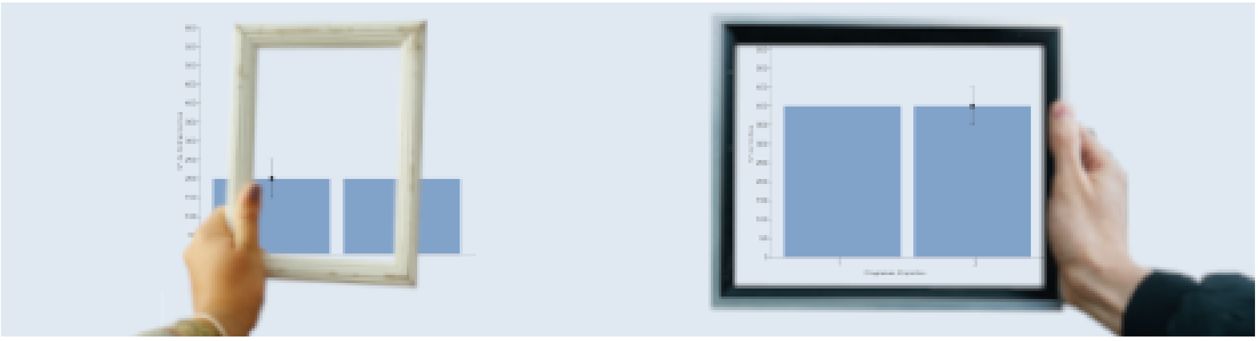


Framing Vis

The Effect of Personality on the Framing Bias in Information Visualization

Alexandra Santos Maroco

Thesis to obtain the Master of Science Degree in

Information Systems and Computer Engineering

Supervisors: Prof. Sandra Pereira Gama
Prof. Daniel Jorge Viegas Gonçalves

Examination Committee

Chairperson: Prof. Nuno Miguel Carvalho dos Santos
Supervisor: Prof. Sandra Pereira Gama
Member of the Committee: Dr. Catarina Alexandra Pinto Moreira

May 2022

Acknowledgments

First and foremost, I would like to acknowledge and thank my dissertation supervisors Prof. Daniel Gonçalves, Prof. Sandra Gama, and Tomás Alves for their insight, sharing of knowledge, and tremendous understanding throughout this project. Without your valuable advice, none of this would have been possible.

Thank you to Instituto Superior Técnico for bringing to my life the family I choose today as my own. Evans, for being the sister of another mother. Xavi, for being the big brother I did not have before. Palhas, for all the boops and trust we share. Bia, for teaching me to speak my truth. Ju, for teaching me that it is okay to live as deeply as we feel. Nádia, for guiding me through these years. Mia, for being a little sister and trusting me with anything. Inês, for inspiring me and confiding me to help. Alvoeiro, for all the laughs we share. Cris, for (re-)appearing out of the blue and helping me endure these last couple of years more lightly. Outside of IST, thank you to my girls squad, for always having my back.

A special thank you to Vi, for standing by my side through thick and thin, regardless of the season. For all the mutual and constant understanding, listening, support, caring and love we share and nurture. For this basecamp we create as a team. For growing together as we go. Home is not a place, is a person. Thank you for being my home.

To each one of you, thank you. Thank you for all the laughs, tears, support, trust, caring and memories we share. All the mutual listening ears and shoulders to lean on. Thank you for helping me grow as a person and for always being there for me during the good and bad times in my life. And thank you for trusting me to do the same. Family is not about blood. Is the people you choose. And I am both deeply proud and incredibly grateful to call you my family. I would not be where I am today without each and every one of you and I hope you know that.

I, likewise, want to thank my family, for supporting me and putting up with me through everything these five years brought along my way. Additionally, I would like to thank Helena and Vi's parents as they, too, have been incredible through these last two years with all the support they send my way.

To my two favourite little beans, Bead and Musi. Though life may have decided to take you unexpectedly and painfully before reaching this finish line, I will always carry with me all the love and care we share. Wherever I go, I bring you with me, in my heart. I would not be here today if not for you, too.

Abstract

Undergoing complex cognitive thinking under uncertainty, individuals' judgments and decisions might rely on unconscious individual heuristics. These tend to suffer systematic deviations from rationality, designated as cognitive biases. The framing effect is a cognitive bias, consisting of the alteration of preference or behaviour under different framings of the same information. Recent research in the information visualization field has tackled how human rationale limitations affect visualization-supported decision-making. However, there is such a small body of evidence that it offers little guidance to practitioners. This study explores the framing effect in an information visualization context by depicting the decision problem of Tversky and Kahneman with visual encodings. Additionally, it delves into the influence of neuroticism within such an effect. This personality trait reflects one's tendency to feel negative emotions. We conducted user tests ($N = 91$), collecting personality data alongside user interaction metrics and the decision-making process between a set of options under different framing contexts. Our findings suggest that visualization helps mitigate the framing effect for most of the experiment sample. Moreover, our results reveal a general lack of significance from the neuroticism trait in such an effect. We believe that developing cognitive bias-aware decision support systems is of utmost importance to leverage the full potential of information visualization and make it widely available to jobs where visualization-supported decisions are critical.

Keywords

Information Visualization; Cognitive Bias; Framing Effect; Personality Psychology; Neuroticism.

Resumo

Aquando um pensamento cognitivo complexo sob incerteza, os julgamentos e decisões dos indivíduos podem depender de heurísticas individuais e inconscientes. Estas tendem a sofrer desvios sistemáticos da racionalidade, designados como vieses cognitivos. O efeito de enquadramento é um viés cognitivo que consiste na alteração da preferência ou comportamento perante diferentes enquadramentos da mesma informação. Estudos recentes no campo da visualização da informação abordam como as limitações do raciocínio humano afetam a tomada de decisão apoiada na visualização. Porém, as evidências existentes são tão reduzidas que oferecem pouca orientação. Este estudo explora o efeito de enquadramento em contexto de visualização da informação, retratando o problema de decisão de Tversky e Kahneman com codificações visuais. Ademais, investiga a influência do neuroticismo nesse mesmo efeito. Este traço de personalidade reflete a tendência a sentir emoções negativas. Foram realizados testes de utilizador ($N = 91$) para recolher dados de personalidade junto com métricas de interação do utilizador e do processo de tomada de decisão entre um conjunto de opções em diferentes enquadramentos. As descobertas sugerem que a visualização ajuda a mitigar o efeito de enquadramento para a maior parte da amostra da experiência. Além disso, os nossos resultados revelam uma falta geral de significância do traço de neuroticismo em tal efeito. Acreditamos que o desenvolvimento de sistemas de apoio à decisão cientes de vieses cognitivos é de extrema importância para usufruir de todo o potencial da visualização da informação, tornando-a amplamente disponível a empregos onde as decisões apoiadas por visualização são críticas.

Palavras Chave

Visualização de Informação; Viés Cognitivos; Efeito de enquadramento; Psicologia da Personalidade; Neuroticismo.

Contents

1 Introduction **1**

1.1 Research Objective and Milestones . . . 3

1.2 Document Structure . . . 3

2 Background **5**

2.1 Fundamentals of Personality . . . 6

2.1.1 Neuroticism . . . 7

2.2 Framing Bias . . . 9

3 Related Work **13**

3.1 InfoVis and Personality . . . 14

3.2 Framing Bias and InfoVis . . . 19

3.2.1 Taxonomies and Frameworks . . . 20

3.2.2 Human-Centered Computing . . . 24

3.3 Personality and Framing Bias . . . 27

3.4 Discussion . . . 29

4 Methodology **30**

4.1 Framing Strategy . . . 35

4.2 Measures . . . 36

4.2.1 Independent Study Variables . . . 36

4.2.2 User Interaction . . . 36

4.2.3 Decision-Making . . . 37

4.3 Research Questions and Hypotheses . . . 37

4.4 Statistical Analysis Methods . . . 39

4.4.1 Outliers Removal Criteria . . . 40

4.4.2 Two-Way Repeated Measures ANOVA . . . 41

4.4.3 Two-Way Mixed ANOVA . . . 41

4.4.4 One-Way Repeated Measures ANOVA . . . 42

4.4.5 McNemar's Test . . . 43

4.4.6 Three-Way (BWW) Mixed ANOVA . . . 43
4.4.7 Chi-Square Test of Independence . . . 44
4.5 Data Collection . . . 44
4.5.1 Participants . . . 45
4.5.2 Apparatus . . . 45
4.5.2.A Personality Data . . . 47
4.5.2.B Measures of the Study . . . 47
4.5.3 Procedure . . . 48
4.6 Data Analysis . . . 49
5 Results **52**
5.1 Effect of Framing . . . 53
5.1.1 User Interaction . . . 53
5.1.1.A Number of Hover Events . . . 53
5.1.1.B Decision Completion Time . . . 56
5.1.2 Decision Making . . . 57
5.1.2.A Choice . . . 57
5.1.2.B Perceived Risk . . . 57
5.2 Effect of Neuroticism . . . 58
5.2.1 User Interaction . . . 59
5.2.1.A Number of Hover Events . . . 59
5.2.1.B Decision Completion Time . . . 61
5.2.2 Decision-Making . . . 62
5.2.2.A Choice . . . 62
5.2.2.B Perceived Risk . . . 63
5.3 Neutral Condition . . . 64
5.4 Discussion . . . 66
5.4.1 Answering the Research Questions . . . 66
5.4.2 Experimental Implications . . . 69
6 Conclusion **71**
6.1 Limitations and Future Work . . . 73
A Informed Consent Document **86**
B Experiment Questionnaire **90**

List of Figures

2.1 Negative (left) and positive (right) framing of the same information. 10

3.1 Interface from the work of Brown et al. [1]: (a) shows Waldo hiding among trees; (b) and (c) show distractors, to increase the task's difficulty. 15
3.2 NCBI MapViewer Interface. 16
3.3 GVis Interface. 16
3.4 Interface layouts used by Ziemkiewicz et al. [2]. V1 (list-like) to V4 (containment metaphor), from left to right. 17
3.5 Ziemkiewicz et al. [2] results regarding the participants' neuroticism scores. 18
3.6 Sarsam and Al-Samarraie [3] UI design for the two personality groups. 19
3.7 Layered closed-loop perception, action, and choice model. Since no hard boundaries exist between layers, cross-talk is part of the closed loop model (see exemplary dashed arrows) [4]. 22
3.8 The taxonomy developed by Dimara et al. [5]. Each dot is a cognitive bias. 23
3.9 Cognitive biases result in behavioral indicators that are measurable by the proposed metrics. There are numerous other biases, these are the ones included in the scope of the work of Wall et al. [6]. 24
3.10 The visualization conditions used in the study by Bancilhon et al. [7]. 26
3.11 The example lottery sheet used in the study, with a different visualization and reward prize. Participants only needed to select the row where they switched either decision, as the system automatically populated the remaining radio buttons [7]. 27

4.1 The two main framing conditions - *positive* and *negative* - from our study. The order between these two study conditions was alternated from subject to subject. For each condition, the placement of risk was, likewise, arbitrary. 33
4.2 The *neutral* framing condition of our study, where participants would be presented with all four options simultaneously and asked to decide on a single one. 34

4.3 Frequencies of self-reported general willingness to take risks. 46
4.4 Frequencies of familiarity with the visualizations of the study. 46
4.5 Distribution of two levels of neuroticism classification per facet, according to the Portuguese Norm. 51
4.6 Distribution of three levels of neuroticism classification per facet, according to the Portuguese Norm. 51

5.1 Estimated marginal means of the number of hover events triggered in each option across the two main conditions - *positive* and *negative* framings. 54
5.2 Estimated marginal means of the number of hover events triggered in each option across the two possible choices for each of the two main framing conditions of the study. 55
5.3 Estimated marginal means of time taken to make a choice in each of the two main conditions - *positive* and *negative* framings. 56
5.4 Estimated marginal means of perceived risk of choice taken for each of the two main conditions - *positive* and *negative* framings. 58
5.5 Estimated marginal means of the number of hover events triggered in each option across the neuroticism levels of participants for each of the two main framing conditions of the study. 59
5.6 Estimated marginal means of time taken to make a choice in each of the two main conditions - *positive* and *negative* - per neuroticism level group. 62
5.7 Estimated marginal means of perceived risk of choice taken for each of the two main conditions - *positive* and *negative* - for each neuroticism level group. 64

List of Tables

2.1 Three Factor Model: N-Dimension Traits [8]. 8
2.2 Five Factor Model (FFM): Neuroticism Facets [9]. 9
2.3 The four broader groups identified by Beratšová et al. [10]. 11

3.1 Green and Fisher [11] summary of findings. 16

4.1 Tversky and Kahneman original problem [12]. 31
4.2 Framing conditions and respective options of our study. 32
4.3 Variables measured in this study. 36
4.4 Research Questions and Hypotheses with the variables used as well as the respective statistical methods used for the *positive* and *negative* framing conditions of the study. . . . 40
4.5 Neuroticism Level classification by two levels. 50
4.6 Neuroticism Level classification by three levels. 50

5.1 Number of participants who chose each option, at each framing condition. 57
5.2 Chi-Square Test of Independence crosstabulation. In brackets are the expected count values for each cell. 63
5.3 Number of Participants who chose each option, at the neutral framing condition. 65
5.4 Comparison of the perceived risk of the same choice, for participants whose choice held for the *neutral* framing condition. If the one reported for said condition was higher, equal or lower to the one assigned previously to the same choice. 66
5.5 Number of participants and their choices, according to the neuroticism level. 67

Acronyms

FFM	Five Factor Model
NEO PI-R	NEO Personality Inventory-Revised
InfoVis	Information Visualization
ANOVA	Analysis of Variance
SRE	Studentized Residual

1

Introduction

Contents

1.1 Research Objective and Milestones 3
1.2 Document Structure 3

Notwithstanding striving to do so, humans have too limited cognitive abilities and are, hence, unable to truly make rational decisions without said limitations influencing the decision-making process. [13]. Ergo, humankind is forced to rely on *heuristics*. A *heuristic* consists of a mental strategy our brain forms to simplify all the information around us, where merely the parts each individual deems relevant to the situation or decision at hand are considered. While aiding us, said heuristics may also lead to systematic deviations from rationality in judgment, designated by Tversky and Kahneman [14, 15] as *cognitive biases*. Such deviations manifest in distinct ways, which led to the discovery of a broad variety of cognitive biases [5].

Research has shown cognitive limitations by exposing participants to a text narrative before seeing a visualization [16] or the position of data instances [17]. Moreover, some have attempted to begin to understand the impact of visualization in decision-making, such as Bancilhon et al. [7]. There has been a clear promising increased interest in cognitive biases [6, 18] and decision-making [19, 20] within the Information Visualization (InfoVis) community, but such an intersection of fields remains substantially unexplored nevertheless. In point of fact, there is only quite sparse research on said subject [5] and the existing petite number of studies leveraging cognitive biases in visualization leaves little empirical data to provide robust guidelines for practitioners.

We decided to focus our research on the *framing effect*. The **framing bias** is a cognitive bias where the *framing* of information leads to a deviation from a rational choice, i.e., there is a variation of outcomes in the decision-making process due to how information is presented. Therefore, the reference point used to evaluate the consequences of a decision is the key element of *framing* [12, 21]. Tversky and Kahneman [14, 15] assessed that in a ***positive frame***, where information is presented as a gain, individuals tend to avoid risks. In contrast, a ***negative frame*** (information framed as a loss), leads to risk-seeking behaviour. The *framing effect* is a cognitive bias that shows a potential transfer of its priming effect to an InfoVis context. Nonetheless, there seems to be little work done, as evidenced by Dimara et al. [5] when classifying this bias as "discussed in visualization research as important, but not yet studied".

A thriving collection of promising research has been establishing evidence which suggests that individual characteristics - namely, personality traits and cognitive abilities - can have a significant impact on the understanding, interaction and performance of data visualizations [22]. For instance, results from Brown et al. [1] assessed how personality traits are correlated with mouse activity, namely neuroticism. Additionally, the works of Green and Fisher [11] and Ziemkiewicz et al. [2] proved how neurotic individuals present faster task execution times. Taking such results into account, we introduced the *neuroticism* of participants in our study. Despite the lack of a unifying definition for this personality trait, continuous research shows a prevalence of **neuroticism** as a basic dimension of personality. According to the Five Factor Model (FFM), neuroticism consists of the tendency to experience negative emotions such as stress, depression, or anger.

Inspired by these findings, we developed a visual depiction of the decision problem by Tversky and Kahneman [12] using three bar chart visualizations - one for each framing type mentioned alongside an additional condition designed by us. Afterwards, we conducted user tests ($N = 91$) to understand whether the framing together with the neuroticism of individuals affected the decision-making process based on user interaction and reported choices. Our results suggest that visualization helps individuals be less susceptible to the *framing effect*. Moreover, our findings hint at no major significant effect of the neuroticism personality trait within our analysis. Considering the previously mentioned large gap in research regarding the framing effect within the InfoVis field, we prospect our contributions to provide further **understanding to future studies that leverage cognitive bias-aware mechanisms to promote more rational decision-making**.

1.1 Research Objective and Milestones

Weighting how individual differences - namely, both personality and cognitive biases - affect one's interaction with visualizations, our research aims to **understand the effect of personality on the framing bias in information visualization**. In particular, focusing on the *neuroticism* personality trait from the FFM. In order to achieve our goal, it was imperative to define some intermediate steps, consisting of the foundations of this work:

- Literature review both regarding the framing effect and personality within the InfoVis community;
- Development visualizations that set up the priming effect of framing;
- User testing with the established visualizations;
- Analysis of the collected data to understand the possible existent correlations.

Furthermore, we submitted a short paper to a top venue in our research area, VIS 2022[1], and are currently awaiting notification of submission.

1.2 Document Structure

Chapter 2 presents the theoretical background knowledge required for a better understanding of this study. Going in-depth regarding personality and neuroticism trait, it further explains what are cognitive biases - in particular, the framing bias and some factors that may influence it. Next, Chapter 3 presents our literature review together with a brief discussion of the relevant findings to our research. Chapter 4 introduces the followed methodology for our work. From the framing strategy to the metrics of our

[1] http://ieeevis.org/year/2022/info/call-participation/shortpapers

study, posed research questions and hypothesis it also presents the leveraged validation methods, data collection and analysis. Subsequently, Chapter 5 provides the obtained results from our analysis process together with further discussion of the findings and limitations of our research. To sum up, Chapter 6 presents our contributions along with possible future work.

2

Background

Contents

2.1 Fundamentals of Personality 6
2.2 Framing Bias 9

This section presents the theoretical background related to the concepts of personality - namely personality trait theory and the neuroticism trait - as well as cognitive bias - specifically framing bias - both required for a better understanding of our work.

2.1 Fundamentals of Personality

Personality is defined as the set of characteristic behavioural, cognitive, and emotional patterns that evolve from biological and environmental factors [23]. It is what makes us what we are, unique individuals, different from everybody else, in whichever way, larger or smaller [24, 25]. Even though our personality can sometimes vary according to a situation, it is considered relatively stable and predictable [25].

Personality theorists attempt to organize personality data into a coherent framework to help define, organize, and clarify personality - how it develops and changes. Psychologists have developed a wide range of personality theories that help us understand and predict behaviours, each presenting different perspectives on human nature and different emphasis on the core of the field [25]. Examples include the psychoanalysis view [26], the humanistic perspective [27, 28], the cognitive perspective [29], and the genetics perspective [30].

For this work, we will focus on the **trait perspective**, presented by Gordon Allport in the late 1930s [30], where *traits* - consistent and enduring ways of reacting to our environment - perform a prominent role in personality development. His work soon became a classic in the study of personality psychology. Defining personality as "the dynamic organization within the individual of those psychophysical systems that determine (...) characteristic behavior and thought", Allport [30] reflected the importance of heredity and our environment in our personality. He believed that our genetics interact with our social environment and that the inevitable result of such is our uniqueness [25].

A trait is a distinguishing characteristic that guides behaviour and is seen as a more stable part of the personality of an individual [31, 32]. Allport defined personality traits as "generalized and personalized determining tendencies - consistent and stable modes of an individual's adjustment to his environment" [33] and proposed two types of traits [25]:

- *Common Traits* - shared by several people. Influenced by social, environmental, and cultural factors;
- *Personal Dispositions* - unique to a person in the definition of their character. Further categorized according to their intensity or significance:
    1. *Cardinal Trait* - powerful and pervasive, touching almost every aspect of a person's life;
    2. *Central Trait* - building blocks of one's personality, the kind of characteristics used to describe a person's personality;

3. *Secondary Trait* - less conspicuous, generalized, and consistent, appearing inconsistently.

All in all, the core ideas of this approach to personality theory are [25, 32]:

- *Stability:* traits remain fairly stable across a lifespan;
- *Genetic base:* traits can be linked to a genetic structure;
- *Generality:* traits are expressed in multiple situations and contexts;
- *Interactionism:* situational factors moderate expressions of traits.

Whereas a personality theory attempts to explain how an individual's personality develops and evolves, **personality models** are embraced by many researchers as a way of describing how personality traits are organized. Various trait theorists such as Eysenck [34], Cattell et al. [35], and Goldberg [36] developed several personality models under this *trait approach*, aiming to identify the minimum required trait dimension to be able to describe an individual's personality. The Three-Factor Model [8], the FFM [36, 37], the Six-Factor Model (HEXACO) [25], the Dark Triad of Personality [25], and the 16 Personality Factor model [35] are examples of models based on *trait theory*, focusing on *behavioural genetics* - the study field on the connection between genetics and personality. Amongst the various personality models built under this approach, a commonly recognized personality trait has been *neuroticism*.

2.1.1 Neuroticism

A detailed analysis of narrow traits is required for one to have an in-depth understanding of how traits show in different contexts [38]. Despite some disagreement on its definition, as trait-based theories have been proven to be significantly more consistent across the years, continuous research shows a prevalence of ***neuroticism*** as a basic element of personality across the various models developed.

Like other personality traits, neuroticism is typically assessed as a **continuous dimension** rather than a discrete state. **High neuroticism values** indicate an individual who is more likely than average to be moody and to experience feelings such as anxiety, worry, fear, anger, frustration, envy, jealousy, guilt, depression, and loneliness [39]. These individuals tend to respond worse to certain situations, finding them more threatening and frustrating more easily as well as are more likely to develop mental disorders such as mood, anxiety, or substance abuse disorders [40, 41]. On the contrary, individuals with **low neuroticism values** tend to be more emotionally stable, calm, less reactive to stress as well as less likely to feel tense or rattled [42].

According to Eysenck [8, 34], there are three dimensions of personality:

- **E** - Extraversion versus introversion;

- **N** - Neuroticism versus emotional stability;
- **P** - Psychoticism versus impulse control.

In his theory, Eysenck [8] sees neuroticism as the opposite pole of emotional stability and related to an individual's reaction to different situations. This personality dimension encapsulates six different traits, shown in Table 2.1, and is suggested to be largely inherited, rather than a product of learning or experience [25].

Table 2.1: Three Factor Model: N-Dimension Traits [8].

Dimension	***Traits***	
Neuroticism versus Emotional Stability	Anxious	Tense
	Depressed	Irrational
	Guilt Feelings	Shy
	Low Self-esteem	Moody

From an extensive research program starting in the 1980s, McCrae and Costa Jr [9] identified that trait descriptors could largely be grouped into five broad dimensions, the *Big Five* factors. Counting the contributions of Digman [43], Goldberg [44], McCrae and John [45], the FFM of personality, also known as the OCEAN model, was created. According to this model, personality can be described through five broad traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Neuroticism, extraversion, openness, and conscientiousness are factors that show a stronger hereditary component whereas agreeableness was found to have a stronger environmental component [25]. Each of the presented dimensions encompasses more specific traits [46]. According to this model, ***neuroticism*** consists of the tendency to experience negative emotions such as stress, depression, or anger, characterized by fearfulness, anxiety, and empathy. This trait includes six different facets - each representing a distinct aspect of neuroticism (see Table 2.2).

Rival to the aforementioned FFM, Zuckerman [47] developed an alternative five-factor model for personality. Zuckerman argues that the broader personality traits should have a biological-evolutionary basis, such that these should have both a similar identified behavioural traits in non-human species as well as an association to biological trait markers [48]. For this model, the five broad personality factors are [49]: Impulsive Sensation Seeking (ImpSS), Neuroticism-Anxiety (N-Anx), Aggression-Hostility (Agg-Host), Sociability (Sy), and Activity (Act). The neuroticism personality trait is present and divided between the two broad factors:

- **[N-Anx] Neuroticism-Anxiety:** reflects tension, worry, fear, obsessive decision, lack of self-confidence, and sensitivity to criticism;
- **[Agg-Host] Aggression-Hostility:** measures aggression, antisocial behaviour, vengefulness, spitefulness, quick temper, impatience with others, hostility, and anger.

Table 2.2: FFM: Neuroticism Facets [9].

Neuroticism	***Facets***
[N1] *Anxiety:*	being apprehensive, tense, fearful, and worried
[N2] *Angry Hostility:*	the tendency to feel rage, frustration, and bitterness
[N3] *Depression:*	feeling hopeless, guilty, sad, alone, and desperate
[N4] *Self-Consciousness:*	the tendency to feel aware of one-self, inferior, shy, and embarrassed
[N5] *Impulsiveness:*	lack of ability to control an impulse or resist temptations
[N6] *Vulnerability:*	being susceptible to danger or being hurt emotionally

The formerly mentioned 16 Personality Factor model by Cattell et al. [35] is composed of *source traits*, the most stable and permanent traits that give rise to some behavioural aspects. Even though neuroticism was not considered a source trait in his approach, Cattell recognized it as a *surface trait*, meaning that it does not derive from a single source [25]. In his theory, the association of various elements of behaviour such as anxiety, indecision, and fear forms the label of neuroticism. Despite the criticism this model came to receive as the personality trait theory evolved throughout the years, it already recognized the existence of neuroticism as an important personality trait as well.

Psychologists have devoted considerable effort to developing techniques to assess - or measure - personality, including self-ratings, objective tests, and observers' reports. Costa Jr and McCrae [37] developed and validated the **NEO Personality Inventory-Revised (NEO PI-R)**. The NEO PI-R consists of an instrument to assess personality traits, where the subject is asked to rate the various statements - regarding feelings, thoughts, and behaviours - using a five-level Likert scale. Based on how much the individual agrees or disagrees with the presented statements, an average score is calculated.

Even though there is a variety of proposed instruments to measure personality, the NEO PI-R [37,46] remains the most frequently used technique [25]. However, as expected from any self-report inventories, the obtained results may be distorted by the deliberate behaviour of subjects [25].

2.2 Framing Bias

Back in the 1950s, Herbert Simon [13] proposed *bounded rationality*, suggesting that while striving to do so, humans have too limited cognitive abilities to make truly rational decisions without said limitations influencing the decision-making process. Later, in the early 1970s, Tversky and Kahneman developed Simon's idea with their *heuristics-biases* program [50]. As a result of the limitations proved by Simon's work, humans are forced to rely on heuristics. A **heuristic** consists of a mental strategy formed by the brain to simplify all the information around us, by using only a fraction of the available information - the parts an individual deems relevant to the problem at hand. These allow an individual to solve problems and make judgments quickly and effectively, reducing the mental effort inherent to such actions.

However, the use of heuristics does not always provide us with accurate judgments [51] and may lead to what was introduced by Tversky and Kahneman [14, 15] as *cognitive biases*. **Cognitive biases** were referred to as systematic deviations from 'normative' behaviour or rationality in judgment. These occur when people are processing and interpreting information in the world around them, affecting the decisions and judgments they make. At first, Tversky and Kahneman's experiments illustrated 15 biases [14]. Over the years many studies have shown the existence of various types of cognitive biases. As a result, various classification schemes were made, attempting to uncover similarities between the discovered types [14, 52, 53]. For example, based on Wikipedia's page *List of Cognitive Biases*[1] and its raw list of 175 biases, Buster Benson created the Cognitive Bias Codex [54].

Framing bias is a cognitive bias where people make a decision based on the way the information is presented (see Figure 2.1), caused by individual differences in the way people interpret the world around them. The key element of framing is the reference point used to evaluate the consequences of a decision [12, 21]:

- ***Positive Frame:*** framed as a gain, people tend to *avoid* risks;
- ***Negative Frame:*** framed as a loss, individuals *seek* risk.

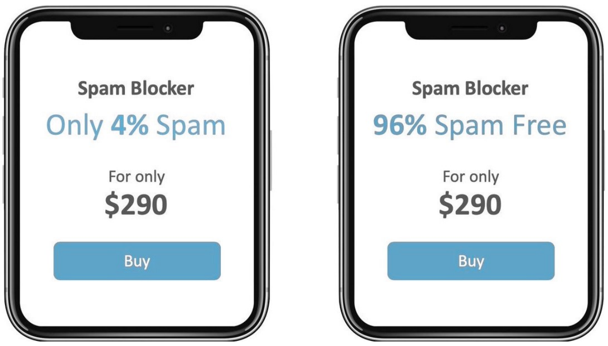


Figure 2.1: Negative (left) and positive (right) framing of the same information.

Back in 1981, Tversky and Kahneman [12] studied framing and the resulting *framing bias* in the decision-maker. For this, they investigated how different phrasing influenced each participant's choice when asked to choose between two treatments, A and B, for a hypothetical deadly disease. It was concluded that when the problem was presented *positively*, from the side of gains (the number of people who would live), participants tended to choose a *less risky* option than when it was presented *negatively*, from the side of losses (the number of people who would die). Thus, **modifications to the reference**

[1] $https://en.wikipedia.org/wiki/List\_of\_cognitive\_biases.$

point of the framing can have a major impact on the way a subject makes a decision [55]. From that, the term *negativity bias* was later introduced, inferring that "bad has a stronger effect than good" in various situations [56, 57].

Kwak and Huettel [58] examined how left-right positioning and the order of information acquisition influence economic gain-loss framing effects. Two different experiments with different approaches were conducted. For the first experiment, the influence of the left-right positioning of risky (gamble) and safe (certain) options was examined through the analysis of behavioural data as well as eye-tracking data. Evidence for an unexpected effect of left-right position upon gain-loss framing was found. Therefore, the second experiment served to evaluate whether it was due to the sequence of information processing or the position of information presentation. The two experiments were done with two different groups of participants - to whom different incentives were provided - which was not ideal and may have influenced the obtained results from the second study. Even so, they were able to conclude that both the left-right positioning and sequence of visual information processing can change the impact the presented information has on the participants and therefore bias their choices.

Adding to the reference point, Levin et al. [59] discovered two other *types of frame manipulation*:

- ***Framing an attribute:*** the description of characteristics of a certain thing in a positive or negative frame;
- ***Framing a goal:*** highlighting such an achievement as gain or loss caused by a certain behaviour.

Beratšová et al. [10] carried out a systematic literature review of recent empirical studies to discover factors that may cause and affect framing or decrease the resulting framing bias. Despite the use of only one database and consequent possible omission of some relevant articles, they were able to identify various factors that have an impact on framing, grouping them into four broader groups, shown in Table 2.3.

Table 2.3: The four broader groups identified by Beratšová et al. [10].

Groups	***Description***
Decision Situation Setup	Amount, order, and framing of information, number of options
Experience	Previous knowledge or engagement in the area of decision-making
Effort	Attention, the complexity of a decision, consideration of alternatives, amount of information to process
Demographics	Cultural habits, nationality, gender

It is important to notice the difference between *framing* and *framing bias*. As considered in this work, **framing** refers to the process of decision-making, highly correlated with the subject's "conception of the acts, outcomes, and contingencies associated with a particular choice" [12] which can lead to framing bias. **Framing bias** is the possible variation of outcomes in the decision-making process, causing a deviation from a rational choice. Despite the terms being linked, framing does not always lead to an irrational choice (biased behaviour) [60, 61]. It is argued that it is very difficult to prevent the influence of framing bias on decision-making as it often involves an individual's unconscious memory [62] and conception of risk [55]. Framing bias continues to be a subject of further research.

3

Related Work

Contents

3.1 InfoVis and Personality 14
3.2 Framing Bias and InfoVis 19
3.3 Personality and Framing Bias 27
3.4 Discussion 29

The following section introduces both procedures as well as drawn conclusions from relevant studies to the proposed work. Given the three major areas - InfoVis, Personality, and Framing Bias - this work approaches, we analyzed works in the intersections of all the aforementioned fields, grouped in two. To conclude stands a discussion, posing the most significant conclusions collected for our work, taken from the presented literature.

3.1 InfoVis and Personality

Due to various advancements in the data visualization field, InfoVis systems have been able to achieve great general usability as well as an application across various domains. As we mentioned, each individual has a distinct personality as well as cognitive abilities. Thus, each person will exhibit differences in behavioural patterns and task-solving approaches [63,64]. Moreover, it has been proven that personality can influence how one uses [65–67] and accepts [68, 69] technologies as well as how efficient the users perceive the design of a system to be [70].

Throughout the years, researchers have started to recognize the shortage of having one-size-fits-all visualization interfaces as well as to acknowledge the influence individual differences - "traits or stable tendencies to respond to certain classes of stimuli or situation in predictable ways" [71] - might have in human-computer systems and the impact their interaction with the systems may have in decision-making processes [22]. Developments in the interaction of the two fields both improve the general understanding of people themselves, as well as people's understanding of data and their interactions with visualization systems.

Being aware of the role of individual differences in the data visualization domain and the absence of a central resource for researchers to learn about studies made in the area, Liu et al. [22] produced a comprehensive survey of relevant literature on the topic. Restricting the scope of their search only to the individual differences classified as *cognitive traits*[1] by Peck et al. [72] on the proposed Individual Cognitive Differences model, the authors found 29 key publications relevant for their main analysis. These 29 findings were analyzed and classified based on their own proposed taxonomy with four dimensions: the studied individual differences/traits, the types of visualizations used, the tasks involved in the associated experiment, and the evaluated measures. The proposed taxonomy allowed to gain several insights, mainly two important conclusions:

1. There is evidence that nearly every cognitive trait mentioned in this review of literature can impact visualization use, with few exceptions such as conscientiousness and agreeableness;

[1] Believed to be stable characteristics throughout adulthood such as features of a person's personality alongside with their cognitive abilities [22].

2. Further investigation is crucial, namely replication studies, in order to complement our understanding of individual differences and how these impact visualizations, to then guide design accordingly.

Concerning studies analyzed in their literature review among the visualization community related to neuroticism, the findings with measurable effects for this particular personality trait under the studied conditions include the works of Brown et al. [1], Green and Fisher [11], and Ziemkiewicz et al. [2].

Brown et al. [1] studied all five dimensions of the FFM of personality and Locus of Control (LOC)[2]. Using a spatial visualization (see Figure 3.1) in which participants were asked to find Waldo, Brown et al. [1] used machine learning techniques to infer user's task performance as well as personality factors, from mouse data (mouse clicks and activity) and speed, in a visual search task. Depending on both the data encoding (state, event, or sequence-based) and the corresponding machine learning algorithm (support vector machines or decision trees), Brown et al. [1] differentiated participants who completed the task quickly versus slowly, with 62% to 83% accuracy. The accuracy of prediction of the user's personality was lower, suggesting that even though such may be recovered from users' interactions, the signals can be noisy and inconsistent. Nonetheless, Brown et al. [1] successfully classified users based on their LOC, Extraversion, and neuroticism scores. Regarding the neuroticism trait, the accuracy of the predictions varied from 62% for an event-based analysis - through mouse events - and 64% when using a state-based analysis, through an "edge space" encoding. Such results were consistent with prior findings [73].

Figure 3.1: Interface from the work of Brown et al. [1]: (a) shows Waldo hiding among trees; (b) and (c) show distractors, to increase the task's difficulty.

Green and Fisher [11] used graphs for search and inference tasks, measuring speed, accuracy, subjective feedback, and insight from the participants. Regarding traits, their research focused on both the

[2]A personality dimension which measures one's tendency to see themselves as either shaped by or in control of external events [2].

Table 3.1: Green and Fisher [11] summary of findings.

	Completion Times	Errors	Insights
Locus of Control	internal locus faster times	none	external locus more insights
Extraversion	more extraverted faster times	none	less extraverted more insights
Neuroticism	more neurotic faster times	none	less neurotic more insights

dimensions of Extraversion and neuroticism from the FFM, as well as the Locus of Control (LOC). The first two were assessed through the IPIP 20-item Mini Big Five Inventory [74], whereas the LOC degree was evaluated through the Internal-External Locus of Control Inventory [75]. Green and Fisher [11] conducted two separate studies - comparing procedural learning behaviours in two different interfaces of genomic relationships (see Figure 3.2 and Figure 3.3) - in order to explore the impact of the aforementioned personality factors on such as well as on interface interaction. Both studies asked participants to interact with the two interfaces and the task completion times were recorded. In the first study, participants were presented with the interfaces prior to the execution of the target identification tasks; while for the second one, there was no prior interaction but rather ”cues” in the tasks to assist in finding the correct answer. Despite the completion times being faster in the MapViewer interface, users still reported a preference for the GVis one regarding interaction. From their research, Green and Fisher [11] were able to find that more neurotic participants complete procedural tasks faster, whereas less neurotic ones derived more insights[3]. Table 3.1 shows a summary of the findings from this study.

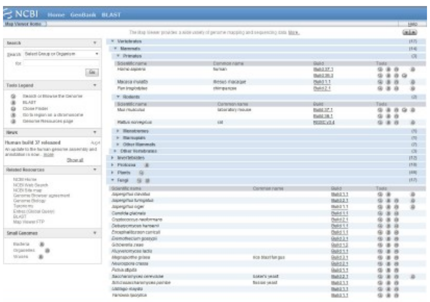


Figure 3.2: NCBI MapViewer Interface.

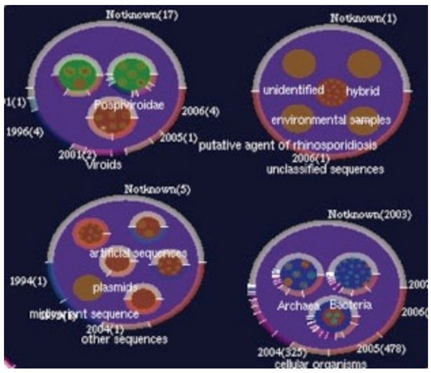


Figure 3.3: GVis Interface.

The more neurotic an individual is, the more attentive to tasks one tends to be [76], which was particularly helpful both in the works of Green and Fisher [11], and Ziemkiewicz et al. [2] when dealing with unfamiliar visualizations and data. However, their possible explanations for such are contradictory. While

[3]In these studies, insights were defined as items or concepts learned or added to the user’s knowledge base, categorized on the basis of the content: interface itself or informational content. No spontaneous insights were evaluated.

Green and Fisher [11] believe that the more neurotic a person is, the more they feel in control, which allows for better manipulation of interfaces; Ziemkiewicz et al. [2] argue that higher neuroticism levels correlate with feeling more ”out of control”, and that is the advantage when interacting with unknown visualizations.

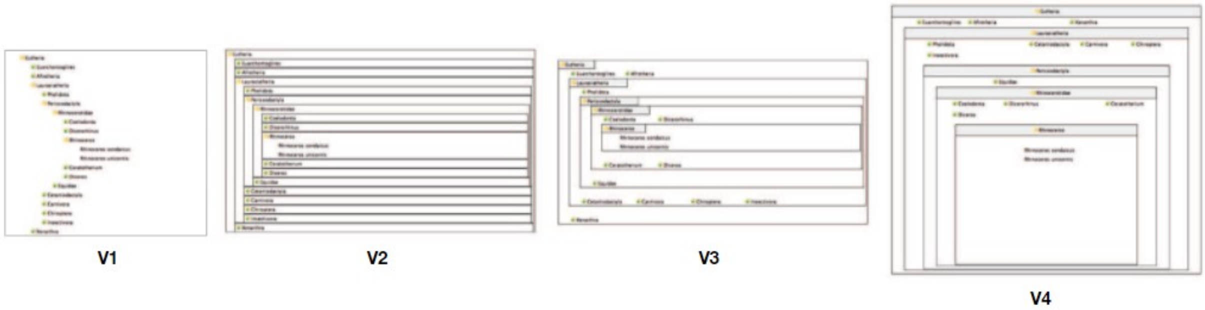


Figure 3.4: Interface layouts used by Ziemkiewicz et al. [2]. V1 (list-like) to V4 (containment metaphor), from left to right.

Ziemkiewicz et al. [2] conducted a study with four graph visualizations (see Figure 3.4), from a list to a containment metaphor, for hierarchy. Such research aimed to explore how those layout differences may lead to the Locus of Control (LOC) effect without differences in visual encoding or interaction. Even though their focus was LOC personality dimensions, the Extraversion and the neuroticism dimensions of the Big-Five personality model were also included in the study, for comparison with the results from Green and Fisher [11]. While measuring speed, accuracy, and subjective feedback in search and inference tasks, Ziemkiewicz et al. [2] found evidence to sustain their hypothesis, concluding that layout is a key variable in the interaction between LOC and compatibility with different design systems. They also discovered that while individuals with higher levels of neuroticism tended to be significantly more accurate overall, such effect was more pronounced in the container-style layouts (V3 and V4). Ones who were less neurotic worked better with indented-tree layouts (V1 and V2). Such findings can be seen in Figure 3.5. Reflecting upon their results, Ziemkiewicz et al. [2] argued on one hand more neurotic participants tend to put more pressure on themselves and, as a consequence, perform the tasks well; on the other hand, less neurotic individuals performed poorly with container-style layouts due to possible less willingness or capability of adapting to unfamiliar visualizations.

Acknowledging the influence individual differences, such as personality, have on technology, Alves et al. [77] composed a review presenting studies related to the impact both design and aesthetics have on user preferences, namely possible preferences in specific interface design features according to certain personality traits. Focusing the review specifically on Graphical User Interfaces (GUIs) - as to how the user perceives and interacts with an interface - they were able to conclude that personality is a crucial and differentiating factor in user interface design. Nonetheless, there is still a lack of work in the area for researchers to be able to create design guidelines for interfaces that could adapt to and help improve

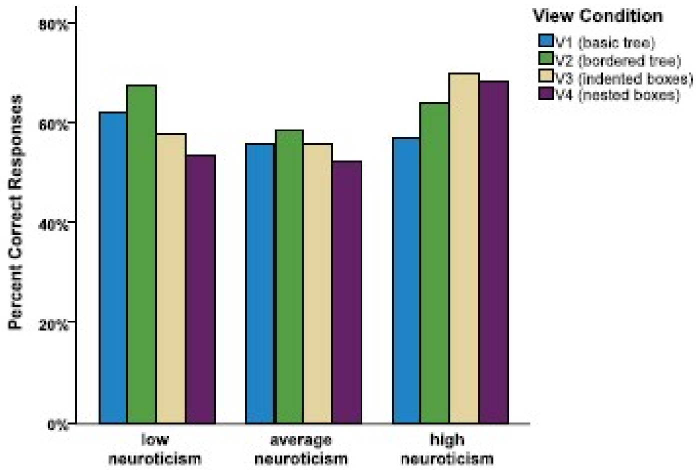


Figure 3.5: Ziemkiewicz et al. [2] results regarding the participants' neuroticism scores.

a user's cognitive abilities. Once created such design guidelines, systems will allow for efficient and accurate use of themselves by displaying information properly to users. In the midst of the mentioned studies throughout this review, the works of Sarsam and Al-Samarraie [3] and Arockiam and Selvaraj [78] have shown results concerning neuroticism.

In a mobile learning context, Sarsam and Al-Samarraie [3] sought to determine whether user visual experience would improve when using a user interface (UI) designed for their personality. From an interview, both the users' personality traits as well as their design preferences were collected; which would further determine the design of the developed interfaces. For the assessment of such, the NEO PI-R questionnaire was used, as well as a multi-scale questionnaire with graphical aids. To gather the users' personality data into groups, hierarchical clustering and k-means algorithms were used, resulting in two clusters: "*neuroticism*" and "*extra-conscientiousness*". Apriori algorithm was then used to obtain the association rules to be applied to the two UI versions, fitting the personality preferences of each group. After experts' assessments and judgments, the final versions of the two designs were reached (see Figure 3.6). Through the analysis of eye-tracking data from the users' interaction with both interfaces, users' cognitive load and attention were examined. Results showed that participants in both personality groups were able to complete the tasks faster as well as invest less attention to irrelevant objects in the interface when using the UI designed based on their preferences. Regardless of the personality group, once the participants interacted with the correspondent design, they exhibited higher visual efficiency and comfort than when using the other; whereas when using the other interface, displayed signs of demotivation. Therefore, Sarsam and Al-Samarraie [3] concluded that no matter the participants' personalities, their visual attention was significantly improved upon the use of a UI designed specifically for their personality characteristics. High neurotic participants preferred the use of calm colours as well as more structured and divided texts.

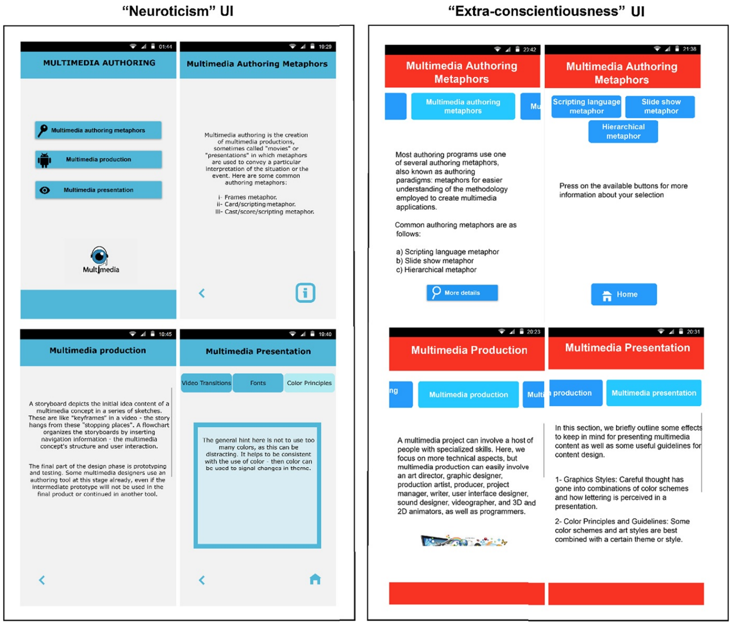


Figure 3.6: Sarsam and Al-Samarraie [3] UI design for the two personality groups.

Focusing on the Recollection and Retention ability[4], Arockiam and Selvaraj [78] conducted a study envisioning finding the existence of a relationship between personality traits and user interface design (UID) in an e-learning context. To accomplish such goals, the researchers developed a procedure called UIDBP, which provides UID preferences based on personality traits, in e-learning environments. The assessment of the participants' personality traits was made through Eysenck's Personality Questionnaire [79], whereas the Retention and Recollection ability data was retrieved via a questionnaire designed based on some interface parameters, such as the Background Color as well as Font Style and Color. Once the procedure collected the participant's data regarding both personality and UID preferences, it formed personality-based rules through the use of the Association Rule Mining tool, and these were exported to build the design of an e-learning page. With the Association Rule Mining tool used in their study, the preferred UID parameters like Background Color, Font Type, and Font Color which influence the users were found for all the three personality dimensions analyzed. Arockiam and Selvaraj [78] showed that the neuroticism group of participants (14%) easily recollected the UID with green Background Color (66.67%), and Times New Roman (52.38%) in black as the Font Type and Color.

3.2 Framing Bias and InfoVis

During the design process of visualizations, one must take into account three different kinds of limitations: of computers, of displays, and of human beings [80]. In regards to the latter, it is imperative to

[4]Recollection consists in the retrieval or recall memory. Retention is an ability to recall or recognize what has been learned [78].

consider human vision limitations taken together with the ones of human reasoning. Not only may a visualization system be imperfect, our cognitive system, too, has pitfalls [4]. Thus, to begin to understand how visualizations may be able to support both judgment and decision making it is necessary to study and understand how such limitations can affect data visualization [5].

Given both the limited time and cognitive resources humans have, the use of heuristics and rules of thumb our brains create allows us to simplify complex problems and make optimal decisions; nonetheless, we know that such is not always the case and the use of heuristics do not consistently lead to optimal decisions [81]. As aforementioned in this document - defined by Tversky and Kahneman [14] as a deviation from rational behaviour - *cognitive biases* consist of the imperfections present in the heuristics our brain forms as an attempt to facilitate the decision-making process. Such imperfections may manifest in a collection of distinct ways, which led to several studies proving the existence of a wide variety of cognitive biases. For example, in an experiment, Tversky and Kahneman [12] found that participants preferred a treatment described to have a "33% chance of saving a life" over one with a "67% chance of death" - even though both treatments reflected the exact same results. Concluding the participants' choices varied based on the way the treatments' information was framed, such cognitive bias was entitled *framing bias*.

Even though a concept such as cognitive bias is as hard to define as is to study - namely due to the major difficulty of deciding what constitutes such a deviation as well as assessing the quality of a certain decision or judgment - these are important and one crucial human limitation a visualization researcher must be aware of [5]. As a consequence, there has been a growing interest within the visualization field, both in cognitive biases [6, 18, 82, 83], as well as decision making [19, 20, 84]. However, as stated by Dimara et al. [5], empirical work on such remains limited and there are very few researches that explore a particular cognitive bias in information visualization.

3.2.1 Taxonomies and Frameworks

Despite their importance being recognized, the intersection between data visualization and cognitive biases remains largely unexplored. As a consequence of both the diverse variety of proven cognitive biases as well as their importance in various fields - for instance, psychology, decision systems, intelligence analysis, and visualization - many different **taxonomies of cognitive biases** have been built. Such taxonomies generally aim to help both organize the biases and spark research questions and studies that arise regarding biases, in the various fields.

Taking inspiration from Don Norman's Human Action Cycle [85], Valdez et al. [4] proposed and discussed a simple conceptual framework, to serve both as a frame of reference when investigating a bias as well as a guide to research on biases in visualization, for the InfoVis community. Whereas the aforementioned Cognitive Bias Codex [54] categorizes biases according to causes and strategies, Valdez et al. [4] developed a framework (see Figure 3.7) which proposes a three-tier model of perception, action, and choice. This proposed framework works orthogonally to Benson's categorization and provides a multi-scale model of cognitive processing:

- *Perceptual Biases:* corresponds to biases that occur on a perceptual level, happening in the motor-sensory-motor loop of the framework;
- *Action Biases:* cover biases made in decision making, where the interpretation or evaluation of the adequate percept is distorted. Occurs in the human-action loop;
- *Social Biases:* opposite to action ones, these are affected by culture, involving biases that affect judgment on a social level and arise in the bounded rational-choice loop of the framework.

Each tier corresponds to different levels of cognitive processing as well as distinct methods to study bias effects. These levels are not considered hard biological limits [86], as cross-talk across diverse steps of different layers is accounted for (represented in Figure 3.7 by the dashed arrows). As for the methods to study biases at each of the levels, whereas perceptual biases can be measured effectively from psychophysics methods, both action and social biases methodologies are far more diverse and tailored to each particular bias.

Most of the existing taxonomies for cognitive biases are *explanatory* - organizing them according to why they occur, by considering cognitive mechanisms and explanatory theories - as was the classification Tversky and Kahneman [87] used, where biases were classified according to which strategy (*heuristic*) is hypothesized that people follow to make a decision or judgment [5]. Rather than following the same approach and recognizing the lack of research on cognitive biases within the visualization community, Dimara et al. [5] proposed a ***task-based* taxonomy**. This suggested taxonomy organizes biases based on the experimental tasks they have previously been observed and measured in, aiming to help visualization researchers identify biases that might affect visualization tasks. Even though cognitive biases taxonomies considering tasks already exist [88,89] these consider some high-level tasks, and not all biases are grouped by task. The work by Dimara et al. [5] provides a grouping based on lower-level tasks, considering a larger number of tasks and, thus, providing a more detailed classification of when biases occur. As data visualization applies to a large variety of scientific domains, researchers ought to be aware of a larger set of biases than researchers in other fields. To accomplish their objective of helping visualization researchers relate their designs to the corresponding possible biases, Dimara et al. [5] gathered an initial list of biases from a standard bibliographic search and selected the most representative paper that empirically tested each one. All the identified cognitive biases were categorized and reviewed from a visualization perspective; both for existing relevant work in the field, and possible future opportunities for visualization work. Ending up with 154 cognitive biases, these were organized in seven different categories (represented in Figure 3.8(a)), according to the tasks users are performing

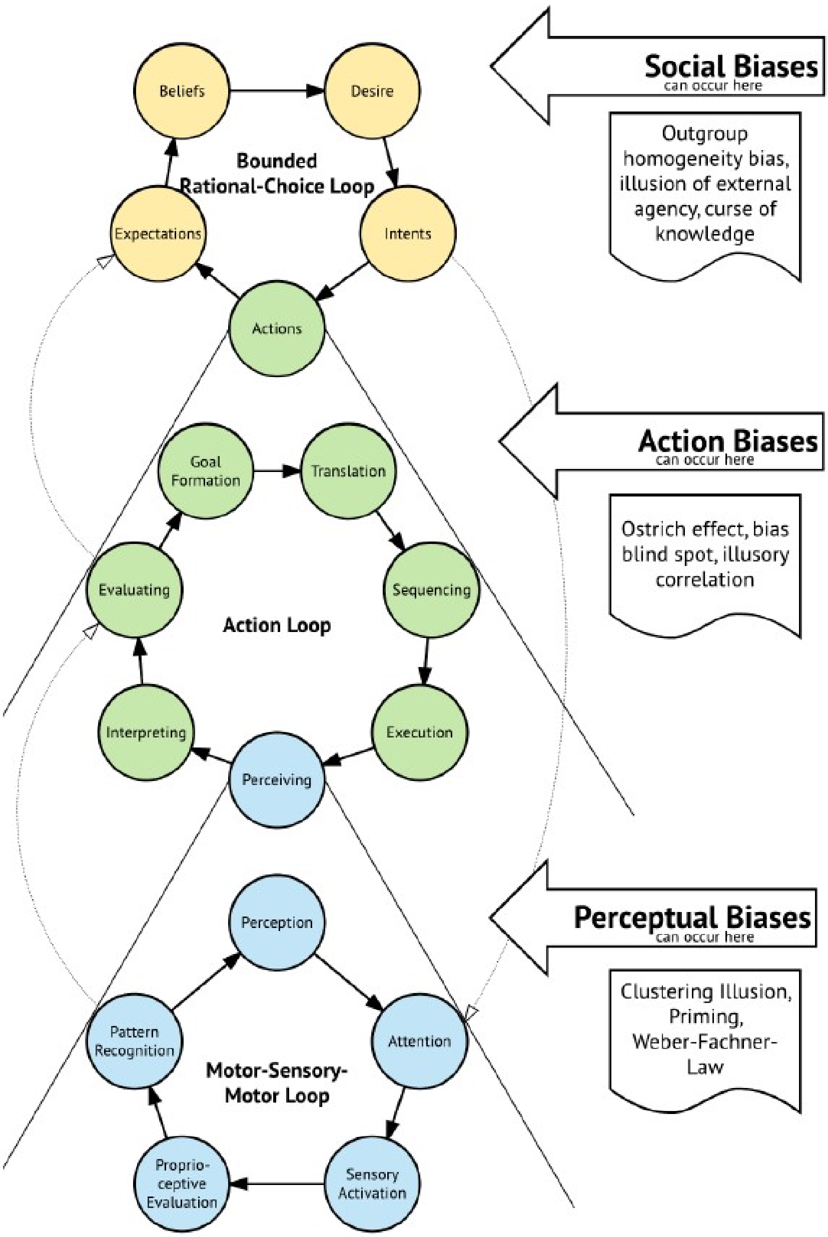
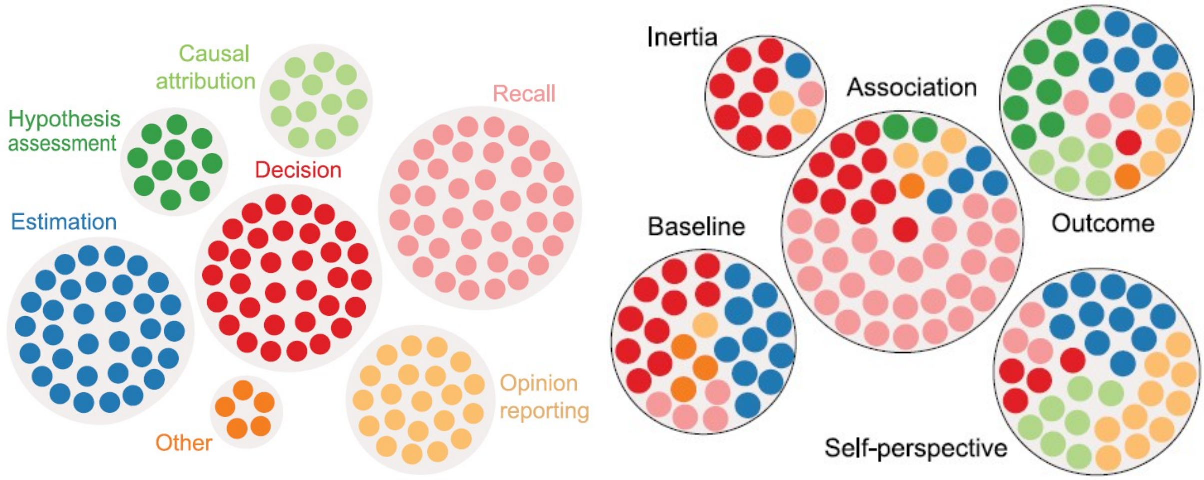


Figure 3.7: Layered closed-loop perception, action, and choice model. Since no hard boundaries exist between layers, cross-talk is part of the closed loop model (see exemplary dashed arrows) [4].



(a) Overview of 154 cognitive biases, organized by experimental task.

(b) Organized by sub-categories, entitled flavors [5]. Colors encode task-category correspondingly to Figure 3.8(a).

Figure 3.8: The taxonomy developed by Dimara et al. [5]. Each dot is a cognitive bias.

when the bias is observed. As each one includes a fairly larger number of biases, the authors decided to add sub-categories (see Figure 3.8(b)) as a way of trying to help readers establish connections between the biases, both within and between categories.

*Biases in **decision tasks***, including 33 of the identified biases, refer to tasks requiring the selection of one over several alternative options - called *choice studies* in Psychology. Although not all, some of these arise when people are dealing with uncertainty, for instance, when the problem is framed either as a gain or a loss, known as *framing bias*, the focus of this work. As for visualization research on the subject, there have been studies which mention decision biases under uncertainty [90–93]; however, there is still very limited empirical work studying their existence in visualization [94, 95] due to a lack of evaluation of the quality of users decisions. *Framing Bias* is identified by Dimara et al. [5] as a bias "discussed in visualization research as important, but not yet studied."

Recognizing that the use of heuristics does not always produce errors in reasoning, but rather is often positive and allows us to make decisions in both a quicker as well as a more efficient way, Wall et al. [6] established a conceptual framework for considering bias assessment through human-in-the-loop (HIL) systems as well as the theoretical foundations for bias measurement. Such work was built under the hypothesis that when data analysis is supported by visual analytic tools, analysts' cognitive biases influence their data exploration - resulting in behavioural indicators of biases - in ways that are measurable through their interactions with the data. The researchers proposed six preliminary metrics to systematically detect and quantify bias from user interactions (see Metric column in Figure 3.9). Such an approach, however, relies on the fact that a certain behavioural indicator does not necessarily tell us

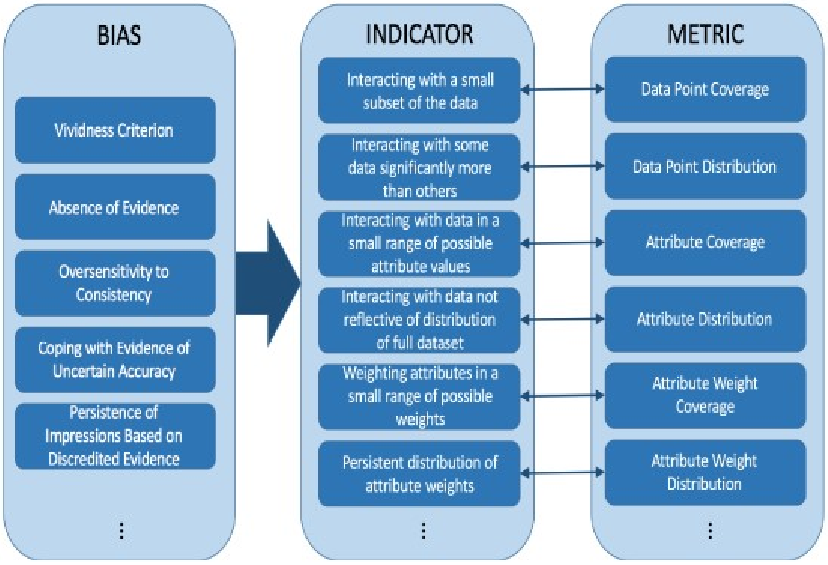


Figure 3.9: Cognitive biases result in behavioral indicators that are measurable by the proposed metrics. There are numerous other biases, these are the ones included in the scope of the work of Wall et al. [6].

the particular bias which may have caused it; thus there is not a one-to-one mapping between a certain bias and the proposed metrics. This many-to-many mapping is represented in Figure 3.9 by the block arrow between the biases and indicators columns. Through the measurement of types of interaction with objects of interaction and interpreting such through Markov chains, Wall et al. [6] proposed six metrics based on such user's interactions - data point coverage, data point distribution. attribute coverage, attribute distribution, attribute weight coverage, and attribute weight distribution - that when compared to a baseline allow for the assessment of meaningful deviations from such baseline, which may reflect cognitive biases. Furthermore, as the proposed behavioural tracking occurs throughout the analysis process, the proposed metrics constitute a real-time user state assessment approach. The correspondent feedback may be provided to the user in three different ways: directly to the users, to the machine, or to a third party agent.

3.2.2 Human-Centered Computing

With the common goal of understanding cognitive biases in data visualization, Wesslen et al. [83] argued Bayesian cognitive modelling [96–98] is a promising approach to studying cognitive biases. The researchers believe the integration of resource-rational analysis through constrained Bayesian cognitive modelling provides a road map for studying cognitive biases in the data visualization context, through a feedback loop between future experiments and theory. An approach like this to the study of cognitive biases is claimed to provide quantitative cognitive models that yield explicit testable hypotheses predicting user behaviour under different experiments. Thus, such a method aids to accelerate innovation, improve the validity of results as well as facilitate replication studies [99]. As previously mentioned, Simon [100, 101] introduced the idea of *bounded rationality*, claiming that due to human's limited cognitive resources, rational decisions must be framed in the context of such limitations as well as the context of the environment. *Resource-rational analysis* [102, 103] reinterprets cognitive biases as an optimal (rational) trade-off between the internal cognitive constraints and the external task demands. Wesslen et al. [83] argued that such an approach provides testable predictions which might be considered empirically through controlled experimentation and could be beneficial in data visualization decision-making, both for identifying and mitigating cognitive biases before they occur.

Prior research has shown that to make decisions, regardless of their complexity, people rely on two types of reasoning that operate in parallel [81]:

- *Type 1:* described as the dominant one, in charge of reasoning and judgment. Guides our intuition and recognition patterns;

- *Type 2:* responsible for our analytical thinking.

This dual-process theory began with the work of Kahneman [81]. However, the notion of the two parallel systems is formalized by the Fuzzy Trace Theory (FTT) [104], which defines Type 1 of reasoning as our gist (high-level) reasoning and Type 2 as verbatim (detail-level) reasoning. The FTT defends that people make decisions through the extraction of meaning from verbatim input to make a gist-based judgment, a "fuzzy" representation of the information extracted. Type 1 reasoning is more susceptible to both false first impressions as well as framing effects; thus, is at the forefront of the cognitive processes. To switch from Type 1 to Type 2 reasoning, to avoid cognitive biases, requires significant effort. Noticing the value in studying which visualization will lead to which outcome, Bancilhon and Ottley [20] argue that the current findings are limited to the task at hand and fail to prove a comprehensive understanding of decision-making processes. Consequentially, they pleaded that understanding when biases occur in the reasoning process of decision-making with visualization, rather than focusing on the binary outcome of a decision, is critical to bridge the existent gap between Psychology and visualization in the context of decision-making.

In everyday domains that involve uncertainty, data visualizations are often used as standard tools both for assessing as well as communicating risks; to both support reasoning about said risks and aid sound decision-making [105]. The same data may be represented using different, yet equally theoretically valid visualization designs [106] and identifying which design is optimal for the problem at hand can be difficult [107]. Thus, it is not always straightforward how design and/or encoding choices might influence risk perception alongside decision-making.

Under the research question *"Does visualization impact decision-making under risk?"*, Bancilhon et

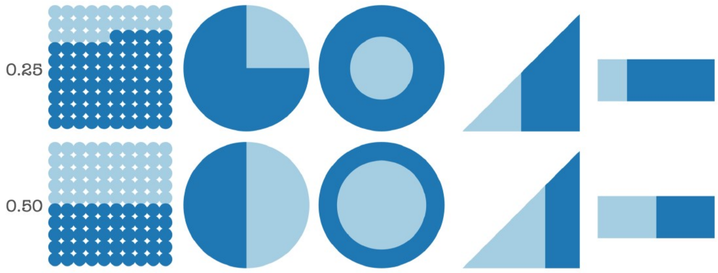


Figure 3.10: The visualization conditions used in the study by Bancilhon et al. [7].

al. [7] conducted a study where participants engaged in a realistic decision-making scenario and were compensated according to the choices they made in the study. Represented by a large-scale gambling game, participants chose to either receive guaranteed monetary gains or enter a lottery - both expressed in terms of gains - based on five common visualization designs (see Figure 3.10).

Using those five common visualization designs as well as a text condition to display seven lottery probability values ranging from 5% to 95%, Bancilhon et al. [7] observed participants' decision-making - the choice between entering a gamble and receiving a guaranteed bonus payoff - and measured risk perception. Prior to the experiment, subjects were shown a short tutorial, including a trial text-only round, and explained the selections and the bonus calculation using the example shown in Figure 3.11. To prevent potential biasing, a different visualization (doughnut chart) from the ones used in the conditions of the study was used for the tutorial. Next, each participant was randomly assigned one of the six visualization conditions and presented with 25 two-outcome lotteries that consisted of choices between risky (gamble) and certain gains. To measure decision quality - how risk-averse or risk-seeking a choice is - the Relative Risk Premia (RRP) [5] was used. Results confirmed their first hypothesis, as participants were risk-seeking for low probabilities ($RRP < 0$) and risk-averse for high probabilities ($RRP > 0$); thus, following Prospect Theory [55]. As for their second hypothesis, it was found that risk-taking behaviours for participants in both the *circle* as well as the *triangle* groups deviated significantly from the *none* group, suggesting that, indeed, visualization can influence decisions.

Applying a regression model for RRP for each group condition, Bancilhon et al. [7] found that the *icon* group led to the least deviation of risk-neutrality ($RRP = 0$) and, as such, applies as the most effective design in the context of monetary decision-making. In spite of that, the goal of the study was to explore the impact of visualization on monetary risk behaviour, implying the comparison to the control (*none*) condition and that the most similar group represents the expected behaviour; on that end, the *bar* group was the one that exhibited behaviour that was the most similar for the *none* group. As there is no consensus on what constitutes sound decision-making, Bancilhon et al. [7] argue that the visualization may be context-dependent.

[5] $RRP > 0$ indicates risk aversion, $RRP < 0$ implies risk seeking behavior, and $RRP = 0$ suggests risk neutrality [7].

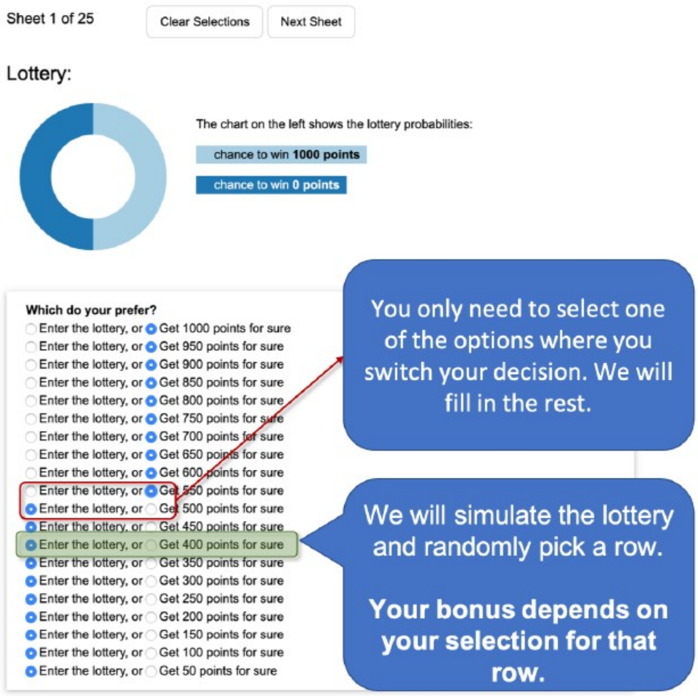


Figure 3.11: The example lottery sheet used in the study, with a different visualization and reward prize. Participants only needed to select the row where they switched either decision, as the system automatically populated the remaining radio buttons [7].

3.3 Personality and Framing Bias

The work Tversky and Kahneman [12] introduced regarding reversals of preferences according to different framings - of problems, contingencies, or outcomes - served as a genesis for various researches focusing on the effect of framing in numerous contexts. As previously mentioned, Levin et al. [59] proposed three major types of framing: risky choice framing, goal framing, and attribute framing - the first being the type of framing initially discovered by Tversky and Kahneman [12]. All three types are distinguishable from each other from their operational definitions, typical results, as well as the likely underlying processes.

Attribute framing consists of presenting a single object or event using different descriptions - through a positive or negative frame - and has been proven to bias the assessment of said object. Focusing on that type of framing, Gamliel et al. [108] examined whether two of the FFM personality traits - Agreeableness and Conscientiousness - moderate their effect in contexts involving or not social justice. The researchers measured this possible effect through the perceived fairness of allocation criteria for distinct hypothetical scenarios. Their study was conducted under the assumption that individuals with either Agreeableness or Conscientiousness high scores are more sensitive to issues of distributive justice. Two studies were designed to assess such inference. The first experiment determined whether the two personality traits moderate attribute framing in a distributive justice scenario. The second experiment attempted to generalize the prior findings to other scenarios of distributive justice as well as examine the possible influence of the two traits in contexts unrelated to social justice. For both experiments, Agreeableness and Conscientiousness scores were measured through the Hebrew translation of the BF-44 [109]. The perceived fairness of the possible allocation criteria determined was measured through designed distributive justice questionnaires. For each study, each participant was randomly assigned to either a positive or negative framing of the scenario at hand. From both experiments, Gamliel et al. [108] observed that, as first hypothesized, all three allocation criteria were perceived as more fair in a positive framing condition rather than in a negative one. *Experiment 1* showed that while individuals who have a low Agreeableness or Conscientiousness score were relatively immune to the attribute framing effect, high-scoring participants were more susceptible to such effect. *Experiment 2* allowed to confirm the previous results regarding the other distributive justice scenarios and observe that these personality traits did not moderate the framing bias in a scenario unrelated to social justice. Thus, concluding that the effect of framing on highly involved people might be context-dependent, as these two personality traits are believed to be related to social attitudes.

Following the work of Nosić and Weber [110] by seeing risk-taking behaviour as a function of *risk attitude, risk perception*, and *return expectation*, Oehler and Wedlich [111] conducted a study to analyze whether personality traits - namely the individuals' degree of extraversion and neuroticism - influence those three determinants of risk-taking behaviour, in investment decisions. Having found no prior works that addressed the three risk determinants within one experimental setting alone, the researchers provided a unique contribution to the literature. Despite the focus on Extraversion and neuroticism, all the FFM personality traits were measured through the German version of the 10-item Big Five Inventory [112, 113], which can replicate results from more extensive scales as is the NEO PI-R of Costa and McCrae [114]. As for the three risk determinants, both *risk perception* and *return expectations* were captured in the context of hypothetical investment decisions, by showing participants 5-year charts of three different stocks and asking for their subjective estimates. As a stable *risk attitude* has been proven difficult to assess and there are various methods to collect it, the researchers decided to use two different approaches, by measuring it with the certainty equivalent method in a lottery context as well as through subjective feedback from the participants. From a pure student sample, Oehler and Wedlich [111] were able to find that extraversion, neuroticism, and conscientiousness are personality traits that strongly influence risk attitude. As for the neuroticism trait, the results indicate that more neurotic individuals are more risk-averse; finding a positive correlation between this personality trait and the degree of risk aversion measured through subjective feedback. The results for this risk determinant through the lottery task remained insignificant.

Gamliel et al. [108] showed that personality traits can moderate attribute framing effects. Unfortunately, to the best of our knowledge, the gap in the investigation of the influence of personality traits upon risk-taking behaviour evidenced by Oehler and Wedlich [111] extends to studies evaluating the impact of personality traits in framing bias.

3.4 Discussion

The above-mentioned studies suggest that both personality traits, as well as cognitive biases, are correlated with user interactions, as shown by the works of Brown et al. [1] and Wall et al. [6]. Namely, Brown et al. [1] proved how personality traits are correlated with mouse activity, notably neuroticism. As for the completion time of tasks, the results obtained in the studies of Green and Fisher [11] and Ziemkiewicz et al. [2] lead us to believe that, due to their greater attentiveness, neurotic participants execute tasks faster. Moreover, despite differing explanations for such, both assume that higher neuroticism levels can be particularly helpful upon interaction with unknown visualizations.

In the context of visualization design for different personality traits, both the works of Sarsam and Al-Samarraie [3] and Arockiam and Selvaraj [78] provide findings related to the neuroticism personality trait stating that more neurotic individuals prefer an interface with a more calm colour palette, such as blue or green, more structured and divided texts and information presented with Times New Roman font type. Regarding previous work concerning framing bias upon information visualization, there seems to be little work done, as evidenced by Dimara et al. [5] when classifying this bias as ”discussed in visualization research as important, but not yet studied”. Nonetheless, the findings of the study Bancilhon et al. [7] performed to understand the impact of visualization in decision-making, revealed that, in the context of this work, the comparison to the control (*none*) group condition is what represents the expected behaviour. Thus, the *bar* group presents the most relevant to our study, as well.

Regarding personality measures, namely the neuroticism personality trait, most of the analyzed studies used the NEO PI-R [37] or shorter and/or translated variations, which can replicate results from it. In the considered literature, no measures to assess the framing bias effect were proposed. In respect to such, studies based the assessment of such effect on subjective feedback from the participants, as Gamliel et al. [108] and the most reliable results obtained in the work of Oehler and Wedlich [111].

4

Methodology

Contents

4.1 Framing Strategy . . . 35
4.2 Measures . . . 36
4.3 Research Questions and Hypotheses . . . 37
4.4 Statistical Analysis Methods . . . 39
4.5 Data Collection . . . 44
4.6 Data Analysis . . . 49

A rational choice requires that the preference between options should not reverse with changes of frame. However, Tversky and Kahneman [12] observed systematic reversals of preference by variations in the framing of acts, contingencies, or outcomes. Such deviations occur due to imperfections present in humankind's cognitive abilities, both regarding human perception and decision. The purpose of our research began with **exploring whether the framing effect transfers to InfoVis by applying priming techniques using well-known graphical encodings**.

Upon studying the *framing effect*, Tversky and Kahneman [12] applied a brief questionnaire to participants. Subjects were asked to choose between two alternative treatments to combat a hypothetical Asian disease, which was expected to affect 600 people. *Problem 1* presented the consequences of its two programs through a *positive* frame, whereas *Problem 2* stated its outcomes with a *negative* frame (see Table 4.1). Problems were identical in terms of the consequences (programs *A* and *C*, and programs *B* and *D*), the only difference being the framing variations of the outcomes of each program. Yet, a majority of participants chose program *A* over *B* (72% versus 28%), while in *Problem 2*, the majority chose program *D* over *C* (78% versus 22%).

Table 4.1: Tversky and Kahneman original problem [12].

Problem	***Options***
Problem 1	*A:* If adopted, 200 people will be saved *B:* If adopted, there is 1/3 probability that 600 people will be saved, and 2/3 possibility that no people will be saved
Problem 2	*C:* If adopted, 400 people will die *D:* If adopted, there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die

With this, Tversky and Kahneman [12] concluded that decisions tend to be riskier when the options are presented through a *negative* frame (Problem 2) as opposed to the ones taken with the problem shown with a *positive* one (Problem 1). In other words, with a problem presented through a ***positive*** frame, the choice tends to be **risk-averse**. In contrast, decisions taken upon a ***negative*** frame favour **risk-taking** behaviour. Therefore, Tversky and Kahneman [12] concluded that changes to the reference point of the framing can have a significant impact on the way a subject makes decisions.

For our research, we based our decision-making problem on the original one from their work - a hypothetical disease expected to affect 600 people -, with minor modifications (see Table 4.2). The same two framing conditions were employed: the *positive* and *negative* framing conditions. These consisted of the two main conditions of our study. Equally, each of these two conditions presented two options, a *risky* - option *B* or *D* - and a *not risky* one - option *A* or *C*. For each condition, participants would choose a single one.

Once decided on the setting of the study itself, the next step was to choose a chart type to represent it. Based on Bancilhon et al. [7], we opted for a bar chart to understand the impact of visualization in

Table 4.2: Framing conditions and respective options of our study.

Framing	***Description***
Positive	*A:* If adopted, 200 people will be saved
	B: If adopted, 150 to 250 people will be saved
Negative	*C:* If adopted, 400 people will die
	D: If adopted, 350 to 450 people will die

decision-making. In particular, such research showed that depicting the possible choices through bar encodings was the approach which exhibited behaviour that was most similar to showing the information solely through text. Hence, represents the expected behaviour and, as argued by the researchers themselves, the *bar* group presented as the most relevant finding in the InfoVis context. Considering the aforementioned (see Chapter 3) gap of research regarding the framing bias within this context [5] together with, to the best of our knowledge, the absence of prior work specifically mentioning visualizations when studying the framing effect, we decided to use bar charts to represent the programs of our study. Regarding the risk factor of the choices, i.e. whether an option is *risky* or *not risky*, we leveraged error bars (confidence intervals) to represent the uncertainty of outcomes - present in options *B* and *D*. The two main visualizations of our study are represented in Figure 4.1 - *positive* study condition in 4.1(a), and the *negative* one in 4.1(b). From this, our research began its exploratory goal with the following **research question**:

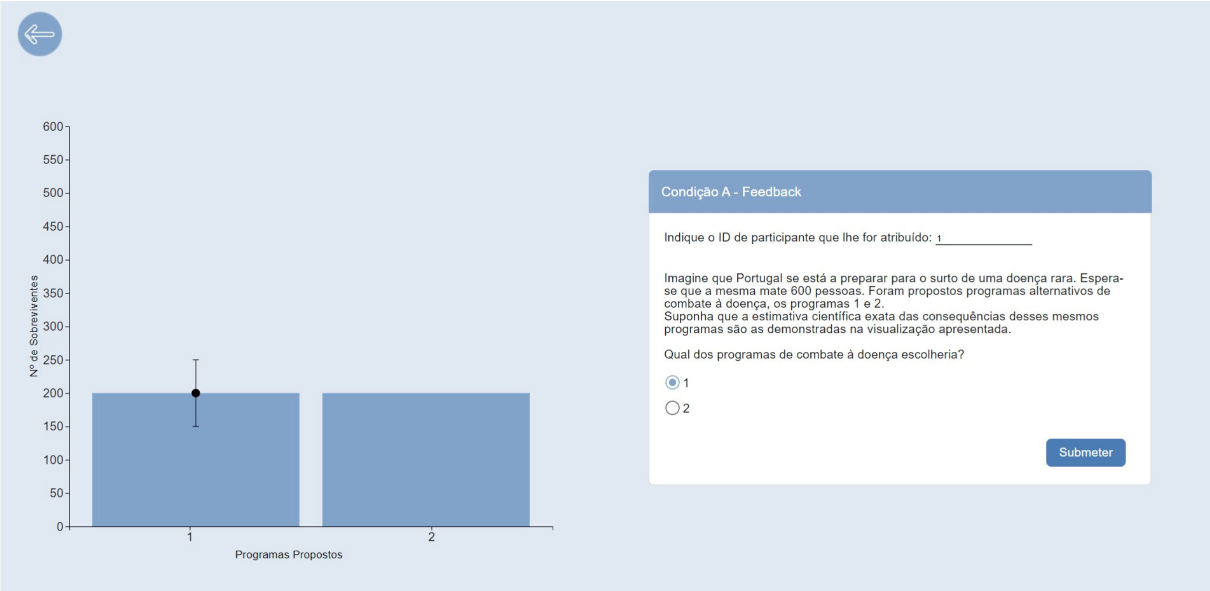
RQ1. Does the framing condition affect decisions presented by bar charts with error bars?

Furthermore, to accomplish the goal of our work stated in Chapter 1, we additionally opted to explore the possible impact personality might have on the interaction of users with visualization systems. In particular, when said systems aid in the process of decision-making. Our research focused on the *neuroticism* personality trait.

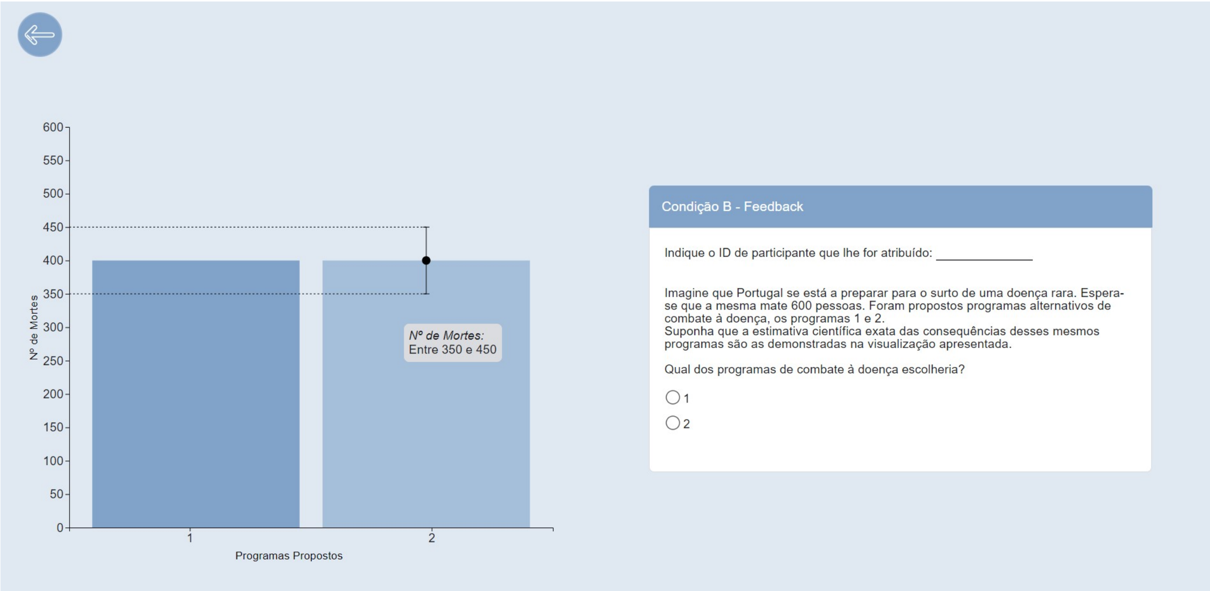
Individuals high on the neuroticism scale are more prone to experiencing negative emotions, such as stress [2]. These tend to be more pessimistic [115], anxious, and depressed [114, 116, 117], and show a tendency to pay more attention to negative information and less attention to positive information [118]. Moreover, high levels of neuroticism are correlated with low problem-solving skills [119]. These individuals have a hard time making decisions [120], notably when in risky situations [121] as they often feel more pressured to answer correctly [2]. Individuals with *average* neuroticism values are significantly faster on problem-solving tasks than the combined *high* and *low* scores ones [2, 122]. From these findings, we determined our **second research question**:

RQ2. Does neuroticism affect being primed by the different framings?

We aimed explore the possible effect different framings of outcomes - *positive* and *negative* - might have with the established visualizations. Moreover, the possible effect neuroticism could bring to our



(a) The *positive* framing condition, indicating the survivors for each program. Participant's ID and choice indicated, thus, showing the submit button.



(b) The *negative* framing condition depicts each program through the deaths it would cause if chosen. Here, hovering a program and, therefore, showing the details about it.

Figure 4.1: The two main framing conditions - *positive* and *negative* - from our study. The order between these two study conditions was alternated from subject to subject. For each condition, the placement of risk was, likewise, arbitrary.

research. Acknowledgement of the importance of decision-making along with cognitive biases over the visualization community has been showing a noticeable rising. Notwithstanding, empirical work on such remains to be comprehensive and there is only sparse dedicated research. In particular, the framing bias remains largely unexplored within the InfoVis field [5]. Accordingly, with the formerly mentioned remark of the work by Tversky and Kahneman [12], we expected decisions taken upon the *positive* framing condition of our study to be more *risk-averse* and the ones for the *negative* one to be *risk-seeking*. Consequently, we presumed participants would opt more for options *A* and *D*, respectively for each of the two conditions. Due to the gaps in research previously mentioned - namely regarding the framing effect within the InfoVis field - that was the single anticipated discovery for our work. Aside from it, we kept a general exploratory approach to our research.

As a result of the said experimental investigation, we designed a third study condition, which we designated as a *neutral* framing condition. In this, participants would have available all four options (see Table 4.2) - *A*, *B*, *C*, and *D* - from both framings together - *positive* and *negative* - at the same time and would be asked to, equivalently, choose a single one. The *neutral* framing condition of our study is shown in Figure 4.2. This third study condition led to our **third research question**:

RQ3. Do decisions taken in individual contexts hold when contexts are seen simultaneously?

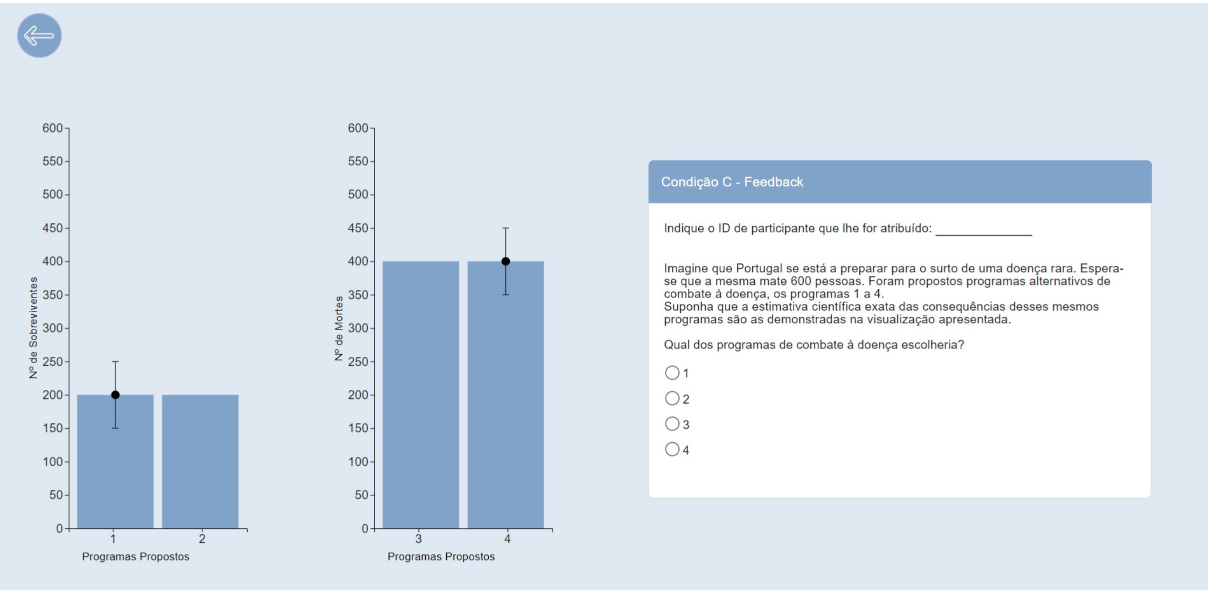


Figure 4.2: The *neutral* framing condition of our study, where participants would be presented with all four options simultaneously and asked to decide on a single one.

Each participant in our study was exposed to all three framing conditions - *positive*, *negative*, and *neutral*. As previously referenced, work by Kwak and Huettel [58] discovered that not only may the left-right positioning change the impact of the information shown has on the participants and, therefore, bias their choice, but also the sequence of visual information processing. In light of these findings, the order in which individuals underwent each of the conditions would be randomized, starting with either the *positive* or *negative* one. After that first decision, the other condition would be next. The *neutral* study condition would consistently be the last decision to be taken. Moreover, for each condition of our study, the position of the *risky* (*B* and *D*) and *not risky* (*A* and *C*) options was displayed randomly on either the left or right side of the visualization. Likewise, for our *neutral* framing, both the positioning of options - *risky* and *not risky* - for each visualization - *positive* and *negative* - together with the positioning of the visualization themselves was arbitrary. As indicated in Figure 4.1(a) the submit button would only show once both the participant ID and choice fields were indicated. This was the same for all conditions in our research.

The following section introduces the chosen approach for our study. Starting with our framing strategy and measures it, then introduces both the research questions as well as the derived hypotheses for each one. Additionally, it also explains the statistical methods used for each of our hypotheses and presents information regarding the data collection - participants, apparatus, and procedure - and further analysis of said data.

4.1 Framing Strategy

Not only is there a gap in research when considering the framing effect within the visualization context, but also regarding an (algorithmic) measure to evaluate the framing bias, i.e. a measure to determine whether an individual has been a subject to it or not. To proceed with our study, it was required to define how we categorized an individual as primed. Taking into account that to the best of our knowledge such gaps remain present, we based this decision of ours on utility theory. Thus, we opted to fix the expected value of each option within a frame condition as the same - as seen in Table 4.2, 200 survivors for the *positive* framing condition and 400 deaths for the *negative* one. Leveraging this approach implies the lack of an optimal decision since both options (per condition) are expected to provide the same outcome value. Therefore, the decision-maker would solely be deciding whether to follow a *risk-averse* (options *A* and *C*) or a *risk-taking* (options *B* and *D*) strategy.

To identify whether a participant was primed in the individual evaluation, we considered that we primed the participant if they changed their decision between the *positive* and *negative* frames. For instance, if the participant chose the *risky* option in the *positive* framing and the *not risky* choice in the *negative* framing, we assume that the frame primed the individual.

4.2 Measures

Following along with the purpose of our research, we stored multiple variables. Plucking inspiration from the previously mentioned literature work (see Chapter 3), we collected data not only regarding the personality of users but also related to the hover events, decision completion time, final decisions, and perceived risk of said decisions. All variables analysed during our study are presented in Table 4.3.

Table 4.3: Variables measured in this study.

Measure	***Type***	***Dependency***	***Description***
Framing Condition	Categorical	Independent	The framing condition {positive, negative, neutral}
Neuroticism Level	Ordinal	Independent	Individual's level of neuroticism {low, average, high}
Number of Hover Events	Quantitative (ratio)	Dependent	The number of hovers per program, per framing condition
Decision Completion Time	Quantitative (ratio)	Dependent	The time taken to make a decision, per framing condition (in seconds)
Choice	Categorical	Dependent	Individual's choice, per framing condition {risky, not risky}
Perceived Risk	Ordinal	Dependent	Perceived risk of the choice taken, per framing condition

4.2.1 Independent Study Variables

As formerly mentioned, our research focused specifically on the framing of outcomes of the programs - *A*, *B*, *C* and *D* -, as Tversky and Kahneman [12] did in their originally posed problem. Our study had three framing conditions - ***positive***, ***negative***, and ***neutral***. The *positive* and *negative* were the focus of our work. Given the exploratory basis of this research, the *neutral* one was designed merely to draw some possible relevant information throughout the study.

Alongside the framing effect, our study, likewise, aimed to explore the effect of personality within the InfoVis context. As mentioned in Chapter 2, the focus here was the ***neuroticism*** personality trait. Such was evaluated through the FFM and assessed through the Portuguese norm [123]. Each participant present in the study was assigned a neuroticism classification, in accordance with participants of the same age and gender, as explained further in the document.

4.2.2 User Interaction

As discussed in Chapter 3, works like the one from Brown et al. [1] prove how personality traits are correlated with mouse activity, notably *neuroticism*. Taking such into account together with the established visualization for our research, we opted to measure mouse activity through the *number of hovers each* *individual triggered per program* (bar) while taking their choice for each of the framing conditions. Once hovering over a specific program, the tester would have access to the exact values of the hovered program. As seen in Figure 4.1(b), if the individual hovered over a *risky* option such as option *D*, the upper and lower bounds of the confidence interval were provided with a tooltip on the bar. In contrast, when the hovered option was a *not risky* one - *A* or *C* - the exact value - 200 or 400, respectively - would be added with a tooltip to the bar. We collected the number of hover events per option (bar) by counting them from the moment testers opened each of the study conditions until their final answer was submitted.

Green and Fisher [11] and Ziemkiewicz et al. [2] showed how neurotic participants execute tasks faster, due to their greater attentiveness [76]. As such, we collected the *decision completion time* in seconds of each choice taken. We opted to count the time by starting after the student finished the explanation of the procedure to the participant and stopping the timer once the tester had submitted their decision, per framing condition.

4.2.3 Decision-Making

As far as we are aware, and as formerly alluded to, there is an absence of (algorithmic) measures to evaluate the framing bias. Considering this, we recorded the *final choice* of each participant (*risky* or *not risky*), per framing condition. Regarding the decision taken in the *neutral* framing condition, we would do so indicating, too, the frame of the chosen option - *positive* or *negative*. For example, if a participant chose option *A* it was recorded as the *positive* $+$ *not risky* option.

Subjective feedback has proven to provide further insights into the decision process [108,111]. Thus, we additionally collected the self-reported *perceived risk* of each of the choices taken. All participants had to subjectively assess the riskiness of their decision through a seven-point Likert scale ranging from Not risky at all (1) to Extremely risky (7). This measure also allowed us to sustain the intended experimental and general approach to the research as well as seek to draw more results.

4.3 Research Questions and Hypotheses

Regardless the rising acknowledgment mentioned, empirical work on decision-making and cognitive biases in the InfoVis field has yet to be comprehensive. As previously mentioned, *framing bias* is a cognitive bias that, although widely known and already recognized as important in the InfoVis field, remains largely unexplored and is yet to be further studied [5]. Therefore, our research followed a generally exploratory approach throughout. To reach the goal of this study, declared in Chapter 1, and taking the aforesaid into account, our study began with the following **research question**:

RQ1. Does the framing condition affect decisions presented by bar charts with error bars?

In particular, we aimed to explore and focus on the possible effect different framings of outcomes - *positive* and *negative* - might have with the established visualization. As such, under this research question, we derived the following **hypotheses**:

H1.1 The type of frame influences the number of hovers made per program (*A, B, C, D*).

H1.2 The type of frame affects the amount of time users take to make a choice.

H1.3 The type of frame impacts the choice users take.

H1.4 The type of frame impacts the perceived risk of users.

After the focus on merely the framing of outcomes with our visualizations for the *positive* and *negative* framing conditions, we incorporated the personality of the participants - namely, their neuroticism scores - into our research.

Researchers have found that more neurotic individuals are more risk-averse [124–126]. Additionally, it was found that in the domain of gains, more neurotic individuals show less risk-taking behaviour; yet, in the domain of losses, these are willing to take higher risks [127]. From such findings, researchers concluded that more neurotic individuals have a tendency to focus more on the negative consequences of the guaranteed losses and are therefore more willing to take risks as a way to avoid the guaranteed losses. As stated by Oehler and Wedlich [111], the empirical findings respecting the possible correlation between neuroticism and risk-taking behaviour, are quite diverse [111]. Even so, the overall expected behaviour of more neurotic individuals is less risky. From the mentioned wide variety of findings, we determined our **second research question**:

RQ2. Does neuroticism affect being primed by the different framings?

For this research question, due to the aforementioned assortment of findings, our intent kept being to maintain a general approach to it. We studied not only the interaction effect between the personality trait alongside the framing condition - *positive* and *negative* - but also continuous and additionally explored the possible effects the personality trait itself might have. As such, we formulated the following **hypotheses**:

H2.1 Neuroticism influences the number of hovers made per program (*A, B, C, D*), depending on how risky an option is.

H2.2 Neuroticism has an effect on the time users take to make a choice, in different framing conditions.

H2.3 Neuroticism affects the choice users take, in different framing conditions.

H2.4 Neuroticism has an effect on the perceived risk of users, in different framing conditions.

Whereas the **RQ.1** of our work merely explores the effect of *framing* in itself in the measures of our study, our **RQ.2** adds the possible interaction *neuroticism* might have when playing an additional role together with the framing - *positive* and *negative*. Accordingly, each of the *H1* hypotheses has a correspondent *H2* hypothesis, where the same study measure is being evaluated, adding the neuroticism personality trait to the analysis.

As above mentioned, the exploratory approach to our research led us to design a third study condition designated as a *neutral* framing condition. Here, participants would have to decide on a single program out of all four - *A*, *B*, *C*, and *D* - of them together. The possible information to be drawn that we considered relevant to assess from this condition was regarding the choices of participants. In particular, if the decision taken previously with either the *positive* and *negative* framing individually would hold or change for this *neutral* framing condition, according to the frame present in the *final* decision of each individual. Thus, we formulated our **third research question** as follows:

RQ3. Do decisions taken in individual contexts hold when contexts are seen simultaneously?

Taking how the *neutral* framing condition consisted of an additional one to our study, we kept this research question open without any particular hypotheses for our investigation.

4.4 Statistical Analysis Methods

To effectively explore the framing effect and the impact of the neuroticism personality trait together with their possible interaction in the context of our work, we leveraged multiple statistical analysis methods. These included various types of Analysis of Variance (ANOVA) (according to the variables involved in each particular analysis), a McNemar's Test, and Chi-Square Tests of Independence. Table 4.4 indicates the correspondence between our research questions and hypotheses mentioned in Section 4.3 with the statistical methods used for validation of each one, for the *positive* and *negative* framing conditions. The *risk factor* variable indicates whether an option is *risky* - programs *B* and *D* - or *not risky* - options *A* and *C*. The *neutral* study condition consisted of a plus to our study to attempt to further investigate possible results. Therefore, the analysis of such condition remained separate from the other two and was done only through the assessment of the final choices taken.

For each of the statistical analyses performed, we checked for outliers either through boxplots or Studentized Residual (SRE). For the ANOVAs, we tested for sphericity through Mauchly's test, and we followed the ANOVAs with posthoc Tukey's range tests including Bonferroni corrections. Normality was continuously tested through the Shapiro-Wilk test of normality. As mentioned in the previous section, the *perceived risk* of each choice taken was measured through a seven-point Likert scale, making it an ordinal variable. Be that as it may, we opted to analyse it rather as an *interval* variable and ANOVAs analyze the involving hypotheses - *H1.4* and *H2.4*.

Table 4.4: Research Questions and Hypotheses with the variables used as well as the respective statistical methods used for the *positive* and *negative* framing conditions of the study.

Research Question	***Hypothesis***	***Independent Variable(s)***	***Dependent Variable(s)***	***Statistical Method***
RQ 1.	***H1.1***	Frame and Risk Factor	Hovers	Two-Way Repeated Measures ANOVA
		Choice and Risk Factor	Hovers	Two-Way Mixed ANOVA (per framing condition)
	H1.2	Frame	Time	One-Way Repeated Measures ANOVA
	H1.3	Frame	Choice	McNemar's Test
	H1.4	Frame	Perceived Risk	One-Way Repeated Measures ANOVA
RQ 2.	***H2.1***	Frame, Risk Factor, and Neuroticism	Hovers	Three-Way (BWW) Mixed ANOVA
	H2.2	Frame and Neuroticism	Time	Two-Way Mixed ANOVA
	H2.3	Neuroticism and Choice		Chi-Square Test of Independence
	H2.4	Frame and Neuroticism	Perceived Risk	Two-Way Mixed ANOVA

4.4.1 Outliers Removal Criteria

The detected outliers all consisted of genuinely unusual values. Outliers were assessed - and removed - individually for each of the statistical analyses indicated in Table 4.4. Specifically, both for the Two-Way Mixed and Repeated Measures ANOVAs carried out during our data analysis process, outliers were assessed by examination of SREs. Data points with SREs greater than $\pm\ 3$ standard deviations are considered outliers, i.e. less than -3 and greater than 3. Values falling, in either case, were (locally) removed from the specific ongoing analysis.

As for the remaining statistical tests performed, the determination of outliers was done through the inspection of boxplots. All the executed statistical analyses were made with the *SPSS Statistics* tool. As such, there were two categories of outliers (as classified by SPSS Statistics) found in the produced boxplots: *outliers* and *extreme points*. Respectively, data points more than 1.5 and 3 box-lengths from the end of their box. Taking into account how SPSS Statistics states that "Generally speaking, data points that are labelled outliers in boxplots are not considered as troublesome as those considered extreme points and might even be ignored."[1] we decided to consider only the points labelled as *extreme outliers* as the relevant outliers for each of the analyses in our study and (locally) removed the correspondent ones in each analysis individually.

[1] https://statistics.laerd.com/premium/spss/mabww/mabww-in-spss-7.php

4.4.2 Two-Way Repeated Measures ANOVA

The Two-Way Repeated Measures ANOVA[2] is used to understand if there is a statistically significant interaction effect between two *within-subjects* independent variables on a *continuous dependent variable*. To be able to run this ANOVA there are five basic requirements one needs to consider. The dependent variable should be *continuous* (interval or ratio), and both independent variables should consist of *within-subjects* variables presenting two or more *categorical* levels. There should be no outliers in any cell of the design (i.e., in any combination of levels of the two within-subjects variables). Even though this ANOVA is fairly resistant to outliers, we followed the formerly mentioned outliers removal criteria for the hypothesis in our work - *H1.1* - requiring this statistical method. Additionally, the dependent variable should be approximately normally distributed across all cells of design, tested using the Shapiro-Wilk test of normality. Given how this test tolerates some violations of this assumption and still provides valid results, we carried out our analysis regardless of this assessment. Lastly, known as the assumption of sphericity and tested using Mauchly's test, the variances of the differences between all combinations of levels of the within-subjects factor must be equal. However, both our within-subjects factors - *frame* and *risk factor* - have only two categories - *positive* and *negative* and *risky* and *not risky*, respectively. Therefore, we did not have to test this and were able to always proceed to the interpretation of the results as though we had met this last assumption.

We leveraged the Two-Way Within ANOVA to test part of our ***H1.1*** hypothesis. As indicated in Table 4.4, such a method was run to determine the effect of different *framing* conditions (*positive* and *negative*) over different *risk factors* (*risky* and *not risky*) on the number of hovers per program.

4.4.3 Two-Way Mixed ANOVA

The primary purpose of the Two-Way Mixed ANOVA[3] is to determine whether an interaction between a *within-subjects* and *between-subjects* variables on a *continuous dependent variable* exists. To achieve such a goal, this ANOVA compares the mean differences between groups that have been split on the two independent variables. To be able to carry out a Two-Way Mixed ANOVA the data needs to fulfil eight basic requirements. This method requires a single *continuous* (interval or ratio) dependent variable, and a *within-subjects* and *between-subjects* variables for independent ones. Both the *within-subjects* variable as well as the *between-subjects* one must be measured at a *categorical* level, with two or more categories. Moreover, there should be no significant outliers in any cell of the design and the dependent variable should be approximately normally distributed for each one. Following the outliers removal criteria mentioned previously and locally removing outliers from each analysis leveraging this method, we opted to ignore the assumption of normality as this statistical test is considered "robust" to deviations of

[2] https://statistics.laerd.com/premium/spss/twrma/two-way-repeated-measures-anova-in-spss.php
[3] https://statistics.laerd.com/premium/spss/twma/two-way-mixed-anova-in-spss.php

normality while still being able to provide valid results. The variance of the dependent variable should be equal between the groups of the between-subjects variable - homogeneity of variances -, and there should also be homogeneity of covariances. These two assumptions were tested using Levene's Test of Equality of Error Variances and Box's test of equality of covariance matrices, respectively. Lastly, the data should also meet the assumption of sphericity, meaning that the variance of the differences between groups should be equal. As the within-subjects factors - *frame* or *risk factor* - for the hypotheses analysed using this validation method always had only two categorical levels - *positive* and *negative* and *risky* and *not risky*, respectively - we were continuously able to proceed with the analysis as though we had met this last assumption without having to test this assumption.

Regarding the study of the *positive* and *negative* framing conditions of the study, the Two-Way Mixed ANOVA was used for hypotheses ***H1.1*** (one per framing condition), ***H2.2***, and ***H2.4***. These analyses allowed us to explore the various possible two-way interactions: (i) between the *choice* taken and the *risk factor* of programs on the number of hovers, individually for the *positive* and *negative* framing conditions; (ii) determine the effect of different *neuroticism* level groups over the different *framing* conditions on the amount of time taken to make a choice; and (iii) the interaction between different *neuroticism* level groups and both *framing* conditions on the perceived risk of the choice taken. The prior mentioned *H1.1*, *H2.2*, and *H2.4*, respectively.

4.4.4 One-Way Repeated Measures ANOVA

The One-Way ANOVA[4] determines the existence of any statistically significant differences between the means of three or more levels of a *within-subjects* variable, where the levels are related as they contain the same cases (e.g., participants). This method can also be used when the *within-subjects* factor has only two levels, which was our case for the hypotheses analysed through this ANOVA - *frame* with *positive* and *negative* levels. To perform this test, one must have a *continuous dependent variable* and a single *within-subjects* factor that consists of two or more levels. Additionally, it is required that there are no significant outliers in any of the said levels, that the dependent variable follows an approximately normal distribution throughout the two or more levels, and that the assumption of sphericity is met - i.e., the variances of the differences between all combinations of levels of the within-subjects factor must be equal. Regarding outliers, the outlier removal criteria were followed. Similarly to the previous Two-Way ANOVAs mentioned, this method can be considered "robust" to non-normality and, thus, we opted to proceed regardless of the correspondent findings. As for the assumption of sphericity, our within-subjects factor *frame* only has two levels - *positive* and *negative* - which meant that we were able to not test this assumption and continue as if we had met it.

Hypotheses ***H1.2*** and ***H1.4*** were both validated through this method. Thus, allowing us to determine

[4] https://statistics.laerd.com/premium/spss/owrma/one-way-repeated-measures-anova-in-spss.php

whether there were any statistically significant differences in the time taken to make a choice or in the perceived risk of said choice between the *positive* and *negative* framing conditions of our study, respectively.

4.4.5 McNemar's Test

The primary purpose of a McNemar Test[5] is to understand if there are statistically significant differences in a *dichotomous dependent variable* between two *related* groups. Three basic requirements need to be considered: (i) there is a single *dichotomous* (two levels) dependent variable with two mutually exclusive groups, (ii) there is one independent variable that consists of two *categorical*, related groups, and (iii) the cases (e.g., participants) should be a random sample from the population of interest.

The only occurrence in our data analysis process where we performed this statistical method was for our ***H1.3*** hypothesis, when in the context of the *positive* and *negative* conditions. We opted for this statistical test to determine whether the proportion of participants who chose to risk differed when upon the *positive* framing condition as opposed to when shown the problem in the *negative* framing condition of the study. This means that our dependent variable for this analysis was the final *choice* of participants, which has two categories: *risky* or *not risky*.

4.4.6 Three-Way (BWW) Mixed ANOVA

Comparing the mean differences between groups of three independent variables, the primary purpose of a Three-Way Mixed ANOVA[6] is to understand the interaction between them on a *continuous dependent variable*. It can take on two possible forms, one of them being with one *between-subjects* and two *within-subjects* variables, which was the case for the Three-Way ANOVA performed in our research. To leverage this statistical method, one must have one *continuous* (interval or ratio) dependent variable, one *between-subjects* independent variable that is *categorical* with two or more groups, and two *within-subjects* independent variables also measured at a *categorical* level, again with two or more levels in each factor. There are four other additional assumptions that need to be met to be able to perform this analysis: (i) there should be no significant outliers in any cell of the design, (ii) the dependent variable should be approximately normally distributed in every cell of the design, (iii) there should be homogeneity of variances between the groups of the between-subjects factor for each combination of the levels of the within-subjects factors, (iv) the assumption of sphericity must be met. As for (i) the previously mentioned outliers removal criteria were followed and outliers were accordingly removed. The normality assumption (ii) was discarded as this ANOVA is, too, considered fairly "robust" to deviations. The assumption of homogeneity of variances (iii) was tested using Levene's test of Equality of Error Variances and the

[5] https://statistics.laerd.com/premium/spss/mt/mcnemars-test-in-spss.php
[6] https://statistics.laerd.com/premium/spss/mabww/mabww-in-spss.php

sphericity was not needed to be assessed as our within-subjects factors - *frame* and *risk factor* - have only two levels - *positive* and *negative*, and *risky* and *not risky*, respectively. Thus, we were able to proceed as though we met this last assumption.

As seen in Table 4.4, for the context of the *positive* and *negative* study conditions, this statistical test was solely used for our hypothesis ***H2.1*** to understand the effects of the *frame* (*positive* or *negative*), *risk factor* (*risky* or *not risky*), and the *neuroticism* level of participants (*low*, *average* or *high*) on the number of hovers (per program).

4.4.7 Chi-Square Test of Independence

Also known as Chi-Square Test for Association, the Chi-Square Test of Independence[7] determines whether there is an association between *two (nominal) variables*. This statistical method is only adequate when the data meets the four assumptions. There must be two *nominal* variables. Whilst possible to use with *ordinal* variables as well, one loses the ordered nature of the data by doing so. This was our case: we took the *neuroticism* level of participants as a *nominal* variable for this analysis. Thus, conscientiously losing the extra information provided by knowing the order of the categories - *low*, *average*, *high*. There should be no relationship between the observations in each group of each variable or between the groups themselves, i.e., one should have independence of observations. Moreover, this procedure is only adequate for cross-sectional sampling, which our study followed. Lastly, all cells should have expected counts greater than or equal to five.

As seen from Table 4.4, our hypothesis ***H2.3*** was assessed through this statistical method. In the context of the *positive* and *negative* framing conditions, we aimed to understand whether there was a statistically significant association between the *neuroticism* level (*low*, *average*, *high*) of participants and the changing of final answers between those two study conditions. This last variable was derived for this analysis as a categorical variable that takes the value of 1 when participants changed their answer between conditions and 0 when the final decision remained the same in both frames.

4.5 Data Collection

Our study had to be conducted remotely through Zoom meetings, as a consequence of the COVID-19 pandemic. Once recruited for the study, we solicited individuals to fill a personality survey which recorded data regarding various personality traits, namely neuroticism. Next, prior to any interaction with our visualizations, we presented a small questionnaire regarding general information - participation consent, visual impairments, overall willingness to take risks, and familiarity with both visualizations used in our research. During the test session itself, we would record the video conference - both video and audio -

[7] https://statistics.laerd.com/premium/spss/cstoirxc/chi-square-test-of-independence-rxc-in-spss.php

to be analysed afterwards and extract the required measures for our study (see Table 4.3). Thus, there were four main steps in our research for the collection of the data from the participants in our study: personality survey, initial questionnaire, user test, and review of the test recordings. The latter additionally allowed for the discovery and correction of anomalies, as well as taking note of feedback given by the participants. All this information was further stored together in a comma-separated file containing a list of all the data of the tests performed, already with the correction of the detected anomalies.

4.5.1 Participants

There was a total of 91 participants in our study (51 females, 39 males, and 1 other) aged 17 – 59 (M = 26.33, SD = 10.646). The skewness of ages was due to the recruitment process. Most participants were recruited through direct contact, ergo, friends and university colleagues. All testers were recruited through standard convenience sampling procedures together with word of mouth.

Another key aspect of our study was the visual impairments of individuals and if they were using the vision corrections upon participation in our study or not. The initial survey regarding personality included a colour-blindness test. Out of the total 91 in our study, only 3 showed inconclusive results (88 presented a negative result). Additionally, 53 participants wore either glasses or contact lenses during the experiment, and 38 did not. Nonetheless, not a single participant reported visual difficulties when interacting with the visualizations.

Both the overall risk willingness to take risks and the familiarity of individuals with both visualizations used in our work were, too, deemed relevant to our study. Both of these were collected through the use of seven-point Likert scales. Figure 4.3 indicates the frequencies of the self-reported risk attitude of participants (M = 4.40, SD = 1.201). As shown, most participants either reported to be either indifferent (4) or take a slightly risky (5) approach, generally speaking.

Moreover, the bulk of participants in our study was familiar (6) or very familiar (7) with the bar chart visualization, as seen in Figure 4.4. No individual reported familiarity level with this visualization to be either 1 or 2 (M = 6.52, SD = 0.765). As anticipated by us, for the second visualization in our work - bar chart with the error bar -, the self-reported familiarity levels were more scattered across the seven-point Likert scale used to assess it (see Figure 4.4, M = 4.59, SD = 1.646). This visualization with a total of 24 participants reported a familiarity level between 1 and 3.

4.5.2 Apparatus

Due to constraints from COVID-19, all our experiments were conducted remotely, via Zoom video meetings with a single experimenter at a time. Therefore, a computer and mouse were the only required materials for participation in our study. The development of the visualizations (shown in Figure 4.1 and

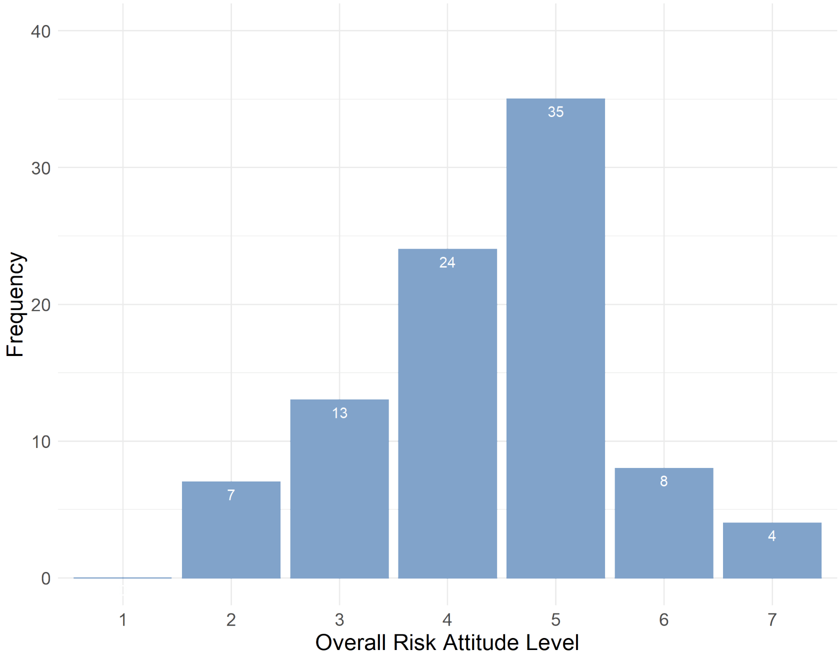


Figure 4.3: Frequencies of self-reported general willingness to take risks.

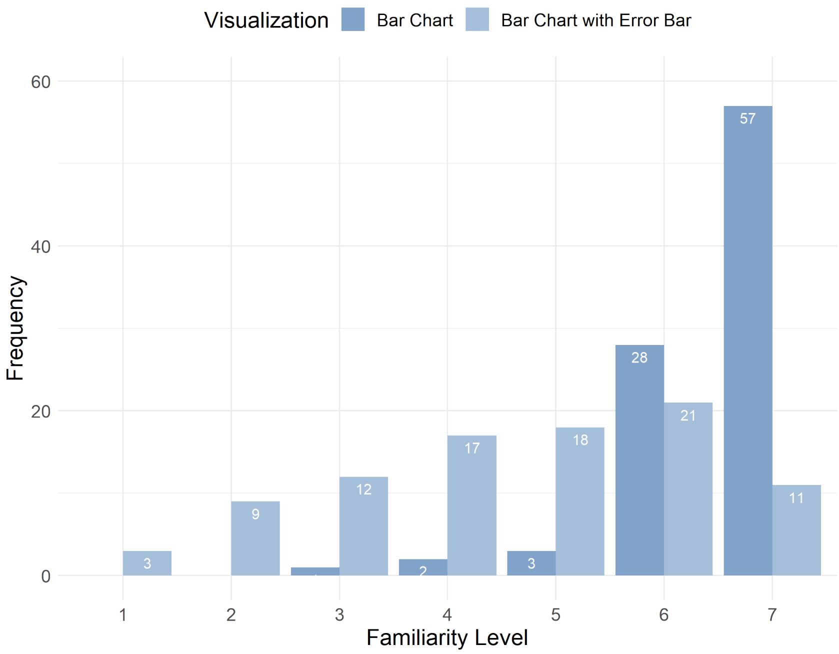


Figure 4.4: Frequencies of familiarity with the visualizations of the study.

Figure 4.2) used to present the data was made by us and we performed all tests with the use of a computer as well. These constraints also required that our visualizations were developed so that they would remain adjustable to different screen sizes to avoid any distortion in the visualization of the data. This way, we ensured that the information was displayed in the same way, regardless of the resolution of the device used for each participant.

4.5.2.A Personality Data

The very first step for participants in our research was the collection of their personality data. This was done through the use of the NEO PI-R questionnaire [37], which provides a comprehensive description of the *Big Five* personality traits - namely, neuroticism. Composed of 240 items, there are 48 items per each of the *Big Five*. For our study, in particular, we applied the European Portuguese version of the NEO PI-R by Lima and Simões [123]. This step was where we assessed the neuroticism score of individuals.

4.5.2.B Measures of the Study

Prior to participation in our experiment, individuals verbally consented to a form (Appendix A). Thus, allowing us to collect and analyse their personality data together with the remaining data to be collected during the experiment. The remaining data consisted of the measures mentioned in Table 4.3 alongside the video and audio recordings of the Zoom conference session.

Both the demographics and additional data mentioned in sub-section 4.5.1 were collected through the use of Google Forms (Appendix B) which would further guide participants throughout the various stages of the experiment session. This brief questionnaire included questions such as regarding visual impairments, subjective classification of their overall willingness to take risks, together with the familiarity with both visualizations used in this study. The latter two aspects were asked through a seven-point Likert scale. General risk attitude ranged from 1 (no willingness) to 7 (total willingness); whereas familiarity would range from 1 (not familiarized) to 7 (completely familiarized).

As mentioned, for our research we opted for two visualizations to display the data to the testers: a simple bar chart and a bar chart with error bars. Due to it being less common, we anticipated the latter not to be widely known within our sample (which was the case, as shown in Figure 4.4). Therefore, aside from the recording of said data, this brief survey also included tutorial images for both visualizations included in the study. Independently of what users would report as their familiarity with either visualization, they were provided with a tutorial image explaining the idioms shown during the experiment and how to interpret the data. To avoid potential biasing, the tutorial images only presented abstract data, irrespective of the problem context of our study.

The Google Forms questionnaire was additionally used to present the problem-context of our experiment to the users, alongside the collection of the final choices and the perceived risk of each one, for all framing conditions. As for the other dependent variables of our research (see Table 4.3), the number of hovers per program was initially assessed with a counter. However, this being an online study led to some inaccuracies in said counter due to inherent online limitations. Therefore, we verified such metric during the study phase of reviewing the user tests recordings. In this stage, we determined the number of hovers manually and retrieved the decision time through the use of a chronometer.

4.5.3 Procedure

Each Zoom session was done with one participant at a time, taking a maximum of 30 minutes. Each of the sessions began with an introductory text describing the research project - both what should be expected from the experiment together with what would be asked of individuals during - alongside the problem's context. Subsequent to the verbal consent to the participation, collection and further analysis of the recorded data, participants filled the demographics survey as well as the risk attitude and familiarity levels questions.

Following the flow of the Google Forms and prior to the interaction with the visualizations themselves, the tutorial images were then presented to the testers. There was one tutorial image per idiom - bar chart and bar chart with error bars - used revealing how to interpret the data from each one. Individuals would be analysing these images as long as they wanted to and then decide when to proceed with the remaining of the experiment. As aforementioned, these explanatory images presented abstract data unrelated to the problem of the study itself to prevent potential biasing. Such was additionally explicitly mentioned to the individuals, as well.

Thereafter, the interaction and decision-making part of the experiment would begin. Each participant was randomly assigned to start with either the *positive* or *negative* framing condition, and next received the opposite one. For each of these two framing conditions, participants would choose a single program between the two presented options (see Figure 4.1). For all the participants, the last study condition was the *neutral* framing condition (shown in Figure 4.2), where participants would equally choose a single option but now from all four. The order through conditions was so to minimize possible biasing. Moreover and, too, in light of the mentioned findings of Kwak and Huettel [58], for each condition in our research, the position of the *risky* (*B* and *D*) and *not risky* (*A* and *C*) options was displayed at random on either the left or right side of the visualization. For the *neutral* condition, the position of the two framed visualizations themselves was, too, arbitrary.

Once the experiment was over and a participant had gone through all the framing conditions in our study, we would thank them for their time and explain the goal of our research - solely at the very end of the session to prevent potential bias. By participating in our study, individuals entered a contest to win one of three FNAC gift cards in the value of 20€ we had to offer.

For all framing conditions, both the number of hover events per program and decision completion time were collected during the study phase of reviewing the audio and video recordings of the Zoom sessions. The hover events had a counter which would show the results when the submission confirmation screen was presented to the individuals. However, limitations caused by the experiments being executed remotely (such as low or bad Wi-Fi connection) caused some anomalies in these counters. Therefore, this measure of our study was then collected manually by reviewing all the user tests. The decision completion time was also obtained when in the study phase of reviewing the Zoom sessions. We would start the chronometer when the student finished the explanation of the procedure for the tests and stop it when the confirmation screen would show, once the participant submitted their choice. The collection of each of the final choices together with the perceived risk of each one was done through the Google Forms used to guide the experiment.

4.6 Data Analysis

In order to analyse the obtained results as aforestated in Section 4.4, we leveraged several validation methods for our statistical analysis. As gone into detail in said Section, for these methods it was required that the *neuroticism* score of participants was considered a *categorical* variable (with at least two levels) rather than a continuous one. Ergo, we established a division of participants into different levels of neuroticism through the European Portuguese version of the NEO PI-R by Lima and Simões [123]. We explored two different possible divisions: two (see Table 4.5) and three (see Table 4.6) levels of neuroticism according to the Portuguese Norm and, thus, each participant present in the study was assigned a neuroticism classification, in accordance with participants of the same gender and age. Regarding the age group, 21 years old individuals or younger are considered young adults and beyond that age are considered adults. Through the use of One-Way ANOVAs, we assessed whether the two distinct applied divisions kept a balanced distribution between the different neuroticism levels and whether the levels were significantly different from each other, i.e. if participants with significantly different scores were assigned different neuroticism levels.

When splitting the individuals present in our research into two neuroticism levels using the Portuguese Norm, we verified that there were 35 participants with a *low* neuroticism level, and 56 individuals presenting a *high* neuroticism classification (see Table 4.5). These results show that, even though there is a 21 participants difference between the two groups, these are rather balanced between the levels. Additionally, we assessed that individuals were significantly different from each other in the different facets of neuroticism. All *p*-values were less than 0.001, meaning that testers were always distinct from each other. Figure 4.5 shows the scores of individuals for each neuroticism level across the different neuroticism facets.

Moreover, by performing the three-level classification in the participants' neuroticism scores using the Portuguese Norm, 41 participants presented a *high* neuroticism classification. Additionally, 26 and 24 individuals with *average* and *low* neuroticism levels, respectively. This information is presented in

Table 4.5: Neuroticism Level classification by two levels.

Neuroticism Level	***Neuroticism Percentile***	***Number of Participants***
Low	[0% - 50%]	35
High	]50 % - 100%]	56

Table 4.6. The biggest difference between groups in this division was 17 participants, meaning that the balance between groups is slightly better as opposed to only two neuroticism levels. Upon leveraging a One-Way ANOVA, we determined that the three levels were statistically significantly different from each other (see Figure 4.6). Again, *p*-values were all less than 0.001, indicating that participants in different levels of neuroticism were always distinct across all facets of this personality trait.

Table 4.6: Neuroticism Level classification by three levels.

Neuroticism Level	***Neuroticism Percentile***	***Number of Participants***
Low	[0% - 25%]	24
Average	]25% - 75%]	26
High	]75 % - 100%]	41

Given these findings, we chose to leverage the *three neuroticism levels* classification according to the Portuguese Norm distribution. This implies that the testers' classification was not done according to our specific sample but rather taking into account the average scores of a large sample from the Portuguese population. As our entire sample is composed of only Portuguese individuals, such consists of an advantage of this approach. Furthermore, both divisions - two and three neuroticism levels - assigned participants in our research with significantly different scores to different levels. Thus, we opted for the three-level classification as it would allow us to better understand the differences among the distinct levels, while also not limiting our analysis to extreme neuroticism scores.

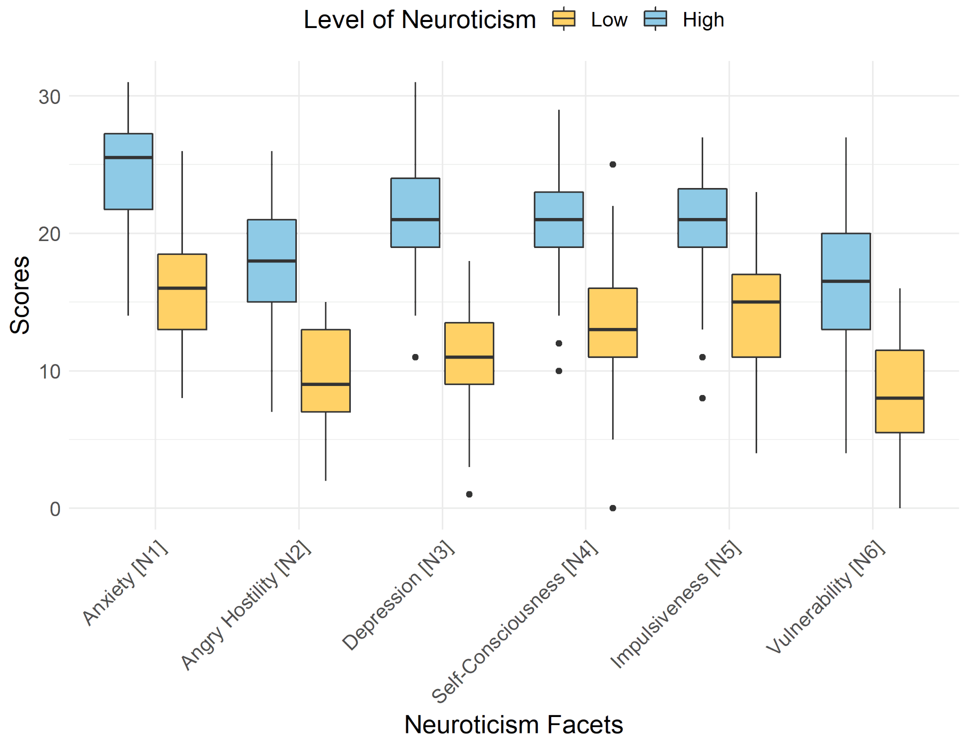


Figure 4.5: Distribution of two levels of neuroticism classification per facet, according to the Portuguese Norm.

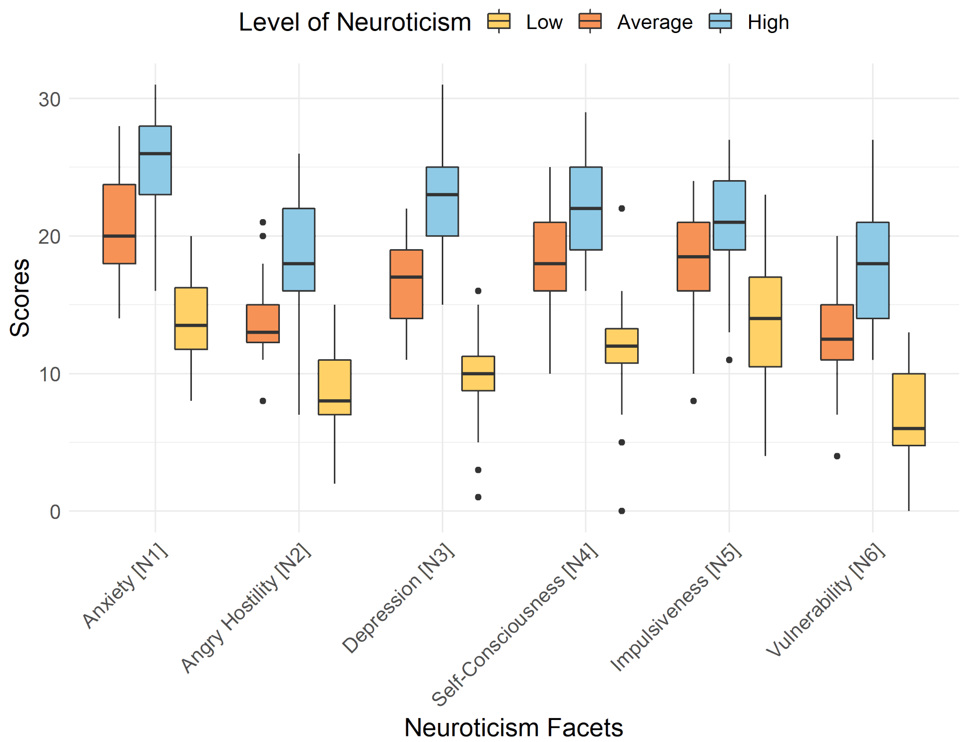


Figure 4.6: Distribution of three levels of neuroticism classification per facet, according to the Portuguese Norm.

5

Results

Contents

5.1 Effect of Framing 53
5.2 Effect of Neuroticism 58
5.3 Neutral Condition 64
5.4 Discussion 66

Leveraging the variables and statistical analysis methods mentioned in Chapter 4, the present chapter offers the obtained results of our exploratory research. Considering our three research questions, we organized our analysis into three distinct parts: Effect of Framing, Effect of Neuroticism, and Neutral Condition of the study. We begin by demonstrating our findings in regards to our first research question (**RQ.1**), i.e., analysing merely the two main conditions - *positive* and *negative* framings - and not taking into account the personality of individuals. Afterwards, we bring the *neuroticism* level of participants into the investigation, under our second research question (**RQ.2**). Moreover, we explore our third research question (**RQ.3**) and the *neutral* condition of our study. Finally, we discuss our results including the experimental implications of our work. Data are mean $\pm$ standard deviation, unless otherwise stated.

5.1 Effect of Framing

Ignoring individuals' personalities in the first instance, we initiated our analysis by focusing solely on the framing bias and its possible effect on the variables of our research. In particular, we studied the potential effect different framing of outcomes - *positive* and *negative* - might have with the established visualizations in the metrics of our work. To do so, here we focused merely on the said two main conditions of the study and neglected the third additional one (*neutral* framing condition).

5.1.1 User Interaction

5.1.1.A Number of Hover Events

In light of the metrics collected in our research, we opted to analyse the number of hovers events from two perspectives: both from the possible interaction between the *frame* and *risk factor* of a program upon this measure as well as between the final *choice* and *risk factor* (as indicated in Table 4.4 from the Chapter 4).

A Two-Way repeated measures ANOVA was run to determine the effect of different *framing* conditions - *positive* and *negative* - over different *risk factors* - *risky* and *not risky* - on the number of hovers per option (bar) - *A, B, C* and *D* (see Figure 5.1). There were four outliers detected through the inspection of SREs. All four data points were removed (locally) from this analysis. Results showed there was no statistically significant two-way interaction between frame and risk factor on the number of hovers per program, $F(1, 86) = 0.557, p = 0.457$, partial η^2 = 0.006. With this, we continued our analysis by determining the presence of any statistically significant main effects.

The main effect of frame - *positive* and *negative* - did not show a statistically significant difference in the number of hovers, $F(1, 86) = 3.393, p = 0.069$, partial η^2 = 0.038. The number of hovers in the *positive* framing condition - 2.98 ± 1.917 hovers for the *risky* option and 2.55 ± 1.891 hovers for the *not*

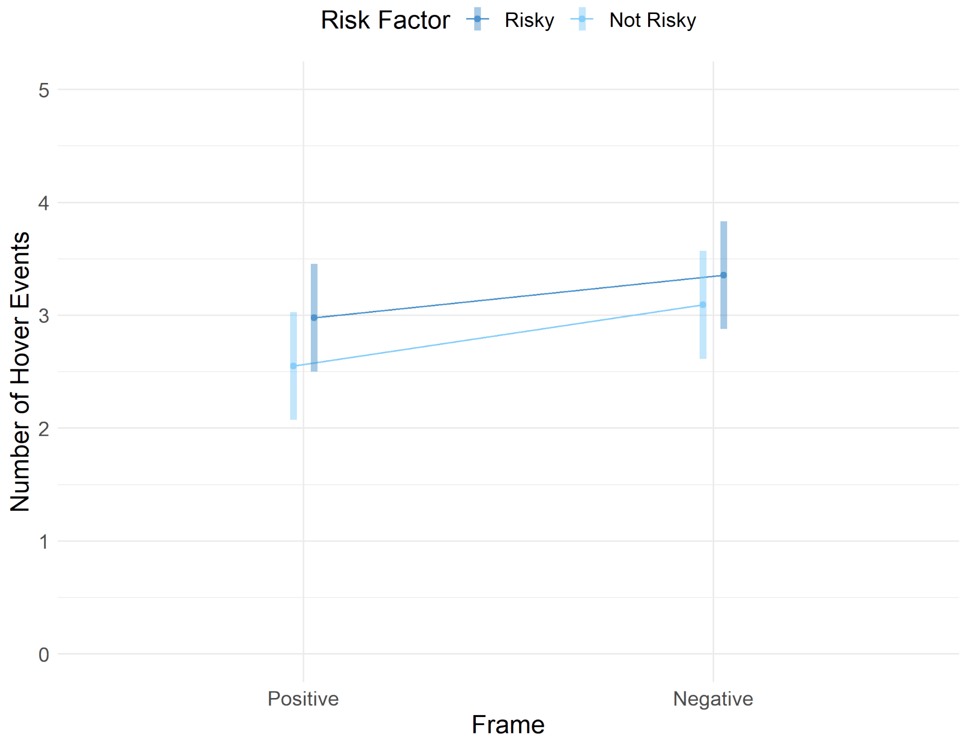


Figure 5.1: Estimated marginal means of the number of hover events triggered in each option across the two main conditions - *positive* and *negative* framings.

risky one - was not statistically significantly different (lower) as opposed to the *negative* framing condition of the study - 3.36 ± 2.592 hovers for the *risky* option and 3.09 ± 2.568 hovers for the *not risky* one. A difference of 0.460 (95% CI, -0.956 to 0.036) hovers between the two conditions.

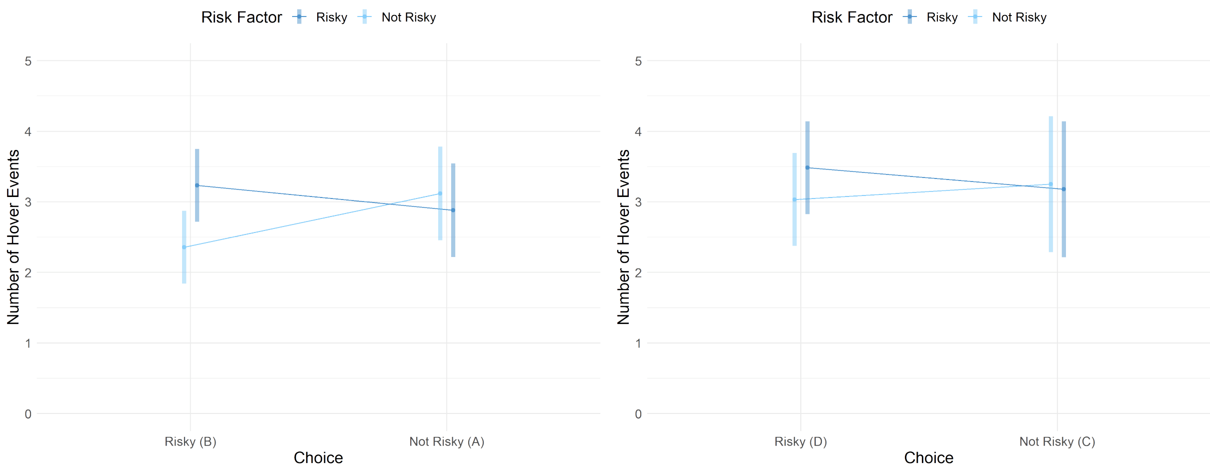
In contrast, the main effect of risk factor did show a statistically significant difference in the number of hovers between options - *risky* and *not risky* -, $F(1, 86) = 7.793, p = 0.006$, partial η^2 = 0.083. The mean number of hovers was 0.345 (95% CI, 0.099 to 0.590) hovers higher in the *risky* option - 2.98 ± 1.917 hovers for the *positive* framing condition and 3.36 ± 2.592 hovers for the *negative* one - as opposed to the *not risky* one - 2.55 ± 1.891 hovers for the *positive* framing condition and 3.09 ± 2.568 hovers for the *negative* one.

These results go **against** our hypothesis **H1.1**. As matter of fact, neither the two-way interaction nor the frame by itself showed effects on the number of hover events. However, the factor that did show a significant difference in the number of hovers was the risk factor of a certain option, indicating that individuals tend to hover more over the *risky* options rather than the *not risky* ones.

Additionally, we decided to explore the possible interaction between the *choice* of each participant and the *risk factor* of each option on the same measure. Therefore, we conducted two Two-Way Mixed ANOVAs, one per framing condition - *positive* and *negative* (see Figure 5.2).

As for the *positive* framing condition, there was a single outlier detected through the inspection of

SREs which was removed from this particular analysis. We found that there was a statistically significant interaction between the choice taken and risk factor of the program on the number of hovers in the context of the *positive* framing condition of our study (see Figure 5.2(a)), $F(1, 88) = 19.743, p < 0.0005$, partial η^2 = 0.183. Thus, reporting the main effects could be misleading and we followed our analysis through the assessment of simple main effects. The single statistically significant simple main effect of this analysis was of risk factor for the group of participants who opted for the *risky* option (program *B*), $F(1, 55) = 28.031, p < 0.0005$, partial η^2 = 0.338. For the group of participants who made such a choice, the number of hovers was 0.875 (95% CI, 0.544 to 1.206) hovers higher for the *risky* option (*B*, with 3.23 ± 2.123 hovers) as opposed to the *not risky* one (program *A*, with 2.36 ± 1.813 hovers).



(a) *Positive* framing condition. **(b)** *Negative* framing condition.

Figure 5.2: Estimated marginal means of the number of hover events triggered in each option across the two possible choices for each of the two main framing conditions of the study.

Oppositely, there was not a statistically significant two-way interaction between the choice taken and risk factor on the number of hovers events for the *negative* framing condition of the study (see Figure 5.2(b)), $F(1, 86) = 1.661, p = 0.201$, partial η^2 = 0.019. For this analysis, there were three data points detected as outliers through SREs inspection which were removed. Determining the possible main effects, we found that neither risk factor - $F(1, 86) = 0.876, p = 0.352$, partial η^2 = 0.010 - nor choice - $F(1, 86) = 0.006, p = 0.937$, partial η^2 = 0.000 - showed significant main effects. The mean number of hovers in the *risky* option (3.39 ± 2.593) was 0.189 (95% CI, -0.213 to 0.591) hovers higher as opposed to the *not risky* option (3.10 ± 2.555). Moreover, the mean number of hovers of the group of participants who chose the *risky* option (*D*) - 3.258 (95% CI, 2.635 to 3.882) - was 0.044 (95% CI, -1.062 to 1.150) hovers higher than the mean number of hovers for the group of participants who chose the *not risky* (*C*) one - 3.214 (95% CI, 2.301 to 4.127).

5.1.1.B Decision Completion Time

A One-Way repeated measures ANOVA was conducted to determine whether there were any statistically significant differences in the time taken to make a choice (in seconds) between the *positive* and *negative* framing conditions (see Figure 5.3). Given as our hypothesis **H1.2** is not specific about possible differences across the levels of the within-subjects factor - *frame* -, we ran this ANOVA with a post hoc analysis with the Bonferroni adjustment, as mentioned in Section 4.4.

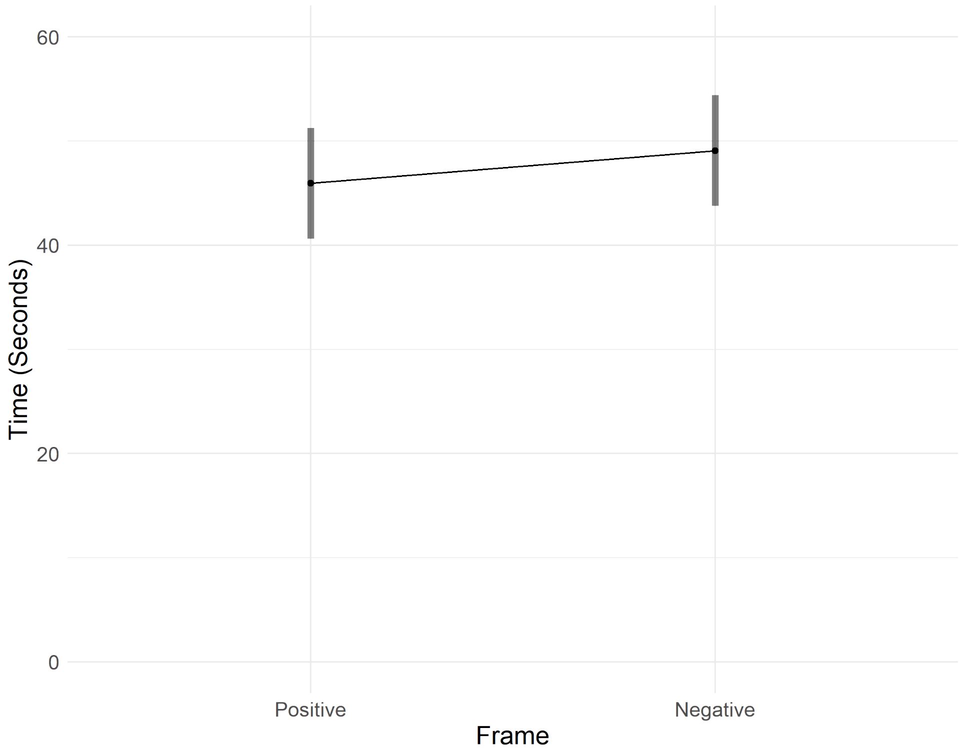


Figure 5.3: Estimated marginal means of time taken to make a choice in each of the two main conditions - *positive* and *negative* framings.

There were no (extreme) outliers detected upon inspection of boxplots. The mean amount of time taken to make a choice increased from 45.95 ± 24.324 seconds in the *positive* framing condition to 49.08 ± 26.954 seconds in the *negative* framing condition of our research. An increase of 3.132 (95% CI, -8.883 to 2.619) seconds. The One-Way repeated measures ANOVA showed that there was insufficient evidence to reject the null hypothesis, as there was not a statistically significant difference in the time taken to make a choice between the two conditions, $F(1, 90) = 1.170, p = 0.282$, partial η^2 = 0.013. These results **contradict** our hypothesis **H1.2**, which suggested the type of frame affects the amount of time users take to make a choice.

5.1.2 Decision Making

5.1.2.A Choice

As indicated in Table 5.1, 57 participants (62.63%) opted for the *risky* option in the *positive* framing condition of our work, while 34 individuals (37.36%) settled for the *not risky* one. As for the *negative* framing condition, the number of testers who picked out the *risky* program was 62 testers (68.13%), with a concomitant reduction in the number of individuals who decided not to take a risk in their choice to 29 participants (31.87%). Such differences were a consequence of 5.5% (i.e., $0.681 - 0.626$ x 100 = 5.5%) more participants choosing to take a risk when in the *negative* framing condition of the study. Out of the 91 total participants, 20 of them went for the *not risky* option upon the *positive* framing condition giving a different answer while in the *negative* one, whilst other 15 individuals chose the *risky* option during the *positive* framing condition of the investigation and opted for the *not risky* one when in the *negative* framing condition.

Table 5.1: Number of participants who chose each option, at each framing condition.

		Negative Framing		
		Risky (D)	*Not Risky (C)*	*Total*
Positive Framing	*Risky (B)*	42	15	57
	Not Risky (A)	20	14	34
	Total	62	29	91

We leveraged a McNemar's test [128] with continuity correction [129] to determine whether there was a difference in the proportion of participants who took a risk in their choice between the *positive* and *negative* framing conditions. As mentioned, the proportion of participants who opted for the *risky* option increased from 62.63% in the *positive* framing condition to 68.13% in the *negative* one, a not statistically significant difference, $\chi^2(1)$ = 0.457, $p = 0.499$. In view of this, we assessed that the proportion of participants who chose to risk did not (significantly) differ between framing conditions - *positive* and *negative*, meaning that we were unable to reject the null hypothesis. These findings **refute** our hypothesis **H1.3**, as the test results indicated there is not sufficient evidence to state that the differences in the dichotomous dependent variable - *choice* - between two related groups - *positive* and *negative* conditions - were not equal in the population.

5.1.2.B Perceived Risk

A One-Way repeated measures ANOVA was performed to assess whether there were statistically significant differences in the perceived risk of the choices taken in the *positive* and *negative* framing conditions of our work. Accordingly, as our hypothesis **H1.4**, too, did not specify possible differences between the levels of our within-subjects factor - *frame* -, this ANOVA was run with a post hoc analysis with the Bonferroni adjustment (Section 4.4).

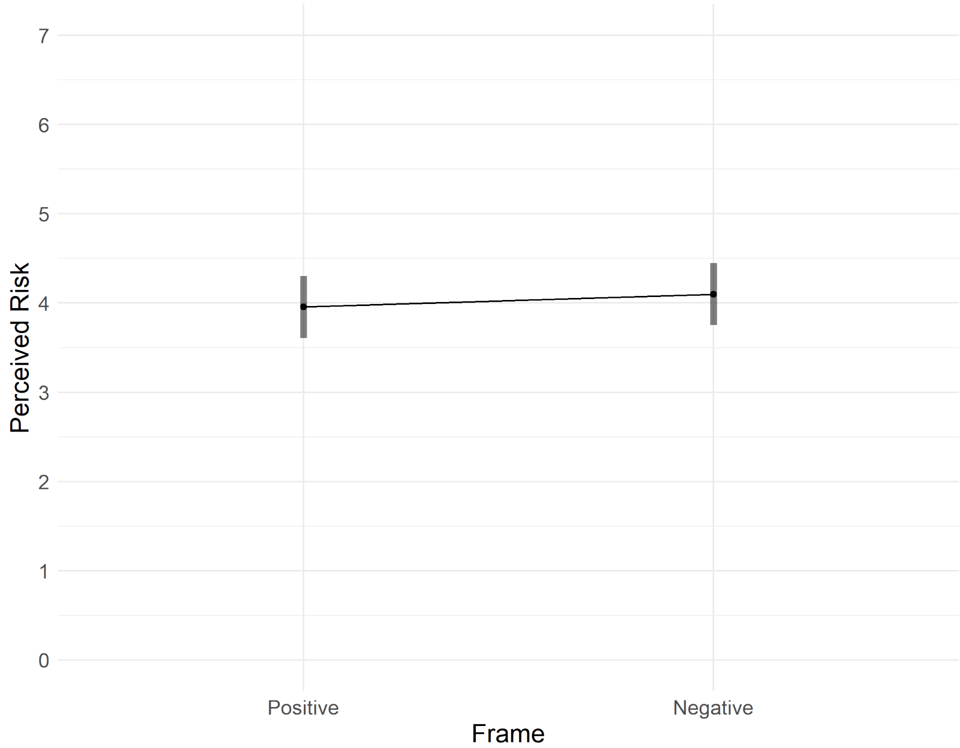


Figure 5.4: Estimated marginal means of perceived risk of choice taken for each of the two main conditions - *positive* and *negative* framings.

For this analysis, no outliers were detected in the data through the inspection of boxplots. Whereas the mean self-reported perceived risk for the choice taken in the *positive* framing condition was 3.96 ± 1.686, the mean of the same study metric for the *negative* framing condition was 4.10 ± 1.674 (see Figure 5.4). An increase of 0.143 (95% CI, -0.499 to 0.213), which was not statistically significant, $F(1, 90) = 0.635, p = 0.428$, partial η^2 = 0.007. These findings **counteract** our study hypothesis **H1.4**, which stated that the type of frame impacts the perceived risk of users.

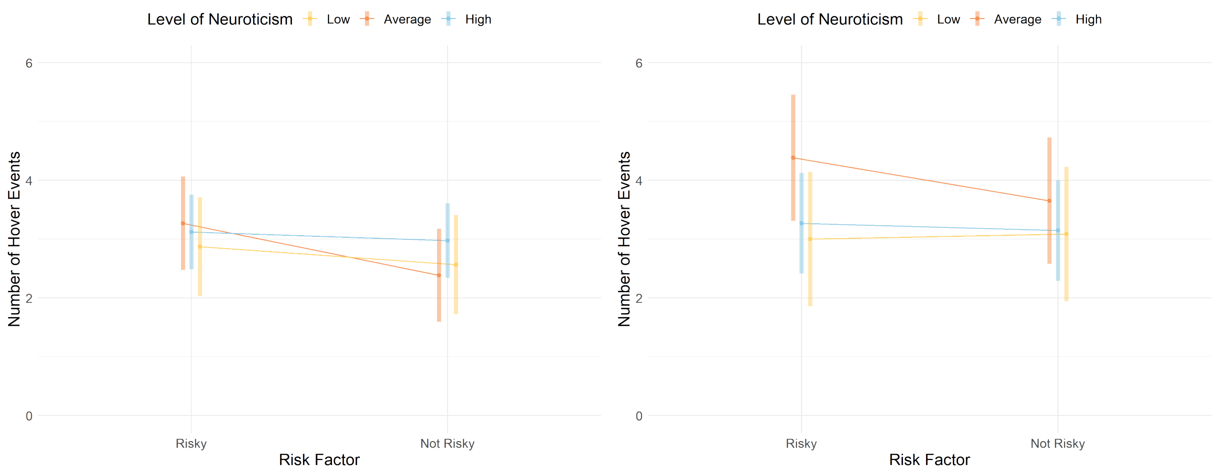
5.2 Effect of Neuroticism

Subsequent to the investigation focusing solely on the different framing of outcomes - *positive* and *negative* - and their possible effect with the developed visualizations in the metrics of our work, we incorporated the personality of participants into our analysis. Namely, the *neuroticism* level of individuals. Accordingly, this analysis only took into account the *positive* and *negative* framing conditions and discarded the *neutral* framing condition of our work.

5.2.1 User Interaction

5.2.1.A Number of Hover Events

We leveraged a Three-Way Mixed ANOVA to understand the effects of *frame* - *positive* and *negative* -, *risk factor* of a program - *risky* or *not risky* -, and the *neuroticism* level of participants - *low, average* and *high* - on the number of hover events per option (bar). A single extreme outlier was detected upon inspection of boxplots and discarded from this particular analysis. Additionally, there was homogeneity of variances between the groups of the between-subjects factor - *neuroticism* level - for most combinations of the levels of the within-subjects factors - *frame* and *risk factor* -, as assessed by Levene's test for equality of variances (i.e., for most $p > 0.05$; $p = 0.013$ for the *risky* option, at the *negative* framing condition). Even so, the Three-Way Mixed ANOVA is somewhat robust to the heterogeneity of variance. Therefore, we opted to carry on with the analysis regardless of these findings. No statistically significant three-way interaction between the three factors was found, $F(2, 87) = 0.195, p = 0.823$, partial $\eta^2 = 0.004$ (see Figure 5.5). Afterwards, we addressed the three possible two-way interactions.



(a) *Positive* framing condition. **(b)** *Negative* framing condition.

Figure 5.5: Estimated marginal means of the number of hover events triggered in each option across the neuroticism levels of participants for each of the two main framing conditions of the study.

The two-way interaction between frame and the neuroticism level of participants was not statistically significant, $F(2, 87) = 1.557, p = 0.217$, partial $\eta^2 = 0.035$. Upon further analysis of the pairwise comparisons, we assessed that the mean number of hover events was statistically significantly different between frames - *positive* and *negative* - for the *average* neuroticism level group of individuals. For this particular neuroticism level group, the mean number of hovers in the *positive* frame was 2.827 (95% CI, 2.064 to

3.590) hovers. In contrast, for the *negative* framing condition, it was 4.019 (95% CI, 3.002 to 5.037) hovers. Such was an increase of 1.192 (95% CI, -2.128 to -0.257), with a p-value of 0.013. In contrast, for both the *low* and *high* neuroticism level groups, the differences between the mean number of hover events upon both framing conditions were not statistically significantly different. There was an increase of 0.326 (95% CI, -1.321 to 0.669) hovers from the *positive* - 2.717 (95% CI, 1.906 to 3.529) - to the *negative* - 3.043 (95% CI, 1.962 to 4.125) - framing condition for the *low* neuroticism level group. Regarding the *high* neuroticism level group, there was a difference of 0.159 (95% CI, -0.903 to 0.586) hovers lower for the *positive* condition - 3.049 (95% CI, 2.441 to 3.656) - as opposed to the *negative* one - 3.207 (95% CI, 2.397 to 4.018).

Nonetheless, there was a statistically significant two-way interaction between risk factor and the neuroticism level of testers, $F(2, 87) = 3.365, p = 0.039$, partial η^2 = 0.072. The mean number of hover events was statistically significantly different between risk factors for the *average* neuroticism level group - a difference of 0.808 (95% CI, 0.366 to 1.249) hovers higher for the *risky* - 3.827 (95% CI, 3.028 to 4.626) - as opposed to the *not risky* one - 3.019 (95% CI, 2.220 to 3.818) -, $p < .0005$. The differences between risk factors for the *low* and *high* neuroticism level groups, however, were not statistically significant. For the *low* neuroticism group, there was an increase of 0.109 (95% CI, -0.361 to 0.578) hovers. From 2.935 (95% CI, 2.085 to 3.784) for the *risky* one to 2.826 (95% CI, 1.976 to 3.676) hovers in the *not risky*. The *high* neuroticism level group showed a higher number of hovers in the *risky* options as well - 3.195 (95% CI, 2.559 to 3.831) hovers - it being 0.134 (95% CI, -0.217 to 0.486) hovers higher as opposed to the *not risky* - 3.061 (95% CI, 2.425 to 3.697) - options.

For this specific analysis, we assessed the two-way interaction between frame and risk factor again, assessing that it remained as non-significant, $F(1, 87) = 0.601, p = 0.440$, partial η^2 = 0.007. Upon assessment of the pairwise comparisons, we verified that the mean number of hovers was only statistically significantly different between risk factors for the *positive* framing condition. For this study condition, there was a difference of 0.445 (95% CI, 0.178 to 0.712) hovers higher ($p = 0.001$) for the *risky* option - 3.10 ± 2.006 - as opposed to the *not risky* one - 2.70 ± 2.074 hovers. As for the *negative* framing condition, the difference was 0.225 (95% CI -0.153 to 0.664) hovers higher for the *risky* option - 3.52 ± 2.769 - when compared to the hovers made in the *not risky* one - 3.28 ± 2.789. However, such a difference was not statistically significantly different.

Lastly, we verified for any statistically significant main effects for each of the three factors involved in this analysis. We discovered that there was a statistically significant difference in the mean number of hover events between framing conditions - *positive* and *negative* - $F(1, 87) = 4.592, p = 0.035$, partial η^2 = 0.050. The mean number of hovers was 0.559 (95% CI, -1.077 to -0.041) hovers lower in the *positive* framing condition - 3.10 ± 2.006 for the *risky* option and 2.70 ± 2.074 for the *not risky* one - as opposed to the *negative* framing condition of the study - *risky:* 3.52 ± 2.769, and *not risky:* 3.28 ± 2.789.

Risk factor did show a statistically significant difference in the mean number of hovers, $F(1,87) = 8.096, p = 0.006$, partial η^2 = 0.085, where it was 0.350 (95% CI, 0.106 to 0.595) hovers higher in the *risky* options - 3.10 ± 2.006 for the *positive* framing condition and 3.52 ± 2.769 for the *negative* one - as opposed to the *not risky* ones - 2.70 ± 2.074 for the *positive* framing and 3.28 ± 2.789 for the *negative* framing.

Finally, there were no statistically significant differences in the mean number of hover events between neuroticism level groups, $F(2,87) = 0.468, p = 0.628$, partial η^2 = 0.011. The *low* neuroticism level presented a mean of 2.880 (95% CI, 2.064 to 3.697), the *average* one of 3.423 (95% CI, 2.655 to 4.1941), and the *high* group of 3.128 (95% CI, 2.516 to 3.740). Thus, the biggest difference was between the *average* and *low* neuroticism groups, with a difference of 0.543 (95% CI, -0.834 to 1.919) hovers higher for the *average* one. The smallest one was 0.248 (95% CI, -1.005 to 1.501) between the *high* and *low* neuroticism levels.

This collection of findings proved **against** our **H2.1** hypothesis, where we believed that neuroticism influences the number of hovers made per program, depending on how risky an option is. Notwithstanding, we were able to assess that the *average* neuroticism level group did show statistically significant two-way interactions between *frame* and *neuroticism* together with the one between *risk factor* and *neuroticism*. Regarding the *positive* framing condition of the study, we were able to verify that there is a significant difference between the *risk factors* of programs, over the number of hovers per each one. Lastly, complementary to the previously mentioned findings, the *risk factor* of options remained significant for the number of hovers per each one. Additionally, the main effect of *frame* became significant when analysing the number of hover events.

5.2.1.B Decision Completion Time

We performed a Two-Way Mixed ANOVA to determine the effect of different *neuroticism* level groups - *low, average* and *high* - over different *framing* conditions - *positive* and *negative* - on the amount of time (in seconds) taken to make a choice. There were two outliers detected and removed through SREs inspection. Results showed no statistically significant interaction between the two factors - frame and neuroticism level - on the time taken to make a choice, $F(2,86) = 0.127, p = 0.881$, partial η^2 = 0.003 (see Figure 5.6). Therefore, we investigated the possible main effects.

For this analysis, the main effect of frame remained a not statistically significant difference in the mean amount of time required to make a choice, $F(1,86) = 2.447, p = 0.121$, partial η^2 = 0.028. The mean amount of time (in seconds) taken to choose in the *positive* framing condition - 44.37 ± 21.323 seconds - was 4.207 (95% CI, -9.552 to 1.139) seconds lower as opposed to the one in the *negative* framing condition - 48.26 ± 25.830. Additionally, there too was no main effect of neuroticism level, $F(2,86) = 0.240, p = 0.787$, partial η^2 = 0.006. Participants present in the *low* neuroticism level group showed a mean amount of time of 47.870 (95% CI, 39.371 to 56.368) seconds. As for the *average* group,

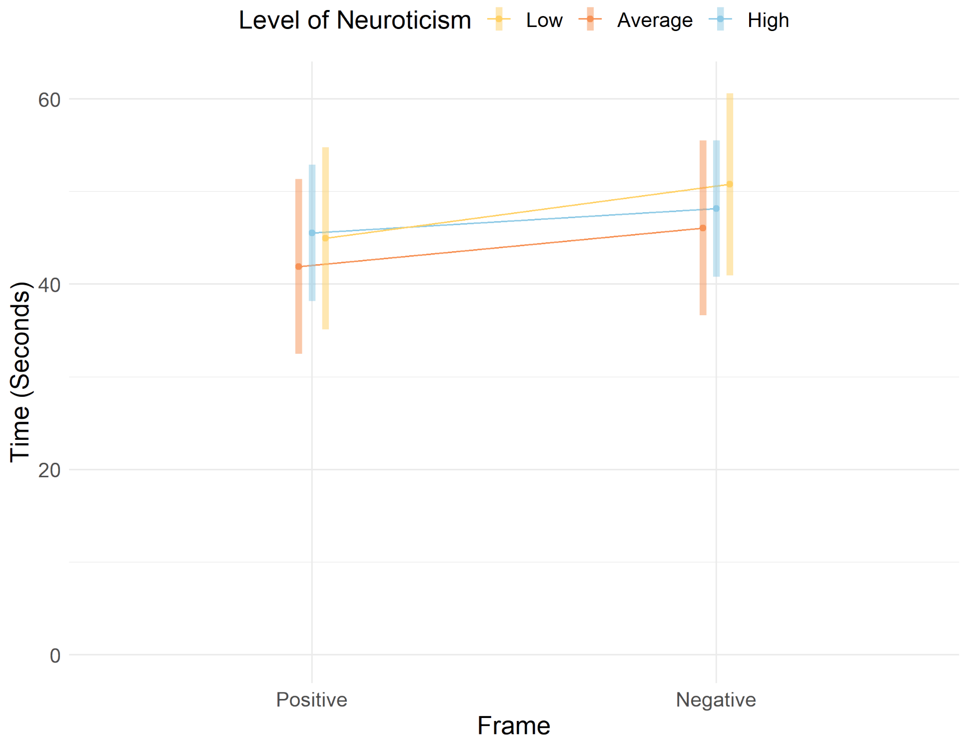


Figure 5.6: Estimated marginal means of time taken to make a choice in each of the two main conditions - *positive* and *negative* - per neuroticism level group.

the mean was 44.000 (95% CI, 35.848 to 52.152) seconds. Lastly, *high* neuroticism level individuals presented a mean of 46.854 (95% CI, 40.488 to 53.219) seconds. Therefore, the biggest difference was between the *low* neuroticism level group when compared to the *average* one, a difference of 3.870 (95% CI, -10.595 to 18.334) seconds. The smallest difference occurred when comparing the *low* neuroticism group with the *high* one, a difference of 1.016 (95% CI, -12.026 to 14.058) seconds. The results from this Two-Way Mixed ANOVA **contradict** our hypothesis **H2.2**.

5.2.2 Decision-Making

5.2.2.A Choice

For this analysis, we leveraged the mentioned derived variable indicating whether a participant had reversed their final choice - regardless of it being from *risky* to *not risky* or *not risky* to *risky* between the two frames. A Chi-Square Test of Independence was conducted between said variable and the *neuroticism* level of participants. We defined both our alternative and null hypotheses - is there or not an association amid the variables, respectively.

As our two variables had two - *yes* or *no* - and three - *low*, *average*, and *high* - categories (i.e., 2 x 3 crosstabulation), there were 6 cells in our design that needed to be checked, as presented in Table 5.2.

Table 5.2: Chi-Square Test of Independence crosstabulation. In brackets are the expected count values for each cell.

		Neuroticism Level			**Total**
		Low	*Average*	*High*	
If a participant changed choice	*No*	14 (14.8)	19 (16.0)	23 (25.2)	56 (56.0)
	Yes	10 (9.2)	7 (10.0)	18 (15.8)	35 (35.0)
Total		24 (24.0)	26 (26.0)	41 (41.0)	91 (91.0)

All indeed present expected count values greater than or equal to five, as required to obtain valid results. From our data, we can see that the majority of participants who did change their answers between the two framing conditions, mainly presented a *high* neuroticism level (i.e., 18 out of 35 participants who did change their answers between study conditions). Additionally, one can observe how the bulk of each neuroticism level group opted not to alter their choice between frames - i.e., 14 out of 24 participants with a *low* neuroticism level; 19 out of 26 participants from the *average* neuroticism level group; lastly, 23 out of 41 participants presenting a *high* neuroticism level group. There was not a statistically significant result to our analysis, as $p = 0.354$ (i.e., it does not satisfy $p < 0.05$). This indicates there is no association between our two variables (i.e., an association between the *neuroticism* level of participants and the *changing choice* between the *positive* and *negative* framing conditions of our study), $\chi^2(2)$ = 2.079, $p = 0.354$. The association was small [130], with Cramer's V = 0.151. These results indicate that there is insufficient evidence to reject the null hypothesis and accept the alternative one, going **against** our hypothesis **H2.3**.

5.2.2.B Perceived Risk

We ran a Two-Way Mixed ANOVA to determine the effect of different *neuroticism* level groups over different *framing* conditions - *positive* and *negative* - on the perceived risk of the choices taken. There were no outliers for this analysis as assessed by examination of SREs. There was not a statistically significant interaction between the neuroticism level group of participants and frame on the perceived risk of the choice taken, $F(2, 88) = 0.517, p = 0.598$, partial η^2 = 0.012 (see Figure 5.7). Therefore, we carried out our analysis by determining whether there were any statistically significant main effects.

The main effect of frame verified again that there is not a statistically significant difference in the mean perceived risk of the choice taken between conditions, $F(1, 88) = 0.669, p = 0.416$, partial η^2 = 0.008. The (mean) perceived risk of the choice taken in the *negative* framing condition - 4.10 ± 1.674 - was 0.152 (95% CI, -0.217 to 0.520) higher as opposed to the mean perceived risk of the one taken upon the *positive* framing condition - 3.96 ± 1.686. Moreover, neither the main effect of neuroticism showed a statistically

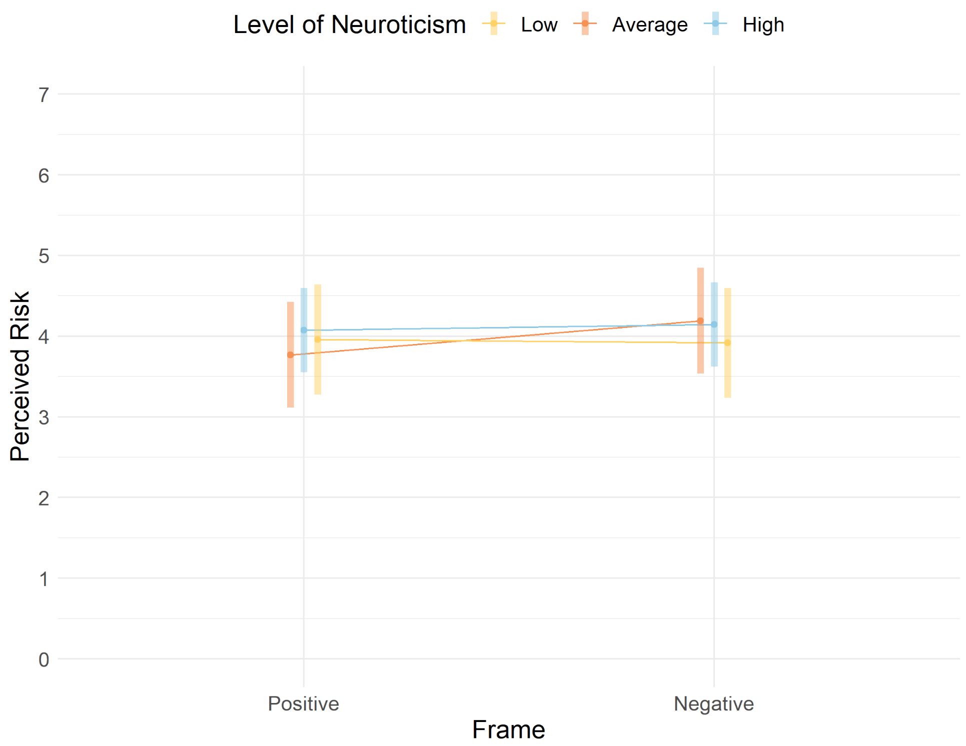


Figure 5.7: Estimated marginal means of perceived risk of choice taken for each of the two main conditions - *positive* and *negative* - for each neuroticism level group.

significant difference in the mean perceived risk of the choices taken, $F(2, 88) = 0.124, p = 0.884$, partial η^2 = 0.003 - *low:* 3.938 (95% CI, 3.345 to 4.530), *average:* 3.981 (95% CI, 3.412 to 4.550), and *high:* 4.110 (95% CI, 3.657 to 4.563). The lowest difference was 0.043 (95% CI, -1.052 to 0.966) between the *low* and *average* neuroticism level groups. The highest difference was between the *high* and *low* groups, one of 0.172 (95% CI, -0.744 to 1.088).

These findings **refute** our hypothesis **H2.4**, contradicting our assumption of neuroticism affecting the perceived risk of users, in different framing conditions.

5.3 Neutral Condition

The additional *neutral* framing condition was designated as such due to it offering all four programs - *A, B, C* and *D* - at the same time. Hence, offering both frames - *positive* and *negative* - simultaneously. All the while, for each frame offering, equally, both the *risky* (*B* and *D*) and *not risky* (*A* and *C*) options. Considering how a subtle change in the framing of decision problems may have a large impact on behaviour - consisting of the *framing effect* - we deemed it interesting to assess if the choices taken in both the *positive* and *negative* frames isolated would hold (in risk) when receiving both at the same time

(**RQ.3** of our study, mentioned in Chapter 4). For example, an individual chooses option *B* and option *C* under the *positive* and *negative* conditions, respectively. If when undergoing the *neutral* study condition, the same participant opts for a *positively* framed program and chooses *B*, we considered that they held the answer taken (as in the one taken for the particular framing condition chosen in the *neutral* one).

Table 5.3 indicates the number of participants ($N = 91$) who decided on each of the available options. 34 testers decided on the *risky* program presented through a *positive* frame - option *B*. These findings immediately clash with the ones of Tversky and Kahneman [14, 15] seeing how a *positive* frame tends to trigger risk aversion. In contrast, next, we had 27 individuals choosing option *D*, the *risky* option decipted through a *negative* framing. Thus, going in harmony with the fact that said frame tends to be associated with risk-seeking behaviour. Additionally, we can assess that the majority of individuals (54) opted for a *positively* presented option (*B* or *A*), whereas 37 decided on a *negatively* one (*D* or *C*). A bigger contrast is seen when comparing the number of participants who decided to take a *risk* in this last choice (*B* or *D*) - 61 - with the number of ones who went for a *not risky* option (*A* or *C*) - 30.

Table 5.3: Number of Participants who chose each option, at the neutral framing condition.

Choice	***Number of Participants***
Positive + Risky (B)	34
Positive + Not Risky (A)	20
Negative + Risky (D)	27
Negative + Not Risky (C)	10

Moreover, when assessing the comparisons between the choices taken in the *positive* and *negative* frames individually and the one taken in the *neutral* condition of our work, we determined that there were merely 4 participants whose choices did not hold between conditions. There were 3 participants who had chosen option *B* for the *positive* framing condition and opted for option *A* in the last decision (*neutral* condition). A single participant who did the opposite and initially decided on program *A* for the *positive* framing condition and switched to *B* when undergoing the *neutral* one. For the remaining 87 participants, the choice taken in the *neutral* condition was in accordance with the one taken in the correspondent isolated framing condition. Furthermore, we broadly investigated if when holding their decision, the perceived risk of such would hold as well or change to a higher or lower value (see Table 5.4, $N = 87$). The majority did assign the same perceived risk (45 individuals). However, 15 and 27 participants assigned a lower and higher perceived risk of choice taken when in the *neutral* condition, respectively. Out of the participants who accredited a lower perceived risk, 10 were ones who opted for a *risky* option. For the ones who elected a higher perceived risk when taking the same choice in the *neutral* condition, 17 out of the 27 decided on a *risky* option. These findings allowed us to explore our third and last condition of the study in a general manner.

Table 5.4: Comparison of the perceived risk of the same choice, for participants whose choice held for the *neutral* framing condition. If the one reported for said condition was higher, equal or lower to the one assigned previously to the same choice.

Perceived Risk Comparison	***Number of Participants***
Lower	15
Equal	45
Higher	27

5.4 Discussion

The gathered results (described throughout Chapter 5) evidence that *framing bias* is a worthy subject of further and deeper research within the InfoVis community. In particular, when the core function of these systems is to support the human decision-making process. We additionally explored if an individual's *neuroticism* personality trait had an impact on such an effect in this distinct context.

5.4.1 Answering the Research Questions

Our exploratory work began with the sole investigation of the *framing effect* within the established visualizations (**RQ.1**). For the *negative* framing condition, the majority of individuals opted to take a risk in their choice, having 62 out of the 91 subjects choosing option *D* (29 going for option *C*, see Table 5.5). This was in line with what was expected given the work of Tversky and Kahneman [14, 15]. However, contrarily to what was anticipated, for the *positive* framing condition the bulk of participants, likewise, decided on the *risky* option (*B*) - 57 out of the total of 91 participants in our study (34 opting for *A*, see Table 5.5). Although there were no significant findings of interaction between *frame* and *risk factor* (*H1.1*) nor for *frame* on such metric of our research, the number of hover events was higher for the *negative* framing condition. As for the hovers between the *risky* and *not risky* options within each condition - *positive* and *negative* -, these were statistically significantly different. The *risky* options, *B* and *D*, withheld a higher number of hovers overall - possibly due to how these two were the most chosen options for the *positive* and *negative* conditions, respectively. Furthermore, we discovered that the *choice* and *risk factor* presented a significant interaction on the number of hovers per program. This significant interaction only held for the *positive* framing condition of our study. Specifically for the group of participants who elected the *risky* option (*B*), the number of hovers was significantly higher for that particular program in comparison to the correspondent *not risky* option (*A*).

Regardless of it not being a statistically significant difference, the perceived risk of the choice taken in the *negative* framing condition was higher as opposed to the decision made in the *positive* one (*H1.4*). Such occurrence goes in line with the - as well not statistically significant result - higher amount of time taken to choose in the *negative* study condition (*H1.2*). We assume that we were able to prime 38.5%

Table 5.5: Number of participants and their choices, according to the neuroticism level.

Framing	***Possible Choices***	***Neuroticism Level***	***Number of Participants***	***Total***
Positive	*Risky (B)*	*High*	25	57
		Average	18	
		Low	14	
	Not Risky (A)	*High*	16	34
		Average	8	
		Low	10	
Negative	*Risky (D)*	*High*	27	62
		Average	19	
		Low	16	
	Not Risky (C)	*High*	14	29
		Average	7	
		Low	8	

of the individuals since 56 (61.5%) participants did not change their decision. Despite the difference between proportions not being significantly different (*H1.3*), some participants appear to have been primed, reinforcing the possibility of framing bias within this context. Thus, these findings support our **RQ.1** and how **the framing condition may affect decisions presented by bar charts with error bars**. In particular, how visualizations may aid **reducing** this bias upon interaction with visualization-supported decision-making systems.

Subsequent to the analysis of the framing effect by itself, we introduced the personality of the participants into it. Namely, by combining the *neuroticism* level of participants into each of our analyses done previously (**RQ.2**). As a consequence of most of our sample presenting a *high* neuroticism level (41 out of the total 91 participants), the bulk of individuals opting for each existing option within the two framing conditions - *positive* and *negative* - presented that same neuroticism level (see Table 5.5) - 25, 16, 27, and 14 participants for the options *B, A, D* and *C*, respectively.

Upon investigating the three-way and two-way interactions between *frame*, *risk factor* and *neuroticism* on the hover events per bar (*H2.1*), we found a single significant two-way interaction between *risk factor* and *neuroticism* ($p = 0.039$). Exclusively present for the *average* neuroticism group ($p < .0005$), where the mean number of hovers was higher for the *risky* options. Even though the results were not statistically significant, we assessed the same for the *high* and *low* groups. Such findings were in accordance with the previous ones when studying solely the *framing effect* within the metric of our work. Regardless of it not being a statistically significant two-way interaction per se, we found that the *average* neuroticism group likewise showed the only significant difference ($p = 0.013$) in the mean hover events between framings - *positive* and *negative* -, hovering more when choosing for the *negative* one. For both the *high* and *low* neuroticism level groups, the differences between the mean number of hover events upon each of the framing conditions were not statistically significantly different ($p = 0.516$ and $p = 0.673$). However, both groups hovered slightly more when deciding on the *negative* condition. These results, too, agree with the initially assessed (**RQ.1**, *H1.1*) when stating that - although previously not significant and only with this three-way model the main effect of *frame* becoming significantly different - the *negative* framing condition withheld a higher number of hover events overall. Unable to detect previously, this analysis (*H2.1*) also showed that the interaction between *frame* and *risk factor* became statistically significant specifically for the *positive* framing condition, where the number of hovers was lower for the *not risky* option. These findings may also correlate to the presence of a significant interaction between *choice* and *risk factor* solely for this separate framing condition (*H1.1*). Lastly, results showed no statistically significant main effect of *neuroticism*. The biggest difference was between the *average* and *low* groups.

The mean self-reported perceived risk of decisions taken was 3.938 (95% CI, 3.345 to 4.530), 3.981 (95% CI, 3.412 to 4.550), and 4.110 (95% CI, 3.657 to 4.563) for the *low*, *average*, and *high* neuroticism level groups, respectively. Although the absence of statistically significant results both for the perceived risk of the decisions made (*H2.4*) as well as for the time taken to make said decisions (*H2.2*), the overall obtained statistics remained in agreement with our previous findings. As in, a higher perceived risk corresponded to a higher amount of time taken to choose *low*, *average*, and *high* neuroticism groups presenting time means of 47.870 (95% CI, 39.371 to 56.368), 44.000 (95% CI, 35.848 to 52.152), and 46.854 (95% CI, 40.488 to 53.219) seconds, correspondingly.

Following our framing strategy, we consider that 35 participants (38.5%) within our research were primed as these changed their choice between the *positive* and *negative* framing conditions. Albeit not finding a significant association between the changing of choice (i.e., being primed) and the *neuroticism* level of participants (*H2.3*), we were able to check that considering each neuroticism level group - *low, average* and *high* - individually, the greater part in all of them did not alter their decision between the two conditions. Nonetheless, the majority of primed participants presented a *high* neuroticism level. The obtained results for our analysis under **RQ.2** suggest that perhaps **neuroticism does not affect being primed by the different framings**. Even so, such may be a consequence of the possibility that visualizations help reduce the *framing effect* of individuals. Such may be so that it aids in contradicting the general tendency of more neurotic individuals to be more risk-averse.

The curious and experimental basis approach to our research led us to design a third supplementary condition for our work - the *neutral* framing condition (**RQ.3**). We aimed to delve into the choices of participants and investigate whether these would hold between getting the frames - *positive* and *negative* - isolated and seeing them simultaneously. From our study sample ($N = 91$) we assessed that the bulk of participants did hold their answer (87), whereas merely 4 did not. Moreover, only 45 individuals of those 87 assigned an equal perceived risk of choice when taking the same one between getting the frame isolated versus seeing them simultaneously. Lastly, for this condition, participants tended to pick a program presented with a *positive* frame (*A* or *B*, 54) and the majority of our sample (61) decided to take a risk in their choice - options *B* or *D* - upon our *neutral* framing condition, regardless of the option's frame. These findings allowed us to explore our third and last research question **RQ.3**, supporting that **decisions taken in individual contexts do hold when contexts are seen simultaneously**.

All this evidences the importance of further exploration of the framing bias within InfoVis systems; namely to better support the decision-making process and avoid biased choices. Moreover, due to the peculiar findings when exploring the incorporation of participants' personalities, it also attests to possibly interesting research of such interaction of fields. Namely, with the facets of neuroticism or even other personality traits and/or dimensions.

5.4.2 Experimental Implications

To the best of our knowledge, there is no measure to assess the *framing effect* of individuals. Considering the definition of this cognitive bias, we considered the priming of individuals to be the changing of behaviour - *risk-taking* or *risk-averse* - between the two main conditions of our work - *positive* and *negative* framings. Attending to the applied framing strategy, the obtained results suggest that **visualizations may help individuals be less susceptible to the framing effect**.

As aforementioned, there is a sharp gap in research regarding how humankind's cognitive limitations can affect visualization-supported decision-making. In particular, a lack of investigation into how the *framing effect* may affect such a process. Ergo, there is no consensus on what constitutes a good visualization to support decision-making, notably when investigating the possible inherent *framing bias* present. Considering this current lacuna, we began our research with the initial problem that led to the discovery of this bias. Attempting to build on it and bring it into the InfoVis community, we plucked inspiration from the small body of research found within our literature review phase. Namely, studies intersecting the decision-making process and visualization such as the one by Bancilhon et al. [7].

There are, likewise, very few studies approaching the influence of personality traits - including *neuroticism* - upon risk-taking behaviour [111]. Unfortunately, such extends to studies evaluating the impact of personality traits in *framing bias*. Despite our findings on this front being mostly non-significant, their singularity attests to the interest in further investigation of the subject. For instance, how far do visualizations help mitigate the *framing effect* and counter the expected behaviours of certain personality traits and dimensions.

Thus, our research offers some implications for future studies. These shall take into consideration the ample implications different problem contexts may have within the decision-making process itself alongside the disparity between online and in-person studies may bring. Additionally, these should consider the impact of different personality traits and dimensions can introduce to the equation. Likewise, it should be noted that factors such as decision situation setup, experience, effort, and demographics can influence the effects of framing in experiments [10] and that the *framing effect* on highly involved subjects - according to their personality, for instance - may be context-dependent [108]. We believe the gathered results provide further understanding for future research that aims to leverage cognitive bias-aware mechanisms to promote more rational decision-making. Additionally, our research reinforces the formerly need to further explore the *framing bias* within this context. Namely, with other visualizations alongside distinct problem contexts and other psychological constructs such as distinct personality dimensions and/or traits and respective facets.

6

Conclusion

Contents

6.1 Limitations and Future Work 73

Throughout the years, improvements made within the InfoVis field have brought a wider acknowledgement of the shortage of one-size-fits-all visualization systems. Increasingly, researchers have become to recognize the influence individual differences - namely, cognitive abilities and personality - can have on the interaction with the mentioned human-machine systems [22]. Albeit designing a visualization one shall take into account three kinds of limitations: computers, displays, and humans [80]. Hence, it becomes imperative to consider the limitations present within human judgement and decision making in such a process [5] alongside individual differences. This was precisely what our exploratory study focused on, with a particular aim to delve into the influence *framing bias* may have within the visualization community. Moreover, the potential effect of personality alongside it, specifically the *neuroticism* personality trait.

A rational choice implies that changes in the frame - identical alternatives under different frames, *positive* and *negative* - should not affect preferences or behaviour - *risk-averse* or *risk-seeking* - since both the alternatives as well as consequences of each choice are exactly the same [131]. Yet, ample evidence has risen establishing the existence of the *framing effect*, i.e., the systematic deviation from rational judgment as a consequence of different framings of the same decision-making problem. This particular cognitive bias has shown plausible evidence to transfer its priming effect onto the InfoVis context. However, upon our literature review, we verified an acute research gap between this intersection of fields and found that, despite its recognition, the *framing bias* is yet to be further investigated within the visualization field [5]. Moreover, within the domain of personality, *neuroticism* has proven to be a trait that interacts with the use of visualization systems and with the potential to play a role in shaping interaction with said systems. In particular, some works have found that *neuroticism* is correlated with both mouse activity and task completion time.

To achieve the objective of our work mentioned in Chapter 1, we began our research by investigating the *framing bias* alone. That is, to assess the potential effect different framings - *positive* and *negative* - could have within the established visualizations. The bulk of our results was non-significant, hinting that visualizations might be a helpful tool to reduce this bias upon interaction with visualization-supported systems. Especially, when the basis of a system is to aid in a decision-making process. Afterwards, we incorporated participants' personality data into our analysis, particularly their *neuroticism* scores. Such data were collected according to the European Portuguese version of the NEO PI-R by Lima and Simões [123]. Our findings with such interaction - *framing effect* and *neuroticism* - were, as well, mostly not statistically significant, likely reflecting the previously mentioned *framing effect* results. Nonetheless, we did encounter some singular findings involving the *neuroticism* trait, which reflects the potential to further novelty research. Lastly, we discovered that, within our study sample, the decision taken in individual contexts - *positive* and *negative* framings - did hold when the same contexts were seen simultaneously.

Altogether, our results shed new light on the understanding of the *framing bias* within the InfoVis field suggesting that **visualization helps mitigate the framing effect**. Furthermore, lifting the possibility of it being so that it additionally lightens the generally expected behaviour of certain personality traits. In particular, how *neurotic* individuals tend to be risk-averse. We believe that we can leverage this knowledge to explore which visualization techniques prime individuals based on utility theory and devise a set of design guidelines to improve the design of visualization-based decision support systems. Namely, when likewise considering the personality of users.

6.1 Limitations and Future Work

Existing gaps in research together with the usage of Zoom meetings for the user tests posed some limitations to this research and offer some implications for future studies. The biggest limitation of our work stemmed from the research gap evidenced which is particularly noticeable concerning the *framing bias*. Namely, the lack of an (algorithmic) measure to evaluate the framing effect, i.e., a validated apparatus to assess whether individuals were affected by it and/or the quality of the decisions taken.

Our research was merely able to encompass the one chart type - bar charts with error bars. Such leaves ample room for further research to explore not only other encodings - being those simple or complex - but also other types of framing (mentioned in Chapter 2). Future research would benefit from adding at least a control group to the experiment - i.e., where the information is merely presented through text - enabling the comparison between the two groups, with and without the visualization. Another feasible approach would be to conduct an investigation consisting of multiple trials - not only with a control group but also with other encodings - and/or scenarios. Such experiments could perhaps help uncover whether individuals would be consistent with their choices and behaviours or not.

Moreover, there is the possibility that the usage of confidence intervals (CI, see Figure 4.1 and Figure 4.2) indicating two values rather than a fixed (not risky) one can affect the number of hovers events of each option. Thus, future work may also profit from exploring other ways to convey the uncertainty inherent to the different options presented to the users. Comparison experiments with alternative uncertainty visualization techniques could, likewise, be informative. The hover events metric of our study may also have suffered some skewness due to the collection method used. Further research would benefit from not considering random/accidental mouse movements by applying a time threshold for this measurement, for instance. Especially if executed in an online setting like ours. Another suggestion would be instead to collect user interaction through clicks, avoiding accounting for unplanned and/or involuntary mouse movements.

Familiarity levels with the established visualizations alongside the self-reported overall risk attitude of the participants in our sample (see Chapter 4) may both have influenced the interpretation, interaction and decisions taken with the visualizations of the study. As such, introducing both these as well as other individual characteristics (e.g., gender, education, and others) in the analytic models could also be explored in future work. Additionally, future works shall take into account the ample implications different problem contexts may have within the decision-making process itself.

Considering the scope of our work, we deemed our sample size ($N = 91$) to be satisfactory. Nevertheless, future research would benefit to aim for as large a sample size as possible to better corroborate the respective findings. While doing so, it must also be taken into account the desirable balance between personality groups to avoid potential skewness of data.

The usage of Zoom meetings conference brought a higher number of individuals willing to participate together with a higher versatility in schedule and location for the participants. However, for some, it also meant occasional weak and/or unstable Wi-Fi connection. This contributed to some inaccuracies in the initially done counters for the hover events and affected some decision completion times, could have led to some inevitable data skewing. Considering these implications, the disparity between online and in-person and inherent limitations should be considered by subsequent studies.

We believe the gathered results provide further understanding for forthcoming research that aims to leverage cognitive bias-aware mechanisms to promote more rational decision-making. Furthermore, our research reinforces the aforementioned need to further explore the framing bias within this context. Namely, with other visualizations as well as distinct problem contexts.

Finally, complex thinking through visualization becomes more susceptible to individual characteristics [2]. We argue that it is possible to enrich the user profile of the decision-maker with synergies from psychological constructs. Therefore, it is important to likewise investigate the interaction of the *framing effect* with the personality field. Namely, other traits and/or dimensions. In particular, InfoVis systems with access to personality data can detect if the decision-maker will be more susceptible to making an irrational decision. In that case, the system can adapt its content or provide further assistance to counter the priming effect and, consequently, allow the user to make a (more) rational decision.

Bibliography

[1] E. T. Brown, A. Ottley, H. Zhao, Q. Lin, R. Souvenir, A. Endert, and R. Chang, "Finding waldo: Learning about users from their interactions," *IEEE Transactions on visualization and computer graphics*, vol. 20, no. 12, pp. 1663–1672, 2014.

[2] C. Ziemkiewicz, A. Ottley, R. J. Crouser, A. R. Yauilla, S. L. Su, W. Ribarsky, and R. Chang, "How visualization layout relates to locus of control and other personality factors," *IEEE transactions on visualization and computer graphics*, vol. 19, no. 7, pp. 1109–1121, 2012.

[3] S. M. Sarsam and H. Al-Samarraie, "Towards incorporating personality into the design of an interface: a method for facilitating users' interaction with the display," *User Modeling and User-Adapted Interaction*, vol. 28, no. 1, pp. 75–96, 2018.

[4] A. C. Valdez, M. Ziefle, and M. Sedlmair, "A framework for studying biases in visualization research," 2017.

[5] E. Dimara, S. Franconeri, C. Plaisant, A. Bezerianos, and P. Dragicevic, "A task-based taxonomy of cognitive biases for information visualization," *IEEE transactions on visualization and computer graphics*, 2018.

[6] E. Wall, L. M. Blaha, L. Franklin, and A. Endert, "Warning, bias may occur: A proposed approach to detecting cognitive bias in interactive visual analytics," in *2017 IEEE Conference on Visual Analytics Science and Technology (VAST)*. IEEE, 2017, pp. 104–115.

[7] M. Bancilhon, Z. Liu, and A. Ottley, "Let's gamble: How a poor visualization can elicit risky behavior," *arXiv preprint arXiv:2010.14069*, 2020.

[8] H. Eysenck, "The biological basis of personality. charles c. thomas.[mz](1990) biological dimensions of personality," *Handbook of personality: Theory and research, ed. LA Pervin*, p. 244276, 1967.

[9] R. R. McCrae and P. T. Costa Jr, "The five-factor theory of personality." 2008.

[10] A. Beratšová, K. Krchová, N. Gažová, and M. Jirásek, "Framing and bias: A literature review of recent findings," *Central European Journal of Management*, vol. 3, no. 2, 2018.

[11] T. M. Green and B. Fisher, "Towards the personal equation of interaction: The impact of personality factors on visual analytics interface interaction," in *2010 IEEE Symposium on Visual Analytics Science and Technology*. IEEE, 2010, pp. 203–210.

[12] A. Tversky and D. Kahneman, "The framing of decisions and the psychology of choice," *science*, vol. 211, no. 4481, pp. 453–458, 1981.

[13] H. A. Simon, "Models of man; social and rational." 1957.

[14] A. Tversky and D. Kahneman, "Judgment under uncertainty: Heuristics and biases," *science*, vol. 185, no. 4157, pp. 1124–1131, 1974.

[15] D. Kahneman, S. P. Slovic, P. Slovic, and A. Tversky, *Judgment under uncertainty: Heuristics and biases*. Cambridge university press, 1982.

[16] C. Xiong, L. Van Weelden, and S. Franconeri, "The curse of knowledge in visual data communication," *IEEE transactions on visualization and computer graphics*, vol. 26, no. 10, pp. 3051–3062, 2019.

[17] J. Wood, D. Badawood, J. Dykes, and A. Slingsby, "Ballotmaps: Detecting name bias in alphabetically ordered ballot papers," *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 12, pp. 2384–2391, 2011.

[18] E. Dimara, A. Bezerianos, and P. Dragicevic, "The attraction effect in information visualization," *IEEE transactions on visualization and computer graphics*, vol. 23, no. 1, pp. 471–480, 2016.

[19] ——, "Conceptual and methodological issues in evaluating multidimensional visualizations for decision support," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 1, pp. 749–759, 2017.

[20] M. Bancilhon and A. Ottley, "Did you get the gist of it? understanding how visualization impacts decision-making," *arXiv preprint arXiv:2010.04096*, 2020.

[21] S. Plous, *The psychology of judgment and decision making.* Mcgraw-Hill Book Company, 1993.

[22] Z. Liu, R. J. Crouser, and A. Ottley, "Survey on individual differences in visualization," *arXiv preprint arXiv:2002.07950*, 2020.

[23] P. J. Corr and G. Matthews, *The Cambridge handbook of personality psychology*. Cambridge University Press Cambridge, 2009.

[24] T. Millon, C. M. Millon, S. E. Meagher, S. D. Grossman, and R. Ramnath, *Personality disorders in modern life*. John Wiley & Sons, 2012.

[25] D. P. Schultz and S. E. Schultz, *Theories of personality*. Cengage Learning, 2016.

[26] M. Kahn, *Basic Freud*. Basic Books, 2002.

[27] A. W. Combs, A. C. Richards, and F. Richards, *Perceptual psychology: A humanistic approach to the study of persons.* University Press of America, 1976.

[28] P. Stefaroi, "Humanistic personology, a humanistic-ontological theory of the person & personality: Applications in therapy," *Social Work, Education, Management, and Art (Theatre). Charleston SC, USA [United States of America]: Create Space*, 2015.

[29] C. S. Dweck and E. L. Leggett, "A social-cognitive approach to motivation and personality." *Psychological review*, vol. 95, no. 2, p. 256, 1988.

[30] G. W. Allport, "Personality: A psychological interpretation." 1937.

[31] G. Matthews, I. J. Deary, and M. C. Whiteman, *Personality traits*. Cambridge University Press, 2003.

[32] J. Heinström, "Personality theory," *Theory in information behaviour research*, pp. 225–239, 2013.

[33] G. W. Allport, "Concepts of trait and personality." *Psychological Bulletin*, vol. 24, no. 5, p. 284, 1927.

[34] H. J. Eysenck, "Biological basis of personality," *Nature*, vol. 199, no. 4898, pp. 1031–1034, 1963.

[35] R. B. Cattell, H. W. Eber, and M. M. Tatsuoka, *Handbook for the sixteen personality factor questionnaire (16 PF): In clinical, educational, industrial, and research psychology, for use with all forms of the test*. Institute for personality and ability testing, 1970.

[36] L. R. Goldberg, "The structure of phenotypic personality traits." *American psychologist*, vol. 48, no. 1, p. 26, 1993.

[37] P. T. Costa Jr and R. R. McCrae, *The Revised NEO Personality Inventory (NEO-PI-R).* Sage Publications, Inc, 2008.

[38] S. V. Paunonen and M. C. Ashton, "Big five factors and facets and the prediction of behavior." *Journal of personality and social psychology*, vol. 81, no. 3, p. 524, 2001.

[39] E. R. Thompson, "Development and validation of an international english big-five mini-markers," *Personality and individual differences*, vol. 45, no. 6, pp. 542–548, 2008.

[40] J. Ormel, B. F. Jeronimus, R. Kotov, H. Riese, E. H. Bos, B. Hankin, J. G. Rosmalen, and A. J. Oldehinkel, "Neuroticism and common mental disorders: meaning and utility of a complex relationship," *Clinical psychology review*, vol. 33, no. 5, pp. 686–697, 2013.

[41] B. Jeronimus, R. Kotov, H. Riese, and J. Ormel, "Neuroticism's prospective association with mental disorders halves after adjustment for baseline symptoms and psychiatric history, but the adjusted association hardly decays with time: a meta-analysis on 59 longitudinal/prospective studies with 443 313 participants," *Psychological medicine*, vol. 46, no. 14, pp. 2883–2906, 2016.

[42] R. R. McCrae and P. T. Costa, "Validation of the five-factor model of personality across instruments and observers." *Journal of personality and social psychology*, vol. 52, no. 1, p. 81, 1987.

[43] J. Digman, "Personality structure: Emergence of the five-factor model," *Annual Review of Psychology*, vol. 41, pp. 417–440, 11 2003.

[44] L. Goldberg, "The structure of phenotypic personality traits." *The American psychologist*, vol. 48 1, pp. 26–34, 1993.

[45] R. R. McCrae and O. P. John, "An introduction to the five-factor model and its applications," *Journal of personality*, vol. 60, no. 2, pp. 175–215, 1992.

[46] P. T. Costa Jr, R. R. McCrae, and D. A. Dye, "Facet scales for agreeableness and conscientiousness: A revision of the neo personality inventory," *Personality and individual Differences*, vol. 12, no. 9, pp. 887–898, 1991.

[47] M. Zuckerman, "An alternative five-factor model for personality," *The developing structure of temperament and personality from infancy to adulthood*, pp. 53–68, 1994.

[48] ——, "What is a basic factor and which factors are basic? turtles all the way down," *Personality and individual differences*, vol. 13, no. 6, pp. 675–681, 1992.

[49] ——, "Zuckerman-kuhlman personality questionnaire (zkpq): An alternative five-factorial model," *Big five assessment*, pp. 377–396, 2002.

[50] J. E. Korteling, A.-M. Brouwer, and A. Toet, "A neural network framework for cognitive bias," *Frontiers in psychology*, vol. 9, p. 1561, 2018.

[51] G. Ellis, *Cognitive Biases in Visualizations*. Springer, 2018.

[52] D. Arnott, "A taxonomy of decision biases," *Monash University, School of Information Management and Systems, Caulfield*, 1998.

[53] C. R. Carter, L. Kaufmann, and A. Michel, "Behavioral supply management: a taxonomy of judgment and decision-making biases," *International Journal of Physical Distribution & Logistics Management*, 2007.

[54] J. Manoogian and B. Benson, "Cognitive bias codex," 2017.

[55] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," in *Handbook of the fundamentals of financial decision making: Part I*. World Scientific, 2013, pp. 99–127.

[56] R. F. Baumeister, E. Bratslavsky, C. Finkenauer, and K. D. Vohs, "Bad is stronger than good," *Review of general psychology*, vol. 5, no. 4, pp. 323–370, 2001.

[57] P. Rozin and E. B. Royzman, "Negativity bias, negativity dominance, and contagion," *Personality and social psychology review*, vol. 5, no. 4, pp. 296–320, 2001.

[58] Y. Kwak and S. Huettel, "The order of information processing alters economic gain-loss framing effects," *Acta psychologica*, vol. 182, pp. 46–54, 2018.

[59] I. P. Levin, S. L. Schneider, and G. J. Gaeth, "All frames are not created equal: A typology and critical analysis of framing effects," *Organizational behavior and human decision processes*, vol. 76, no. 2, pp. 149–188, 1998.

[60] C. R. McKenzie and J. D. Nelson, "What a speaker's choice of frame reveals: Reference points, frame selection, and framing effects," *Psychonomic bulletin & review*, vol. 10, no. 3, pp. 596–602, 2003.

[61] S. Sher and C. R. McKenzie, "Information leakage from logically equivalent frames," *Cognition*, vol. 101, no. 3, pp. 467–494, 2006.

[62] C. Janiszewski, T. Silk, and A. D. Cooke, "Different scales for different frames: The role of subjective scales and experience in explaining attribute-framing effects," *Journal of Consumer Research*, vol. 30, no. 3, pp. 311–325, 2003.

[63] I. Ajzen, *Attitudes, personality, and behavior*. McGraw-Hill Education (UK), 2005.

[64] L. S. Woolhouse and R. Bayne, "Personality and the use of intuition: Individual differences in strategy and performance on an implicit learning task," *European Journal of Personality*, vol. 14, no. 2, pp. 157–169, 2000.

[65] J. Kim, A. Lee, and H. Ryu, "Personality and its effects on learning performance: Design guidelines for an adaptive e-learning system based on a user model," *International Journal of Industrial Ergonomics*, vol. 43, no. 5, pp. 450–461, 2013.

[66] M. Kosinski, Y. Bachrach, P. Kohli, D. Stillwell, and T. Graepel, "Manifestations of user personality in website choice and behaviour on online social networks," *Machine learning*, vol. 95, no. 3, pp. 357–380, 2014.

[67] O. Nov, O. Arazy, C. López, and P. Brusilovsky, "Exploring personality-targeted ui design in online social participation systems," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2013, pp. 361–370.

[68] S. Devaraj, R. F. Easley, and J. M. Crant, "Research note—how does personality matter? relating the five-factor model to technology acceptance and use," *Information systems research*, vol. 19, no. 1, pp. 93–105, 2008.

[69] G. B. Svendsen, J.-A. K. Johnsen, L. Almås-Sørensen, and J. Vittersø, "Personality and technology acceptance: the influence of personality factors on the core constructs of the technology acceptance model," *Behaviour & Information Technology*, vol. 32, no. 4, pp. 323–334, 2013.

[70] A. M. Viveros, E. H. Rubio, and D. E. V. Ceballos, "Equivalence of navigation widgets for mobile platforms," in *International conference of design, user experience, and usability*. Springer, 2014, pp. 269–278.

[71] A. Dillon and C. Watson, "User analysis in hci: the historical lesson from individual differences research," 1996.

[72] E. M. Peck, B. F. Yuksel, L. Harrison, A. Ottley, and R. Chang, "Towards a 3-dimensional model of individual cognitive differences: position paper," in *Proceedings of the 2012 BELIV Workshop: Beyond Time and Errors-Novel Evaluation Methods for Visualization*, 2012, pp. 1–6.

[73] B. Steichen, G. Carenini, and C. Conati, "User-adaptive information visualization: using eye gaze data to infer visualization tasks and user cognitive abilities," in *Proceedings of the 2013 international conference on Intelligent user interfaces*, 2013, pp. 317–328.

[74] M. B. Donnellan, F. L. Oswald, B. M. Baird, and R. E. Lucas, "The mini-ipip scales: tiny-yet-effective measures of the big five factors of personality." *Psychological assessment*, vol. 18, no. 2, p. 192, 2006.

[75] J. B. Rotter, "Generalized expectancies for internal versus external control of reinforcement." *Psychological monographs: General and applied*, vol. 80, no. 1, p. 1, 1966.

[76] M. C. Ioannou, K. Mogg, and B. P. Bradley, "Vigilance for threat: Effects of anxiety and defensiveness," *Personality and Individual Differences*, vol. 36, no. 8, pp. 1879–1891, 2004.

[77] T. Alves, J. Natálio, J. Henriques-Calado, and S. Gama, "Incorporating personality in user interface design: A review," *Personality and Individual Differences*, vol. 155, p. 109709, 2020.

[78] L. Arockiam and J. C. Selvaraj, "User interface design for effective e-learning based on personality traits," *International Journal of Computer Applications*, vol. 61, no. 14, 2013.

[79] H. J. Eysenck, "A short questionnaire for the measurement of two dimensions of personality." *Journal of Applied Psychology*, vol. 42, no. 1, p. 14, 1958.

[80] T. Munzner, *Visualization analysis and design*. CRC press, 2014.

[81] D. Kahneman, *Thinking, fast and slow*. Macmillan, 2011.

[82] I. Cho, R. Wesslen, A. Karduni, S. Santhanam, S. Shaikh, and W. Dou, "The anchoring effect in decision-making with visual analytics," in *2017 IEEE Conference on Visual Analytics Science and Technology (VAST)*. IEEE, 2017, pp. 116–126.

[83] R. Wesslen, D. Markant, A. Karduni, and W. Dou, "Using resource-rational analysis to understand cognitive biases ininteractive data visualizations," *arXiv preprint arXiv:2009.13368*, 2020.

[84] X. Chen, S. D. Starke, C. Baber, and A. Howes, "A cognitive model of how people make decisions through interaction with visual displays," in *Proceedings of the 2017 CHI conference on human factors in computing systems*, 2017, pp. 1205–1216.

[85] D. Norman, *The design of everyday things: Revised and expanded edition*. Basic books, 2013.

[86] E. Ahissar and E. Assa, "Perception as a closed-loop convergence process," *Elife*, vol. 5, p. e12830, 2016.

[87] A. Tversky and D. Kahneman, "Judgment under uncertainty: Heuristics and biases (pp. 141-162)," *ed: Springer Netherlands*, 1975.

[88] W. E. Remus and J. E. Kottemann, "Toward intelligent decision support systems: An artificially intelligent statistician," *MIS Quarterly*, pp. 403–418, 1986.

[89] D. Arnott, "Cognitive biases and decision support systems development: a design science approach," *Information Systems Journal*, vol. 16, no. 1, pp. 55–78, 2006.

[90] T. Zuk and S. Carpendale, "Visualization of uncertainty and reasoning," in *International symposium on smart graphics*. Springer, 2007, pp. 164–177.

[91] G. Ellis and A. Dix, "Decision making under uncertainty in visualisation?" in *IEEE VIS2015*, 2015.

[92] S. Rudolph, A. Savikhin, and D. S. Ebert, “Finvis: Applied visual analytics for personal financial planning,” in *2009 IEEE symposium on visual analytics science and technology*. IEEE, 2009, pp. 195–202.

[93] A. Dasgupta, J. Poco, Y. Wei, R. Cook, E. Bertini, and C. T. Silva, “Bridging theory with practice: An exploratory study of visualization use and design for climate model comparison,” *IEEE transactions on visualization and computer graphics*, vol. 21, no. 9, pp. 996–1014, 2015.

[94] J. Hullman, P. Resnick, and E. Adar, “Hypothetical outcome plots outperform error bars and violin plots for inferences about reliability of variable ordering,” *PloS one*, vol. 10, no. 11, p. e0142444, 2015.

[95] M. Fernandes, L. Walls, S. Munson, J. Hullman, and M. Kay, “Uncertainty displays using quantile dotplots or cdfs improve transit decision-making,” in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018, pp. 1–12.

[96] A. Karduni, D. Markant, R. Wesslen, and W. Dou, “A bayesian cognition approach for belief updating of correlation judgement through uncertainty visualizations,” *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[97] Y.-S. Kim, L. A. Walls, P. Krafft, and J. Hullman, “A bayesian cognition approach to improve data visualization,” in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 2019, pp. 1–14.

[98] Y. Wu, L. Xu, R. Chang, and E. Wu, “Towards a bayesian model of data visualization cognition,” in *IEEE Visualization Workshop on Dealing with Cognitive Biases in Visualisations (DECISIVe)*, 2017.

[99] L. M. Padilla, “A case for cognitive models in visualization research: Position paper,” in *2018 IEEE Evaluation and Beyond-Methodological Approaches for Visualization (BELIV)*. IEEE, 2018, pp. 69–77.

[100] H. A. Simon, “A behavioral model of rational choice,” *The quarterly journal of economics*, vol. 69, no. 1, pp. 99–118, 1955.

[101] ——, “Rational choice and the structure of the environment.” *Psychological review*, vol. 63, no. 2, p. 129, 1956.

[102] F. Lieder and T. L. Griffiths, “Resource-rational analysis: understanding human cognition as the optimal use of limited computational resources,” *Behavioral and Brain Sciences*, vol. 43, 2020.

[103] F. Lieder, T. L. Griffiths, Q. J. Huys, and N. D. Goodman, “The anchoring bias reflects rational use of cognitive resources,” *Psychonomic bulletin & review*, vol. 25, no. 1, pp. 322–349, 2018.

[104] V. F. Reyna and C. J. Brainerd, “Fuzzy-trace theory: An interim synthesis,” *Learning and individual Differences*, vol. 7, no. 1, pp. 1–75, 1995.

[105] L. M. Padilla, S. H. Creem-Regehr, M. Hegarty, and J. K. Stefanucci, “Decision making with visualizations: a cognitive framework across disciplines,” *Cognitive research: principles and implications*, vol. 3, no. 1, p. 29, 2018.

[106] J. Mackinlay, P. Hanrahan, and C. Stolte, “Show me: Automatic presentation for visual analysis,” *IEEE transactions on visualization and computer graphics*, vol. 13, no. 6, pp. 1137–1144, 2007.

[107] A. V. Pandey, K. Rall, M. L. Satterthwaite, O. Nov, and E. Bertini, “How deceptive are deceptive visualizations? an empirical analysis of common distortion techniques,” in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2015, pp. 1469–1478.

[108] E. Gamliel, A. H. Zohar, and H. Kreiner, “Personality traits moderate attribute framing effects,” *Social Psychological and Personality Science*, vol. 5, no. 5, pp. 584–592, 2014.

[109] O. P. John, E. M. Donahue, and R. L. Kentle, “Big five inventory,” *Journal of Personality and Social Psychology*, 1991.

[110] A. Nosić and M. Weber, “How riskily do i invest? the role of risk attitudes, risk perceptions, and overconfidence,” *Decision Analysis*, vol. 7, no. 3, pp. 282–301, 2010.

[111] A. Oehler and F. Wedlich, “The relationship of extraversion and neuroticism with risk attitude, risk perception, and return expectations.” *Journal of Neuroscience, Psychology, and Economics*, vol. 11, no. 2, p. 63, 2018.

[112] B. Rammstedt and O. P. John, “Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german,” *Journal of research in Personality*, vol. 41, no. 1, pp. 203–212, 2007.

[113] B. Rammstedt, C. J. Kemper, M. C. Klein, C. Beierlein, and A. Kovaleva, “Eine kurze skala zur messung der fünf dimensionen der persönlichkeit: Big-five-inventory-10 (bfi-10),” 2012.

[114] P. Costa and R. McCrae, “Neo five-factor inventory (neo-ffi),” *Odessa, FL: Psychological Assessment Resources*, vol. 3, 1989.

[115] D. G. Williams, “Dispositional optimism, neuroticism, and extraversion,” *Personality and individual differences*, vol. 13, no. 4, pp. 475–477, 1992.

[116] N. Bolger, "Coping as a personality process: A prospective study." *Journal of personality and social psychology*, vol. 59, no. 3, p. 525, 1990.

[117] M. F. Scheier, C. S. Carver, and M. W. Bridges, "Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the life orientation test." *Journal of personality and social psychology*, vol. 67, no. 6, p. 1063, 1994.

[118] K. Noguchi, C. L. Gohm, and D. J. Dalsky, "Cognitive tendencies of focusing on positive and negative information," *Journal of Research in Personality*, vol. 40, no. 6, pp. 891–910, 2006.

[119] J. M. Chartrand, M. L. Rose, T. R. Elliott, C. Marmarosh, and S. Caldwell, "Peeling back the onion: Personality, problem solving, and career decision-making style correlates of career indecision," *Journal of Career Assessment*, vol. 1, no. 1, pp. 66–82, 1993.

[120] R. El Othman, R. El Othman, R. Hallit, S. Obeid, and S. Hallit, "Personality traits, emotional intelligence and decision-making styles in lebanese universities medical students," *BMC psychology*, vol. 8, pp. 1–14, 2020.

[121] J. Müller and C. Schwieren, "What can the big five personality factors contribute to explain small-scale economic behavior?" 2012.

[122] F. Farley, "Individual differences in solution time in error-free problem solving," *British Journal of Social and Clinical Psychology*, vol. 5, no. 4, pp. 306–309, 1966.

[123] M. Lima and A. Simões, "Neo pi-r: Manual profissional [neo pi-r: Professional manual]," *Lisboa, Portugal: CEGOC*, 2000.

[124] A. Becker, T. Deckers, T. Dohmen, A. Falk, and F. Kosse, "The relationship between economic preferences and psychological personality measures," 2011.

[125] L. Borghans, J. J. Heckman, B. H. Golsteyn, and H. Meijers, "Gender differences in risk aversion and ambiguity aversion," *Journal of the European Economic Association*, vol. 7, no. 2-3, pp. 649–658, 2009.

[126] C. Mayfield, G. Perdue, and K. Wooten, "Investment management and personality type," *Financial services review*, vol. 17, no. 3, pp. 219–236, 2008.

[127] M. Lauriola and I. P. Levin, "Personality traits and risky decision-making in a controlled experimental task: An exploratory study," *Personality and individual differences*, vol. 31, no. 2, pp. 215–226, 2001.

[128] Q. McNemar, "Note on the sampling error of the difference between correlated proportions or percentages," *Psychometrika*, vol. 12, no. 2, pp. 153–157, 1947.

[129] A. L. Edwards, “Note on the “correction for continuity” in testing the significance of the difference between correlated proportions,” *Psychometrika*, vol. 13, no. 3, pp. 185–187, 1948.

[130] J. Cohen, “Statistical power analysis jbr the behavioral,” *Sciences. Hillsdale (NJ): Lawrence Erlbaum Associates*, pp. 18–74, 1988.

[131] J. Apesteguia and M. A. Ballester, “A measure of rationality and welfare,” 2010.

A

Informed Consent Document

Consentimento Informado

Objetivo

Estamos a conduzir um estudo observacional sobre como indivíduos interagem com visualizações de informação. Iremos também validar se fatores de personalidade modelam este comportamento. O objetivo desta sessão é executar um conjunto de tarefas com diferentes visualizações e recolher as suas observações sobre as mesmas.

Características da sessão

A duração desta sessão não deve ser maior que 30 minutos e terá lugar na plataforma de videoconferência Zoom. Não identificámos riscos que não sejam os da vida quotidiana.

Tratamento dos dados pessoais recolhidos durante a sessão

Na sessão serão gravados os seus dados referentes a (i) *interações com interfaces (e.g. movimentos de rato e cliques)*, (ii) *respostas a questionários*, (iii) *áudio*, e (iv) *gravação de tela*. Todos os dados recolhidos serão mantidos em sigilo. Os dados mencionados em (i) e (ii) poderão também ser utilizados para apresentação ou exibição de resultados, devidamente pseudonimizados, em publicações científicas, conferências ou eventos semelhantes. Os dados mencionados em (iii) e (iv) serão exclusivamente usados para ajudar a interpretação da experiência. A gravação de tela não inclui a face do participante. Assim, nenhum destes dados será divulgado em publicações científicas, conferências ou eventos semelhantes.

Estes dados vão ser armazenados em unidades de armazenamento externas privadas a cargo do responsável pelo tratamento de dados. De forma a preservar a pseudo-anonimidade dos seus dados, ser-lhe-á atribuído um identificador numérico único. Os seus dados de contacto e os seus dados da experiência serão guardados em unidades de armazenamento externas privadas diferentes de forma a manter a confidencialidade dos mesmos. Os dados pseudonimizados da experiência (não incluem identificador) serão analisados, exclusivamente, pelos membros da equipa de investigação. Para além destes dados, vamos também usar os seus dados referentes aos questionários de personalidade que preencheu numa fase anterior. O seu tratamento será igual aos que recolhemos nesta sessão.

Os seus direitos

A sua participação é voluntária e livre, sendo que tem o direito de desistir a qualquer momento sem qualquer prejuízo pessoal. Caso tal aconteça, os dados relativos à sua experiência serão removidos e destruídos. Tem igualmente o direito de solicitar ao responsável pelo tratamento acesso aos dados pessoais que lhe digam respeito, bem como os direitos de rectificação, apagamento, limitação e oposição do tratamento, incluindo o direito de retirar consentimento em qualquer altura, sem prejuízo da licitude do tratamento eventual e previamente consentido. Tem igualmente o direito de apresentar uma reclamação à CNPD (Comissão Nacional de Proteção de Dados). Todos os dados serão destruídos ao fim de três anos desde a data desta sessão, de acordo com a Lei de Proteção de Dados Portuguesa. Por último, tem também o direito de saber as entidades a quem possam os dados ser comunicados e possibilidade da transferência dos dados para países terceiros (fora do Espaço Económico Europeu).

Se tiver alguma questão, sinta-se à vontade para a colocar. Para participar nesta experiência, pedimos-lhe que leia o consentimento informado e caso concorde em participar de acordo com os termos abaixo, pedimos-lhe que assine o formulário no local indicado.

---

1 - Li e compreendi o significado deste estudo. Tive a oportunidade de colocar questões, caso necessário, e recolher as respetivas respostas.

2 - Compreendo que a participação neste estudo é voluntária e que posso desistir a qualquer momento, sem apresentar qualquer explicação. Caso tal aconteça, não serei alvo de qualquer penalização e os dados relativos à minha experiência serão removidos e destruídos.

3 - Autorizo a gravação dos dados durante a sessão.

4 - Autorizo o processamento dos dados no âmbito deste projeto para fins de análise, investigação e disseminação de resultados em publicações científicas ou conferências na área do projeto, pelos investigadores deste projeto.

5 - Compreendi que os dados recolhidos neste estudo serão utilizados como mencionado anteriormente.

6 - Autorizo novamente o processamento dos meus dados demográficos e de personalidade recolhidos anteriormente.

7 - De acordo com o descrito acima, autorizo a minha participação neste estudo e aceito as suas condições.

Obrigado pela sua colaboração!

____
(participante)

____
(investigador responsável)

____
(data)

Ao participante será entregue uma cópia assinada deste formulário.

Equipa

Sandra Gama (Investigador responsável)
sandra.gama@tecnico.ulisboa.pt

Tomás Alves (Responsável pelo tratamento de dados)
tomas.alves@tecnico.ulisboa.pt

Tatiana Nunes (Encarregado de proteção de dados)
dpo@inesc-id.pt

Daniel Gonçalves
daniel.goncalves@inesc-id.pt

Carlota Dias
carlota.lopes.dias@tecnico.ulisboa.pt

Alexandra Maroco
alexandra.maroco@tecnico.ulisboa.pt

Ricardo Velhinho
ricardo.velhinho@tecnico.ulisboa.pt

Vasco Pires
vascocfpires@tecnico.ulisboa.pt

Tiago Delgado
tiago.delgado@tecnico.ulisboa.pt

Graphics and Interaction - INESC-ID
Instituto Superior Técnico
R. Alves Redol 9,
1000-029 Lisboa, Portugal

Joana Henriques-Calado
jhcalado@psicologia.ulisboa.pt

CICPSI, Faculdade de Psicologia,
Cidade Universitária,
Alameda da Universidade,
1649-004 Lisboa, Portugal

B

Experiment Questionnaire

Framing Vis

Bem-vindo(a)!

Sou a Alexandra Maroco, aluna de 2º ano de Mestrado em Engenharia Informática e de Computadores, no Instituto Superior Técnico. No âmbito da minha tese de mestrado, desenvolvi um projeto de investigação, com orientação por parte dos professores Sandra Gama(sandra.gama@tecnico.ulisboa.pt), Daniel Gonçalves (daniel.goncalves@inesc-id.pt) e Tomás Alves (tomas.alves@tecnico.ulisboa.pt).

Neste estudo, vamos pedir que faça parte duma experiência onde, durante a sua participação na mesma, iremos pedir-lhe que tome três decisões relativamente a programas propostos para combate de doenças hipotéticas. Estas decisões serão tomadas com base em visualizações desenvolvidas por nós. De notar que todos os dados usados para a experiência foram inventados por nós e, como tal, não possuem qualquer relação com a realidade. Na totalidade, a participação neste estudo não deverá demorar mais que 30 minutos, sendo que, em qualquer fase do mesmo, está à vontade para colocar qualquer questão.

Todos os dados recolhidos serão mantidos confidenciais e analisados, exclusivamente, para propósitos académicos, pelos investigadores envolvidos neste projeto. A qualquer momento e sem qualquer penalização e/ou prejuízo pessoal, poderá pausar ou desistir da experiência. A acontecer, os dados recolhidos até esse momento serão devidamente descartados e removidos da nossa experiência. Ademais, no final da sua participação e se assim o desejar, poderá requisitar os seus dados recolhidos durante a mesma.

Relembro que não existem respostas certas ou erradas e em nenhum ponto da experiência será avaliado(a). A única avaliação é somente a do nosso projeto de investigação.

Caso tenha alguma questão, sinta-se à vontade para a(s) colocar à investigadora principal deste estudo através do e-mail alexandra.maroco@tecnico.ulisboa.pt

Obrigada pela sua colaboração!

*Obrigatório

1. Consente em participar na experiência com as condições que lhe foram apresentadas? *

Marcar apenas uma oval.

- ◯ Sim
- ◯ Não

Identificação de Participante

2. Indique o ID de participante que lhe foi atribuído: *

3. Irá utilizar óculos ou lentes de contacto durante a sua participação na experiência? *

Marcar apenas uma oval.

- Sim
- Não

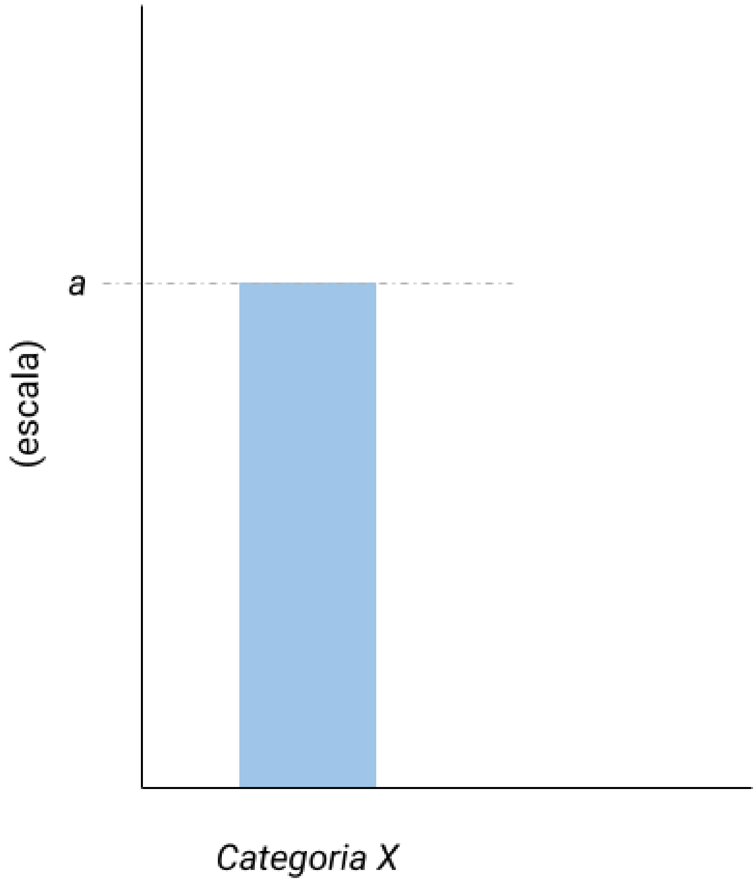
4. Como classifica a sua disposição a tomar riscos? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Nenhuma disposição								Total disposição

Familiaridade com Visualizações

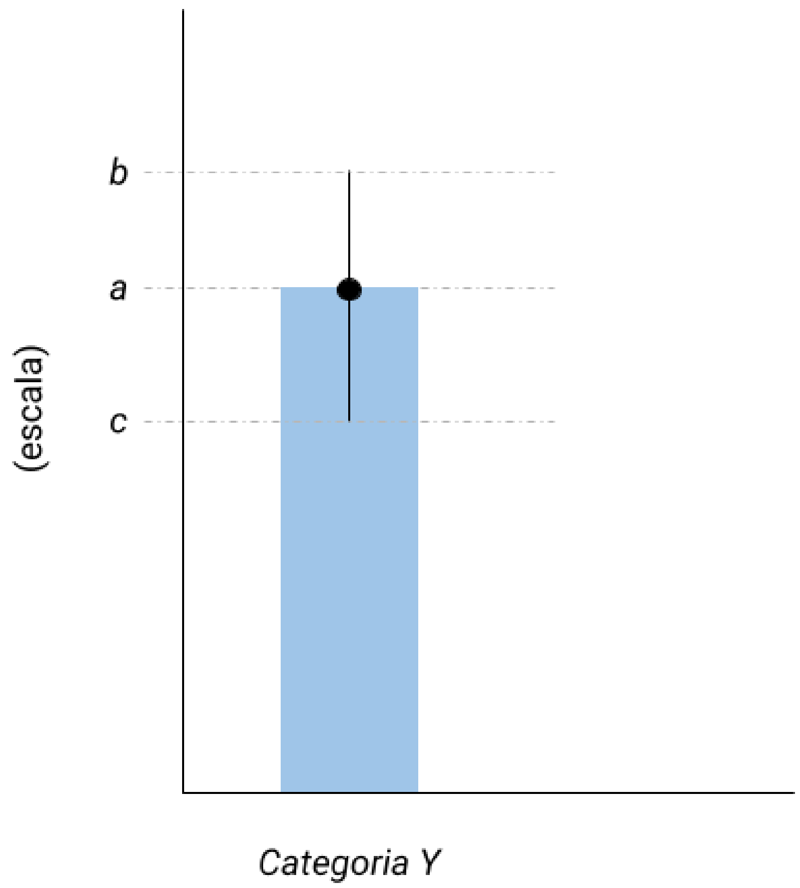
5. Como classifica a sua familiaridade com este tipo de visualização? *



Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Nada familiarizado	◯	◯	◯	◯	◯	◯	◯	Completamente familiarizado

6. Como classifica a sua familiaridade com este tipo de visualização? *



Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Nada familiarizado								Completamente familiarizado

Como Interpretar as Visualizações deste Estudo

Gráfico de Barras

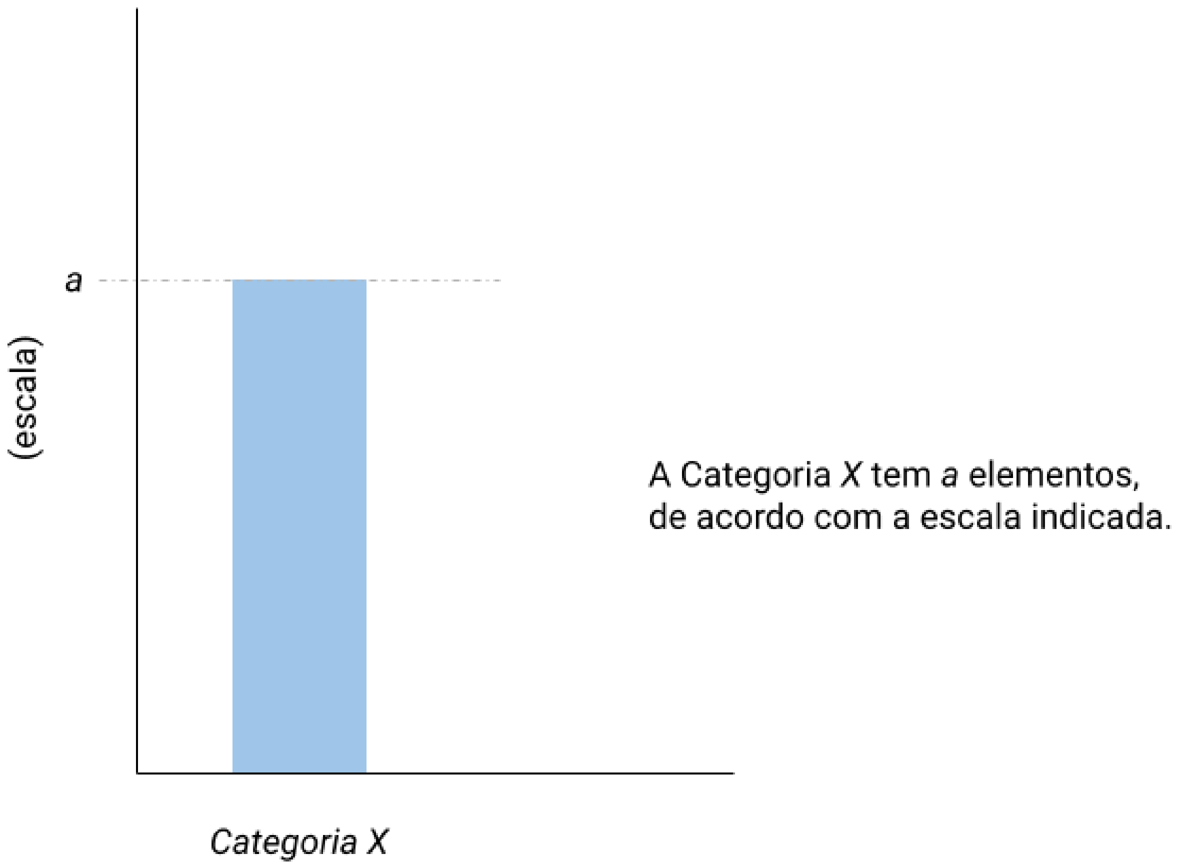
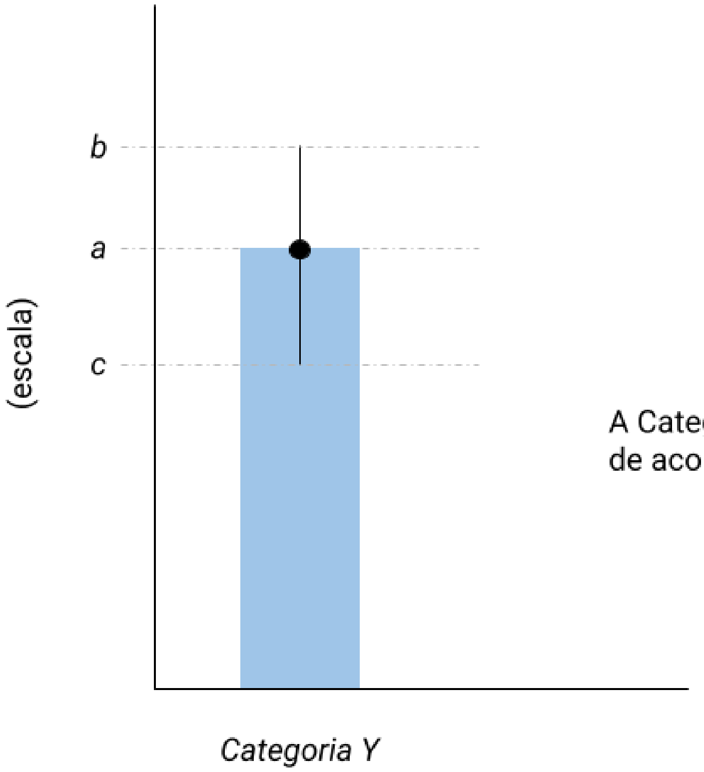


Gráfico de Barras com Intervalo de Confiança



A Categoria *Y* tem entre *b* a *c* elementos, de acordo com a escala indicada.

Introdução: Contexto do Problema

Imagine que Portugal se está a preparar para o surto de três doenças raras. Espera-se que cada doença mate 600 pessoas. Foram propostos programas alternativos de combate a cada uma das doenças hipotéticas.

Durante a nossa experiência, irá observar a estimativa científica exata das consequências desses mesmos programas, para cada uma das três doenças, através de visualizações desenvolvidas por nós.

Importante relembrar que todos e quaisquer dados utilizados neste estudo não têm qualquer relação com a realidade, tendo sido inventados por nós apenas para o propósito do nosso estudo.

Primeira Decisão

Podemos agora proceder para a primeira decisão da nossa experiência.

Em primeiro lugar, peço que indique o tipo de decisão na questão apresentada. De seguida, solicito que abra o outro separador e clique no botão correspondente.

7. Tipo de decisão (a ser-lhe indicado pela investigadora): *

Marcar apenas uma oval.

- A
- B

Primeira Decisão - Feedback

8. O quão arriscada considera a sua escolha? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Nada arriscada								Extremamente arriscada

Segunda Decisão

Passemos agora para a segunda decisão do nosso estudo, referente a uma outra doença hipotética.

Novamente, peço que abra o outro separador e analise a visualização correspondente. Ao submeter a sua decisão, por favor, retome ao questionário para a questão adicional.

Segunda Decisão - Feedback

9. O quão arriscada considera a sua escolha? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Nada arriscada								Extremamente arriscada

Terceira Decisão

Procedemos para a terceira e última decisão do nosso estudo, onde o procedimento é o mesmo - analisar a visualização apresentada e indicar a decisão correspondente.

Terceira Decisão - Feedback

10. O quão arriscada considera a sua escolha? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Nada arriscada								Extremamente arriscada

Agradecimento

Obrigada pela sua participação!

Novamente, realçamos que todos os dados utilizados para este estudo são meramente hipotéticos.

Relembramos que todos os dados daqui retirados serão tratados de forma anónima e exclusivamente utilizados em análise no âmbito do nosso projeto de investigação. Caso pretenda receber os dados recolhidos durante a sua participação, sinta-se à vontade para os requisitar através do e-mail alexandra.maroco@tecnico.ulisboa.pt