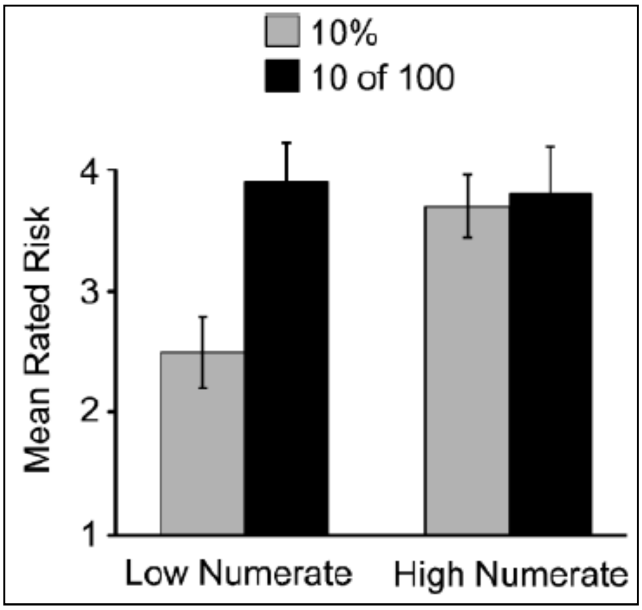



***Figure 6.6.2.1*** Evaluation of a patient's risk by numeracy level and frame (percentage vs. frequency) from Peters et al. (2006).

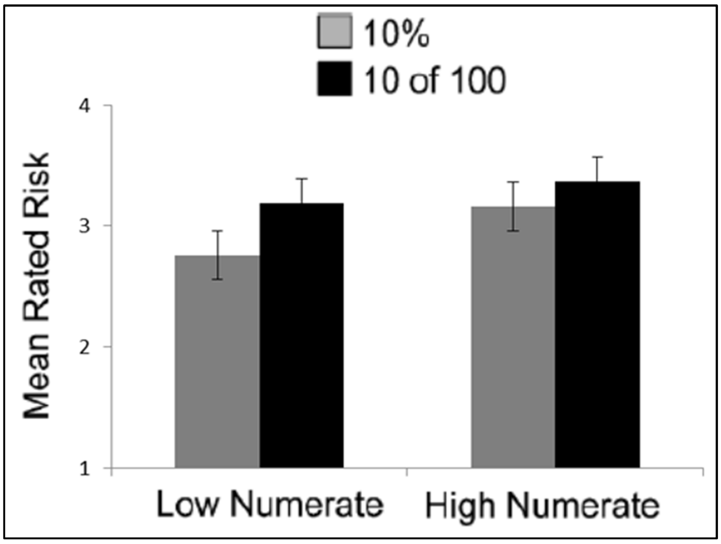



***Figure 6.6.2.2*** Evaluation of a patient's risk by high and low numerates depending on the framing of information (percentage vs. frequency) results from current study. Means on Table 6.6.2.1.

To check whether a dichotomous scale might cause a loss of variance and therefore make it more difficult to find statistically significant effects, we ran the same model as above using numeracy as a continuous variable in a regression model. The model included Frame, Numeracy (ANS), and the interaction Frame by Numeracy as predictors. However, this still did not yield any significant main effect or interactions in the model.

We then checked whether visualization has an effect on ratings of risk. To this end, we built a regression model which checks for order effects, Spatial visualization, Object visualization, Frame, and the interactions of Visualization and Frame. The model proved marginally statistically significant, F[6,129]=2.15, p=.053, revealing that higher spatial visualization predicts increased risk ratings (p=.027) as shown in Table 6.6.2.2.

**Table 6.6.2.2**

Task 4, Visualization x Frame regression

**Coefficients**[a]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 1.13 | 1.43 | | .79 | .431 |
| | PetersPatientFrame | .79 | 1.90 | .30 | .41 | .679 |
| | ObjectScore | .07 | .28 | .029 | .24 | .812 |
| | SpatialScore | .66 | .29 | .28 | 2.24 | .027 |
| | ObjectbyFrameInteraction | -.28 | .43 | -.36 | -.65 | .517 |
| | SpatialbyFrameInteraction | -.07 | .42 | -.08 | -.18 | .862 |
| | Order Effects | .17 | .23 | .07 | .74 | .464 |

| R | R Square | Adjusted R Square | Std. Error of Estimate |
|---|---|---|---|
| ,31 | ,10 | ,05 | 1,28 |

a. Dependent Variable: PetersPatientA

In summary, unlike Peters et al. (2006), we did not find that numeracy caused different risk ratings depending on the whether the results are presented in a probabilistic or in a frequentistic frame. Interestingly, however, we did find that higher levels of spatial visualization were seemingly associated with higher risk scores, irrespective of the frame. There is no clear hint in the literature suggesting a theoretical explanation for why higher spatial visualization ratings predict higher risk ratings.

## *6.7 Discussion*

In the first task (Student Framing), we failed to find a replication of Peters et al. (2006) and Weller et al. (2012) findings that numeracy was associated with less affect from attribute framing. Similarly, visualization (both object and spatial visualization) were not related to attribute framing. Peters et al. (2006) argued that high numerates might be able to see through the frame manipulation and compare the alternative frame, so this attenuated their differences between the two different frames. Our results do not warrant this explanation although in principle it could be hypothesized that spatial visualization, as it is related to higher numeracy, could predict lower levels of framing effect. The contrary would hold true for object visualization, which would indicate higher levels of framing effect in this particular task. Instead, we found that neither Numeracy nor object or spatial visualization predicted framing effect in this first task.

The second task used Denes-Raj & Epstein’s (1994) paradigm, by which Peters et al. (2006) and Weller et al. (2012) found that high numeracy was associated with a higher likelihood of people choosing the bowl with the objectively better probabilities of drawing a colored jelly bean. We could not replicate this finding for numeracy. Interestingly, we found that spatial visualization could predict better choices in this task. The finding that numeracy was not associated with a higher likelihood of choosing from the objectively better bowl goes against what Peters et al. (2006) and Weller et al.

(2012) found in their studies. These authors found the high numerates to be more likely than the low numerates to choose from the objectively better bowl, and argued that this happened because although at first sight the larger bowl would seem more attractive, the high numerates would experience more affect towards the smaller bowl than the low numerates because high numerates are more likely to calculate and compare probabilities, therefore allowing for a more positive view, and arguably increased affect towards the smaller bowl after the cognitive process of calculating which bowl was objectively better. This comparison of probabilities, which high numerates can perform in an easier manner, and seems to drive the choice of the best option, also occurs in individuals whose level of Spatial visualization is higher. In contrast, object visualization does not have any statistically significant effect (though higher object visualization predicts worse choices). This experiment shows how spatial visualization is a better predictor than numeracy of individuals making normatively better choices. An alternative possibility would be that the relationship between visualization and numeracy might be different in this sample. However, this was not the case, as preliminary checks on these aspects confirmed the pattern of higher spatial visualization predicting higher numeracy and higher object visualization predicting lower numeracy.

Denes-Raj & Epstein (1994) had originally argued that people in general tend to choose from the larger bowl rather than the smaller bowl because seeing the larger number of colored jelly beans in the larger bowl seems more attractive than the lone colored bean in the smaller bowl. Peters et al. (2006) demonstrated that the numerical calculation could also be a source of affect guiding preferences. In this manner, the generally higher appeal of the larger bowl with more colored beans would be counteracted by the affect derived from recognizing higher probabilities in the smaller bowl. This numerical advantage would be more easily recognized by the higher numerates, therefore giving the results Peters et al. (2006) reported - that higher numeracy was associated with choosing from the objectively better bowl. Having shown that Spatial visualization predicts objectively better choices in this task, we extend the finding that numeracy can be a source of affect in numerical calculations, and our findings open up the possibility that the same process of an affective hit from calculations could also apply to those individuals with higher spatial visualization. As we have seen, spatial visualization was a predictor of better choices in this particular task even when numeracy was not. Therefore, it would be reasonable to argue that spatial visualization may offer the possibility of detecting better choices in a situation when numeracy cannot.

The third task was primarily focused on whether an objectively worse bet would receive higher ratings of attractiveness than a better one, as reported by Peters et al. (2006). This task failed to replicate Peters et al (2006) and found instead that high and low numerates do not rate bets differently. The results of this task demonstrated that neither numeracy nor object or spatial visualization could predict different ratings of attractiveness of the bet. Instead, we found that numeracy and spatial visualization predicted overall higher evaluations of attractiveness of the bet (regardless of the loss condition). This finding is consistent with what Weller et al. (2012) found, that high numerates evaluated the bets higher than low numerates. Although we failed to see a replication of the original findings in which high numerates (and we could therefore expect, the high Spatial visualizers too) rated the worse bet as more attractive, we did find that numeracy and spatial visualization predicted results in the same way, pointing to the fact that that spatial visualization does mimic numeracy predictions in most instances.

Finally, we investigated whether individuals attribute a higher level of risk to information about potential hazards when the information is presented in a probabilistic or a frequentistic format. Peters found that when two high numeracy groups were given information about recidivism of a patient, the format of information did not affect risk perception for the high numerates, whereas the low numerates in the group with frequentistic information gave higher risk ratings than the group with the probabilistic information. The results of this task failed to replicate Peters et al. (2006) original findings that the frequentistic format elicited higher risk ratings than the probabilistic format only for low numerates (with no effect for the high numerates). Our replication did not find any main effect of numeracy or interaction between numeracy and frame. In addition, we did not find the interaction between frame and object or spatial visualization.

The fact that Peters et al.'s (2006) studies were not replicated could be explained by the use of a different numeracy measure. However, Weller et al. (2012) used the same numeracy measure employed in this thesis (ANS) and did replicate the results of Peters et al. (2006). The lack of replication for the numeracy results compared with Weller et al. (2012) could hardly be attributed to different numeracy levels, as both this sample and that of Weller et al were virtually the same (M=4.07, SD=1.83 from Weller, vs. M=4.30, SD=1.50 current sample). One potential explanation about the lack of replication is the fact that three of the studies (those where evaluations, instead of calculations, are elicited), have a between-subjects design. Between-subjects designs are in many occasions difficult to replicate due to the fact that each between-subjects condition lacks the reference that the alternative condition would offer and participants would therefore focus more on external contextual cues (the wording of the problem, participants' own experiences, etc.) rather than on the comparison between conditions which the experiment contrasts (Lambdin & Shaffer, 2008; Zhang et al. 2005). The fact that there were framing effects on the tasks shows that the frame manipulation did indeed work. However, as we explained, it remains unclear why the expected replication did not occur.

Regardless of the myriad of potential explanations, the results did indicate that in the tasks where only evaluations are elicited, visualization does not predict the responses of individuals. However, in tasks where there is a component of calculation and reporting an objectively correct answer, spatial visualization acts in a similar manner as numeracy, and predicts more normatively correct answers. In fact, we have shown that spatial visualization even produces this effect more than numeracy in the Jelly Beans task.

# Chapter 7

# Visualization Style and Information Format

The prior research questions investigated the relationship between object and spatial visualization, and the relationship of these constructs with numeracy (Research Question1). Research Question 2 went on to investigate whether presenting information in the form of tables or bar graphs altered judgments of how good a financial scenario was. Furthermore, Research Question 2 investigated whether visualization style affected judgments of the positivity of a financial scenario represented with graphs whose slope was manipulated by truncating the Y-axis. Finally, Research Question 2 investigated whether visualization style affected the ability to predict the continuation of a given set of data. Research Question 3 investigated the influence of visualization style on a series of decision-making scenarios in which past studies showed numeracy to have an effect. These questions formed a body of research that established the relationship between numeracy and visualization. Having found that object and spatial visualization predict, respectively, worse and better performance in numeracy, it was reasonable to assume that tasks in which numeracy proved to have an effect would be similarly affected by visualization. This was investigated in further research questions as detailed above, and it was found that numeracy and spatial visualization were both similar predictors of results in decision-making and numerical tasks. Having established such a relationship, the next natural step is to starting unveiling the reasons why different visualization styles interpret numerical information differently. Admittedly, discovering all possible mechanisms is well beyond the scope of a single thesis.

In this Chapter will build on and replicate Research Question 1 with this sample and such replication will also be extended to Research Question 2, which tests the relationship between Object, Spatial visualization, and Numeracy.

The core of the current Chapter will be devoted to investigate whether different visualization styles weigh numerical, object, and spatial information differently in financial scenarios. Specifically, this research question will investigate whether visualization style affects judgments and decisions in a financial scenario when this information is presented alone or in conjunction with a picture of a person whose facial (positive/negative look) and postural (thumbs up/down) demeanor will be either congruent with the financial information (both graph and picture are either positive, or both negative), or incongruent (positive data trend and negative face, or vice versa). The numerical information to be presented will be in the form of a bar graph or a table.

As proposed in Chapter 2.1, the matching of information with the cognitive style of individuals has important implications in decision-making. Specifically, according to the cognitive styles previously reviewed in the literature, information that fits the cognitive style of an individual is given more weight in the decision-making process. This argument leads to the hypothesis that the newly developed cognitive style of visualization preference might also determine the type of stimuli which receive more weight when processing information and therefore have more effect on the decisions made by individuals. This is precisely what the following hypotheses will investigate.

As hypothesized from extant literature, the image of a person could constitute an object visualization stimulus, whereas a graph could be a spatial one. A human figure conveys the elements inherent to an object stimulus, as understood by Blazhenkova & Kozhevnikov (2009) when they created the OSIVQ. A human figure is rich in details and, as laid out in the literature review part of this thesis, this type of stimuli is processed in the temporal cortex, which is the brain area in charge of processing information pertaining to object stimuli (such as colors and pictures). Concurrently, the processing of faces also takes place in the temporal cortex, specifically in the FFA (Kanwisher & Yovel, 2006). In contrast, Spatial and numerical information is processed in common areas of the parietal region.

Although literature has not previously defined what an “object” or a “spatial” visual stimulus is, from the evidence reviewed above we can argue that a graph constitutes a spatial stimulus whereas a human figure constitutes an object stimulus. In spite of this argument, to our knowledge no study has until now defined what an object or spatial stimulus is as understood by the OSIVQ. This constitutes both a problem and an opportunity. The absence of a prior definition of object and spatial visual images makes the task of experimental design more challenging in finding the appropriate stimuli to use. However, this also constitutes an opportunity: by proposing object or spatial stimuli, we can contribute to the solution of the question of what constitutes an object or a spatial visual stimulus.

## *7.1 Replication of Object-Spatial Relationship*

Similar to the analyses carried out in all preceding chapters to further validate the observed relationship between Object and Spatial Visualization and their relationship with Numeracy, in the current section we will perform a correlation analysis between the OSIVQ components and Numeracy (ANS) as well as a regression model to predict numeracy from the different components of visualization.

### 7.1.1 Correlation Analysis

Similar to the prior chapters, a correlation analysis including the OSIVQ components and Numeracy (ANS) scores was run to verify the solidity of the reported findings of visualization being negatively correlated with numeracy and spatial visualization following the opposite pattern, with a positive correlation to numeracy.

As shown in Table 7.1.1.1, the correlational analysis confirms all the previous findings regarding the correlations between Numeracy and Object and Spatial visualization. Specifically, object visualization is significantly negatively correlated with Numeracy, $r(865)= -.08$, $p= .02$.

Confirming all previous results, spatial visualization follows the opposite pattern of object visualization in its relationship with numeracy and we find a significantly positive correlation between numeracy and spatial visualization, $r(865)= .30$, $p< .001$. We see that, contrary to all previous findings, the correlation between Spatial and Object visualization is in this case statistically significant, though the level of correlation is very small, $r(865)= ,12$, $p<,001$.

**Table 7.1.1.1**

*Correlation Analysis Between Numeracy and Visualization*

| | | Object Score | Spatial Score |
|---|---|---|---|
| Numeracy (ANS) | Pearson Correlation | -,08* | ,30** |
| | Sig. (2-tailed) | ,021 | ,000 |
| | N | 865 | 865 |
| SpatialScore | Pearson Correlation | ,12 | |
| | Sig. (2-tailed) | ,000 | |
| | N | 865 | |

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

### 7.1.2 Predictive Value of Visualization on Numeracy

The same regression model run in previous chapters, predicting Numeracy from Object and Spatial visualization, while controlling for Gender, was conducted to verify the solidity of the predicted relationships between these variables. Again, Major was not necessary to be included in this recession, as students all belonged to the Business Administration department, and no engineers or history majors were present in the survey.

The aforementioned regression model predicting numeracy scores from object and spatial visualization while controlling for gender was statistically significant, $F(3,861)= 43{,}87$, $p<.001$ (Table 7.1.2.1).

**Table 7.1.2.1**

*Regression Model Predicting Numeracy from Object and Spatial Visualization*

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 350,85 | 3 | 116,95 | 43,87 | ,000[b] |
| | Residual | 2295,26 | 861 | 2,67 | | |
| | Total | 2646,12 | 864 | | | |

| R | R Square | Adjusted R Square | Std. Error of Estimate |
|---|---|---|---|
| ,36 | ,13 | ,13 | 1,63 |

a. Dependent Variable: ANS b. Predictors: (Constant), SpatialScore, ObjectScore, Gender

As shown on Table 7.1.2.2, higher spatial visualization predicts higher numeracy scores (p<.001), while higher object visualization predicts lower numeracy scores (p=.017). Similar to the prior sections checking for replication of the current results, the tests showed no grounds for concern regarding collinearity problems.

**Table 7.1.2.2**
*Regression Coefficients and Collinearity Results for Regression Predicting Numeracy from Object and Spatial Visualization*

| Model | | Unstandardized Coefficients | | Standardized Coefficients | | | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | t | Sig. | Tolerance | VIF |
| 1 | (Constant) | 2,47 | ,42 | | 5,90 | ,000 | | |
| | Gender | ,67 | ,12 | ,19 | 5,59 | ,000 | ,87 | 1,15 |
| | ObjectScore | -,25 | ,11 | -,08 | -2,39 | ,017 | ,94 | 1,06 |
| | SpatialScore | ,72 | ,10 | ,25 | 7,37 | ,000 | ,88 | 1,14 |

a. Dependent Variable: ANS

## *7.2 Design*

### 7.2.1 Stimuli

The study will use bar graphs and tables to convey numerical information. In the case of bar graphs as stimuli, it is fairly accepted in the literature that a bar graph is a spatial representation of magnitudes (Vessey, 1991) and the understanding of graphs uses spatial cognition (Tricket & Trafton, 2006). Thus, bar graphs will be used as spatial stimuli, and this will result in testable hypotheses about the influence of spatial information for different types of visualizers.

In a different set of conditions, tables will be used to convey numerical information. This will ascertain whether tables affect different types of visualizers' judgments in the same manner as graphs.

In addition, this information will be, in some conditions, accompanied by the picture of a professional-looking woman from the waist up, showing a positive or negative demeanour by depicting a smiling face and thumbs up or a frowning face with and thumbs down. A pre-test to check whether the positive- and negative-looking images affected individuals' impressions of the performance of a company was carried out and showed the expected results. A group of 50 individuals randomly approached at a major business school in the UK were given the following information:

"*The picture of the person below is being used to represent the performance of a company in an annual report. We would like to know your opinion of the impression the picture gives of how the company is doing. Please look at the picture and tell us the impression it gives you.*

*The picture suggests that the company is doing:* ".

Participants were given a likert scale from 0 (very badly) to 10 (very well) to show their impression. The positive-looking image elicited significantly higher ratings ($M=7.08$, $SE=.34$) than the negative-looking image ($M=2.18$, $SE=.44$), $t(48)=-9.23$, $p<.001$.

### 7.2.2 Bar Graphs Conditions

Participants see a bar graph displaying the yearly net profits of a company from 2004 to 2011. As shown in Figure 7.2.2.1, the profits either increase or decrease year after year, displaying, respectively, either a graph bar showing a steady linear increase (positive condition) or a steady linear decay (negative condition).

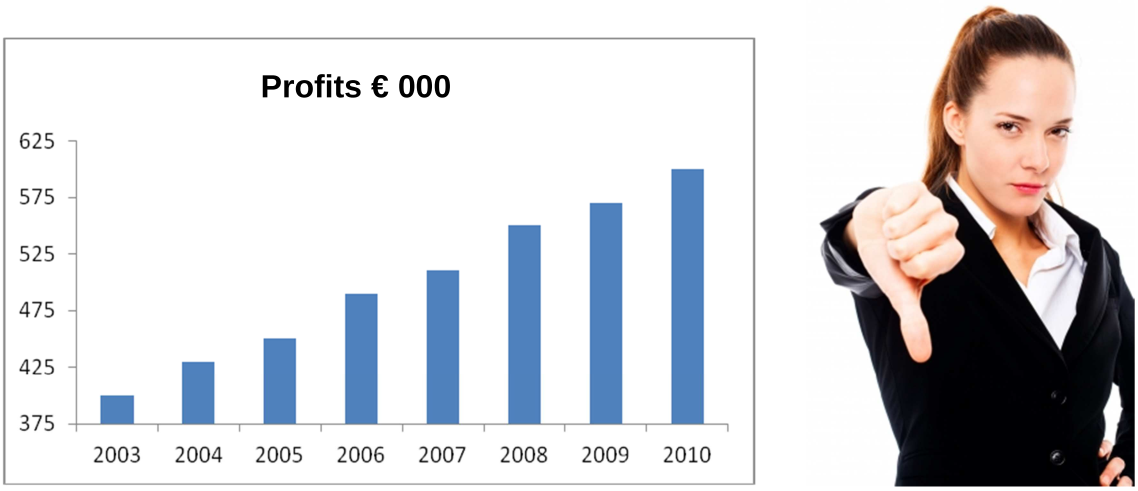



***Figure 7.2.2.1*** Example of the “Positive Trend, Incongruent” condition.

The graph was presented either alone (“No Picture” condition), or with a picture of a businesswoman smiling and making a thumbs up gesture, or with a frowning expression and a thumbs down gesture. The match between the graph trend and affect displayed by the face and thumb generates a congruent (trend and picture both positive, or both negative), or an incongruent condition (trend positive and picture negative, or vice versa).

The profits displayed a steady linear growth (positive condition), or a steady linear decay (negative condition), in all cases ranging from 400.000 to 600.000 (order reversed in the negative trend), and each year showing a difference from the previous year from (20.000 to 40.000) to show a steady increase/decrease; “Trend” (positive/negative) is a between-subjects condition.

As shown in Figure 7.2.2.2, the task consists of a factorial 2x3 design where the factors are trend (positive/negative) and congruency (No Picture/Congruent/Incongruent).

| | | Congruence | | |
|---|---|---|---|---|
| | | No Picture | Congruent | Incongruent |
| Trend | Positive | | | |
| | Negative | | | |

***Figure 7.2.2.2*** Display of the experimental design

Immediately after seeing the stimuli, participants responded to the question: “Based on the information given, how do you evaluate the results of this company?” (0 Very Bad, to 10 Very Good). Later in the experimental package participants completed the Numeracy and OSIVQ tests.

### 7.2.3 Table Condition

In a second condition, a different set of participants saw a table displaying the same information as that of Figure 7.2.2.1 before, but in a tabular format (Figure 7.2.3.1).

| **Year** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
|---|---|---|---|---|---|---|---|---|
| **Profits (€ 000)** | *400* | *430* | *450* | *490* | *510* | *550* | *570* | *600* |

***Figure 7.2.3.1*** Example of the “Positive Trend, Congruent” condition.

As shown in Figure 7.2.3.1, participants saw the yearly net profits of a company from 2004 to 2011, but in this task the information was in the form of a table, which was presented either alone, or with a human figure which is either congruent (positive/negative) or incongruent with the trend.

The table was presented either alone ("No Picture" condition), or with a picture of either a businesswoman smiling and making a thumbs up gesture, or with a thumbs down gesture and a frowning face. The match between the table trend and affect displayed by the face generates a congruent (trend and face both positive, or both negative), or an incongruent condition (trend positive and face negative, or vice versa).

In summary, the task consists of a factorial 2x3 design where the factors are trend (positive/negative) and congruency (No Picture/Congruent/Incongruent) as shown previously in Figure 7.2.2.2.

Following the experimental stimuli, participants were asked "Based on the information given, how do you evaluate the results of this company?" (0 Very Bad, to 10 Very Good). Later in the experimental package participants completed the Numeracy and OSIVQ tests.

### 7.2.4 Overall design

As previously explained, the design intends to test whether consistency of information and cognitive style result in heavier weighing of information. To this end, a series of spatial (bar graphs) and object (human figure) stimuli were combined in a design to check the specific hypotheses explained in the next points. In addition to bar graphs and human pictures, tables are also used in the current design, as they are ubiquitous in the presentation of information in publications of all sorts and the understanding of this stimulus is also important in the context of current research.

The stimuli explained above will also be presented in the form of numerical information in a table or graph displaying a positive or negative trend. This manipulation is necessary to create a set of experimental conditions where the numerical information is congruent (trend and figure both positive, or both negative) or incongruent. This manipulation will be useful in detecting which element of the information display is given more weight when making the judgments and decisions.

In sum, the experiment has a fully factorial, between-subjects design as shown on Figure 7.2.4.1, with the following conditions:

Format: Graph or Table

Trend: Positive or Negative

Congruence: Congruent, No Picture, or Incongruent.

<table>
<tr><td></td><td></td><td colspan="3">Congruence</td></tr>
<tr><td rowspan="2">Graph</td><td>Positive Trend</td><td rowspan="4">Congruent</td><td rowspan="4">No Picture</td><td rowspan="4">Incongruent</td></tr>
<tr><td>Negative Trend</td></tr>
<tr><td rowspan="2">Table</td><td>Positive Trend</td></tr>
<tr><td>Negative Trend</td></tr>
</table>

***Figure 7.2.4.1*** Experimental design, Chapter 7

Participants received a package with the experimental tasks and were informed that the information showed the performance of a company based on the net yearly profits, and that this was the only information on the company available to them.

Following this statement, they saw the Table or Graph in one of the conditions explained above and were asked to answer the question: “Based on the information given, how do you evaluate the results of this company?” This question was intended to determine whether the matching of information and cognitive style resulted in the matched information being given a heavier weight in the judgment or decision.

## *7.3 Visualizer Types*

The predictions that follow will test whether different types of visualizers make judgments depending on whether the information seen is consistent with their cognitive style and therefore whether the consistency of this information results in the information having heavier weight in the final judgment or decision.

As previously reported, an individual’s visualization style has two components: object and spatial. These two components, we have previously demonstrated, are independent of each other and an individual can be higher or lower in either dimension independently. By performing a median-split on the object and spatial visualization scores, a 2 x 2 matrix can classify individuals according to their status in each of the visualization dimensions. Creating such a matrix depending on an individual’s cognitive style for the purposes of research and predictions about their decision-making is customary in the literature. Examples mentioned in the early literature review include, Ruiz & Sicilia (2004) or Soijka & Giese (1997; 2006), who have demonstrated how classification of individuals according to their status in two independent dimensions of their cognitive style yielded predictions of their judgments, which they later investigated.

In this case, the classification of individuals according to such a 2 x 2 matrix depending on their visualization style is important, as this research question hypothesizes that the visualization cognitive style of an individual influences the information which receives heavier weighting when making a decision or judgment.

Therefore, for the analyses and hypotheses below, individuals were split into four different groups according to their visualization style. In each of the analyses, the continuous variables of object and spatial visualization were median-split, giving a four-category classification of the participants depending on whether they were high or low in each of the dimensions, yielding the matrix shown in Figure 7.3.1.

| | | **Object** | |
|---|---|---|---|
| | | **High** | **Low** |
| **Spatial** | **High** | ObjectSpatial | Spatial |
| | **Low** | Object | Undefined |

***Figure 7.3.1*** Classification of individuals according to visualization style

In the argumentation that follows we will make specific predictions about two of the four groups of visualizers defined in Figure 7.3.1: spatial and object visualizers. The focus will be on these groups, as they are the two groups from which testable predictions can be made.

The hypotheses to be tested start from the assumption that individuals will pay attention to a specific type of information depending on their cognitive style, not showing a clear preference for any one type of visualization. Therefore, the Undefined group might pay poor attention to object and spatial information, while spatial individuals might pay great attention to both elements. Due to this, it is difficult to discern which type of information is weighed more heavily, and predicting results from the assumption of which information will be taken into account by these individuals is a guesswork exercise.

In contrast to the Undefined and ObjectSpatial individuals, it could be inferred that spatial individuals will weigh spatial information more heavily, and object visualizers will weigh object information more heavily. Therefore it should be expected that the evaluations given by object visualizers will focus on the human figure, whereas spatial visualizers' evaluations will be more affected by the graph.

By using an experimental design in which the numerical information, represented in a tabular form or a bar graph display, is congruent or incongruent with the human figure, the evaluations of the different visualizers should reflect which elements receive heavier weight when making the judgment. It is reasonable to assume that the addition of the human figure and its congruence or incongruence with the trend will not affect the ratings of spatial visualizers as much as those of object visualizers. Spatial visualizers also have low levels of object visualization, therefore the weight of the picture will be less than that of the graph.

In contrast, object visualizers might weigh the picture more heavily, and therefore the evaluations will be affected by the value of the human figure, which will be manifested in higher ratings of a positive figure and lower ratings of a negative figure.

When the numerical information is presented in a tabular format, the influence of the human figure on the object and spatial visualizers should be apparent, since a table does not constitute an object or a spatial stimulus. Thus, the value of the human figure should determine the ratings object visualizers give to the performance of the company, while for spatial visualizers, seeing a positive or negative human figure should not make a difference.

## *7.4 Manipulation Check & Hypotheses*

### 7.4.1 Manipulation Check

Before the analyses of the hypotheses, a basic manipulation will verify whether the positive and negative trends elicit, as expected, higher and lower ratings respectively. This effect of higher ratings in the positive trend and lower in the negative trend will occur across both visualizer types due to the fact that regardless of format or visualizer type, the direction of the trend should be obvious. Therefore we should expect all visualizer types to show this effect, and we should also see this effect both in the graph as well as in the table condition.

### 7.4.2 Hypotheses

As we have argued in the literature reviewed and later proposed at the beginning of the current chapter, information which is consistent with a person's cognitive style receives heavier weight when making decisions and judgments. In addition, the experimental design we proposed offers the possibility of checking how judgments and decisions based on data from a table, which in principle does not constitute a clear spatial or object stimulus, compare to judgments from a graph, which is a spatial stimulus.

From the premise that consistency of information and cognitive style will result in heavier weighing of information, we could make a series of hypotheses with regard to how participants in the current experimental scenario will evaluate the results of a company. In particular, we formulate the following hypotheses:

#### 7.4.2.1 Format

We will firstly investigate whether the format of information presentation, tables or graphs, influences the judgments of individuals depending on their visualization style. In particular, we will assess whether individuals with different visualization styles are affected differently by tables and graphs in their judgments about the performance of a company when the information on this performance is presented to them in the form of a table or a graph.

The following hypotheses will be investigated:

H1: Overall, the graph format will generate less stable ratings (more variance) than the table format.

H2a: When evaluating the results of the company from a table, spatial visualizers will give less stable ratings (more variance) than object visualizers.

H2b: In the graph condition there will be no significant differences in variance between spatial and object visualizers.

As we have seen in Chapter 6, Task 4, when observing data from a table and matching this information with a corresponding graph, high spatial visualization predicts the correct identification of the shape of the graph described in the table. This could indicate that high spatial visualization results in a greater ability to translate the symbolic information (numbers) into a specific shape. Object visualization was not, however, a predictor of the correct or incorrect identification of the graph depicted by the data given on the table.

The previous pattern of results might indicate that when judging the performance of a company (and the willingness to invest in such a company) shown in the form of a Table, high spatial visualization could result in a clearer identification of the trend depicted by the data. This clearer identification may result in higher spatial visualization individuals giving higher ratings in the positive trend and lower ratings in the negative trend than lower spatial visualization individuals.

In the current setting, graphs offer an easier evaluability and therefore better affective mapping, with easier mapping of judgments of positivity or negativity, due to the fact that the slope is clearly defined. As opposed to graphs, in which the point at which the abscissa crosses the Y-axis gives a sense of the slope determined by the trend of bar graphs, tables do not have such a visual guidance or reference point from which to picture a slope. This lack of reference in the table causes the numerical information to be vaguer in terms of its context and although a positive or negative trend can clearly be seen, the slope cannot be mapped, and therefore the affective precision of the judgments is not as strong as that of graphs. The lack of precise affective mapping would lead participants to be more cautious in their evaluations of the table, whereas in the evaluation of the graph they would be able to map the positivity or negativity of the information much more clearly, therefore giving clear high ratings in the positive trend and low ratings in the negative trend. In other words, the graphs would present a clearer scenario to evaluate, and as a result they would reflect participants' judgments of the situation more faithfully. The more the slope is inclined, the more this should be the case.

In contrast to tables, graphs depict a clearly visible trend, without the need to translate from a symbolic format (numbers) into a specific shape. Therefore, it could be concluded that when the information is presented in the form of bar graphs, visualization preference would not have an impact on the judgments of performance of a company, as the trend depicted by the information is obvious to the reader regardless of visualization style.

The effect will occur because the trend in the graph will be immediately obvious, whereas in the table the slope will be less clear. The better clarity of the slope in the graph condition would lead participants to give a rating that clearly reflects a truer opinion or evaluation. This would result in a higher variance of scores, as the scores would reflect participants' evaluations more faithfully. In contrast, although in the table condition the trend should be distinguishable, the slope is not as clear just by looking at the values. This would cause the ratings given in the table condition to be less precise (more variance between individuals) than those given in the graph condition. Participants would give a score which might be more conservative, but also less precise with regard to their real evaluation. The effect of more variance in ratings for the graph than in the table condition will be stronger for the spatial than for the object visualizers, since spatial visualizers have a higher ability to translate from the symbolic information conveyed by the table into a specific shape, and because they also weigh the graphical information of graphs more heavily than the object visualizers.

Both in the case of graphs and in the case of tables the affective mapping (the clear judgment of goodness or badness) would be much clearer for the spatial visualizers, as they can better see a more clearly defined slope. In contrast, object visualizers would not evaluate the trend slope as clearly as spatial visualizers, particularly when evaluating tables.

This effect will occur because spatial visualizers have a high level of spatial cognition and they will be able to perform a transformation from the simple data into a slope, whereas the object visualizers, having a lower level of spatial cognition, would therefore be less able to perform such a transformation. As Trafton & Trickett (2001) argue citing Bertin (1983), there are three levels of spatial cognition when dealing with graphs. The first one is the visual encoding of the elements of the display, the second is the translation of these elements into patterns, and finally the highest level of spatial cognition would be the mapping of these patterns to transform it into values. Trafton & Trickett (2001) argue that this process happens when visualizing graphs. Although Trafton & Trickett (2001) do not specifically study the use and interpretation of tables, they argue that spatial transformations are cognitive operations performed on a visualization to aid understanding. Because these activities use spatial cognition, they would be more easily achieved by spatial rather than object visualizers. Therefore, the judgments of spatial visualizers should be more stable than those of object visualizers

In the graph condition this process would not occur, as the interpretation of a graph is easily achieved, and the higher level of spatial cognition of spatial visualizers would not represent an advantage due to the interpretation of the slope being much easier. To check whether the different visualization styles make a different appraisal of how good a given numerical amount is (e.g. How good is €500?), we will investigate if different visualization types give the Table-No Picture condition different ratings. Evidence collected from Task 1 in Chapter 6 does not point to a difference between groups. In this Task, where participants had to evaluate the performance of a company using a single table of profits, it was shown that different visualizers did not make different appraisals of the company. However, we will further verify this by contrasting the ratings given to Table/Graph by the different visualizer types in this particular task.

#### 7.4.2.2 Congruence

Hypothesis 3 (H3): Regarding the No Picture condition, there will be a general effect of congruent pictures magnifying the effect of trend (more positive ratings in the positive trend and more negative in the negative trend), whereas incongruent pictures will attenuate the effect of trend. As detailed in H4 below, this will effect will be different for different visualization types.

This effect will occur because although the evaluation of the company would be primarily based on the information given by the graph or table, the human figure will also be a source of information. As we have demonstrated in the pre-test, a positive human figure elicited higher ratings of a company than a negative-looking figure. The human figure should thus enhance or attenuate the effect of the graph/table depending on whether this value is consistent or inconsistent with that displayed by the trend, and the strength of the positivity or negativity of the company based on its results will be enhanced by the value of the accompanying picture. Alternatively, we might see that this magnifying effect occurs only when the picture is consistent with the value of the graph/table. When the value (positive or negative) of the picture contradicts the table, individuals may see through the manipulation, discounting the value of the picture and correcting their ratings, thus eliminating the difference in ratings between the positive and negative trend, or even overcorrecting ratings in such a way that the negative trend would have higher ratings than the positive trend.

Hypothesis 4 (H4): The magnification/attenuation effect will be higher for object visualizers than for spatial visualizers.

This effect will occur because as the literature on cognitive styles supports, information that is consistent with a person’s cognitive style influences judgments of a situation. In this case, the human figure being an object stimulus, it should be seen that high object visualization leads individuals to consider the hedonic value of the figure more than low object visualization.

High or low spatial visualization, in contrast, will not modify the effect of the congruent or incongruent human figure, as spatial visualization will determine only whether the graphical/tabular information is understood and acted upon, whilst it is object visualization which dictates the effect of the congruent or incongruent human figure. Furthermore, high spatial visualization may result in a heavier reliance on the graph regardless of the congruence of the figure. For congruent figures, high spatial visualizers might focus on the graph alone, as the figure provides no extra information. For incongruent figures, a high spatial visualizer might focus even more in the graph, recognizing that the figure could be a distractor.

### 7.4.3 Summary of Hypotheses

From the arguments provided above, we generated a series of five hypotheses which will be tested in the remainder of the current Chapter. As stated, the hypotheses to investigate are the following:

H1: Overall, the graph format will generate less stable ratings (more variance) than the table format.

H2a: When evaluating the results of the company from a table, spatial visualizers will give less stable ratings (more variance) than object visualizers.

H2b: In the graph condition there will be no significant differences in variance between spatial and object visualizers.

H3: Regarding the No Picture condition, congruent pictures will magnify the effect of trend (more positive ratings in the positive trend and more negative in the negative trend), whereas Incongruent pictures will attenuate the effect of trend.

H4: The magnification/attenuation effect will be higher for object visualizers than for spatial visualizers.

## *7.5 Analyses*

### 7.5.1 Participants

Participants were recruited from the University of Granada, Faculty of Economics and Business Administration and voluntarily participated in the data collection during class time. A total of 934 participants took part in the experiment. Cases with missing data on any of the visualization or numeracy measures were eliminated. In addition, those cases where answers evidenced a lack of commitment to the experiment (e.g. consistently ticking the same column in the answers) or where the participant used external aid (i.e. calculator) were also deleted. The total of valid data collected gave 865 participants (396 males) with an average age of 19.29 (SD=2.62, Min= 17, Max=45). The materials were presented in the form of a paper-and-pencil questionnaire to groups of 40 to 70 students. To avoid contamination of answers, participants were distributed in the classroom in a manner that did not allow them to share their thoughts or answers. In addition, the experimenter remained in the classroom to monitor behavior, collect the materials and clarify questions should they arise.

### 7.5.2 Results

#### 7.5.2.1 Trend Manipulation Check

In this section we investigated whether trend manipulation had an effect, and the positive trend generated higher ratings than the negative trend.

This was investigated using the No Picture condition, to isolate the effect of trend and avoid any effect of the addition of a congruent or incongruent picture. A 2 x 2 ANOVA model with the factors Trend (0= Negative, 1= Positive) and Format (0= Table, 1= Graph) was run to check whether the expected effect of trend was present in both the table and the graph condition. The model showed the experimental manipulation to be successful. As shown on Table 7.5.2.1.1, the model demonstrated the main effect of Trend ($F[1,280]=256.85$, $p<.001$), and an interaction of Trend by Format ($F[1,280]=8.75$, $p=.003$).

Figure 7.5.2.1.1 shows how the expected higher ratings in the positive trend were found, and how they were qualified by the format in which the trend was presented, with the Graph condition generating higher ratings in the positive condition and lower ratings in the negative condition than the Table (for means see Table 7.5.2.1.2).

**Table 7.5.2.1.1**
*Trend Manipulation Check, ANOVA model*

**Tests of Between-Subjects Effects**

Dependent Variable: Task3.1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1058.37[a] | 3 | 352.79 | 89.60 | .000 |
| Intercept | 8456.79 | 1 | 8456.79 | 2147.74 | .000 |
| Task3Trend | 1011.37 | 1 | 1011.37 | 256.85 | .000 |
| Task3Format | 8.10 | 1 | 8.10 | 2.06 | .153 |
| Task3Trend * Task3Format | 34.43 | 1 | 34.43 | 8.75 | .003 |
| Error | 1102.51 | 280 | 3.94 | | |
| Total | 10686.00 | 284 | | | |
| Corrected Total | 2160.87 | 283 | | | |

a. R Squared = .490 (Adjusted R Squared = .484)

**Table 7.5.2.1.2**
*Means, Trend Manipulation Check*

**Descriptive Statistics**

Dependent Variable: Task3.1

| Trend | Format | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Negative | Table | 3.75 | 1.95 | 72 |
| | Graph | 3.39 | 2.45 | 69 |
| | Total | 3.57 | 2.21 | 141 |
| Positive | Table | 6.83 | 1.93 | 70 |
| | Graph | 7.86 | 1.52 | 73 |
| | Total | 7.36 | 1.81 | 143 |

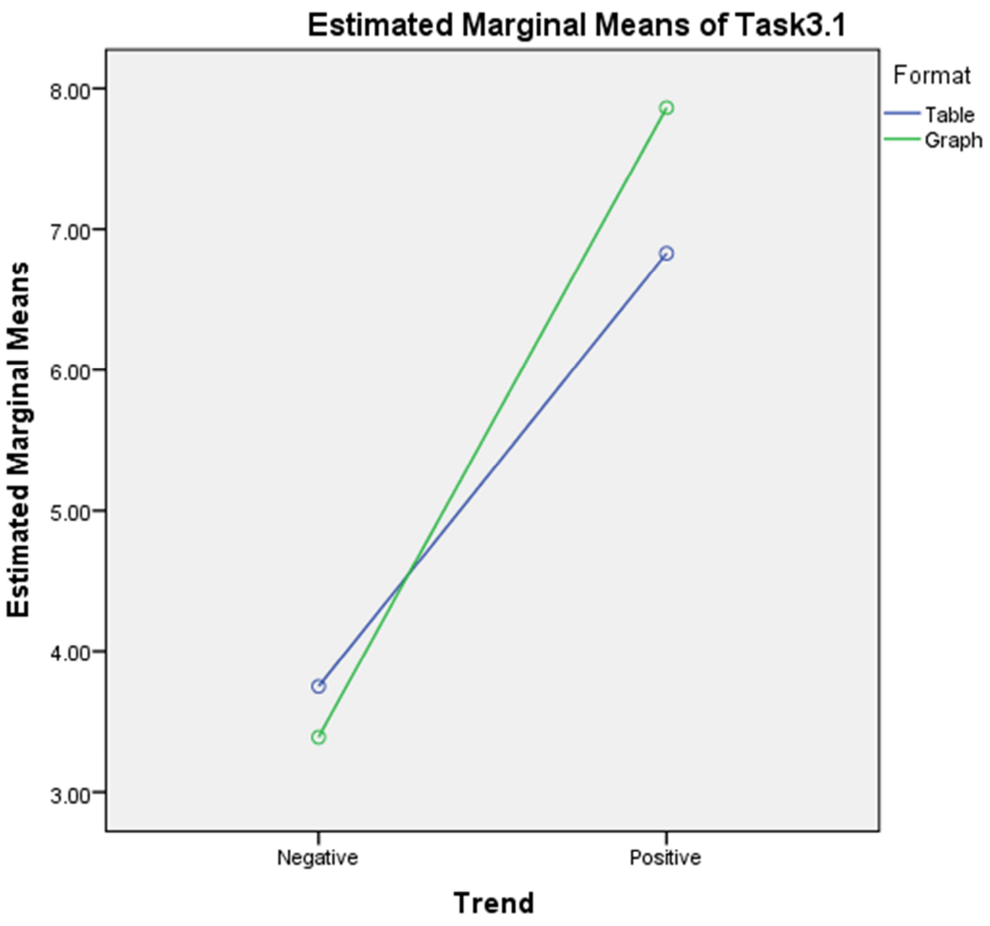



***Figure 7.5.2.1.1*** Interaction Trend by Format

The above results show how trend manipulation worked as intended, with the positive trend eliciting higher ratings than the negative trend. In addition, it was found that ratings in the graph condition were more extreme than in the table condition. The finding that a graph elicits higher ratings in the positive trend and lower ratings in the negative trend than a table could mean that individuals find the graph easier to interpret in general, as the tilt of the slope is evident in the graph condition, whereas in the table condition the tilt of the slope cannot be identified.

Trying to identify whether ease of understanding the information, informativeness, ambiguity, and attractiveness of the stimuli were different in the graph and table conditions, four different t-tests (one for each point: ease of understanding information, informativeness, ambiguity, and attractiveness) showed that only attractiveness was different between the table and graph conditions (Table 7.5.2.1.3). Specifically, the graph condition elicited statistically marginally significantly higher ratings ($M= 5.21$, $SD= 2.58$) than the table condition ($M=4.59$, $SD=2.86$), $t(282)= 1.89$, $p=.059$ (see Table 7.5.2.1.4 for means). Thus, it seems that even though more extreme ratings were given to the graph than to the table condition, participants do not find either format to be easier to interpret, more informative, or more ambiguous. Attractiveness, however, seems to differ statistically (though only marginally), and information presented as a graph is rated as more attractive than the same information in a table. It is not immediately obvious, however, how finding graphs more attractive than tables in displaying information could drive more extreme ratings for graphs than for tables. It might be, as we previously argued, that in this task graphs display the evaluations participants make of the data more faithfully.

**Table 7.5.2.1.3**
*T-tests Table vs. Graph*

| | t-test for Equality of Means | | | | |
|---|---|---|---|---|---|
| | t | df | Sig. (2-tailed) | 95% Confidence Interval of the Difference | |
| | | | | Lower | Upper |
| Ease | .75 | 281 | .457 | -.30 | .66 |
| Informativeness | -.49 | 281 | .625 | -.74 | .44 |
| Ambiguity | .07 | 279 | .947 | -.59 | .63 |
| Attractiveness | -1.89 | 282 | .059 | -1.25 | .02 |

**Table 7.5.2.1.4**
*T-tests Means, Table vs. Graph*

| Group Statistics | | | | | |
|---|---|---|---|---|---|
| | Format | N | Mean | Std. Deviation | Std. Error Mean |
| Ease | Table | 142 | 8.30 | 1.94 | .16 |
| | Graph | 141 | 8.11 | 2.17 | .18 |
| Informativeness | Table | 142 | 5.66 | 2.54 | .21 |
| | Graph | 141 | 5.81 | 2.50 | .21 |
| Ambiguity | Table | 140 | 5.91 | 2.60 | .22 |
| | Graph | 141 | 5.89 | 2.61 | .22 |
| Attractiveness | Table | 143 | 4.59 | 2.86 | .24 |
| | Graph | 141 | 5.21 | 2.58 | .22 |

### 7.5.2.2 Hypothesis 1

H1: The graph format will generate more stable ratings (less variance) than the table format. This effect will occur for all visualizer types.

An independent-samples t-test was run to compare the table and graph conditions. As shown in Table 7.5.2.2.1, Hypothesis 1 was supported, with significantly greater variance in the graph (SD=3.02) than in the table (SD=2.48) condition, as found in a Levene's test of equality of variances (F=11.27, p<.001).

As we argued in the development of H1, this finding supports the notion that individuals are more cautious when rating the table due to its more difficult interpretation. In contrast, graphs would elicit more extreme ratings because people might feel surer about their own interpretation of the positivity or negativity of the situation, as the graph would be easier to interpret. In this manner, a graph will elicit more extreme ratings as shown previously in Figure 7.5.2.1.1, and also greater variance reflecting an individual's true evaluation.

**Table 7.5.2.2.1**
*Hypothesis 2 Variance test*

| Group Statistics | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Format | N | Mean | Std. Deviation | Std. Error Mean | Levene's Test for Equality of Variance | |
| | | | | | | F | Sig. |
| Task3.1 | Table | 142 | 5.27 | 2.48 | .21 | 11.27 | .001 |
| | Graph | 142 | 5.69 | 3.02 | .25 | | |

We checked whether the information in the table and graph were different in terms of their ambiguity and also in how easy they were to understand, to see whether these could be two factors explaining why people give different ratings to tables and to graphs. To this end, we created two 2 x 2 x 4 factorial ANOVA models, with the factors of Trend (Positive/Negative), Format (Graph/Table) and Visualizer Type (Object/Spatial/ObjectSpatial/Undefined), and dependent variables of, respectively, ambiguity in understanding the information (0=Ambiguous, 10=Not Ambiguous), and difficulty of understanding the information (0=Very Difficult, 10=Very Easy).

The ANOVA model checking for differences in the level of ambiguity reported by different groups of visualizers did not reveal any effect of format or visualizer type. In contrast, as shown in Table 7.5.2.2.2, the ANOVA model analyzing the difficulty of understanding the information revealed only a main effect of visualizer type, $F(3,267)=7.6$, $p<.001$. Specifically, post-hoc analyses (Table 7.5.2.2.3) revealed that the groups with high spatial visualization (Spatial and ObjectSpatial) did not significantly differ among themselves in the degree to which they found the information easy to understand, but they did find the information significantly easier to understand than any of the groups with low spatial visualization (Figure 7.5.2.2.1). There were no significant differences in the difficulty of understanding the information among the low spatial visualizer groups (Undefined and Object).

It seems then, that individuals with high spatial visualization find numerical information, whether in the form of tables or graphs, easier to understand than individuals with high object visualization.

**Table 7.5.2.2.2**

*ANOVA, difficulty of understanding information from Graphs vs. Tables*

**Tests of Between-Subjects Effects**

Dependent Variable: Task3.3, Difficulty to Understand the Information

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 123.85[a] | 15 | 8.26 | 2.06 | .012 |
| Intercept | 18513.26 | 1 | 18513.26 | 4618.52 | .000 |
| Task3Format | .84 | 1 | .84 | .21 | .648 |
| VisualizerType | 91.33 | 3 | 30.44 | 7.60 | .000 |
| Task3Trend | 7.08 | 1 | 7.08 | 1.77 | .185 |
| Task3Format * VisualizerType | 5.64 | 3 | 1.88 | .47 | .704 |
| Task3Format * Task3Trend | .37 | 1 | .37 | .09 | .761 |
| VisualizerType * Task3Trend | 4.11 | 3 | 1.37 | .34 | .795 |
| Task3Format * VisualizerType * Task3Trend | 12.74 | 3 | 4.25 | 1.06 | .367 |
| Error | 1070.26 | 267 | 4.01 | | |
| Total | 20246.00 | 283 | | | |
| Corrected Total | 1194.11 | 282 | | | |

**Table 7.5.2.2.3**

*Post-hoc analyses, difficulty of understanding information from Graphs vs. Tables*

Dependent Variable: Task3.3

Multiple Comparisons Correction: Fisher's Least Significant Difference

| Visualizer Type | Visualizer Type | Mean Difference | Std. Error | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| Object | ObjectSpatial | -1.19* | .35 | .001 | -1.87 | -.50 |
| | Undefined | .24 | .34 | .491 | -.44 | .92 |
| | Spatial | -.69 | .35 | .050 | -1.38 | .00 |
| ObjectSpatial | Undefined | 1.43* | .33 | .000 | .79 | 2.07 |
| | Spatial | .50 | .33 | .132 | -.15 | 1.15 |
| Undefined | Spatial | -.93* | .33 | .005 | -1.57 | -.28 |

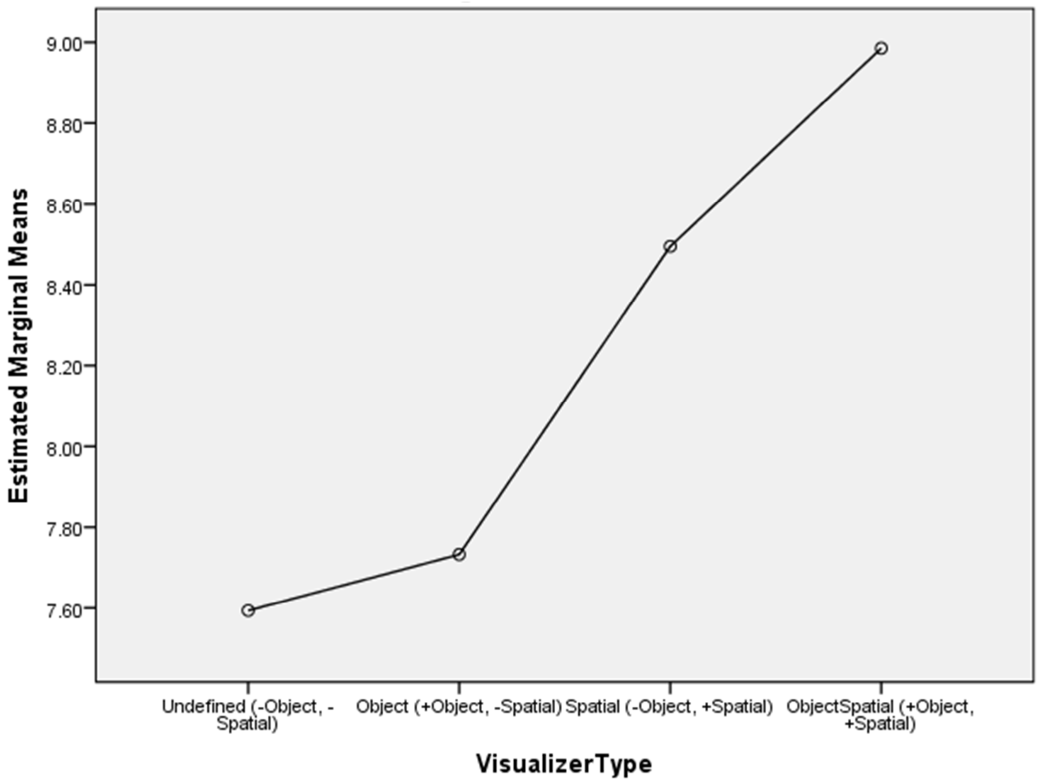



***Figure 7.5.2.2.1*** Difficulty of understanding information, different visualizers

### 7.5.2.3 Hypotheses 2a & 2b

H2a: When evaluating the results of the company from a table, spatial visualizers will give less stable ratings (more variance) than object visualizers.

H2b: In the graph condition there will be no significant differences in variance between spatial and object visualizers.

To analyse H2a, an independent-samples t-test was run on the performance ratings of the company, comparing the spatial and the object visualizers in the table condition only. According to the reported analysis of variance shown in Table 7.5.2.3.1, H2a was marginally supported, with object visualizers showing smaller variance (SD=2.18) when evaluating the table than spatial visualizers (SD=2.64). A Levene's test for equality of variances showed this difference to be marginally significant (F=2.88, p=.095). This pattern might indicate that spatial visualizers were indeed able to picture the situation from the table more clearly in their minds, and this elicited stronger ratings, therefore creating more variance from one individual to the next. In contrast, object visualizers would be more cautious in their ratings, avoiding giving more extreme ratings because they would not have a clear picture in mind of the positivity or negativity of the situation.

**Table 7.5.2.3.1**
*Hypothesis 2a Variance test*

| Group Statistics | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Visualizer | N | Mean | Std. Deviation | Std. Error Mean | Levene's Test for Equality of Variance | |
| | | | | | | F | Sig. |
| Task3.1 | Object | 31 | 5.81 | 2.18 | . 39 | 2.88 | .095 |
| | Spatial | 37 | 5.22 | 2.64 | . 43 | | |

To analyse H2b, an independent-samples t-test was run on the performance ratings of the company comparing the spatial and the object visualizers in the graph condition only. According to the reported analysis of variance shown on Table 7.5.2.3.2, H2b was not supported. Instead, object visualizers showed smaller variance (SD=2.73) when evaluating the graph than spatial visualizers (SD=3.38). A Levene's test for equality of variances showed that this difference was significant (F=6.72, p=.012). This result may indicate that when interpreting a graph, spatial visualizers have a stronger reaction to the image and this is reflected in the ratings, which would reflect more the individual's true interpretation. Object visualizers would not have such a strong reaction, as the graphical information, being of innate spatial nature, does not affect their leaning to extremes as much as it does for spatial visualizers.

**Table 7.5.2.3.2**

*Hypothesis 3b Variance test*

| Group Statistics | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Visualizer | N | Mean | Std. Deviation | Std. Error Mean | Levene's Test for Equality of Variance | |
| | | | | | | F | Sig. |
| Task3.1 | Object | 28 | 6.25 | 2.73 | .52 | 6.72 | .012 |
| | Spatial | 35 | 5.31 | 3.38 | .57 | | |

All of the above indicates that a graph does generate more extreme ratings than a table, therefore from individual to individual the variance would be greater. This is true both for graphs and tables with regard to spatial visualizers. In the case of graphs, being more attuned to the interpretation of graphical information, spatial visualizers would form stronger opinions about the positivity or negativity of a situation (though the statistical significance in this case is only marginal). In the case of tables, because spatial visualizers are better at transforming a table into a corresponding trend, their ratings show less conservatism than those of object visualizers.

### 7.5.2.4 Hypotheses 3 & 4

H3: Compared with the No Picture condition, congruent pictures will magnify the effect of trend (more positive ratings in the positive trend and more negative in the negative trend), whereas Incongruent pictures will attenuate the effect of trend.

H4: The magnification/attenuation effect will be more pronounced among object visualizers than spatial visualizers.

To investigate H3 and H4, the data was split into the positive and negative trend and these trends were analyzed separately, as the complexity of the experimental design is such that the simplification of the analyses is necessary.

##### *7.5.2.4.1 Positive Trend*

Hypotheses 3 and 4 were not supported in the Positive Trend condition.

A 2x3x2 factorial ANOVA model was run with the factors of Visualizer Type (Object/Spatial), Congruence (Incongruent/No Picture/Congruent) and Format (Graph/Table). According to this model, only Format ($F$ [1,180]= 29.96, $p$=.002) was a statistically significant factor (Table 7.5.2.4.1.1).

The main effect of format revealed by the model showed how performance ratings in the positive trend were higher when the information about the company was presented in the form of a graph than in the form of a table (Table 7.5.2.4.1.2).

We therefore failed to find support for H3 and H4 in the positive trend condition, and the addition of a picture, congruent or not, does not seem to affect object or spatial visualizers' ratings of either a graph or a table. We did find, however, that in the positive trend condition, a graph generates more positive ratings than a table.

**Table 7.5.2.4.1.1**

*ANOVA Model Positive Trend*

**Tests of Between-Subjects Effects[b]**

Dependent Variable:Task3.1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 45,40[a] | 11 | 4,13 | 1,41 | ,170 |
| Intercept | 10588,15 | 1 | 10588,15 | 3626,05 | ,000 |
| ObjectorSpatial | 2,22 | 1 | 2,22 | ,76 | ,385 |
| Task3Congruence | 7,56 | 2 | 3,78 | 1,30 | ,276 |
| Task3Format | 29,96 | 1 | 29,96 | 10,26 | ,002 |
| ObjectorSpatial * Task3Congruence | 3,38 | 2 | 1,69 | ,58 | ,561 |
| ObjectorSpatial * Task3Format | ,03 | 1 | ,03 | ,01 | ,914 |
| Task3Congruence * Task3Format | ,03 | 2 | ,01 | ,01 | ,995 |
| ObjectorSpatial * Task3Congruence * Task3Format | 2,36 | 2 | 1,18 | ,40 | ,668 |
| Error | 525,61 | 180 | 2,92 | | |
| Total | 11734,00 | 192 | | | |
| Corrected Total | 571,00 | 191 | | | |

a. R Squared = ,080 (Adjusted R Squared = ,023)

b. Trend = Positive

**Table 7.5.2.4.1.2**

*Means, Format Main Effect in Positive Trend*

**2. Format[a]**

Dependent Variable:Task3.1

| Format | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|
| Table | 7,28 | ,18 | 6,93 | 7,63 |
| Graph | 8,10 | ,19 | 7,73 | 8,46 |

a. Trend = Positive

### *7.5.2.4.2 Negative Trend*

Hypotheses 3 and 4 were not supported in the negative trend condition.

To test Hypotheses 3 and 4 in the negative trend condition, we replicated the same 2x3x2 ANOVA model with the same factors as that of the positive trend.

As shown on Table 7.5.2.4.2.1, this model showed only an interaction between visualizer type and task congruence (F[2,196]= 3,59, p=.029). No other main effects or interactions were found.

**Table 7.5.2.4.2.1**
*ANOVA Model Negative Trend*

**Tests of Between-Subjects Effects**[b]

Dependent Variable:Task3.1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 54,36[a] | 11 | 4,94 | 1,08 | ,379 |
| Intercept | 2281,30 | 1 | 2281,30 | 498,68 | ,000 |
| ObjectorSpatial | 2,66 | 1 | 2,66 | ,58 | ,446 |
| Task3Congruence | 10,82 | 2 | 5,41 | 1,18 | ,309 |
| Task3Format | 5,93 | 1 | 5,93 | 1,30 | ,256 |
| ObjectorSpatial * Task3Congruence | 32,86 | 2 | 16,43 | 3,59 | ,029 |
| ObjectorSpatial * Task3Format | 3,28 | 1 | 3,28 | ,72 | ,398 |
| Task3Congruence * Task3Format | 2,71 | 2 | 1,352 | ,30 | ,744 |
| ObjectorSpatial * Task3Congruence * Task3Format | ,74 | 2 | ,37 | ,08 | ,922 |
| Error | 896,63 | 196 | 4,58 | | |
| Total | 3327,00 | 208 | | | |
| Corrected Total | 951,00 | 207 | | | |

a. R Squared = ,057 (Adjusted R Squared = ,004)

b. Trend = Negative

The interaction, pictured in Figure 7.5.2.4.2.1, shows a pattern whereby the expected effect of a downward trend accompanied by an incongruent picture did result in higher ratings, and the congruent in lower ratings than the No Picture condition only for the spatial visualizers. In contrast, object visualizers showed a different pattern, with the addition of any picture, whether congruent or incongruent, resulting in lower ratings than the No Picture condition.

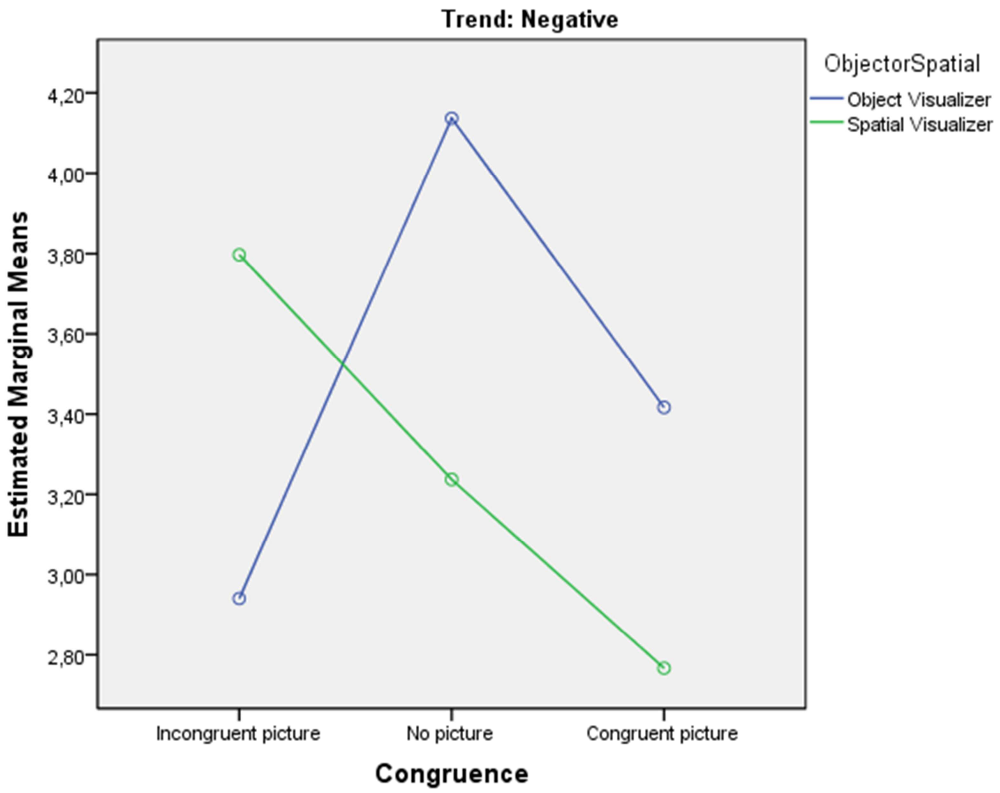



***Figure 7.5.2.4.2.1*** Interaction Visualizer Type by Congruence

A potential explanation for this effect could be that spatial visualizers, being more attuned to the numerical context, do not scrutinize the picture thoroughly, so the addition of the picture would only contribute slightly to the evaluation of the numerical information, which is their main focus. In contrast, object visualizers, who examine the picture more closely than the spatial visualizers, might consider that the congruent picture reinforces the message conveyed by the numerical information. In contrast, when the image is incongruent with the numerical information, object visualizers might focus on this incongruence, potentially find it deceiving, and then overcorrect their ratings, therefore resulting in lower ratings than the No Picture, and even the Incongruent condition.

## 7.6 Discussion

In this Chapter we were interested in analyzing whether different formats of information presentation, containing both spatial and object information, would affect individuals differently depending on their visualization style. The reviewed literature supported the idea that information congruent with an individual's cognitive style would be given more weight in the process of judgment and decision-making. However, these findings do not fit this basic assumption in a straightforward manner.

We have seen how the manipulation of trend worked as intended, with the positive trend eliciting higher ratings than the negative trend. We also hypothesized that the graph condition would generate greater variance in ratings than the table condition. We found precisely this pattern, with the table condition giving rise to less variance than the graph condition. We then found that this effect was driven primarily by the object visualizers, who showed less variance in their ratings than the spatial visualizers. As we discussed in the elaboration of the hypotheses, this pattern of the tables generating less variance than the graph and the object visualizers showing less variance than the spatial visualizers might indicate that in this particular context graphs let participants see clearly a trend or pattern to be evaluated, and therefore they made a more internalized evaluation of the ratings. This results in more extreme ratings being given to graphs than to tables, and also a greater variance from individual to individual in the graph condition. It seems apparent that in our experimental design the tables cause individuals to give less extreme evaluations, as the pattern shown by tables is not as discernable as that described by graphs.

Our results also indicated that spatial visualizers do show this pattern more than object visualizers. In the table condition, this effect might be driven by the fact that spatial visualizers are more able to transform the numerical content of a table into a specific shape. This makes spatial visualizers more prone to show a higher extremity and variance of ratings as compared to object visualizers. The same is true for the graph condition. Although in principle we hypothesized that the graph condition might not result in different variance in ratings because the trend would be obvious, we found that again spatial visualizers did show higher variance in ratings than object visualizers. This could indicate that, again, a graph might result in a truer internal evaluation of the graph by the spatial visualizers, who derive more evaluative meaning from a form of information presentation that is according to their cognitive style, and for whose interpretation spatial cognition is needed.

Supporting the aforementioned arguments, we found that individuals with high spatial visualization found the information contained in both the tables and graphs easier to understand than individuals with low spatial visualization.

As we have seen, the prediction of graphs generating less stable ratings than tables was supported. We saw how tables had more stable ratings than graphs, both in terms of the variance of ratings, as well as the extremity of these, with tables showing less extreme ratings than the graphs. The evaluability hypothesis could explain the mechanism which causes the effect of more variance and extremity of ratings in the graph condition. As we previously mentioned, the positivity or negativity of the data in a table might be difficult to evaluate given the fact that by simply looking at the numbers, the tilt of the slope cannot be plotted. In contrast, a graph would give a clear image of the slope of the trend. The lack of a clear tilt of the slope in the table condition might prompt people to give more conservative ratings in this condition, as the degree of positivity or negativity of the situation was not immediately obvious. However, in the graph condition, people would see more clearly that a trend is clearly positive or negative, and therefore give more extreme ratings (higher in the positive trend, lower in the negative trend) than in the table condition.

When checking for the effect of incongruence or congruence decreasing or enhancing the ratings given to a table or to a graph, we largely found that congruence or lack thereof did not cause the difference we had hypothesized. Specifically, in the positive trend we did not find any effect of an accompanying picture reinforcing or attenuating the ratings according to its congruence with the numerical information. In the negative trend, however, we found that only spatial visualizers show the hypothesized pattern of reporting increased ratings with an incongruent picture and decreased with a congruent picture. For object visualizers, however, the addition of a picture, whether congruent or incongruent, resulted in decreased ratings.

A potential explanation for this pattern could be that spatial visualizers might not scrutinize the picture as closely as object visualizers, and they only use the face as a secondary source of information, therefore slightly guiding their ratings upwards (when the figure is incongruent), or downwards (when it is congruent). Object visualizers, in contrast, would pay much more attention to the figure and would lower their ratings when the figure is congruent, but they would also lower them when the figure is incongruent, as they might detect that the figure could be deceiving and therefore overcorrect their ratings. This explanation, however, cannot explain the full picture, as this pattern should therefore be present in the positive trend condition, though our results do not demonstrate this to be the case.

In any event, the results showed that the experimental manipulation of congruent and incongruent information of spatial and object nature did not fulfil the aim of clarifying what type of information individuals value the most when evaluating numerical information accompanied by a human figure. Two causes come to mind to explain the failure to find support for such hypotheses. Firstly, it could be that a human figure does not specifically constitute an object stimulus. Although in principle the argument for a human figure being an object stimulus does not depart from current literature on the matter, it must be noted that the Face Fusiform Area (FFA), although hosted by the same brain area as that processing object information, is an entity in its own right and might follow different functioning than the processing of colours, brightness of images, etc. The second potential explanation is that individuals might attribute more value to numerical information than other types of information. Problems containing numerical information are widely presented in educational settings from infancy as having an objective solution, and this could mean that numerical information receives the heaviest weight when being considered in a setting such as the current one, regardless of the addition of other external information.

Overall, the results of this chapter reveal that format of information presentation (Tables or Graphs) does elicit different responses in people, and that different visualizer types do evaluate the information in a different manner. However, the experimental section where we made use of a paradigm of congruent/incongruent information to identify whether visualization style caused different weighing did not yield support for the hypothesized pattern of individuals weighing Object or Spatial information differently depending on their cognitive style.

# Chapter 8

# Discussion

This thesis has investigated the relationship between visualization style and numeracy. Clarifying the relationship between numeracy and cognitive style of visualization is important for several reasons. The first reason is that visualization style could be a key psychological construct underpinning people's ability to process numbers. The literature review argued that spatial visualization and numerical abilities do indeed share some brain areas in charge of their processing. We have also seen how damage to brain areas in charge of processing spatial information results in dyscalculia (the impossibility of processing numbers). In contrast to the evidence supporting how preference for spatial visualization might be related to numeracy, there is no previously published plausible evidence pointing to the potential relationship between object visualization and numeracy. We have investigated the relationship of spatial and object visualization with each other and of both of these constructs with numeracy. This investigation fills a gap in the literature on numerical abilities and individuals' visualization.preference.

Investigating the relationship between visualization preference and numeracy also has further implications beyond the discovery of a mechanism underpinning  numerical abilities. Having demonstrated the relationship between numeracy and visualization style, it could be that visualization preference predicts tasks in much the same manner as numeracy does, or more reliably. Until this study, no other study had investigated whether visualization style does indeed predict judgment and decision-making in numerical tasks. As stated in the literature review, there is evidence of the importance of numeracy in certain decision-making tasks, especially in tasks where numerical processing is necessary. As a cognitive style, the unique visualization preference of an individual should therefore be stable throughout time and is thus a trait that could be used to predict the same tasks that numeracy has proven to predict, but with a greater degree of reliability. Whereas numeracy is an ability than an individual acquires and therefore is subject to being modified by external factors such as training, culture, exposure to numerical environments, etc., the unique way that an individual processes information, cognitive style, is a permanent trait. There is, however, the possibility that a cognitive style evolves throughout one´s lifespan. Although to the best of our knowledge literature on cognitive styles has not proposed such an evolution, this is not a point that could be dismissed. In fact, it is widely accepted that cognitive abilities do change with ageing, and although the same is not assumed in the literature about a person´s cognitive style, the lack of research can´t be interpreted as the lack of existence of the phenomenon of cognitive styles being modified by ageing, training, or experience. As we have shown, Experiential Learning Theory (Kolb, 1984) proposes that the way people approach novel situations might be modified by a process of learning and exposure to recurrent scenarios. Such an exposure would modify people´s cognitive strategies dealing with problems at hand, adopting measures that in the past were successful when dealing with these same problems. Whether the modification of one´s approach to cognitively solve a problem would constitute a modification of cognitive style as described in the literature is another debate, as the more orthodox definition of “cognitive style” is one that´s the “default” or the “innate” way of cognitive processing. Thus, one could argue that the innate trait or the “virgin” trait is a cognitive style, and maybe when such a style is modified by training or exposure, it would become a cognitive strategy, the result of which would be an ability. In this way, there might be the existence of three different concepts, which would be cognitive style, cognitive strategy, and ability. Since, to the best of our knowledge, such a debate over the definitions, conceptualizations and operationalizations has not been proposed, and therefore not solved, we adopt in the current thesis the view of cognitive style as it currently exists in the literature: the innate way in which a person cognitively processes information.

Assuming what has so far been proposed in the literature, whereas the predictive ability of numeracy could change throughout the development of an individual, a person’s innate visualization style might be a more stable predicting factor in numerical decision making tasks. Therefore, the fact that visualization style is a permanent individual trait, as opposed to an ability (like numeracy is), opens up the possibility of predicting numerical decision-making tasks, overcoming the limitations that numeracy scales might be subject to. For instance, whereas numerical abilities may be determined by training and culture, therefore varying across countries, with some countries particularly challenged and others exceptionally advantaged, visualization style should be immune to these changes in geography, and might therefore be able to predict decision-making in a more reliable manner.

As we have seen in the literature review section, there was previous scientific evidence that numerical and spatial abilities might be positively correlated. However, until the current investigation, there has not been a solid conclusion of whether visualization as a cognitive style had any relationship with numerical abilities. Some studies argued that numeracy could be positively related to the cognitive style of visualization, but the evidence was contradictory. In Chapter 4, we investigated the specific relationship between numeracy and the cognitive style of visualization. Using a sample with varying levels of numeracy as well as spatial and object visualization, our results support the idea that spatial and object visualization are two independent constructs. Whereas some previous research had argued for a dichotomy of object and spatial visualization, with these constructs at two opposite ends of a continuum line, our findings do not warrant this view. Instead, the findings reported in Chapter 4 found object and spatial visualization not to be correlated with each other. The various samples of data participating in the studies detailed in Chapter 4, 5, 6 and 7 are all consistent in the lack of a strong correlation between spatial and object visualization. In all four studies the correlations were very low, ranging between -0,07 to 0,12. In all cases the correlation was statistically insignificant, except in the last case. However, the statistical significance of the study in Chapter 7 has to be put in the context of the full set of results across our studies, from which we do not see a clear picture of different studies yielding any sign of a strong correlation in between object and spatial visualization. Furthermore, the statistical significance found in Chapter 7 might have been driven by the very large sample (n=854) of the study. The lack of a clear correlation between object and spatial visualization favors the interpretation that both systems are independent of each other, instead of being at the opposite ends of a continuum line. In fact, if object and spatial visualization were at two opposite ends of the same spectrum, the biggest (though still extremely small) correlation found, should be negative and not positive. Of all the four studies, only in Chapter 4 the correlation was of negative sign (-0,07). The evidence stemming from our studies would, thus, be consistent with the literature supporting the independence of these constructs. As we indicated in the literature review section of this thesis, physiological evidence points to the existence of two clearly different paths to process object or spatial information. Our results would thus be consistent with such an independence of these two dimensions which, physically present in the brain, would result in object and spatial information being processed independently, hence the lack of relationship found between the two constructs.

Further investigating the cognitive style of visualization, Chapter 4 moved on to investigate the relationship between numeracy and object and spatial visualization. The findings of Chapter 4 confirm the plausible arguments found in the literature which hint at a positive relationship between preference for spatial visualization and numeracy. In contrast, object visualization predicts lower performance in numeracy. Although they are independent mental constructs, object and spatial visualization seem to predict numeracy in opposite manners. Whereas object visualization is a negative predictor, spatial visualization is a positive predictor. The finding that numeracy is predicted negatively by object visualization and positively by spatial visualization opened the door to further research in this thesis to investigate whether visualization preference could predict judgment and decision-making in numerical tasks. Figure 4.2.4.2 shows graphically how the combination of low and high in each dimension results in different numeracy scores, and particularly, how the group of spatial visualizers, who combine high spatial and low object visualization, have the highest numeracy scores. In this combination, numeracy is maximal. All four visualizer types do not differ in their numerical abilities among themselves. At the opposite extreme of numeracy is the group of object visualizers, displaying a combination of high object and low spatial visualization. The mix of high spatial and high object visualization (ObjectSpatial visualizers) and that of low object and low spatial visualization (Undefined visualizers) seems to mutually cancel each other out. The groups of ObjectSpatial and Undefined are in between the spatial and the object visualizers who have, respectively, the highest and lowest numeracy scores. We should apply caution, however, when interpreting the mix of visualization caused by the mutual cancelling effect of ObjectSpatial and Undefined. Although this is the pattern shown, from a statistical point of view, the post-hoc analyses did not reveal that the difference between the Object, ObjectSpatial, and the Spatial groups was significant. However, there is no doubt that the combination of preference for high spatial and low object visualization sets individuals at a higher level of numeracy.

Having found evidence of numeracy being negatively predicted by object visualization and positively by spatial visualization is in itself an important finding. However, it is difficult to explain with the current methodology the origin of such relationship. Particularly difficult to explain is the prediction of lower numeracy by higher object visualization. The brain systems of both numerical processing and object visualization processing are, according to extant literature two independent structures. Maybe there a brain process or structure that explains the antagonism of object visualization and numeracy. There is no apparent explanation, however, that we can put forth with the given evidence extant in the literature, and this might be a point to be solved with a different research approach involving the use of brain imaging techniques which at the moment were not available for the current thesis. In the case of the positive prediction of numeracy by enhanced levels of spatial visualization, it might be that being the spatial and numerical processing hosted by the same brain structures, a better functioning in this particular part of the brain will affect positively the areas of which such region is in charge, namely. Delving further into literature on neurobiology, there appears to exist evidence that enhanced levels of Fractional Ansiotropy would drive both the high level of spatial cognition and numerical processing. As Grieve et al. (2007) have shown, increased FA levels result in enhanced cognitive functioning in the areas with these enlarged levels. That is, it could be conjectured that being FA a measure of connectivity in the brain whose enhanced levels would result in better cognitive performance, the levels of FA are the drivers of performance both in spatial and numerical tasks, as these are governed by the same brain areas. Thus, one could hypothesize from our results and extant research, that numerical performance and spatial visualization might well have the same root cause.

Despite the proven relationship between visualization preference and numeracy shown in Chapter 4, the relationship between visualization preference and numerical abilities was not fully explored, but instead rather reduced to the specific realm of numeracy as a construct operationalized and measured with the recently developed Abbreviated Numeracy Scale. We overcame this limitation in Chapter 5, where we moved beyond the relationship between visualization style and numeracy as a construct operationalized and measured by the ANS, and checked visualization preference and the interpretation of numerical information in domains beyond the ANS.

Specifically, Chapter 5 was focused on how visualization style and numeracy had a different effect on perceptions and judgements of numerical information presented in various formats. Of particular interest was whether the format in which information was presented affected the judgments of different types of visualizers and of individuals with differing numerical abilities. To this end, a series of four tasks was created to check for differences in the judgments of individuals differing in visualization style and numeracy.

In the first task, a simple table was used to check whether differences in visualization and numeracy affected the perception of how good or bad a financial scenario was when this scenario was presented in the form of a table.

The results showed that tables displaying descending or ascending profits did indeed generate different ratings, with tables showing a positive trend generating higher judgments of the performance of a company than tables showing an equivalent negative trend. This confirmed that the Trend manipulation in this experiment was successful, so we then checked whether individuals differing in visualization style and in numeracy showed any differences in their judgments. The results showed that when treating numeracy, object, and spatial visualization as continuous variables predicting the ratings of a table, none of these variables affected the judgments. However, when dichotomizing numeracy, object and spatial visualization into high and low groups, the results were different. For no apparent reason, the higher numerates tended to give higher ratings of performance across trends. Interestingly, although high and low object visualization did not have an effect on ratings, high and low spatial visualizers did differ in their ratings. Specifically, low spatial visualizers gave more extreme ratings than the high spatial visualizers. We argued that a potential interpretation could be that the low spatial visualizers give more conservative ratings due to their more in-depth spatial cognitive understanding of the numbers, from which they may attempt to imagine the tilt of a slope. Given the impossibility of finding such a tilt, their ratings are more conservative. In contrast, low spatial visualizers might not engage in such deep processing and simply provide a stronger response as they can see that the situation is positive or negative (depending which trend they are evaluating), and the fact that they do not see a slope is not necessarily taken into consideration.

In sum, the first experiment showed that when judging the performance of a company based on tabular information, individuals with high numeracy or spatial visualization tended to give different ratings of performance. Examining the literature on numeracy and visualization, it is not immediately obvious why numeracy and spatial visualization affect judgments of performance in this manner. However, this task does indicate that, regarding judgments of numerical information, considering the level of spatial visualization of an individual might be of importance in interpreting the ratings given to a numerical task.

In the following tasks of Chapter 5, we investigated how visualization and numeracy affected not only judgments, but also how performance in numerical tasks was determined by both numeracy and visualization preference. To this end a second experiment investigated whether numeracy and visualization affected the ability to extrapolate a given trend, predicting future data points. As we have seen in the literature review, predicting a given trend beyond the data that is presented is considered the highest stage of spatial cognition. Similarly, when extrapolating a given trend from tabular data, numeracy should act in the same manner and higher numeracy should predict a better ability to find the next data point. However, in the case of object visualization, which as we have seen predicts lower numerical performance, higher levels of object visualization might hinder the ability to extrapolate the trend beyond the given information.

To check these hypotheses, the second experiment in Chapter 5 presented participants with a table displaying information on two companies, representing the performance of each one of them over a series of years. Afterwards, participants were asked which company, if the trend was to continue, would have higher profits the following year. The results demonstrated that the hypothesized pattern was true.  Higher numeracy and spatial visualization acted much in the same way and both predicted a higher likelihood of arriving at the right answer, whereas object visualization did not show statistical significance.

When this pattern is contrasted with that shown in the first experiment of Chapter 5, where visualization and numeracy were investigated in predicting judgments of performance from tabular information, we see that numeracy and spatial visualization do have some sort of effect, though no discernible pattern of a relationship between them emerges. What is starting to emerge is that object visualization does not seem to have much effect in this processing of numerical information. Although there is no body of literature addressing why this pattern of results emerges, it could be that in tasks requiring cognitive capacity to analyze data, object visualization will not make any difference. However, when faced with a cognitively demanding numerical task, high spatial visualization has a similar effect as high numeracy.

The third task in Chapter 5 investigated whether individuals differing in numeracy and visualization were affected differently by graph distortion. To this end, an experiment was conducted with individuals rating the performance of a company based on annual profits displayed in the form of bar graphs. The participants rated the graphs either in an ascending or descending trend, and either with the graphs distorted or undistorted, showing a steeper or flatter slope respectively.

The results indicated that the distortion manipulation worked as intended, with the steeper slopes generating more extreme ratings (higher in the positive trend, lower in the negative trend). However, neither numeracy nor visualization had any effect on the ratings given to distorted vs. undistorted graphs. We did not expect to find this pattern of results, as it was hypothesized that both higher numeracy and higher spatial visualization individuals would detect the trend manipulation, as they would look more closely at the values of the Y-scale, and detect the manipulation of the trend. This should particularly have been true for individuals with higher numeracy, as it was argued by Peters et al. (2006) and Weller et al. (2012) that individuals with higher numeracy delved further into numerical information than lower numeracy individuals. Higher spatial visualization, whilst predicting higher numeracy, may also cause people to focus more on the spatial shape of the trend, noticing the differences between the adjacent graph bars. However, since spatial visualizers perform a part-by-part analysis of spatial relations between parts of the graph, we should expect that this itemized analysis would detect the Y-axis manipulation and therefore the graph distortion effects would be minimized in the case of spatial visualizers as compared to object visualizers. Since object visualizers would process the coherent whole of the image, they should be more likely to show the graph manipulation effect. However, this was not the case.

The finding that the effects of graph manipulation are pervasive, without even high spatial visualization or numeracy eliminating this bias, is a very important one. Although the literature on graph distortion had never considered numeracy or visualization preference in this context, we found that regardless of numeracy or spatial visualization differences, consumers of information presented in form of bar graphs will have the potential of being misled.

In all, the third experiment of Chapter 5 found that the effects of graph distortion are persistent, so much so, that neither being highly numerate or a high spatial visualizer attenuates the effects of graph distortion.

Finally, the fourth experiment in Chapter 5 extended the findings of the second experiment and investigated whether numeracy and visualization style predicted the ability to correctly identify the shape of a graph displayed by tabular data. The results indicate that higher numeracy and higher spatial visualization both predict the correct identification of the graph corresponding to a table. This is yet another example of how numeracy and spatial visualization act in much the same manner when predicting performance in a cognitive task involving the processing of numbers and graphical information.

In summary, Chapter 5 found that numeracy and spatial visualization act in much the same manner when it comes to numerical and graphical tasks, when these tasks require a correct answer to be found after a cognitive process. In this case, the predictions of numeracy and spatial visualization are comparable and show how higher levels of either one tend to yield higher performance. However, even this relative advantage provided by higher numeracy and higher spatial visualization is not enough to remove the pervasive effects of graph distortion. It is difficult to hypothesize why spatial visualization and numeracy are a proxy of each other in performance tasks, that is, cognitive numerical tasks from which to derive objectively correct answers, but there is no clear relationship between numeracy and spatial visualization in evaluative tasks (tasks where judgements or impressions are asked). Although not having literature to back up potential explanations, one could venture that cognitive performance tasks involving numerical calculations activate the area in charge of processing numbers, which is common to spatial and numerical processing. However, when asked to evaluate a situation that does not demand a correct answer, but rather an appraisal, maybe other areas of the brain are activated, involving different functions beyond the purely numerical, and this might result in the evaluations being motivated by different brain systems, thus the lack of relationship between spatial visualization and numeracy when predicting the answers in such tasks. This explanation, however, lacks a solid ground on the literature and is to be understood as a conjecture which would need to be further explored using means such as neuroimaging equipment and techniques which were not available to the researcher in the current project.

Having seen how high numeracy and spatial visualization act in a similar manner in the previous tasks, Chapter 6 set about replicating the findings of numeracy and checking whether they extended to spatial visualization in the context of a set of more traditional tasks in the field of Decision-Making. To this end, the three common tasks of two studies (Peters et al. 2006; Weller et al., 2012) were investigated to check, firstly, whether the set of studies was replicated using numeracy as a predictor, and secondly, to see whether any of the visualization components affected the predictions in the same manner as numeracy.

The first task common to Peters et al. (2005) and Weller et al. (2012) was the “Attribute Framing” task. In this task both previous studies, in a between-subjects design with frame as the between-subjects condition, found an interaction between frame and numeracy which caused the differences across frames to be higher for low numerates than high numerates. In Chapter 6, this first task confirmed a main effect of framing, showing that the manipulation of scores did have an effect, and the positive frame elicited higher ratings than the negative frame. However, the expected interaction between numeracy and frame was not found. When analyzing the effects of visualization, we did not find that either object or spatial visualization had any effect on scores either as a main effect or as part of an interaction.

These results do not replicate the findings originally reported by Peters et al. (2006) and Weller et al. (2012) of the interaction between frame and numeracy. Although there is no apparent reason why in this case the results failed to replicate the original findings, and why neither object nor spatial visualization had an effect, the absence of an effect of numeracy and object or spatial visualization is not inconsistent with the proposal of numeracy predicting the same results as spatial visualization. Although in our experiment numeracy and spatial visualization did not act in a discrepant manner, the question remains of why this study failed to replicate the results of Peters et al. (2006) and Weller et al. (2012). Peters et al. (2006) argued that high numerates were more able to retrieve numerical concepts and see alternative scenarios. That is, seeing a numerical scenario in one frame would also allow higher numerates to see the alternative frame. This would, thus, attenuate the framing, as they showed to occur in their studies. Were this the true explanation about the process that takes place, it is difficult to argue why this did not happen in our study.

The second task to replicate was the “Ratio Bias” task, where participants were asked to pick a colored jelly bean from one of two bowls. Bowl A contained 100 jelly beans, of which 9 (9%) were colored, and Bowl B contained 10 jelly beans, of which 1 was colored (10%). Participants received this information and were asked which bowl they would select the jelly bean from. In the original Peters et al. (2006) and Weller et al. (2012), higher numeracy was associated with a tendency to favor the objectively better bowl.

In our results, we could not replicate this finding. Instead, numeracy was not shown to predict the choice of the objectively better bowl. In contrast, spatial visualization was a significant predictor in choosing the better bowl.

This task demonstrated how in some cases, where numeracy fails to predict better choices involving probabilities, spatial visualization is still a valid predictor of better choices. The fact that spatial visualization was a predictor of correct responses better than numeracy in this case is an important point arguing for the benefit of using a cognitive trait, rather than an ability, as a predictor of responses. However, in this task the original results of Peters et al. (2006) and Weller et al. (2012) were not replicated. The process argued in the original studies suggests that participants perform a conflictive affective evaluation, by which a bowl with more colored balls looked more inviting, but the alternative bowl with fewer colored balls offering a higher probability of drawing the desired ball. This conflict is resolved by the higher numerates choosing the objectively better bowl, as they form a computation and derive an affective hit from it. It might be that in our case the spatial visualization scale offered a better way to discern the population of higher numerates more finely than the very numeracy scale.

The third task replicated was the “Bets Task”, where previous studies had found that high numerates valued a bet of 29/36 probabilities of winning $9 and 7/36 of losing nothing as less attractive than an objectively better bet of 29/36 probabilities of winning $ and 7/36 of losing 5 cents. This was not true for low numerates. Both Peters et al. (2006) and Weller et al. (2012) found this pattern. However, our results did not replicate these findings. Instead, our studies found only a general trend of both higher numerates and higher spatial visualizers giving higher ratings of attractiveness regardless of the type of bet they were judging.

Although these results do not replicate the original findings, in this task we found again that numeracy and spatial visualization do indeed predict similar judgments.

Finally, although Weller et al. (2012) did not conduct a study to replicate the “Mental Patient” framing task by Peters et al. (2006), we nevertheless included this task in the current experiment. In the “Mental Patient” framing task, participants were informed that a patient in a mental institution was being examined for discharge.  Some participants were given information in a frequentisitic format (10 out of 100) about the potential risk of recidivism of such a patient, and some other participants received the same scenario and questions but with the information about recidivism in a percentage format (10%). The general finding was that the frequentistic format elicited higher ratings of risk, with this being particularly true for the low numerates. In contrast, high numerates in both conditions did not differ significantly from each other in their risk ratings. Our analyses failed to replicate the original finding of Peters et al. (2006), and also failed to find any evidence of object or spatial visualization affecting the judgments of risk differently depending on the frame in which the information was presented.

In summary, Chapter 6 investigated the replication of four different Decision-Making tasks where numeracy had previously been demonstrated to have a predictive effect on the results. In three of these tasks (Student Framing, Bets, and Mental Patient) participants were asked for their judgments about a particular situation that did not involve providing an objectively correct answer.

In fact, these three tasks were presented in a between-subjects design, so participants did not see the two possible conditions and were therefore unable to provide answers that reflected their correct assessment of a situation in terms of their normatively better value of each option. Although the original studies did find that high and low numeracy determined judgments differently, from a purely objectively point of view participants did not provide answers that were normatively abnormal. We found that in these three tasks, neither numeracy nor object or spatial visualization had an effect. Where we did detect a difference was in the Ratio Bias (Bowls) task. In this task, participants had available to them two possible choices, and one of them was objectively better than the other. In this case, it was shown that higher spatial visualization resulted in participants choosing the normatively better bowl. However, numeracy did not have an effect in predicting the preference for a better bowl. We demonstrated, therefore, that where numeracy does not have the predictive power to show differences in judging attractiveness (or risk in the case of the Mental Patient task), spatial visualization followed the same pattern and did not show an effect on judgments of attractiveness. In contrast, in the one task where a normatively better decision had to be made (the Ratio Bias task), spatial visualization was even better than Numeracy at predicting rational choices. It might be the case that the very nature of the tasks (evaluative vs. performance), might be an important element to consider. From our results, it might be sensible to propose that the nature of the task triggers different brain mechanisms, which in the case of numerical performance would be concentrated in the areas of numerical processing, whereas in those of evaluation might activate a wider or less defined brain area, thus making it difficult to pinpoint the actual process that happens.

Finally, Chapter 7 investigated visualization style and its effects on judgments of financial information when such information was presented (1) as a graph or (2) as a table, and when this information was accompanied by the picture of a human figure displaying a positive or negative pose. Investigating how graphs and or tables accompanied by pictures affect the judgments of financial information is important, as financial information in annual reports, advertising of financial products, etc. is often presented in using graphs or tables and on many occasions this information is presented along with human figures displaying a positive mood. Thus, investigating the effects of different types of information presentation, with and without human figures that are congruent or incongruent with the financial information is important if one is to understand the effectiveness of such marketing tactics in the real world.

Chapter 7 showed us that the experimental manipulation of Trend worked as intended, with the positive trend eliciting higher ratings than the negative trend. We found that this trend effect was qualified by the format in which the information was presented. When the financial information was presented without an accompanying human figure, graphs generated more extreme ratings (more positive in the positive trend, and more negative in the negative trend) than tables. This, in itself, is an interesting finding, as it may have practical applications. For instance, a marketer wanting to emphasize the positive results of her company might want to present financial information in the form of a graph instead of in the form of a table. In contrast, to lessen the negative reaction to an annual report containing bad financial results, its author might want to present such information in the form of a table. This enhanced effect of graphs over tables in generating more extreme judgments might be due to the immediacy with which a graph displays a positive or negative impression. Whereas the interpretation of the table would require a more careful analysis, therefore prompting the act of System 2, the interpretation of a graph might rely more on System 1. The explanation of a more direct affective hit was consistent with the finding that the variance in the scores of attractiveness given by participants in the graph condition were significantly higher than those in the table condition. This could indicate that, whereas in the table condition individuals were more careful in providing attractiveness ratings due to a more deliberative process instilled by the table, the more direct hit of affect provided by the graphs created more variability, causing some individuals to have more extreme reactions. Analyzing whether object and spatial visualizers differed in the variance displayed when rating attractiveness of a financial scenario based on tables or graphs, we found that the group of object visualizers showed less variability in their ratings than the group of spatial visualizers. This was true for both the table and the graph conditions (in the table condition this effect was statistically significant). Building on the explanation of a direct affective hit generating more variability in ratings, it could be argued that spatial visualizers might experience a stronger affective hit than object visualizers, both in the table and in the graph condition. This might be caused by the spatial visualizers drawing stronger affective meaning from either form of numerical information presentation.

Further analyses in Chapter 7 focused on whether the addition of congruent or incongruent pictures to a financial scenario would affect the ratings of attractiveness given to the financial performance and, specifically, whether visualization affected these judgments. The analyses discovered that the addition of an incongruent picture does not make any difference in individuals' rating of the attractiveness of the financial scenario. In contrast, when a congruent picture is added to the financial scenario, ratings in the positive trend are magnified and in the negative trend lowered (though in the negative trend this effect does not attain statistical significance). The statistically significant effect of the congruent picture magnifying ratings in the positive trend was further analyzed to see whether this effect was present in all visualizer groups. Of the four groups, the Undefined showed the aforementioned magnifying effect in the table condition, whereas in the graph condition it was the ObjectSpatial group for which this effect was statistically significant. It seems then that in the Table condition, low object and spatial visualization affects the ratings of attractiveness when a congruent human figure is added to a positive trend. In contrast, in the graph condition, high object and spatial visualization gives rise to the magnifying effect.

In summary, the findings of this thesis strongly point to a positive relationship between numeracy and spatial visualization. Furthermore, we have seen that in performance-based tasks, spatial visualization is an equally valid predictor as numeracy, and on occasions (e.g. Jelly Bean task) even better. This key contribution to the area of numeracy and Decision-Making has numerous implications. On the basis that spatial visualization could be a similar type of predictor as numeracy, spatial visualization could be used in further studies to substitute numeracy as the predictor variable of interest. As we have argued in the literature review, an individual's unique visualization style consists of a cognitive style. A cognitive style, being a stable individual trait, might constitute a more reliable predictor of behaviour in Decision-Making tasks. This would be particularly true in situations where the numeracy of an individual might be heavily affected by factors beyond the control of the individual herself. For instance, the numeracy level of populations who have not undergone schooling might not have much impact on predictions related to Decision-Making. In such a case, visualization style might be a better tool to use as a predictor of behaviour.

In terms of immediate contributions to the body of knowledge in publishable format, these results also have clear potential. First of all, the comprehensive literature review on numeracy and decision-making and their relationship with visualization style would make a solid theoretical contribution to the body of knowledge addressing these areas. In addition, the specific empirical demonstration of such results would constitute a potential second publishable project. Thirdly, the results on the different impression-making properties of graphs and tables would make a substantial contribution to the literature.

In addition to the immediately available potential for publication, there is a pipeline of potential research opportunities that stem from this thesis. For instance, having established the relationship between visualization style and numeracy, further research could delve into the implications of visualization and decision-making. In particular, starting from the current OSIVQ, a shorter, easier to administer visualization style questionnaire could be developed. In addition, such a questionnaire could be refined in order to enhance its predictive power in the same way as the former numeracy scales with the development of the ANS.

This research, despite its solid results and interesting findings, also has some limitations. Like much academic research in the area of decision-making, the data collected for the studies comes from a population of university students. This fact means that we should be cautious in affirming that these results can be extrapolated to the general population. However, in establishing the basic relationship between visualization style and numeracy, this study used a varied sample of students from diverse academic specializations, producing results which were in principle consistent with the original OSIVQ results in pointing to a relationship between Numeracy and visualization style. Since the OSIVQ was developed using a general population sample, and our results are in line with what could be hypothesized from this general population sample, this hints at the likelihood that the results found here could indeed be extrapolated to the general population. In any event, validating the current results in a different, a more diverse sample representing the general population would be a natural extension of the current research which would solidify and further contribute to the body of knowledge.

A second point which warrants caution in the interpretation of the current results is the between-subjects methodology used in the experimental section of this thesis. For instance, comparing two groups of high spatial visualizers shown a graph versus a table might not detect differences that a within-subjects methodology would. As research demonstrates, joint and separate evaluations do elicit different results. However useful it might be to use a within-subjects methodology, the risk of research participants discovering the experimental manipulations might advise the use of a between-subjects methodology.

One further limitation is the impossibility to establish a causal relationship between spatial visualization and numeracy. Although we argue that Visualization, particularly Spatial visualization, might be positively correlated with Numeracy, we cannot argue that high Spatial visualization causes enhanced numeracy. In fact, both high Spatial visualization and high Numeracy might be the end result of the same process and not necessarily one causing each other. For instance, it might be that higher levels of fractional anisotropy facilitating the transfer of information in the parietal lobes, which are vital for mathematical as well as spatial information processing, is the underlying mechanism whereby both mathematical and spatial abilities are affected. The establishment of a relation of causality between Visualization and Numeracy, however, is a vast undertaking in itself that, although interesting, is of a scope that is well beyond this current thesis, requiring technical means, techniques and expertise in areas such as neuroimaging that exceed the latitude of this thesis.

Again, this project´s focus is to take the very basic step of uncovering the relationship between visualization and numeracy, and then investigate whether visualization´s components (object and spatial) have a similar effect on decision making. If such a relationship exists, it might be interesting to use neuroimaging techniques to investigate in future research the relationship between visualization and spatial and object visualization so a more elaborate model examining moderating or mediating relationships could be put forward. Also, further research could further expand the findings of this thesis by using different methodology, for instance by experimentally manipulating the level of numeracy. For example, by exposing individuals to mathematical training and testing their responses before and after the training, it could be possible to distinguish to what extent decision making is affected by an innate trait (visualization cognitive style) or by an acquired one (numeracy). Further studies could even investigate whether subjecting individuals to spatial or object visualization training might impact their preferred mode of visualization, and whether that would affect numeracy and/or decision making. An additional line of investigation that is worth mentioning to expand and elaborate on this thesis would be to uncover whether a cognitive style evolves during a person´s lifespan. Extant literature on cognitive styles could benefit from such a study, as the assumption of cognitive styles being permanent vs. being modifiable is not addressed in the literature. Similarly, defining the concepts of cognitive style, cognitive strategies, and abilities and the interplay of them would be illuminating.

Finally, another line of potential further research identified would be about uncovering the predictive nature of numeracy or spatial visualization depending on the nature of the task: performance vs. evaluative tasks.

Despite the aforementioned limitations, this research has produced various interesting findings to enrich the area of individual differences in decision-making. Furthering this project with the outlined agenda would greatly enhance the knowledge in the area of cognitive styles and decision making.

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# List of Abbreviations

ANCOVA – Analysis of Covariance

ANOVA – Analysis of Variance

ANS – Abbreviated Numeracy Scale

BNT – Berlin Numeracy Test

CRT -Cognitive Reflection Test

CFA – Confirmatory Factor Analyses

DRENS – Decision Research Expanded Numeracy Scale

DV – Dependent Variable

FA – Fractional Anisotropy

FFA – Face Fusiform Area

IPS – Intraparietal Sulcus

IV – Independent Variable

OSIQ – Object-Spatial Imagery Questionnaire

OSIVQ – Object-Spatial Imagery and Verbal Questionnaire

SD – Standard Deviation

VVCSQ – Visualizer-Verbalizer Cognitive Style Questionnaire

PFT – Paper Folding Test

WRAT-3 – Wide Range Achievement Test, Third Edition

# Appendix A

# Different Nomenclature of Object and Spatial Visualization

**Table Appendix A.1.** Different nomenclature of types of visualization

| Source | Term | Definition |
|---|---|---|
| Blajenkova, Kozhevnikov, and Motes (2006) | Object Imagery | Object imagery refers to representations of the literal appearances of individual objects in terms of their precise form, size, shape, colour and brightness, representing and processing colorful, pictorial, and high-resolution images of individual objects. |
| | Spatial Imagery | Spatial imagery refers to relatively abstract representations of the spatial relations between objects, parts of objects, locations of objects in space, movements of objects and object parts and other complex spatial transformations, representing and processing schematic images, spatial relations between objects, and spatial transformations. |

**Table Appendix A.1 Cont.** Different nomenclature of types of visualization

| | | |
|---|---|---|
| Hegarty & Kozhevnikov (1999) | Visual Imagery | Refers to a representation of the visual appearance of an object, such as its shape, color, or brightness. |
| | Spatial Imagery | Spatial imagery refers to a representation of the  partial relationships between parts of an object and the location of objects in space or their movement |
| Kozhevnikov, Hegarty & Mayer (2002) | Visual Imagery | Visual imagery refers to a representation of the visual appearance of an object, such as its shape, size, color, or brightness. |
| | Spatial Imagery | Spatial imagery refers to a representation of the spatial relations between parts of an object, the location of objects in space, and their movements, and is not limited to the visual modality (i.e., one could have an auditory or tactile spatial image) |
| | Iconic Visualizers | Construct vivid, concrete, and detailed images of individual objects in a situation. |
| | Spatial Visualizers | Create images that represent the spatial relations between objects that facilitate the imagination of spatial transformations such as mental rotation |

**Table Appendix A.1. Cont.** Different nomenclature of types of visualization

| | | |
|---|---|---|
| Van Garderen & Montague (2003) | Pictorial Representation | Representations that encode persons, places, or things described in the problem. |
| | Schematic Representation | Representations that encode the spatial relations described in the problem |
| Presmeg (1986b, 2006a) | Concrete Imagery | Pictures in the mind. |
| | Pattern imagery | Representation of the arrangements of objects on a plane. Pure relationships striped of concrete details |
| | Dynamic imagery | The image is moved or transformed |

# Appendix B

**Table Appendix B.1.** Descriptions of tests used by Kozhevnikov, Hegarty and Mayer (2002, p. 52)

| Test | | Description |
|---|---|---|
| Spatial Relations Tests | Card Rotation Test | Consisting of 10 questions which ask participants to observe a two-dimensional image and choose from five possible answers which one represents the planar rotation of the source image. Answers are assessed in terms of accuracy and reaction times. The internal reliability of the test is .80. |
| | Cube Comparison Test | Consisting of 21 questions, each of which shows the image of two cubes whose sides depict numbers and letters. The task consists of judging whether the two images could represent the cube seen from different perspectives. The internal reliability of the test is .84. |
| Spatial Visualization Tests | Paper Folding Test | Consisting of 10 questions, each depicting an image of a piece of square paper folded twice or three times, with the last fold depicting a hole through the folded surfaces. Participants are asked to choose from five images which one would show the folded paper when unfolded and opened. The internal reliability of the test is .84. |
| | Form Board Test | Consisting of 24 questions, each presenting a series of pieces, some of which could be assembled to form an image presented in a sketch. Participants are to decide which shapes, when put together, can form the sketched image. The internal reliability of the test is .81 |

**Table Appendix B.1. Cont.** Descriptions of tests used by Kozhevnikov, Hegarty and Mayer (2002, p. 52)

| | |
|---|---|
| Advanced Vocabulary Test | Consisting of 18 questions, each of them testing the "availability and flexibility in the use of multiple meanings of words" (Ekstrom et al., 1976, p. 163). Each question shows five words, and participants are asked to indicate which words have the closest meaning to the word shown. The internal reliability of the test is .83. |
| Visualizer-Verbalizer Cognitive Style Questionnaire | Consisting of two parts, intended to measure the extent to which participants prefer to use imagery or verbal-logical strategies when solving mathematical problems. The first part shows five problems which can be solved by either imagery or verbal-analytical strategies. The second part asked participants about their problem solving strategies and answers were coded as visual, verbal-logical, or combined. The internal reliability of the test is .080. |
| Vividness of Visual Imagery Questionnaire | Consisting of 16 questions, this test measures the degree of vividness with which individuals mentally re-enact images. Individuals are asked to mentally recreate images of statements (e.g. “the sun is rising above the horizon into a hazy sky”, Kozhevnikov, Kosslyn & Shephard, 2005, p.712), and report, on a 1-5 scale how vivid these imagined representations are. The internal reliability of the test is .88. |

**Table Appendix B.1.** Descriptions of tests used by Kozhevnikov, Hegarty and Mayer (2002, p. 52)

| | |
|---|---|
| Shepard and Metzler Mental Rotation Task | Consisting of 109 computer-administered questions, individuals are presented with two two-dimensional figures of three dimensional angular forms which are rotated 0º to 180º. Individuals have to decide whether the two paired images represent a rotated image of the three dimensional form or are a mirror image of it. The internal reliability of the test is .88.. |
| Degraded Pictures Task. | Consisting of 10 questions, this test was adapted from Ekstrom et al's. (1976) "Show Pictures Test", and showed participants on a computer screen a "snowed over" image of an object whose contours participants had to guess to work out what the object was. The internal reliability of the test is .73. |
| Grain Resolution Task | Consisting of 20 questions, this computer-administered test showed participants two words indicating objects on a screen. Participants had to correctly decide which of the paired objects (though only their names appeared, instead of the actual objects) had a denser grain (units per volume). The internal reliability of the test was .62. |

# Appendix C

# Numeracy Scales

**Table Appendix C.** Descriptions of existing numeracy scales

| Study | Items in scale |
|---|---|
| Black, et al., 1995 | **1-** Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)?<br>Answer:________ |
| Schwartz, et al., 1997 | Previous item, plus:<br><br>**2-** In the Big Bucks Lottery, the chances of winning a $10 prize are 1%. What is your best guess about how many people would win a $10 prize if 1,000 people each buy a single ticket from Big Bucks?<br>Answer: _______ people<br><br>**3-** In the Acme Publishing Sweepstakes, the chance of winning a car is 1 in 1,000. What percentage of tickets of Acme Publishing Sweepstakes wins a car?<br>Answer: _______ % |

**Table Appendix C (cont.)** Descriptions of existing numeracy scales

| Study | Items in scale |
|---|---|
| Lipkus, et al., 2001<br><br>Name of scale:<br><br>LIPKUS | Previous items, plus:<br><br>**4-** Which of the following numbers represents the biggest risk of getting a disease?<br><br>__ 1 in 100 __ 1 in 1000 __ 1 in 10<br><br>**5-** Which of the following numbers represents the biggest risk of getting a disease? (1%, 10%, or 5%)<br><br>__ 1% __ 10% __ 5%<br><br>**6-** If Person A's risk of getting a disease is 1% in 10 years, and Person B's risk is double that of A's, what is B's risk?<br><br>Answer: ________ % in ________ years<br><br>**7-** If Person A's chance of getting a disease is 1 in 100 in 10 years, and person B's risk is double that of A, what is B's risk?<br><br>Answer:________ in ______ years<br><br>**8-** If the chance of getting a disease is 10%, how many people would be expected to get the disease:<br><br>Out of 100? Answer:________ people<br><br>Out of 1000? Answer:________ people<br><br>**9-** If the chance of getting a disease is 20 out of 100, this would be the same as having a _____% chance of getting the disease.<br><br>**10-** The chance of getting a viral infection is .0005. Out of 10,000 people, about how many of them are expected to get infected?<br><br>Answer:________ people |

**Table Appendix C (cont.)** Descriptions of existing numeracy scales

Peters, et al., 2007

Name of scale:

DRENS

Previous items, plus:

**11-** Which of the following numbers represents the biggest risk of getting a disease?

___1 chance in 12 ___1 chance in 37

**12-** Suppose you have a close friend who has a lump in her breast and must have a mammogram. Of 100 women like her, 10 of them actually have a malignant tumor and 90 of them do not. Of the 10 women who actually have a tumor, the mammogram indicates correctly that 9 of them have a tumor and indicates incorrectly that 1 of them does not. Of the 90 women who do not have a tumor, the mammogram indicates correctly that 81 of them do not have a tumor and indicates incorrectly that 9 of them do have a tumor. The table below summarizes all of this information. Imagine that your friend tests positive (as if she had a tumor), what is the likelihood that she actually has a tumor?

| | Tested Positive | Tested Negative | Total |
|---|---|---|---|
| Actually has a tumor | 9 | 1 | 10 |
| Does not have a tumor | 9 | 81 | 90 |
| Totals | 18 | 82 | 100 |


| | Tested Positive | Tested Negative | Total |
|---|---|---|---|
| Actually has a tumor | 9 | 1 | 10 |
| Does not have a tumor | 9 | 81 | 90 |
| Totals | 18 | 82 | 100 |


Answer: ________

**13-** Imagine that you are taking a class and your chances of being asked a question in class are 1% during the first week of class and double each week thereafter (i.e., you would have a 2% chance in Week 2, a 4% chance in Week 3, an 8% chance in Week 4). What is the probability that you will be asked a question in class during Week 7?

Answer: ________ %

**Table Appendix C (cont.)** Descriptions of existing numeracy scales

| | |
|---|---|
| Peters, et al., 2007<br><br>Name of scale:<br><br>DRENS | **14-** Suppose that 1 out of every 10,000 doctors in a certain region is infected with the SARS virus; in the same region, 20 out of every 100 people in a particular at-risk population also are infected with the virus. A test for the virus gives a positive result in 99% of those who are infected and in 1% of those who are not infected. A randomly selected doctor and a randomly selected person in the at-risk population in this region both test positive for the disease. Who is more likely to actually have the disease?<br>___They both tested positive for SARS and therefore are equally likely to have the disease<br>___They both tested positive for SARS and the doctor is more likely to have the disease<br>___They both tested positive for SARS and the person in the at-risk population is more likely to have the disease. |

**Table Appendix C (cont.)** Descriptions of existing numeracy scales

<table>
<tr><th>Study</th><th>Items in scale</th></tr>
<tr>
<td>Weller et al. 2012<br><br>Name of scale:<br><br>ANS</td>
<td>
Abbreviated Numeracy Scale (ANS). Developed from a combination of all previous scales + 2 CRT items<br><br>
1- Suppose you have a close friend who has a lump in her breast and must have a mammogram. Of 100 women like her, 10 of them actually have a malignant tumor and 90 of them do not. Of the 10 women who actually have a tumor, the mammogram indicates correctly that 9 of them have a tumor and indicates incorrectly that 1 of them does not. Of the 90 women who do not have a tumor, the mammogram indicates correctly that 81 of them do not have a tumor and indicates incorrectly that 9 of them do have a tumor. The table below summarizes all of this information. Imagine that your friend tests positive (as if she had a tumor), what is the likelihood that she actually has a tumor?<br><br>
<table>
<tr><th></th><th>Tested Positive</th><th>Tested Negative</th><th>Total</th></tr>
<tr><td>Actually has a tumor</td><td>9</td><td>1</td><td>10</td></tr>
<tr><td>Does not have a tumor</td><td>9</td><td>81</td><td>90</td></tr>
<tr><td>Totals</td><td>18</td><td>82</td><td>100</td></tr>
</table>
<br>
<table>
<tr><th></th><th>Tested Positive</th><th>Tested Negative</th><th>Total</th></tr>
<tr><td>Actually has a tumor</td><td>9</td><td>1</td><td>10</td></tr>
<tr><td>Does not have a tumor</td><td>9</td><td>81</td><td>90</td></tr>
<tr><td>Totals</td><td>18</td><td>82</td><td>100</td></tr>
</table>
<br>
Answer: ________<br><br>
2- A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?<br><br>
Answer: ________<br><br>
3- In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?<br><br>
Answer: ________
</td>
</tr>
</table>

**Table Appendix C (cont.)** Descriptions of existing numeracy scales

| | |
|---|---|
| Weller et al. 2012<br><br>Name of scale:<br><br>ANS | **4-** In the Acme Publishing Sweepstakes, the chance of winning a car is 1 in 1,000. What percentage of tickets of Acme Publishing Sweepstakes wins a car?<br><br>Answer: ________ %<br><br>**5--** In the Big Bucks Lottery, the chances of winning a $10 prize are 1%. What is your best guess about how many people would win a $10 prize if 1,000 people each buy a single ticket from Big Bucks?<br><br>Answer: ________ people |

**Table Appendix C (cont.)** Descriptions of existing numeracy scales

| Study | Items in scale |
|---|---|
| Weller et al. 2012<br><br>Name of scale:<br><br>ANS | **6-** Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)?<br><br>Answer:________<br><br>**7-** If the chance of getting a disease is 20 out of 100, this would be the same as having a _____% chance of getting the disease.<br><br>**8-** If the chance of getting a disease is 10%, how many people would be expected to get the disease:<br><br>Out of 1000? Answer:________ people |
| Cokely et al. 2012<br><br>Name of scale:<br><br>BNT | Berlin Numeracy Test<br><br>1. Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a randomly drawn man is a member of the choir?<br><br>Please indicate the probability in percent. ____<br><br>2a. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?<br><br>____ out of 50 throws.<br><br>2b. Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6? ______<br><br>3. In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?<br><br>_____ |

# Appendix D

## Task 1 Chapter 5 (positive trend version)

**TAREA 1**

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

La tabla a continuación muestra los resultados de una compañía basada en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves en la siguiente tabla.

| **Año** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
|---|---|---|---|---|---|---|---|---|
| **Beneficios (€ 000)** | *2800* | *3010* | *3150* | *3430* | *3570* | *3850* | *3990* | *4200* |

Basándote en la información dada, **¿Cómo evaluarías los resultados de esta compañía?**

Por favor, indica tu respuesta:

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|

Muy malos..........................................................................................Muy buenos

**FINAL DE LA TAREA**

SGPHS5V1

**PASA PÁGINA PARA LA SIGUIENTE TAREA**

# Appendix E

# Task 2 Chapter 5

**TAREA 2**

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

La tabla a continuación muestra los resultados de dos compañías basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves en la siguiente tabla.

| Año | | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|---|
| Beneficios (€ 000) | Compañía A | *1498* | *1872* | *2527* | *3672* | *4677* | *8286* | *16325* | *32969* |
| | Compañía B | *1500* | *6250* | *10302* | *16290* | *20995* | *26240* | *32306* | *36200* |

Basándote en la tabla anterior, **si la tendencia para cada compañía continúa, ¿Qué compañía tendrá mayores beneficios en 2012?**

| **Señala tu respuesta:** | |
|---|---|
| **Compañía A** | **Compañía B** |
| **¿Qué nivel de certeza tienes sobre la respuesta previa?** | |
| **Ninguna certeza..........................................................................................Mucha certeza** | |
| **0 1 2 3 4 5 6 7 8 9 10** | |

SGPHS5V1

**PASA LA PÁGINA PARA CONTINUAR LA TAREA**

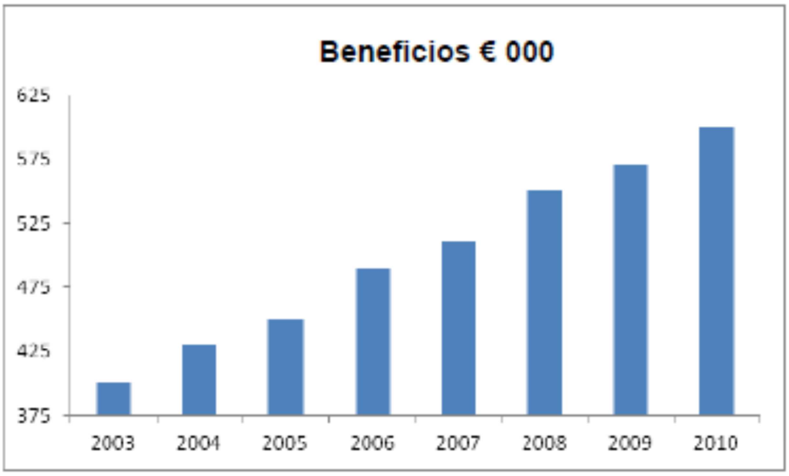
# Appendix F

## Task 3 Chapter 5 (Positive Trend/Distorted)

**TAREA 3**

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

El gráfico a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves en el siguiente gráfico. Basándote en la información dada, **¿Cómo evaluarías los resultados de esta compañía?**




**Muy Malos.....................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €______________**

**FINAL DE LA TAREA**

SGPHS5V1

**PASA PÁGINA PARA LA SIGUIENTE TAREA**

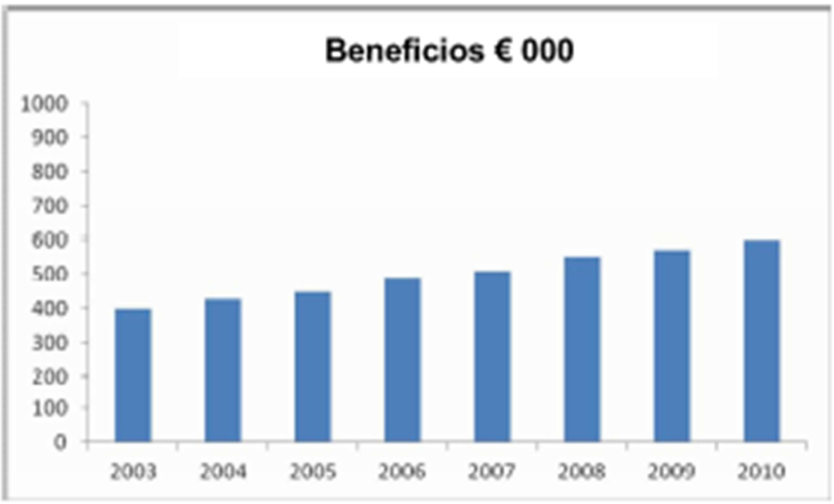
# Appendix F Cont.

## Task 3 Chapter 5 (Positive Trend/Undistorted)

**TAREA 3**

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

El gráfico a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves en el siguiente gráfico. Basándote en la información dada, **¿Cómo evaluarías los resultados de esta compañía?**




**Muy Malos**.............................................................................................................**Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €______________**

**FINAL DE LA TAREA**

SGPHS5V2

**PASA PÁGINA PARA LA SIGUIENTE TAREA**

# Appendix G

## Task 4 Chapter 5 (Positive Trend)

**TAREA 4**

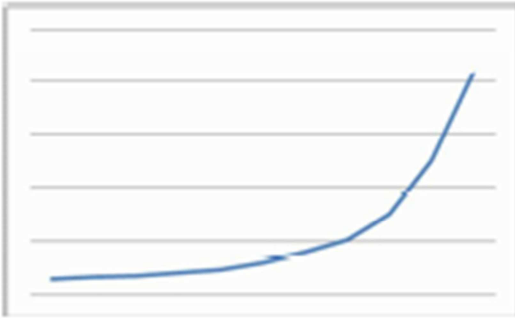
Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

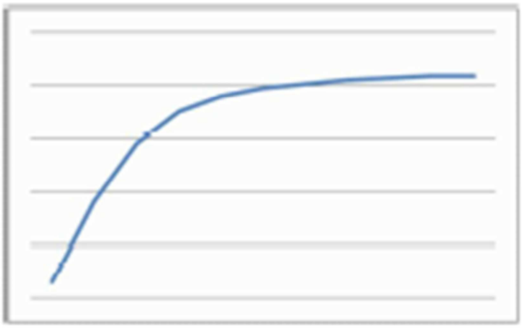
Por favor, considera la tabla a continuación e indica cuál de los gráficos representa mejor los datos mostrados en la tabla.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *145* | *350* | *545* | *752* | *950* | *1148* | *1353* | *1500* | *1702* | *1899* | *2100* |

A

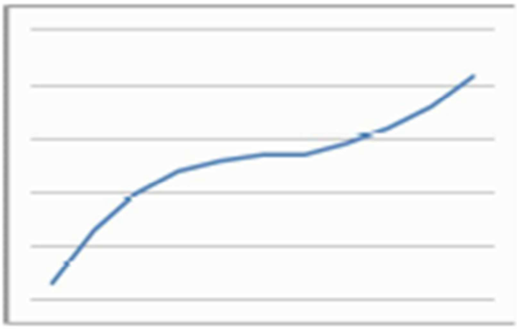
B





C

D



**¿Cuál de los cuatro gráficos se corresponde con la tabla mostrada?**

**A** **B** **C** **D**

**¿Qué nivel de certeza tienes sobre la respuesta previa?**

**Ninguna certeza.................................................................................................Mucha certeza**

**0 1 2 3 4 5 6 7 8 9 10**

**FINAL DE LA TAREA**

SGPHS5V2

**PASA PÁGINA PARA LA SIGUIENTE TAREA**

## Appendix G Cont.

## Task 4 Chapter 5 (Negative Trend)

**TAREA 4**

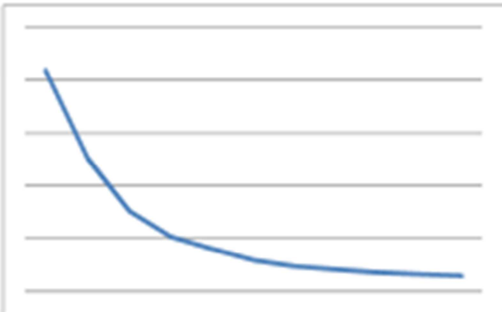
Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

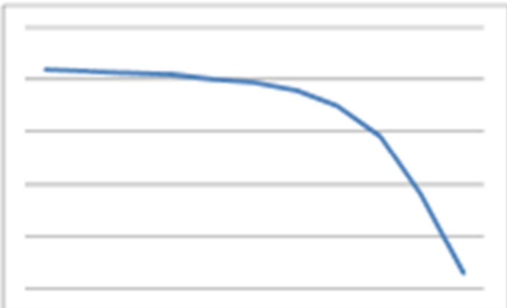
Por favor, considera la tabla a continuación e indica cuál de los gráficos representa mejor los datos mostrados en la tabla.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *2090* | *1254* | *760* | *520* | *400* | *300* | *235* | *205* | *175* | *165* | *150* |

A

B





C

D

¿Cuál de los cuatro gráficos se corresponde con la tabla mostrada?

A B C D

¿Qué nivel de certeza tienes sobre la respuesta previa?

Ninguna certeza.......................................................................................................Mucha certeza

0 1 2 3 4 5 6 7 8 9 10

**FINAL DE LA TAREA**

SGPHS5V16

**PASA PÁGINA PARA LA SIGUIENTE TAREA**

# Appendix H

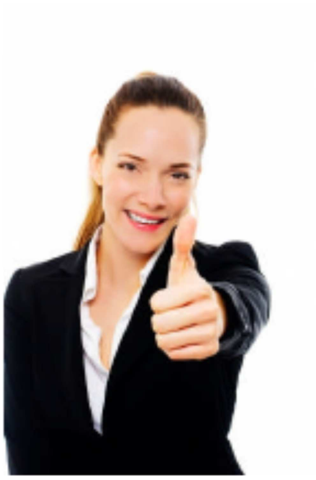
## Chapter 7 Tasks (Table Positive Trend / Positive Face)

**TAREA 3**

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

La información a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.

| Año | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|
| Beneficios (€ 000) | *400* | *430* | *450* | *490* | *510* | *550* | *570* | *600* |



Basándote en la información dada, ¿Cómo evaluarías los resultados de esta compañía?

**Muy Malos.......................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €______________**

SGPHS7V2

**PASA PÁGINA PARA CONTINUAR LA TAREA**

# Appendix H Cont.

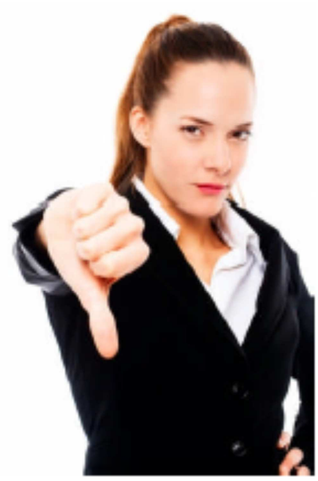
## Chapter 7 Tasks (Table Positive Trend / Negative Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

La información a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.

| Año | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|
| Beneficios (€ 000) | *400* | *430* | *450* | *490* | *510* | *550* | *570* | *600* |



Basándote en la información dada, ¿Cómo evaluarías los resultados de esta compañía?

**Muy Malos.........................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €_______________**

SGPHS7V3

**PASA PÁGINA PARA CONTINUAR LA TAREA**

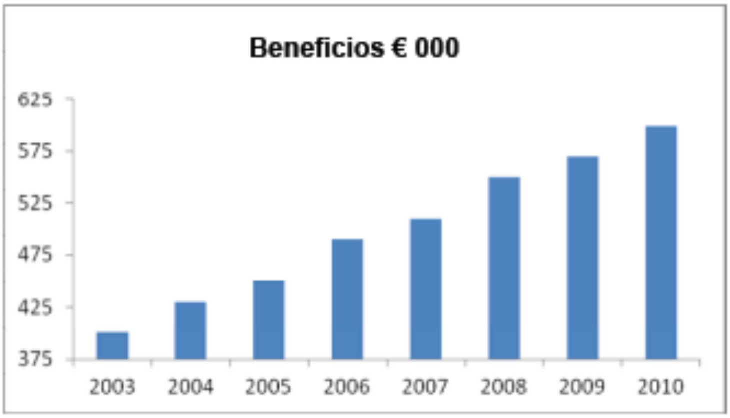
# Appendix H Cont.

## Chapter 7 Tasks (Graph Positive Trend / Positive Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

**La información a continuación muestra los resultados de una compañía basados en los beneficios** netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.




Basándote en la información dada, **¿Cómo evaluarías los resultados de esta compañía?**

**Muy Malos.......................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €_______________**

SGPHS7V5

**PASA PÁGINA PARA CONTINUAR LA TAREA**

# Appendix H Cont.

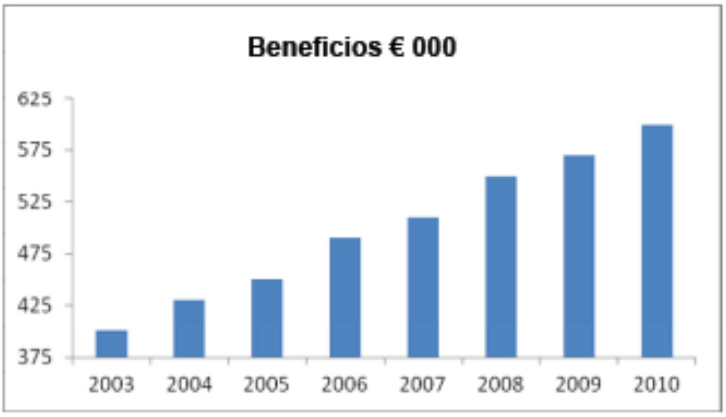
## Chapter 7 Tasks (Graph Positive Trend / Negative Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

**La información a continuación muestra los resultados de una compañía basados en los beneficios**

netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.




Basándote en la información dada, **¿Cómo evaluarías los resultados de esta compañía?**

**Muy Malos.........................................................................................................................Muy Buenos**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €_______________**

SGPHS7V6

**PASA PÁGINA PARA CONTINUAR LA TAREA**

# Appendix H Cont.

## Chapter 7 Tasks (Table Negative Trend / Positive Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

La información a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.

| Año | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|
| Beneficios (€ 000) | *600* | *570* | *550* | *510* | *490* | *450* | *430* | *400* |

Basándote en la información dada, ¿Cómo evaluarías los resultados de esta compañía?

**Muy Malos.................................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €______________**

SGPHS7V8

**PASA PÁGINA PARA CONTINUAR LA TAREA**

# Appendix H Cont.

## Chapter 7 Tasks (Table Negative Trend / Negative Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

La información a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.

| Año | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|
| Beneficios (€ 000) | *600* | *570* | *550* | *510* | *490* | *450* | *430* | *400* |

Basándote en la información dada, ¿Cómo evaluarías los resultados de esta compañía?

**Muy Malos.....................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €______________**

SGPHS7V9

**PASA PÁGINA PARA CONTINUAR LA TAREA**

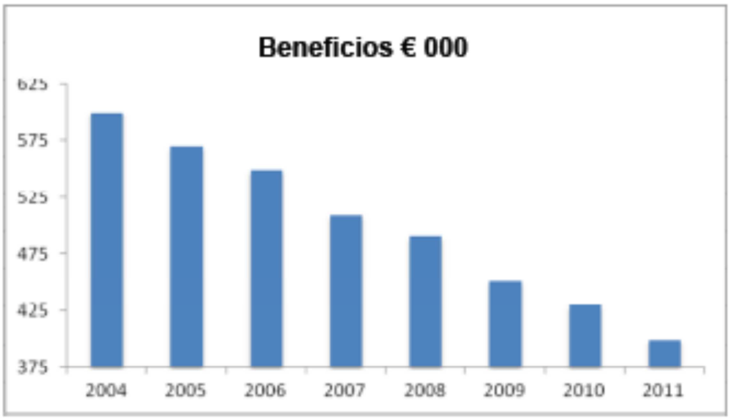
# Appendix H Cont.

## Chapter 7 Tasks (Graph Negative Trend / Positive Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

**La información a continuación muestra los resultados de una compañía basados en los beneficios** netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.




Basándote en la información dada, **¿Cómo evaluarías los resultados de esta compañía?**

**Muy Malos.........................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €________________**

SGPHS7V11

**PASA PÁGINA PARA CONTINUAR LA TAREA**

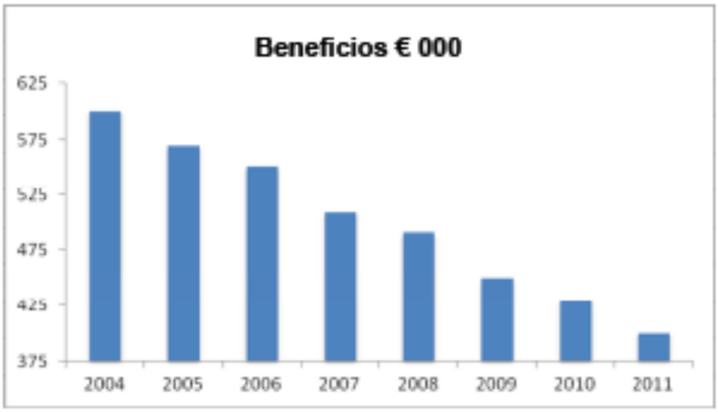
# Appendix H Cont.

## Chapter 7 Tasks (Graph Negative Trend / Negative Face)

TAREA 3

Por favor, responde las preguntas a continuación. Puedes hacer anotaciones en esta hoja si lo necesitas

**La información a continuación muestra los resultados de una compañía basados en los beneficios netos anuales. No tienes más información acerca de la compañía que la que ves a continuación.**




Basándote en la información dada, ¿Cómo evaluarías los resultados de esta compañía?

**Muy Malos..........................................................................................................Muy Buenos**

**0 1 2 3 4 5 6 7 8 9 10**

**Tienes € 1.000 que puedes invertir como desees.**

**¿Cuánto invertirías en la Compañía?**

**Invertiría €______________**

SGPHS7V12

**PASA PÁGINA PARA CONTINUAR LA TAREA**