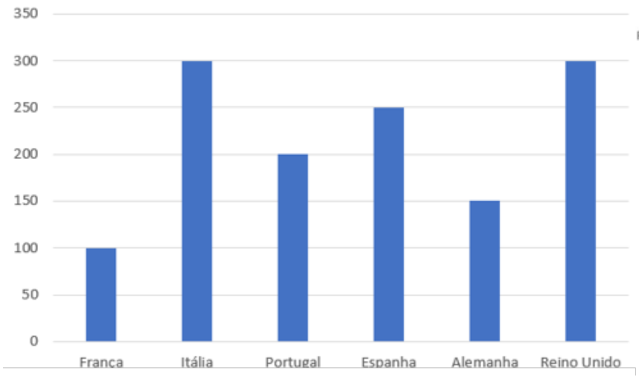

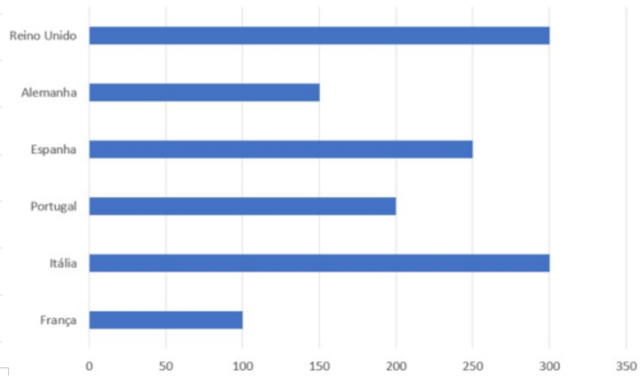

ConsciVis: Exploring the Effect of User-Based Preferences in Information Visualisation

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Abstract

Catering to users' need is one of the main pillars of Human-Computer Interaction. In this study, we explore user differentiation as a way to improve data visualisation interaction by focusing on personality. We focus on the personality trait of conscientiousness which reflects people's tendency to be more organized, attentive to detail and diligent. We explore how conscientiousness shapes user experience towards InfoVis, by relating it with user task efficiency, task efficacy, perceived ease-of-use, perceived usefulness and preference. With the final goal of understanding how conscientiousness shapes user behaviour in the domain of information visualisation, our work creates a set of design features and explores their impact on users upon their validation.

Keywords

Information Visualisation; Five-Factor Model; Conscientiousness; Personality; Data Visualisation.

Resumo

Um dos principais pilares da área de Interação Pessoa-Máquina é servir as necessidades dos utilizadores. Neste estudo exploramos como a personalidade os diferencia, como forma de melhorar a sua interação com a visualização de informação (InfoVis). Este estudo foca-se no traço de conscienciosidade que reflete a tendência das pessoas para serem mais organizadas, atentas aos detalhes e diligentes. Investigamos como a conscienciosidade do individuo molda seu comportamento em relação à InfoVis, relacionando-a com a sua eficiência e eficácia na realização de tarefas, perceção de facilidade de utilização, perceção de utilidade e preferência. Com o objetivo final de compreender como a conscienciosidade molda o comportamento do usuário no domínio da visualização da informação, o nosso estudo cria algumas diretrizes de design, e explora o seu impacto nos utilizadores através da sua validação.

Palavras Chave

Visualização de Informação; Modelo dos Cinco Fatores; Conscienciosidade; Personalidade; Visualização de Dados.

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Acronyms

ANOVA	Analysis of Variance
FFM	Five Factor Model
GUI	Graphical User Interfaces
LOC	Locus of Control
TAM3	Technology Acceptance Model 3 Scale
PS	Perceptual Speed
NFC	Need For Cognition

1

Introduction

Contents

In the current age of big data, visualization takes on an increasingly important role in giving meaning to so much information [5]. Through visual metaphors and functions such as filtering, zooming, and picking, Information Visualisation (InfoVis) gives users the chance to spot patterns, explore datasets, and gain insights through an intuitive visual channel [6, 7]. This useful concept can be applied to a multitude of domains where there is a need to process and present data, including health, business, and media [8–12]. Much of the motivation behind the Human-Computer Interaction related fields is the creation of systems whose interaction with people is as harmonious as possible [5–7, 13, 14]. As it happens, not two people are the same and the best way to present certain information to someone might not have the same effect on someone else. Studies have repeatedly shown that users have more positive interactions with systems that take their individuality into consideration, and current user research practises assimilate these findings by dividing users into groups according to relevant characteristics [2, 4, 15–17]. This methodology allows designers to meet the general needs of users in each group, but fails to address each user on an individual level. Even within each user pool, we can optimise system design by considering what factors differentiate each individual [18–20]. Motivated by this premise, researchers have been investigating how to optimise user experience by creating systems that take into account individual user characteristics [4, 16, 21–26]. Among these psychological elements such as perceptual speed, verbal working memory and visual working memory, personality has shown promising results [4, 16, 21, 27–29].

Within the domain of personality, conscientiousness is a trait that seems to be intrinsically related to the use of information visualisation. It is associated with good impulse control, orientation towards goals and striving towards achievements [30, 31]. It is a good predictor of high work performance, an indicator of approaching tasks with diligence and care, and it is present in more than one personality model, appearing both in the HEXACO and Five-Factor models [32–34].

A few studies on the topic of personality have already uncovered some findings relating to conscientiousness [19]. Al-Samarraie [3, 35, 36] investigated how personality shapes user preference in the design of Graphical User Interfaces (GUI). They grouped users by personality traits and facets into two clusters, one including people with high neuroticism, and the other including people with high conscientiousness and agreeableness. After designing a different GUI for each of these groups, taking into account their design preferences, it was possible to observe that user satisfaction was increased when interacting with a GUI tailored to them [15, 37]. However, in this study conscientiousness was not evaluated as a stand-alone, since it was clustered with the other traits.

Nunes et al. [38] studied the effects of conscientiousness on GUI design for user-adaptive interfaces. They found that conscientiousness was relevant for interface design in particular for users with high levels of conscientiousness. In the end, results showed that conscientiousness did have an effect on user interface preference, as well as in users perceived ease-of-use.

Another study by Saati et al. [39] also gives insight into the preferences of conscientious people by exploring the relationship between colours and personality. Results showed that that users low in extraversion preferred blue, users high in openness preferred black and conscientious users preferred yellow.

Although the aforementioned studies connect conscientiousness and user preference, they are focused in website [38] or mobile-based [35] GUIs. To the best of our knowledge, there is no research that found significant results in the domain of information visualisation [19] regarding this specific trait. In the light of this, we extend prior work [18] by studying in-depth how conscientiousness has an effect in user preference regarding idiom type, visualisation design and its layout. As such, we started by collecting data regarding user preference and personality. Based on the methodology of Sarsam and Al-Samarraie [3, 35], we created a set of three information visualisation systems for different conscientiousness levels. Afterwards, we conducted a user testing phase where we assessed how conscientiousness affected user experience while participants performed tasks in the tailored information visualisation systems. Our results offer new insights to **understand whether preferences based on conscientiousness are relevant for the design pipeline of information visualisation systems.** We found that users with higher conscientiousness have a higher task efficiency. We also observed difference in behaviour between users with higher and lower conscientiousness related to perceived ease-of-use and preference.

1.1 Objectives

This research aims to **understand whether preferences based on conscientiousness are relevant for the design pipeline of information visualisation systems.** To fulfill such goal, some steps were set to guide us through the process of this research. These objectives are:

- Collect data on user preferences and personality.
- Create a set of design guidelines for conscientious users.
- Validate a set of design guidelines that customise visualisations to the trait of conscientiousness.

Furthermore, we also contributed with an article submitted to a top venue in our research area [20], InfoVis 2020[1], and are currently preparing another piece for a book chapter.

[1] http://www.guide2research.com/conference/infovis-2020

1.2 Document Structure

This document is organised as follows: Chapter 2 is a theoretical presentation of important fundamental concepts that will follow you throughout the rest of the study. This includes some background on what is personality, how to measure it using the Five Factor Model (FFM) and what is conscientiousness. Chapter 3 is a description and analysis of other studies that lead to relevant findings in the topics of personality and InfoVis. Chapter 4 covers in detail the creation of the design guidelines. This includes the collection of personality and preferences data, and the data processing methods. Chapter 5 is the evaluation of the results where we present the results obtained, accept or reject the proposed hypotheses, and discuss our findings. Chapter 6 presents the conclusions, limitations and future work.

2

Fundamentals of Personality

Contents

Personality can be described as a set of traits and characteristics that describe a person's behaviour. In this chapter, we give brief explanation of the fundamentals of personality and it's relevance to this study.

2.1 The Five-Factor Model

To study the possible connection between personality and InfoVis it is first necessary to understand the process of personality measurement. Measuring personality is a complex task, however, there are already a range of different psychometric tools created for that purpose. Some of these tools include the Three-Factor model [40, 41], HEXACO [33, 42] and the Five-Factor Model [34, 43].

These models are all valid but differ from each other by what they consider to be the main components of personality. The Five-Factor Model (FFM) is the one we will be using for this research as it is the most well scientifically received to date [32, 34, 43, 44] and one of the most currently used models in personality research.

The model treats personality as a set composed of the following five traits:

- **Neuroticism:** This trait relates to emotional stability. Neurotic individuals are more sensible, have stronger reactions to negative emotions and are more prone to anxiety and depression. On the flip side, individuals with very low neuroticism scores may be too emotionally unattached.

- **Extraversion:** This trait reveals how outgoing an individual is as opposed to preferring solitude. Extraverted people feel energized after interacting with others, while introverts recover their energy from spending time alone.

- **Openness:** This trait discloses the ability an individual has to allow him/herself to face unknown situations. People with high openness tend to face new situations with excitement and curiosity while those with lower scores tend to be more conservative and prefer to engage in familiar patterns.

- **Agreeableness:** This trait depicts the capability someone has to be cooperative and compassionate. People high in agreeableness are more empathetic and prefer avoiding conflict in order to establish positive relationships. Those low in agreeableness take stronger stances for their beliefs but might be more detached and discordant towards others.

- **Conscientiousness:** This trait expresses how diligently someone approaches responsibilities. Conscientious people are reliable, have good impulse control and care to make decisions with self-awareness. Less conscientious individuals are not as perfectionist and tend to let go of rules more easily.

2.2 Conscientiousness

From all the five traits of the FFM, the trait of conscientiousness will be the one we will focus on [39, 45, 46]. As briefly described before, conscientiousness is a personality trait that reveals itself in the inclination towards order, attention to detail, impulse control and discipline. It is related to an achievement-striving personality and is also a predictor of good job performance. This specific trait was chosen for analysis because of how those characteristics possibly affect an individual's interaction with visualizations and because it is a trait that appears both in the FFM and the HEXACO models.

A visualisation is oftentimes a tool used to search for or extract information. Since conscientious individuals are typically more orderly and task-oriented these attributes may affect the way they navigate a visualisation and their preference in terms of layout and design. The characteristics of conscientious individuals seem to be reflective of someone who engages in assignments with diligent effort and attentiveness which are aspects of personality that would be engaged in contexts where the need for a visualisation arises. All of this makes conscientiousness a relevant trait to explore when it comes to InfoVis and user traits.

In the FFM, there are also six facets to each of the five traits [47–49]. These facets are a breakdown of characteristics derived from the main trait. The facets of conscientiousness are:

- **Competence:** To perform a task effectively.
- **Order:** To need structure and neatness in one's environment.
- **Dutifulness:** To take rules seriously, be obedient and fulfill obligations.
- **Achievement-striving:** To work hard towards reaching goals.
- **Self-Discipline:** To have the self-control to be rigorous and persistent.
- **Deliberation:** To act according to well thought out decisions.

When using the FFM as a personality measurement, facets help the researcher to draw deeper conclusions from the test results. For example, two individuals might have similar degrees of conscientiousness but a big difference in their orderliness scores. This factor might lead them to behave in different ways that could possibly translate into different approaches of interacting with technology.

3

Related Work

Contents

This section compiles a series of studies with relevant insights into the research of user characteristics and InfoVis. The purpose of this section is to create an understanding of what research has already been done in the domain of user differentiation in visualizations, what methods were used and what important findings have been uncovered. Besides that, we also want to know what research has been done on personality-based adaptation, and on conscientiousness specifically, to understand the value our research can bring to the current state of the art.

3.1 Impact of User Differences on Technology

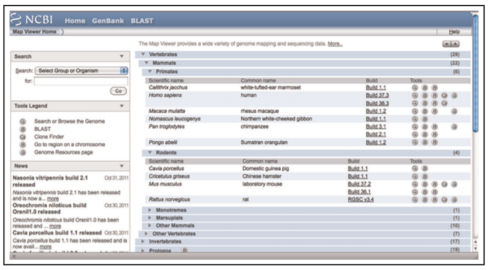
The impact of individual user differences on technology is a topic that can have several approaches. Some of these include cognitive abilities, user performance, perceived usability and personality, in a multitude of contexts [3, 37, 39, 50–54].

Butt et al. [22] contributed to the acknowledgment that it is possible to predict a users' personality type from their pattern of interaction with technological devices. They observed that it is possible to correlate patterns of mobile phone use to specific personality traits by showing that that disagreeable extraverts spend more time than others on their mobile phones performing a variety of actions from receiving calls to changing their phone's appearance. Results also showed that users with extraverted, neurotic disagreeable and unconscientious personality traits spend more time writing and receiving SMS than calling or receiving calls.

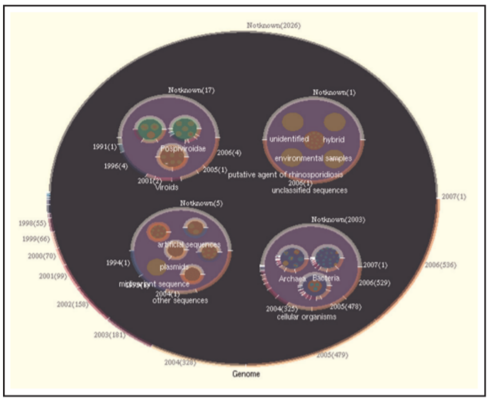
Another study on a similar theme, was conducted by Braun et al. [15]. They investigated the effect of different GUI types on user personality, by using gamification, notifications and quantified-self dashboards on a car simulator. They found that extraverts enjoy proactive dashboards the most, such as notifications, while neurotic users prefer having a constant display of their state, as in the quantified-self interface. Users with high agreeableness liked all approaches equally. This study provides some indication for design guidelines that might appeal to some of the FFM traits, and it gave insight into how different types of visualisation interaction can influence user satisfaction and efficiency.

Green et al. [1] also used the FFM to measure personality and link it to user performance. Using two different visualisations (Figure 3.1), participants were tested for the time it took them to complete tasks, the number of errors made, and the relationship of those factors with their Locus of Control (LOC)[1], extraversion and neuroticism scores. They found that neurotic and extraverted individuals were quicker at learning to manipulate data, which opens up the hypothesis that it might be possible to predict users' learning speed of new systems if their personality is known previously. Table 3.1 shows a difference in results of completion time, errors and insights depending on the interface and the traits tested. From

[1]The LOC is a personality measure that refers to the degree to which people believe they have control over events in their life. People with an internal LOC believe their actions are what determines their situation while people with an external LOC believe their situation is predicated by external factors [55].



(a) MapViewer visualisation



(b) GVis visualisation

Figure 3.1: Hierarchical data visualisations used for user tasks. [1].

the results we can tell that personality traits did affect task completion time and insights, although they did not affect the number of errors performed by users. The choice of interface also affected user behaviour, since users had faster completion times and fewer errors using the MapViewer but reported more insights using GVis.

	Completion time	Errors	Insights
Interface	Faster times in MapViewer	Fewer errors in MapViewer	More insights in Gvis
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

Table 3.1: Table summarising the results obtained for the completion time, errors and insights for each interface, LOC, extraversion and neuroticism [1].

Using different metrics, Toker et al. [56] explored the effect of Perceptual Speed (PS)[2], verbal working memory (verbal WM)[3], visual working memory (visual WM)[4], and expertise in user interaction with bar and radar charts. They evaluated the impact of those factors on user preference, task efficiency and ease-of-use. During the study, users were presented with a set of tasks to perform on one of the charts, and then asked to repeat a similar process with the other one. These tasks varied in complexity, ranging from simpler questions such as *"In how many courses is Maria below the class average?"* to more complex ones that included comparisons, such as *"Find the courses in which Andrea is below the*

[2] Cognitive ability that allows people to quickly and accurately find target information and carry out comparisons [57]

[3] Cognitive ability that allows temporary storage of verbalizable information, such as letters, words, or nameable objects [58]

[4] Cognitive ability that allows temporary storage of visual characteristics of objects as their shape, orientation, and detailed appearance [59]

class average and Diana is above it?". The study found that bar graphs have more favourable results in completion time, and that user performance with radar charts is dependent on their level of PS. Results also showed users with higher visual WM had higher preference ratings for radar graphs, while users with lower verbal WM had a higher ease-of-use rating for bar graphs. These results seem to support the link between personal user characteristics and user's data interpretation when met with different visualizations. In particular, it shows that PS, verbal WM, and visual WM are cognitive characteristics that have an influence on the effectiveness of visualizations from a user's perspective and that users react differently to idioms.

A similar study conducted by Conati et al. [16] also explored the same cognitive abilities of PS, visual, verbal WM and user expertise. Instead of bar and radar charts, they tested value charts with a horizontal and vertical layout. Results show that users with lower expertise could benefit more from support in interpreting visualisations than users with high-expertise in complex low-level tasks. Highlighting certain information or using informative pop-ups could be helpful methods of accommodating users with lower expertise. Users with lower measures of PS performed worst in most tasks and users with lower verbal WM performed worse than their counterparts in sorting-related tasks. It was also found that users with lower values of visual WM perform significantly faster with the horizontal layout than with the vertical visualizations, and curiously, with the horizontal layout they even perform better than users with high visual WM. These results confirm the relevance of the impact of cognitive abilities in the effectiveness of visualisations. But they also extend those findings by suggesting that properly adapting visualisations to user cognitive abilities can compensate faults in those abilities.

In a different study, Conati et al. [21] explored the difference between using a radar graph and a multiscale dimension visualizer to represent information. This study explored some of the traits already explored in the studies mentioned before (PS and VM) but also introduced new ones such as the Need For Cognition (NFC) personality trait, which has a direct correlation to the FFM traits of openness and conscientiousness [21, 60, 61], and can be defined as the intrinsic motivation to engage in and enjoy effortful cognitive endeavors [62]. They gave each user the task of comparing changes in two sets of data. Results show that there is a difference in the user's task accuracy that depends on their PS. Users with high PS performed better using the multiscale dimension visualizer while users with low PS preferred the radar graph. As for the NFC trait, it is suggested that individuals with a low score might prefer the option of getting additional automatic clarification from the system. Further research will be made on how to better identify what problems users with specific traits will encounter. Like the previous ones, these findings support the evidence that cognitive abilities are relevant to user-adaptive interfaces as they can be predictors of task effectiveness. However, they also expand on what characteristics can be user for differentiating users that go beyond cognitive abilities, by entering the domain of personality.

Lallé et al. [4] explored PS, visual WM, visual scanning, visualization literacy, LOC and proposed a set of design guidelines for GUIs based on those characteristics. Contrary to the previous studies, in this one users worked with an interface that they could choose to customise. Results show that users with high visualisation literacy or an internal LOC can benefit from system customisation but are not very likely to do so spontaneously. Other results produced from this study are summarised in Table 3.2 with suggestions of possible customisation related to the user traits studied. It is suggested that to build an interface customised for users with an internal LOC or high visualisation literacy it would be a good idea to prompt the users to use the hide/display buttons. These findings are relevant as they not only dig into the link between personality and customisation but they also propose a set of design guidelines that could be applied in other research related to the traits and abilities studied.

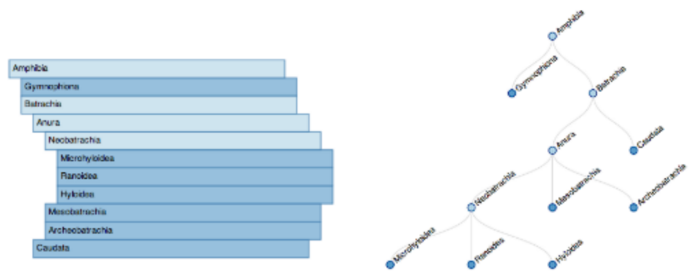
Personalization	For:
Prompts to use the hide/display buttons	Internal locus of control/high vis literacy users
Deemphasize or disable the hide/display buttons	External locus of control users
Get a simpler deviation chart	Low spatial memory users
Prompt to perform visual comparisons	Low spatial memory, visual scanning, vis literacy or perceptual speed users

Table 3.2: Design guideline suggestions for customisation depending on users cognitive abilities and traits [4].

Ziemkiewicz et al. [63] measured user preference for visual metaphors by asking users to rate how well a set of statements described similar hierarchical idioms. The authors tried to relate preference with personality, but were not successful. They did find that users with high openness to experience had less difficulty in navigating conflicting information from verbal and visual sources in hierarchical idioms. An unexpected difference in gender was also found as only women had significant faster response times in their self-reported preferred verbal metaphor.

Another study by Alvitta et al. focuses on how user's cognitive states can be manipulated by priming their LOC and how that affects their behaviour [51]. They suggest that while several studies in line with the topic of user-adaptive interfaces use speed and accuracy as measures for users behaviours, other cognitive characteristics such as the LOC are better behavioural predictors. Results show that priming does alter users behaviour, contribution to the pool of user characteristics that user adaptable interfaces studies can stem from.

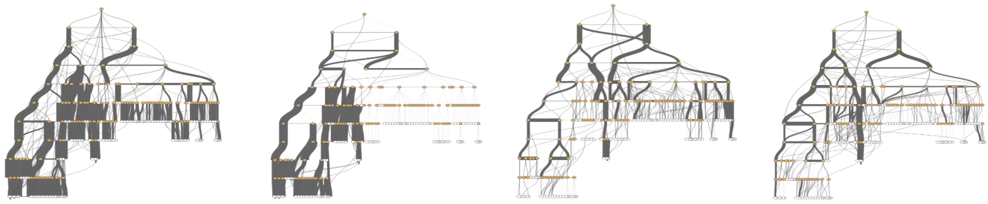
Ottley et al. [2] presented another study that focused on user search strategies and the LOC. This study defends that while most studies explore the effects of the LOC in terms of user's speed and accuracy for obtaining information, it is also important to take into account user's search strategies. Results show that users searching strategy is influenced by the visualization design. Users were given a task to complete using one of the two visualisations available (Figure 3.2). When using dendrograms users tend to use a mix of depth-first and breadth-first strategies while they use more of a top-down strategy when interacting with the indented tree. Using an indented tree invites users to have a more top-down approach to their searches, although it is noticeable that users with an External LOC dove more intro the Top-Down approach (Figure 3.3(a)), while users with an Internal LOC did more horizontal exploration (Figure 3.3(b)). When it cam to the dendrograms, External users used the visualisation less effectively since the diagram was more encouraging of the depth-first breadth-first combination used by Internals (Figures 3.3(c) and 3.3(d)). This study offers the suggestion that designers should take into consideration users mental models in order to offer the best visualisation for each individual. In this case, visualisations for Internal LOC should allow users to do exploratory searches instead of being too structured. Externals on the other hand would likely prefer a more structured visualisation or one that provides more guidance. This study is relevant as it confirms that users are affected by the way information is presented in different visualisations but it relates the visualisations with the way users search for more information. In this case it shows that certain personalities prefer InfoVis that allows them to search for information vertically, while others prefer the horizontal route. It was observed that indented trees usually invite users to have a more top-down approach to their searches, although it was noticeable that users with an External LOC dove more into the Top-Down approach, while users with an Internal LOC did more horizontal exploration. When it came to the dendrograms External users used the visualization less effectively since the diagram was more encouraging of the depth-first breadth-first combination preferred by Internals. This study offers the suggestion that designers should take into consideration users mental models in order to offer the best visualization for each individual.



(a) Indented tree visualisation **(b)** Dendrogram visualisation

Figure 3.2: Visualisations used to investigate user search paths [2].

Another study by Ottley et al. [64] also found that it was possible to classify users personality according to their extraversion, LOC and neuroticism from recording users search patterns through visualisation states, low-level mouse events and interface button clicks. Through those same interactions it was also possible to predict user task completion time.



(a) External LOC using the indented tree **(b)** Internal LOC using the indented tree **(c)** External LOC using the dendrogram **(d)** Internal LOC using the dendrogram

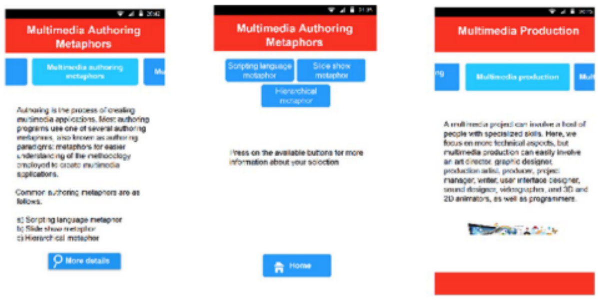
Figure 3.3: Different users search paths depending on their LOC scores and on the visualisation tested [2].

3.2 Conscientiousness Based Adaptation

The studies mentioned so far have showed us a lot of possible ways to explore individual differentiation in users and metrics to evaluate the success of that differentiation. Metrics for success include time users take to complete tasks, errors made in task completion, number of insights, user satisfaction and user preference. Individual differences have been evaluated in terms of personality, PS, verbal WM and visual WM. Within the domain of personality so far we have seen some results related to neuroticism, extraversion, openness, agreeableness, and LOC, however we have not yet discussed studies that focus more on the trait of conscientiousness. Conscientiousness expresses how diligently someone approaches responsibilities. While conscientious people are reliable, have good impulse control and care to make decisions with self-awareness, less conscientious individuals are not as perfectionist and tend to let go of rules more easily.

Al-Samarraie et al. [35] achieved some results when studying the impact of personality traits on users' information-seeking behaviour. They found it was possible to correlate user personality with performance through eye movements and that personality differences lead to different visual processing patterns. They also divided user tasks into three types: factual, interpretative and exploratory. Factual tasks are defined as tasks where the user seeks a specific piece of data, Interpretive tasks require users to actively create possible scenarios to interpret information, and exploratory involve making use of facets in the search process beyond what can be observed from query refinements and click data, to formulate queries or navigate complex information spaces. It was found that individuals with a high degree of conscientiousness were faster at scanning through information in factual tasks, followed by agreeableness and extraversion. High extraversion predicts faster completion times for exploratory tasks, followed by agreeableness and conscientiousness. In interpretive tasks participants with high conscientiousness and high extraversion exhibited similar information-seeking strategies. The relevance of these results can be important in future task-oriented studies relating to conscientiousness as they give insight into what type of tasks highly conscientious are more efficient at processing. When it comes to information-seeking behavior and eye-movement, people with high conscientiousness and extraversion process information with stable fixations in information-seeking tasks [23].

Another study by Sarsam et al. [3] explored how personality can be used to shape interfaces that better suit user preferences. They divided the participants into two groups. The first group contained people with high scores in neuroticism (thus referred to as the neuroticism group) while in the second one users had high scores in the extraversion and conscientiousness traits simultaneously and were referred to as the extra-conscientiousness group. They used the Association Rules Technique (ART) to predict the association between the mobile user interface design elements and the two personality groups, and designed two separate interfaces according to the results of the ART for each group (Figure 3.4). Every group interacted with each interface and answered the User Satisfaction Questionnaire [65] that measured their satisfaction. The results report that each group had a significantly higher score of satisfaction when interacting with the interface that was tailored to their personality when compared to their interaction with the other one. This supports the hypothesis that users react better to interfaces that are built considering their personality, in this case relating more to the traits of conscientiousness, neuroticism, and extraversion.



(a) Interface personalized for the extra-conscientiousness group

(b) Interface personalized for the neuroticism group

Figure 3.4: Two distinct interfaces customised based on user personality [3].

Nunes et al. [38] created a set of guidelines for GUI design based on users conscientiousness.

Results showed that conscientiousness has an effect on users interface preference, usability and overall appreciation of the interface.

Another study by Saati et al. [39] also gives insight into the preferences of conscientious people by exploring the relationship between colours and personality. After answering the IPIP-NEO inventory users were given a calculator and a CD player app and asked to perform five tasks with each one. Users were also told that could change the apps skin however they liked. In the end they had a preference questionnaire to assess which colour the liked the most. Results show that users low in extraversion preferred blue, users high in openness preferred black and conscientious users preferred yellow. These findings might be relevant when developing interfaces specifically for conscientious users where their preferences are to be taken into account.

Another study by Alves et al. [20] investigated how personality models InfoVis preferences in hierarchy, evolution and ranking idioms. Using clustering and correlation based analysis, it was found that conscientiousness showed more effects in the cluster-based analysis than in the correlation one. Results showed that conscientious users preferred line charts with points, possibly because of their natural attention to detail. They also found that both people with low and high conscientiousness preferred sunbursts to treemap visualisations, a preference shared by extraverts.

3.3 Discussion

The above-mentioned studies show us systematically that there is a link between personality and user behaviour towards a system [4, 21, 22]. There also seems to be evidence that the link between personality and behaviour is relevant to the research of user-adaptive interfaces [3, 4, 35]. Users seem to consistently respond more positively to systems that are tailored to their individual characteristics compared to others that were not.

In several studies, the methods used included giving users tasks to complete [2, 3, 56], and comparing their performance with different types of interfaces. Al-Samarraie et al. [35] also showed that conscientiousness has an impact on user behaviour depending on the task type they are given and that users with high conscientiousness are faster at scanning through factual tasks rathen than interpretive or exploratory. These findings are also reflected in Figure 3.3 where we can observe that users search patterns vary, making each personality type prefer one type of task over the others [2]. We can extrapolate those methods and results in the exploration of the role of conscientiousness in InfoVis by having a set of tasks for users to perform in several visualisations and compare their preferences.

Table 3.2 shows a set of design guidelines for interface customisation based on user personality and cognitive abilities. Examples of personalization used include prompts to use hide/display buttons for users with an internal LOC. In order to create several InfoVis to compare user preference in our experiment, we would also have to create a set of guidelines similar to that, but for the trait of conscientiousness specifically. Samer et al. [3] also did something similar even showing us the example of those guidelines applied to mobile interfaces as in (Figure 3.4).

Toker et al [56], Green et al. [1] and Ottley et al. [2] evaluated their systems using completion time as measures of task efficiency. Table 3.1 gives insight into how extraversion and neuroticism had an effect on task completion time. From that table we can also see that there were no reported differences in relation to those traits and the number of errors made by users, showing us there was a difference in task efficiency but not much in task efficacy.

Most of these studies also use an inventory from the FFM to asses user personality, which reinforces our notion that it is a good model use. Although it might be relevant to note that several variations of the model were used such as the IPIP-NEO, NEO PI-R, and the NEO-FFI. In the case of this research, we will use the NEO PI-R since it's the most extensive one, that includes all the facets of the FFM traits.

Overall, we can understand that creating systems tailored to user characteristics is an important endeavor that is being subject to several studies. However, there is still a long way to go in order to achieve good systems that truly bring value to users by differentiating them in the correct way. Studies seem to indicate that personality is a good characteristic to bases these systems on, but there is still little research that understands what components of personality are the most relevant and what system features can adapt to them. Not much research has been done on conscientiousness but studies such that of Al-Samarraie et al. [35] show us that it could be a relevant trait to pursue. Our research can be relevant to understand whether this trait has an impact on adaptive visualisations and what system features it can have an impact on. .

4

Creating Design Guidelines

Contents

Once we defined our objective of understanding whether conscientiousness had an effect on user preference for data visualisation design, we started by collecting user data on personality and design preferences.

4.1 Personality data

The first piece of data we collected was the NEO PI-R personality profile of every user. This inventory consists of 240 seven-point Likert scale questions ranging from *Strongly agree* to *Strongly disagree*. For our experiment, we used the Portuguese version of the NEO PI-R, developed by Lima de Simões [66].

Regarding conscientiousness, the trait can be broken-down into the following six facets:

- **Competence:** To perform a task effectively.
- **Order:** To need structure and neatness in one's environment.
- **Dutifulness:** To take rules seriously, be obedient and fulfill obligations.
- **Achievement-Striving:** To work hard towards reaching goals.
- **Self-Discipline:** To have the self-control to be rigorous and persistent.
- **Deliberation:** To act according to well thought out decisions.

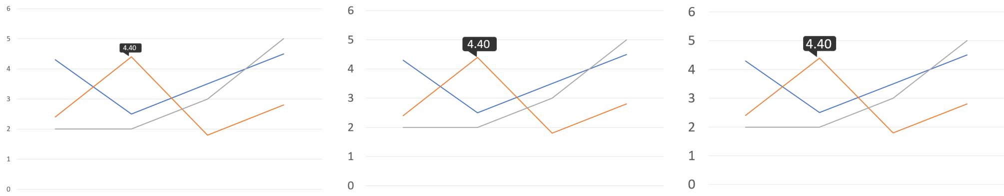
The conscientiousness score obtained by each user is the sum of the scores obtained for each facet.

4.2 Preferences data

After filling in the personality inventory, another questionnaire was prepared with a series of in seven-point Likert Scales in order to rate user preference relative to design features. Based on Sarcasm and Al-Samarraie's (2018) approach [3, 35, 36] we selected some design features that are relevant to the domain of InfoVis (font size, button style, information density, menu bar positioning and idioms):

- **Font style:** It refers to the font family used in the dashboard. The types tested were: Arial, Calibri, Calibri Light, Times New Roman and Lucinda Handwriting.
- **Font size:** It refers to the font size used in the dashboard, in the chats, and on the tooltips associated with the charts. We tested three fonts sizes: 12pt (small), 14pt (medium) and 16pt (large).
- **Info button Style:** How the help button is represented in the dashboard. We tested the button only with an icon, with an icon and text, and only with text.

Figure 4.1: Font Styles for Information Visualisation Preferences.

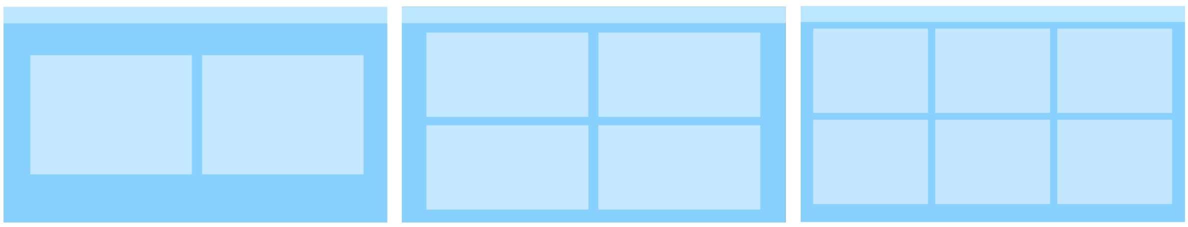


(a) Small font **(b)** Medium font **(c)** Large font

Figure 4.2: Font sizes options for graph and tooltip for Information Visualisation Preferences.

(a) Icon and text **(b)** Icon only **(c)** Text only

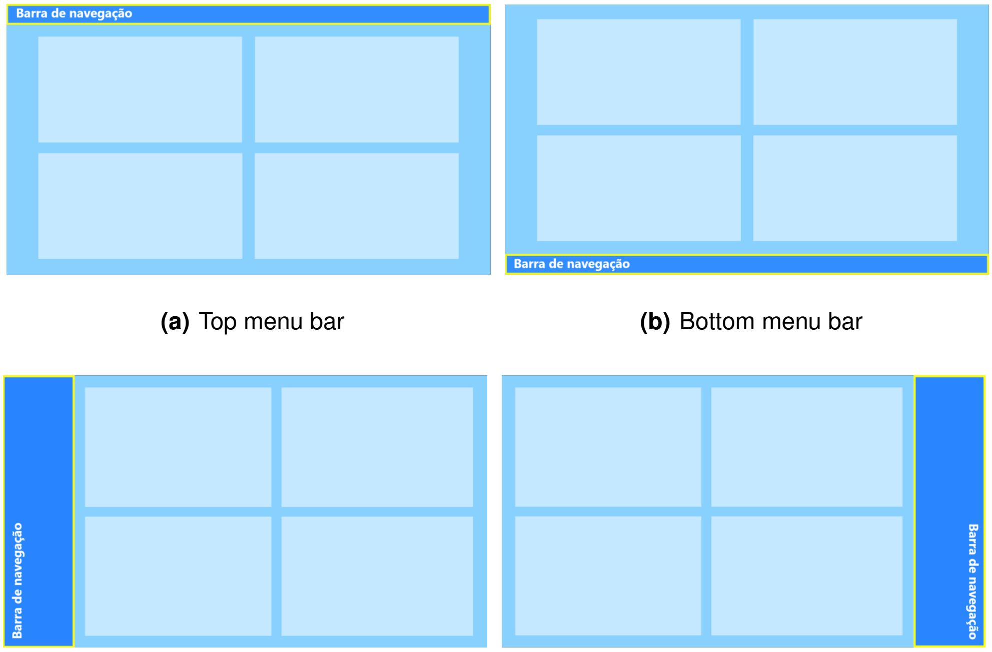
Figure 4.3: Button design options for Information Visualisation Preferences.



(a) Low Information Density **(b)** Medium Information Density **(c)** High Information Density

Figure 4.4: Information Density options for Information Visualisation Preferences.

- **Information Density:** How much information should be represented in the dashboard at the same time. For this we simulated a dashboard divided in two sections, four sections and six sections as represented in Figure 4.4(a).



(a) Top menu bar

(b) Bottom menu bar

(c) Left menu bar

(d) Right menu bar

Figure 4.5: Menu bar positioning options for Information Visualisation Preferences.

- **Menu Bar positioning:** This refers to where the menu bar is positioned: at the top of the screen, at the bottom, on the left or on the right.

Idioms are also an important feature for us to evaluate since they are specific to the domain of InfoVis. From our related work, we know that users react differently to the idioms used to represent information. For that reason we want to test a range of different ones according to user preference. We chose 12 idioms considering how they could fit together in a dashboard and how common they are.

Based on the current state of the art research, we chose three idiom categories that are very present in this area of research as they allows us to study users' preconceived structures of information [18, 19]. The three categories were: hierarchy, evolution and ranking. We created a scenario for each category, an used idioms to represent its information. The data was kept the same across idioms of the same scenario so the users could reflect on the implications of having different idioms represent the same information. We also focused on minimising the number of marks and channels across contexts and keeping the charts consistent.

Regrading hierarchy, those idioms represent information with the idea of containment. The scenario chosen for this category was the a household's food consumption in a month. The idioms displaying this information were a treemap, a circular packing diagram, a sunburst and a sankey diagram. For the context of evolution the scenario was the number of registered participants for a marathon held annually

Table 4.1: Median and standard deviation for conscientiousness and it's facets, for each cluster.

Traits	Cluster 1		Cluster 2		Cluster 3	
	Mdn	*SD*	*Mdn*	*SD*	*Mdn*	*SD*
Conscientiousness	148.0	18.74	128.0	21.13	101.5	19.20
Competence	24.0	3.37	22.0	3.90	18.5	3.09
Order	22.0	4.98	20.0	5.04	14.5	5.80
Dutifulness	28.0	3.09	25.0	3.92	22.5	2.82
Achievement-Striving	26.0	4.17	20.0	5.47	16.5	5.54
Self-Discipline	22.0	5.62	19.0	4.97	14.0	4.64
Deliberation	23.0	3.86	22.0	4.99	15.0	5.48

in the United States. The idioms used were: a line chart with points, a line chart without points, and an area chart. In the context of ranking the scenario was the index of happiness across several countries in Europe (France, Italy, Portugal, Spain, Germany, and the United Kingdom). The idioms were: a radar chart, a word cloud, a vertical bar chart, a horizontal bar chart and a pie chart.

4.3 Procedure

The first step was for the candidates to fill in the NEO PI-R questionnaire. Afterwards they were asked to evaluate several design features, using seven-point Likert scales. Both forms were sent to the participants to be filled online. In the end users received a compensation for their participation.

The recruitment of users was done through convenience sampling. For this experiment our sample was composed of 34 females and 30 males, a total 64 users aged between 18 and 60 $(M = 24.27, SD = 7.09)$. Participants were tested for eye correction such as glasses or contact lenses and the apparatus used to take the survey. Using one-way Analysis of Variance (ANOVA)s we found that neither of those factors affected their answers.

4.4 Personality-Based Clustering

In order to find the personality clusters we started by selecting all the data relative to the personality of the users, including all the traits and facets. Using hierarchical clustering and the Elbow method [36, 64], we identified three main personality clusters. By applying the K-Means Clustering algorithm we grouped the data into the three clusters and filtered the data for the trait of conscientiousness and its facets. Table 4.1 describes our results with the median and standard deviation for each cluster.

The clusters show a clear division in the levels of the conscientiousness trait and its facets. In Cluster 1 $(M = 148.0, SD = 18.74)$ the levels of conscientiousness are the highest while Cluster 3 $(M = 101.5, SD = 19.20)$ shows the lowest values. Cluster 2 $(M = 128.0, SD = 21.13)$ shows values in-between Clusters 1 and 3. All of the six facets of conscientiousness followed this trend, by having

Table 4.2: Association Rules for each Cluster.

Rules for Cluster 1	**Frequency**	**Support**	**Confidence**	**Lift**
highDensity → calibriLight	8	0.120	1.00	4.67
highDensity → iconText	3	0.115	1.00	5.57
calibriLight → iconText	2	0.115	1.00	6.19
highDensity → sankeyDiagram	2	0.115	1.00	4.77
mediumFont → highDensity	2	0.115	1.00	4.46
barDown → mediumFont	1	0.115	1.00	8.67
calibriLight → sankeyDiagram	1	0.115	1.00	3.71
highDensity → barDown	1	0.115	1.00	4.33
highDensity → mediumFont	1	0.115	1.00	4.33
iconText → barDown	1	0.115	1.00	3.71
linechartPoints → highDensity	1	0.115	1.00	3.71
sankeyDiagram → mediumFont	1	0.115	1.00	5.20
Rules for Cluster 2	**Frequency**	**Support**	**Confidence**	**Lift**
mediumDensity → largeFont	66	0.200	1.00	5.00
timesNewRoman → mediumDensity	52	0.200	1.00	5.00
linechart → mediumDensity	38	0.200	1.00	5.00
barChartHorizontal → linechart	37	0.200	1.00	5.00
linechart → largeFont	23	0.200	1.00	5.00
barChartHorizontal → mediumDensity	21	0.200	1.00	5.00
linechart → barChartHorizontal	9	0.200	1.00	5.00
timesNewRoman → barLeft	7	0.200	1.00	5.00
linechart → iconOnly	4	0.200	1.00	5.00
mediumDensity → iconOnly	4	0.200	1.00	5.00
timesNewRoman → iconOnly	4	0.200	1.00	5.00
highDensity → barLeft	3	0.200	1.00	5.00
linechart → treemap	3	0.200	1.00	5.00
Rules for Cluster 3	**Frequency**	**Support**	**Confidence**	**Lift**
barChartHorizontal → linechart	90	0.114	1.00	6.21
timesNewRoman → sankeyDiagram	25	0.107	1.00	5.77
linechart → barChartHorizontal	18	0.113	1.00	5.98
barChartHorizontal → mediumDensity	12	0.107	1.00	5.60
linechart → mediumDensity	10	0.107	1.00	6.16
barChartHorizontal → timesNewRoman	8	0.107	1.00	5.95
linechart → iconOnly	1	0.107	1.00	5.60

the highest values in Cluster 1 and the lowest in Cluster 3. We also conducted an ANOVA to verify the independence of each cluster in relation to conscientiousness and to each facet. We found the p-value to be below 0.05 for each instance, which confirms their independence. Cluster 1 includes users that are predictably the most competent, goal and detail oriented, and organized. Cluster 3 includes users that are are more impulsive, abide less by the rules, and are less perfectionist. After creating and analysing each personality cluster, we had to extract design guidelines from each cluster, using user preference data and the Apriori algorithm.

Table 4.3: Features and design styles for each cluster. Bold styles were derived from the association rules.

Feature	Cluster 1	Cluster 2	Cluster 3
Font Family	**Calibri Light**	**Times New Roman**	**Times New Roman**
Font Size	**Medium**	**Large**	Large
Info Density	**High**	**Medium**	**Medium**
Menu Bar	**Down**	**Left**	Top
Buttons	**IconText**	**IconOnly**	**IconOnly**
Hierarchy	**Sankey**	**Treemap**	**Sankey**
Evolution	**Line Chart- Points**	**Line Chart**	**LineChart**
Ranking	Bar Chart-Vertical	**Bar Chart-Horizontal**	**Bar Chart-Horizontal**

4.5 Extracting Association Rules

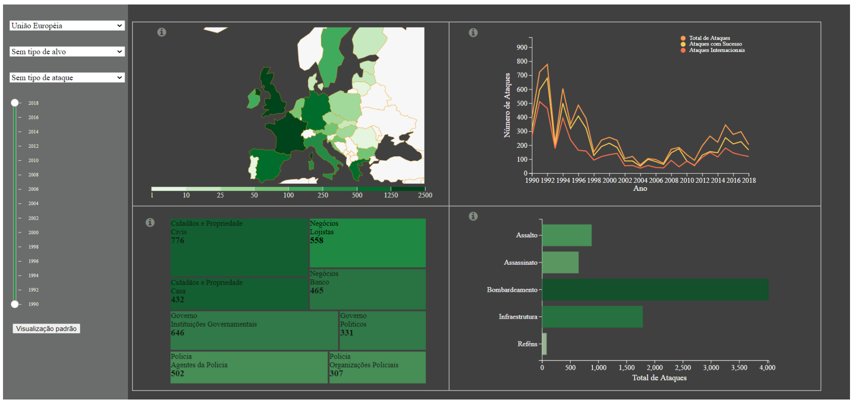
In order to create the design guidelines we investigated what user preferences were associated with each other in each cluster. We started by creating a list with the preferred designed features of each user. In case of ties, we selected all the options with the highest score. After that, we ran the Apriori algorithm for every cluster. Each run was performed with a minimal bound of 0.1 for support, 1 for confidence, and 3 for lift. The inputs were chosen in order for us to obtain a good balance between generating reasonable number of rules that would cover most of our design styles and a strong confidence value. The algorithm yielded a total of 24 rules for Cluster 1, 46 for Cluster 2, and 13 for Cluster 3. From the rules generated from the Apriori output we used the ART to extract the ones that were valid for the creation of the design guidelines. The ART gives an output in the form *Style A* $\rightarrow$ *Style B*. This means *Style B* is usually contained in a set of preferences that also contains *Style A*.

4.6 Guidelines Creation

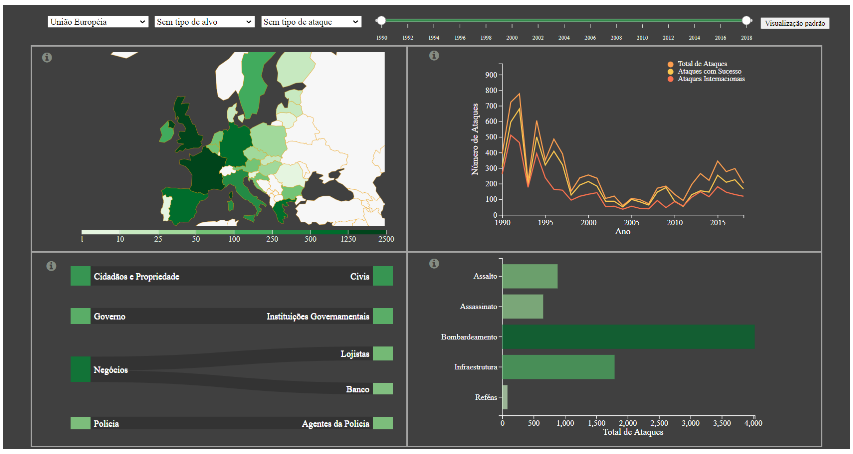
After generating all the rules using the Apriori algorithm, we grouped the rules by frequency and chose the ones that were the most prevalent. First we selected the rules that appeared the most times and that had overlapping output attributes, without incompatibilities between them. After that process there were still some attributes that didn't have a rule associated with them. In these cases we selected the attributes that appeared with the most frequency in that cluster. Table 4.2 show the selected rules for each cluster, while Table 4.3 shows the final design features selected for each cluster. Notably, there is no row with the same feature style across the three clusters. Nonetheless, we can see that the features for Clusters 2 and 3 are quite similar between them, differing only on the menu bar positioning and on the hierarchical idiom. Regarding the features that we were not able to derive from the association rules, these included the ranking chart "Bar Chart-Vertical" in Cluster 1, and the font size "large" and menu bar "top", for Cluster 3. Cluster 2 was fully derived from the association rules.

With the features and the styles obtained for each cluster, it is possible for us to create the design guidelines for each one. The final guidelines obtained were:

(a) High conscientiousness cluster visualisation



(b) Medium conscientiousness cluster visualisation



(c) Low conscientiousness cluster visualisation

Figure 4.6: Visualisations created from the design guidelines extracted from the Apriori and Association Rules.

- People high on conscientiousness prefer visualisations with medium Calibri Light font, high information density, menu bar at the bottom of the screen and buttons with icons and text. Their preferred idiom to represent hierarchical information is a Sankey diagram, for evolution is a line chart with points and for ranking it is a vertical bar chart.

- People with medium conscientiousness prefer visualisations with large Times New Roman font, medium information density, menu bar at the left of the screen and buttons with icons. Their preferred idiom to represent hierarchical information is a Treemap, for evolution is a line chart without points and for ranking it is a horizontal bar chart.
- People with high conscientiousness prefer visualisations with large Times New Roman font, medium information density, menu bar at the top of the screen and buttons with icons. Their preferred idiom to represent hierarchical information is a Sankey diagram, for evolution is a line chart without points and for ranking it is a horizontal bar chart.

5

Evaluation

Contents

5.1 Validation

With the intent of investigating the relationship between conscientiousness and user interaction with information visualisation systems, we formulated the following research question:

- **RQ1**: Is conscientiousness relevant for personality-based adaptive information visualization systems?

We also formed one hypothesis for the outcome of each metric:

In **H1**, task efficiency refers to the amount of time users take to perform each task. This hypothesis anticipates that users will complete tasks at different speeds depending on their conscientiousness, while **H1a** predicts that users will complete tasks in tasks in less time when they interact with the InfoVis designed according to their preferences [1, 22, 64].

- **H1**: Conscientiousness has an effect on user task efficiency.
- **H1a**: Users are more efficient when interaction with visualisations adapted to their conscientiousness.

H2 refers to the amount of wrong answers the users give to the tasks they have to complete. This hypothesis states that users will make a different amount of mistakes depending on their conscientiousness, while **H2a** predicts that users will make less mistakes when interacting with the visualisations designed according to their preferences [1, 63, 67].

- **H2**: Conscientiousness has an effect on the errors while completing tasks.
- **H2a**: Users make less errors when interaction with visualisations adapted to their conscientiousness.

H3 to H5 are similar and refer to the evaluation of perceived usefulness, perceived ease-of-use and preference users attribute to each visualisation [3, 3, 4, 35]. These hypotheses predict that users will evaluate those metrics differently depending on whether the visualisation is customised to their level of conscientiousness. **H3a- H5a** are extensions of the previous hypothesis with more specific outcome expectations.

- **H3**: Conscientiousness has an effect on perceived usefulness.
- **H3a**: Perceived usefulness is higher in information visualization systems designed for the user's conscientiousness level.
- **H4**: Conscientiousness has an effect on perceived ease-of-use.

Table 5.1: Metric classification and description.

Metric	Type	Description
Time	Ratio	Number of seconds users take to complete a task
Errors	Ratio	Number of mistakes users make while completing a task
Perceived Usefulness	Ordered	How practical the system is considering its purpose
Perceived Ease-of-Use	Ordered	How intuitive the system is considering its purpose
Preference	Ordered	How much affinity a user has for the system

- **H4a**: Perceived ease-of-use is higher in information visualization systems designed for the user's conscientiousness level.
- **H5**: Conscientiousness has an effect on user preference.
- **H5a**: User preference is higher in information visualization systems designed for the user's conscientiousness level.

5.2 Research Design

The metrics described in Section 5.1 can be better described by Table 5.1. Time was measured after the test, by reviewing the test screen recordings and measuring, in seconds, the time taken for the user to perform each task. The number of error was measured in real time, and corresponds to the number of wrong answers to task questions a user gave during the test. Perceived usefulness, perceived ease-of-use, and preference are ordered measures that users answered in the Google Forms using Likert Scales. The score obtained for usefulness is the sum of the scores obtained in the Likert scales for the four TAM3 items corresponding to this cognitive ability, that can be seen in Table 5.2. The score for perceived ease-of-use was calculated in a similar way, but using the TAM3 items corresponding to ease-of-use. The preference score was the raw score the user gave on the Likert scale. After obtaining all the results they were processed using two-way ANOVAS to find interaction and main effects between them and the personality clusters.

5.3 Participants

Recruitment was done through convenience sampling. For this experiment our sample was composed of 20 females and 25 males, a total 45 users aged between 19 and 60 ($M = 24.9; SD = 8.1$). Participants were tested for eye correction such as glasses or contact lenses when taking the survey. Using Mann-Whitney U test we found that using contact lenses had an effect on the perceived ease-of-use scores reported by users during the experiment. This information will be taken into account when analysing the results, limitations and future work. Familiarity with certain idioms was also found to have an effect in the

Table 5.2: TAM3 items for perceived usefulness and perceived ease-of-use.

Items	Perceived Usefulness
1	Using the system improves my performance of the tasks.
2	Using the system increases my task productivity.
3	Using the system increases my task efficiency.
4	In general, I find the system to be useful.
	Perceived Ease-of-Use
1	My interaction with the system is clear and easy to understand.
2	Using the system does not require much mental effort.
3	I think using the system is easy.
4	I find it easy for the system to do what I want.

results, and will also be taken into consideration. The participants that took part in the validation phase were all required to take the NEO PI-R questionnaire before proceeding with the rest of the tests, so that we could later associate their results with the cluster they belonged to.

5.4 Apparatus

At the beginning of the experiment we had to use the NEO Pi-R inventory to measure the personality of the users, which we formatted as a Google Forms questionnaire. The guideline validation phase required the researcher and the user to each have a computer in order to perform the session remotely. The researcher also provided the user with the three visualisations of Figure 4.6 and a Google Forms questionnaire where the user was asked for their preference, and evaluated each visualisation using the ease-of-use and usefulness items of the Technology Acceptance Model 3 Scale (TAM3) questionnaire [68]. All the questions were evaluated using a 7-point Likert scale. The TAM3 items are listed in Table 5.2.

5.5 Procedure

The procedure starts by informing the participants of the scope of the project, and clarifying that they can chose to quit at any time. After that the participants asked asked to give their consent for their participation on the project.

The user testing sessions were done via Zoom[1], where the researcher screen-shared a browser with the three visualisations (Figure 4.6) and gave remote control to the user. The experiment then proceeded with the researcher asking the user to open one of the visualisations (their order of testing was randomised beforehand), and asking the user the prepared questions.

Table 5.3 shows the tasks users were asked to perform. For each visualisation users were asked

[1] https://www.zoom.us/

Table 5.3: Tasks users had to perform using the visualisation.

	Factual Tasks
1	What are the three main targets for terrorist attacks in Germany?
2	What are the main targets for terrorist attacks in Ireland?
3	What are the main targets for terrorist attacks in the Netherlands?
4	What is the number of assassinations that happened in Greece between 1990 and 2018?
5	What is the most common terrorist attack type that happened in France between 2004 and 1990?
6	What is the number of terrorist attacks against Infrastructures that happened in Sweden from 2004 to 1990?
	Interpretive Tasks
1	You are planning your next trip to Europe and you want to know how has been the evolution of terrorism cases in Italy. Do you consider that terrorism has been increasing or decreasing? In what year has there been more attacks and what was the number of attacks in that year?
2	You are about to go on a business trip to the United Kingdom. Considering the evolution of terrorist attacks in this country, do you believe it to be safe? In what year has there been more attacks and what was the number of attacks in that year?
3	You are writing an article on the evolution of terrorism in Spain. Considering the evolution of the attacks, do you consider then to be increasing or decreasing? In what year was registered the most number of attacks and what was the number of attacks in that year?

to answer three tasks given by the researcher. The leading question was one of the first three factual tasks, the second question was also a factual task chosen from the remaining ones. The third was an interpretive task. The first set of tasks required interaction with the hierarchical chart, the second set required interaction with the raking charts and the third set with the evolution charts. This sectioning prompted users to use a chart from each of the contexts. The tasks were randomised within each set before the start of the experiment to avoid bias. During the process the screen-sharing was recorded in order to later measure the time the user took to answer each question. The researcher also counted each time the user answered a question with a wrong answer.

After performing three tasks in a visualisation, the user was asked to evaluate it in the questionnaire where he was asked for his preference in relation to each visualisation and to evaluate it using the TAM3 questionnaire. This was repeated for each visualisation, and the user was allowed to change the previous answers as the experiment proceeded in case he changed his mind. We gave users this possibility since they only interacted with one visualisation at a time, and had to evaluate their preference for the first ones without knowing how they compared to the rest. Therefore, users were able to rate each interface based on the overall experience, taking the necessary time to assure that their choices reflected a well-reasoned comparison between the different information visualisations.

5.6 Results

Following the user tests, we performed statistical data analysis in order to arrive at the results. Normality testing through Shapiro-Wilk showed evidence against normality $(p < 0.05)$, hence we turned non-parametric methods to further analyse our data. Since the data groups are independent we used two-way ANOVAS in our analysis. With the data collected on personality, preferences, time, errors, usefulness and ease-of-use, we performed several Two-Way Mixed ANOVA tests to accept or refute the hypothesis posed in Section 5.1.

- **H1: Conscientiousness has an effect on user task efficiency.**
- **H1a: Users are more efficient when interaction with visualisations adapted to their conscientiousness.**

For the first hypothesis **H1a** – Users are more efficient when interaction with visualisations adapted to their conscientiousness –, we conducted a Two-Way Mixed ANOVA to analyse interaction effects between the conscientiousness level and the three information visualization systems. Mauchly's test of sphericity indicated that the assumption of sphericity was met for the two-way interaction, $\chi^2(2) = .904, p = .125$. The interaction effect between the conscientiousness level and the InfoVis system on task efficiency was not significant, $F(4, 84) = 2.269, p = .068$, partial $\eta^2 = 0.098$. However, the p-value was close enough to 0.05 for us to consider that that result could have been due to limitations in the experiment. There was no main effect of the InfoVis system, $F(2, 84) = .372, p = 0.691$, partial $\eta^2 = 0.009$, and none on the conscientiousness level, $F(2, 42) = 1.221, p = .305$, partial $\eta^2 = 0.055$ for task efficiency. In this light, we have inconclusive results for **H1** and refute **H1a**. Indeed, taking a closer look into the differences of distribution (Figure 5.1) and estimated marginal means (EMM) (Figure 5.2), we can observe that C1 has the lowest overall scores in task efficiency. In V1, C1 ($M = 92.4; SD = 26.6; SE = 7.36$) has a significantly lower mean than both C2 ($M = 159; SD = 141; SE = 32.3$), and C3 ($M = 148; SD = 105; SE = 29.0$). In V2, C1 also has the lowest mean score, followed by C3 ($M = 152; SD = 68.7; SE = 19.1$) and then C2 ($M = 139; SD = 100; SE = 22.9$). In the third visualisation C3 ($M = 107; SD = 88.6; SE = 24.6$) has the lowest mean time, closely followed by C1 ($M = 109; SD = 42.8; SE = 11.4$) and then C2 ($M = 166; SD = 121; SE = 27.8$). We can also tell that for each cluster, the estimated marginal means (EMM) is the lowest for the visualisation with the conscientiousness level it was designed for, which would support **H1** and **H1a**.

- **H2: Conscientiousness has an effect on the errors while completing tasks.**
- **H2a: Users make less errors when interaction with visualisations adapted to their conscientiousness.**

Regarding **H2a** – Users make less errors when interaction with visualisations adapted to their conscientiousness. –, the Mauchly's test of sphericity, from the Two-Way Mixed ANOVA test, indicated that the assumption of sphericity was met for the two-way interaction, $\chi^2(2) = .923, p = .195$. There was no statistically significant interaction between the conscientiousness level and the InfoVis system on task errors, $F(4, 84) = .470, p = .758$, partial $\eta^2 = 0.022$. In addition, there were no main effects

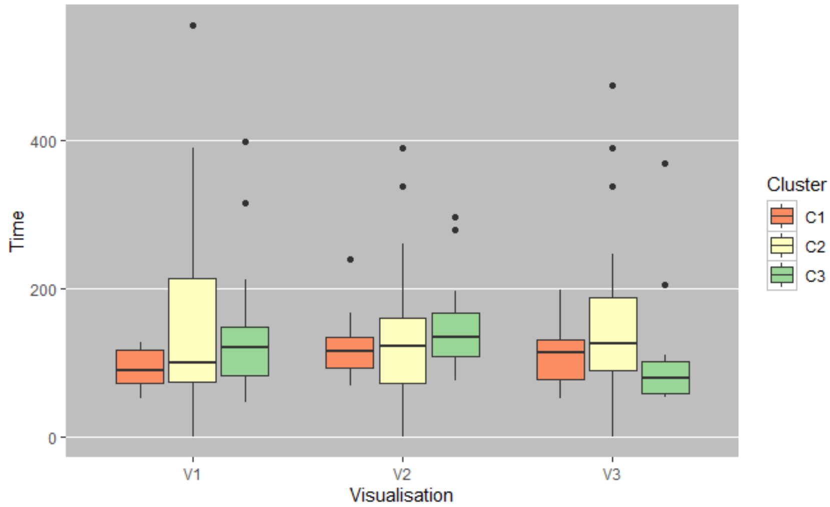


Figure 5.1: Boxplots for the time user took to complete each task.

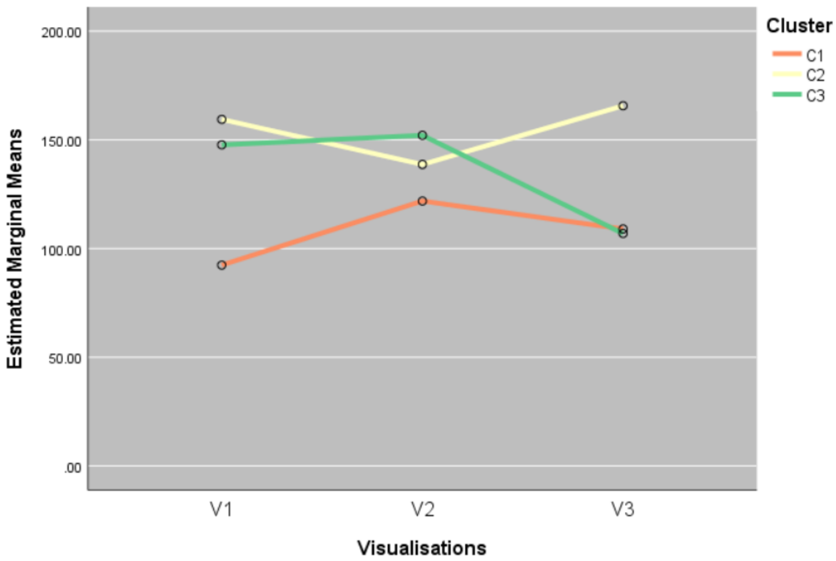


Figure 5.2: Estimated marginal means graph for Time.

of the InfoVis systems, $F(2, 84) = 0.069, p = .933$, partial $\eta^2 = 0.002$, and none of the conscientiousness level, $F(2, 42) = 0.360, p = .700$, partial $\eta^2 = 0.017$ in mean task errors. Therefore, we have to refute both **H2** and **H2a**. Looking at (Figure 5.3) and (Figure 5.4), we can observe that the distribution of mistakes was similar across the visualisations and clusters, with the maximum and minimum values varying mostly between 0 and 3. In the first visualisation, the cluster with the lowest mean of error was C1 $(M = 0.462; SD = 0.877; SE = 0.243)$, followed by C2 $(M = 0.526; SD = 0.772; SE = 0.177)$, and then C3 $(M = 0.615; SD = 0.768; SE = 0.213)$, which would agree with the expectation of the hypothesis. However, in the other visualisations that assumption is broken since the cluster with

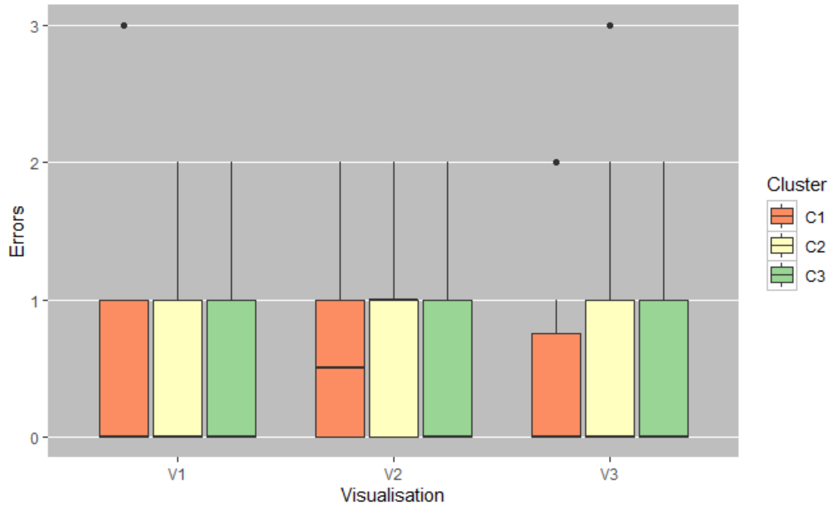


Figure 5.3: Boxplot for the errors.

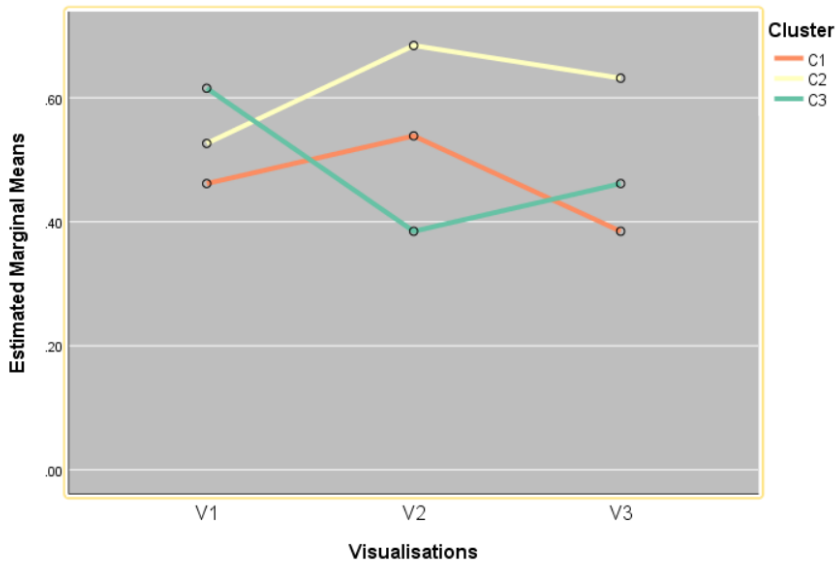


Figure 5.4: Estimated marginal means graph for Errors.

the least mean mistakes for V2 was C3 $(M = 0.385; SD = 0.650; SE = 0.180)$, proceeded by C1 $(M = 0.583; SD = 0.669; SE = 0.193)$ and C2 $(M = 0.684; SD = 0.749; SE = 0.172)$, and for V3 it was C1 $(M = 0.357; SD = 0.633; SE = 0.169)$, and then C3 $(M = 0.462; SD = 0.660; SE = 0.183)$ and C2 $(M = 0.632; SD = 0.831; SE = 0.191)$. Interestingly enough, we can tell that C1 and C3 had opposite behaviours in V2, since it was in that visualisation that C1 made the most errors, and C3 the least.

- **H3: Conscientiousness has an effect on perceived usefulness.**

- **H3a: Perceived usefulness is higher in information visualization systems designed for the**

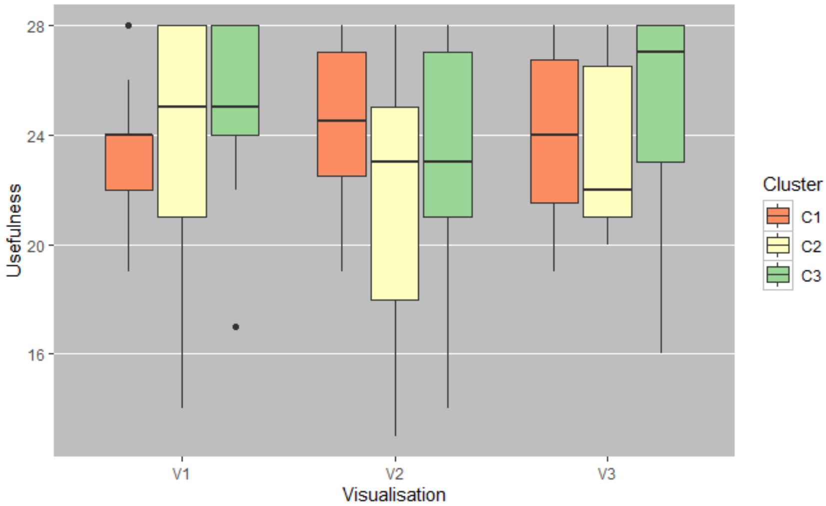


Figure 5.5: Boxplot for perceived usefulness scores.

user's conscientiousness level.

Regarding **H3a** – Perceived usefulness is higher in information visualization systems designed for the user's conscientiousness level –, the assumption of sphericity was met for the two-way interaction, $\chi^2(2) = .967, p = .503$. There was no statistically significant interaction between the conscientiousness level and the InfoVis system on perceived usefulness, $F(4, 84) = 1.023, p = .400$, partial $\eta^2 = 0.046$. Additionally, there were no main effects of the InfoVis systems, $F(2, 84) = 2.040, p = .136$, partial $\eta^2 = 0.046$, and of the conscientiousness level, $F(2, 42) = 9.28, p = .403$, partial $\eta^2 = 0.042$ in mean perceived usefulness. This means we can refute both **H3** and **H3a**. Taking a closer look into the differences of distribution (Figure 5.5) and estimated marginal means (Figure 5.6) in perceived usefulness, we can observe that users belonging to C1 attributed the lowest usefulness scores to V1, while users belonging to C2 and C3 attributed the lowest scores to V2. Users belonging to C1 attributed similar usefulness scores to V2 and V3. In V1, the highest mean belongs to C3 $(M = 24.8, SD = 3.16, SE = 0.876)$, followed by C2 $(M = 24.1, SD = 4.43, SE = 1.02)$ and then C1 $(M = 23.5, SD = 2.73, SE = 0.756)$. For V2, C1 $(M = 24.3, SD = 3.08, SE = 0.89)$ has the highest mean perceived usefulness score, seconded by C3 $(M = 23.5, SD = 4.35, SE = 1.21)$and then C2 $(M = 21.8, SD = 4.98, SE = 1.14)$. In the third visualisation The highest mean score belongs to C3 $(M = 25.3, SD = 3.77, SE = 1.05)$ and then C1 $(M = 24.1, SD = 3.11, SE = 0.83)$, and C2 $(M = 23.6, SD = 3.08, SE = 0.71)$. The distribution of values is similar between the three clusters for the third visualisation, but differs more in the other two, especially for the second cluster.

- **H4: Conscientiousness has an effect on perceived ease-of-use.**
- **H4a: Perceived ease-of-use is higher in information visualization systems designed for the**

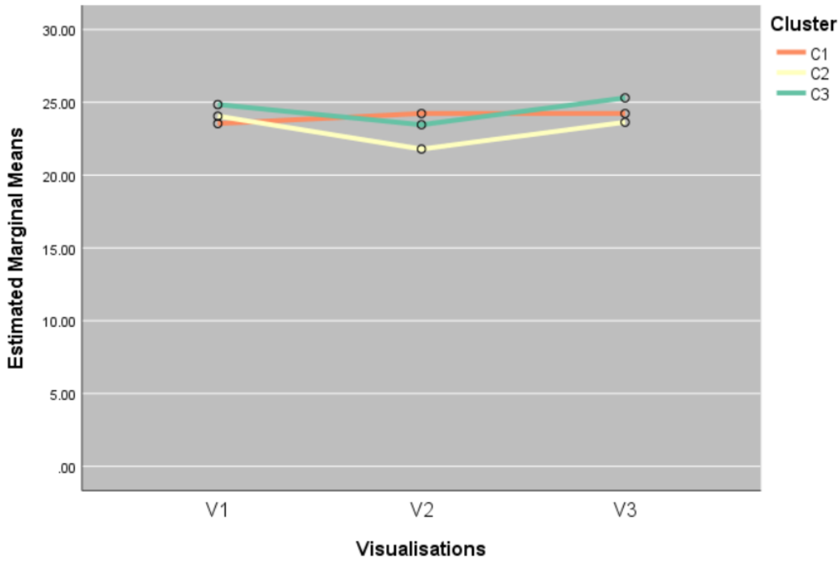


Figure 5.6: Estimated marginal means graph for Usefulness scores.

user's conscientiousness level.

For **H4a** – perceived ease-of-use is higher in information visualization systems designed for the user's conscientiousness level –, the assumption of sphericity was met for the two-way interaction, $\chi^2(2) = .976, p = .611$. There was no statistically significant interaction between the conscientiousness level and the InfoVis system on perceived ease-of-use, $F(4, 84) = .815, p = .519$, partial $\eta^2 = 0.037$. However, there was a main effect for the InfoVis systems, $F(2, 84) = 4.095, p = .020$, partial $\eta^2 = 0.089$. The main effect for the conscientious level was not significant, although close, $F(2, 42) = 2.629, p = .084$, partial $\eta^2 = 0.111$. Therefore we can refute **H4** and consider **H4a** inconclusive. Taking a closer look into the differences of distribution (Figure 5.7) and estimated marginal means (Figure 5.8) in perceived ease-of-use, we can observe that much like the results for **H3** and **H3a**, in the first visualisation C3 has the highest mean score $(M = 22.5; SD = 4.40; SE = 1.01)$, and C1 $M = 22; SD = 3.72; SE = 1.03$ the lowest, while C3 $M = 25.3; SD = 2.43; SE = 0.674$ fitting in the middle. In the second visualisation the highest score belongs to C3 $M = 23.8; SD = 3.59; SE = 0.995$, then C1 $M = 23.1; SD = 3.82; SE = 1.10$ and then C2 $M = 21.3; SD = 4.43; SE = 1.02$. In the third visualisation C3 had the highest score $M = 25.5; SD = 4.07; SE = 1.13$, followed by C1 $M = 23.8; SD = 3.29; SE = 0.878$ and then C2 $M = 23.3; SD = 3.76; SE = 0.862$. Both C2 and C3 chose V2 as the visualisation with lowest perceived ease-of-use, and the three clusters chose V3 as the visualisation with the highest value, which could justify the closely significant main effect.

- **H5: Conscientiousness has an effect on user preference.**
- **H5a: User preference is higher in information visualization systems designed for the user's**

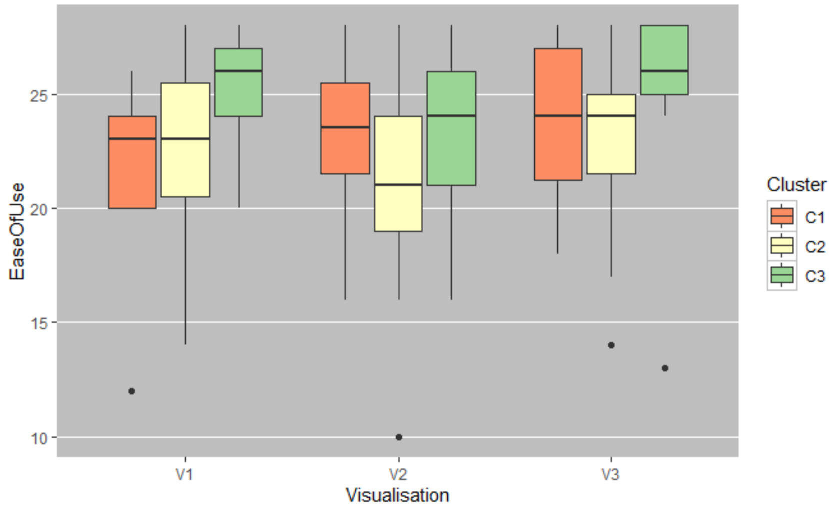


Figure 5.7: Histogram with Ease of Use scores.

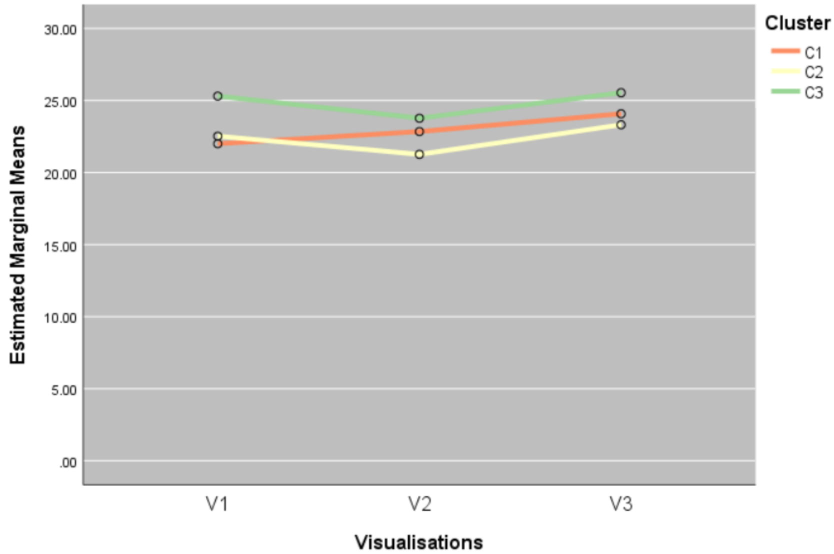


Figure 5.8: Estimated marginal means graph for Ease Of Use scores.

conscientiousness level.

In relation to **H5a** – User preference is higher in information visualization systems designed for the user's conscientiousness level –, the assumption of sphericity was met for the two-way interaction, $\chi^2(2) = .945, p = .313$. There was no statistically significant interaction between the conscientiousness level and the InfoVis system on preference, $F(4,84) = 1.630, p = .174$, partial $\eta^2 = 0.072$. Despite that, there was a main effect on the InfoVis systems, $F(2,84) = 5.834, p = .004$, partial $\eta^2 = 0.122$, but none on the conscientiousness level, $F(2,42) = 0.895, p = .416$, partial $\eta^2 = 0.041$ in mean preference. Therefore, we have to refute **H5** and deem **H5a** inconclusive. Indeed, taking a closer look into the differences of

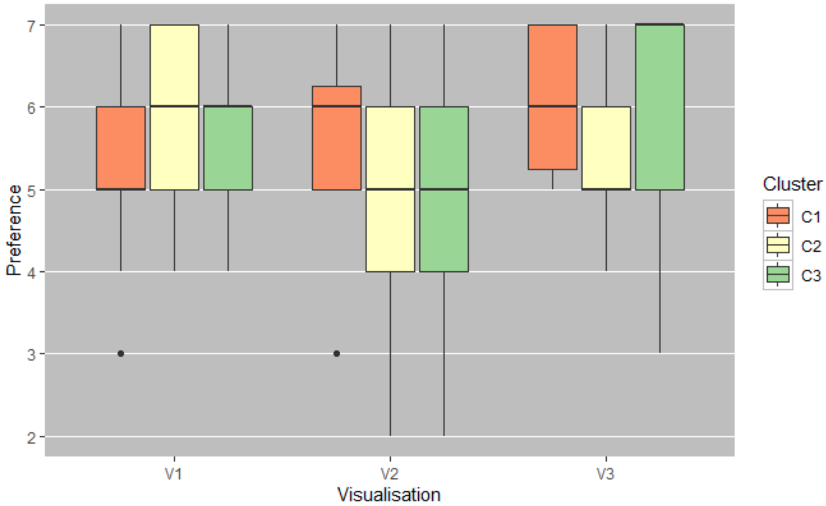


Figure 5.9: Boxplot for preference scores.

Table 5.4: Number of users for each cluster and visualisation preference.

	V1	V2	V3
C1	3	4	6
C2	8	3	8
C3	3	2	8

distribution (Figure 5.9) and estimated marginal means (Figure 5.10) in preference, we can observe that in the first visualisation the order of preference score by cluster was C2 $(5.89; SD = 1.05; SE = 0.241)$, C3 ($M = 5.69; SD = 0.855; SE = 0.237$), and C1 ($M = 5.31; SD = 1.11; SE = 0.308$). For V2 the order of preference was C1 ($M = 5.5; SD = 1.38; SE = 0.399$), C3 ($M = 4.85; SD = 1.52; SE = 0.421$), C2 ($M = 4.74; SD = 1.37; SE = 0.314$), and for V3 it was C1 ($M = 6.14; SD = 0.864; SE = 0.231$), C3 ($M = 5.92; SD = 1.50; SE = 0.415$), C2 ($M = 5.47; SD = 0.772; SE = 0.177$).

From the EMM chart, we can tell once again that the preference score for C2 and C3 lowers at V2, and shows peaks at V1 and V3. C1 shows the lowest preference for V1 and the highest at V3 as well. We can also analyse preference data by looking at Table 5.4. Pearson's chi-square test for the visualisation and clusters $(X(4) = 6.682; p = 0.154)$ tells us users from each clusters equally prefer the existing visualisations. Additionally, with $Phi = 0.385$ and $Cramer'sV = 0.272$, we can tell that the strength of association is not very strong. From that same table, we can observe that a lot of people from C3 chose V3 as their preferred visualisation , as did people from V1. Users from V2 chose equally V1 and V3.

Finally, we can go back and address our research question.

- **RQ1**: Is conscientiousness relevant for personality-based adaptive information visualization systems?

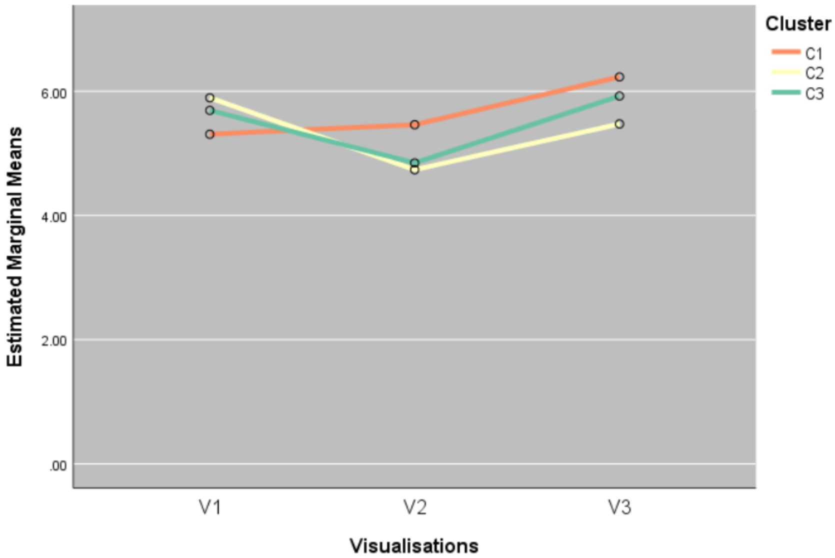


Figure 5.10: Estimated marginal means graph for Preference.

Considering our results, we believe that there is some influence of conscientiousness on users behaviour towards data visualisation systems. However, our results are not conclusive enough to pinpoint which InfoVis characteristics are directly associated with this personality trait. The significant main effects of ease-of-use, and preference, and the closely significant interaction effect obtained on time could be good hints on what elements to explore later. We did not however obtain significant results for errors and perceived usefulness.

5.7 Discussion

In general, there is no deep understanding of how much of users' interaction with visualisations is impacted by their level of conscientiousness. In this study, our results show some effects of task efficiency, perceived ease-of-use, and preference on users depending on visualisations adapted to their level of conscientiousness. We did not however obtain significant results for task efficacy and perceived usefulness.

Although the results for task efficiency were not strongly significant, we found that the interaction effect between the clusters, the InfoVis, and time was very close to significance. This result is reflected in the fact that, as shown in Figure 5.2, each cluster scored a lower average when interacting with the visualisation built for their level of conscientiousness. We can also tell that C1, the cluster with highest conscientiousness, was the cluster with the highest task efficiency, which is something that had been referenced in some of the related work [56]. This observation supports our belief that conscientiousness is an important factor in user differentiation for visualisation design.

There were no significant results for H2, but we can still point out some interesting considerations. Looking at Figure 5.4, it seem like for every cluster, V2 caused an unexpected peak (positive for C1 and C2, and negative for C3). During the test, some users commented on their like or dislike for the treemap representation, which is an element that makes V2 differ substantially from V1 and V3 that have sankey diagrams instead. It is possible that the treemap contributed to this difference in mistake numbers, making people from C1 and C2 make more task errors, even though people from C3 made less. This could indicate a possible relationship between conscientiousness level and interaction with specific idioms. In this case a new question could be posed of whether users with higher conscientiousness use treemaps more effectively, while users with lower conscientiousness would be more competent using sankey diagrams.

The same argument could apply to the trend observed in Figure 5.6 for C2 and C3. It is possible that users in these clusters were sensitive to the treemap visualisation, and thus rated V2 lower in usefulness. Figure 5.11 shows the difference in familiarity scores between the treemap and the sankey diagrams. It is possible to tell that users were in general less familiar with the treemap, which could have contributed to the results given for this visualisation. A different possibility is that C2 shows a different behaviour than C1 and C3, not because of the treemap representation, but because the effect of conscientiousness on user behaviour could be on the extremes of the trait, producing a different reaction for intermediate conscientiousness levels.

Another thing to point out is that during the user tests, several users commented on how the bubble chart was a confusing element in V1. This chart was added to that InfoVis in order to increase the information density of the interface, which followed the results obtained in the user preference questionnaire. However it seems like this ended up making users feel like the visualisation was not as useful, since that chart was not necessary to complete any of the tasks. C1 rated V2 and v3 with similar perceived usefulness scores, which would indicate that C1 users found it was equally useful to perform tasks in either of those visualisations. Given all of this, the was still a lack of significance in the results obtained for H3.

H4 did not get significant results for the interaction effect for ease-of-use, but it did show a significant main effect for the InfoVis system and an almost significant main effect for the level of conscientiousness. Much like the EMM chart for H3, C2 and C3 gave lower scores to V2. In both figures, C2 also gave overall lower scores for usefulness and ease-of-use across the three visualisations. C1 had the opposite behaviour we expected, having attributed the lowest ease-of-use score to V1, and the highest to V3. In fact, every cluster chose V3 as the visualisation with the highest ease-of-use. We can also speculate that the ease-of-use scores could have been influenced by users mental model of a visualisation. Even though our guidelines determined that each cluster preferred to have the menu bar in a different position (top, left and bottom), we gathered from the users tests that in this visualisation context the

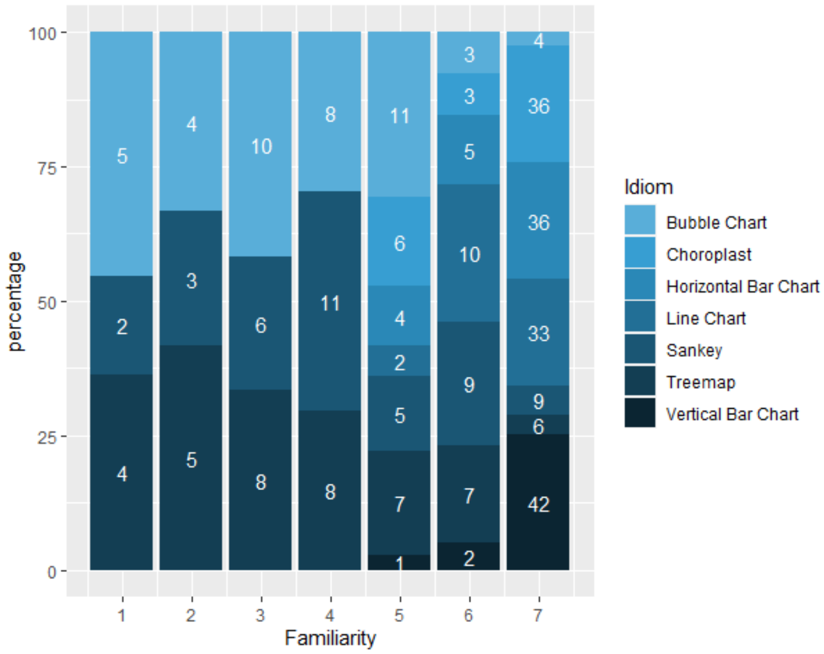


Figure 5.11: Stacked frequency bar chart for the familiarity scores.

top bar seemed more familiar, and the bottom bar the least. Since the menu bar is an important visual element in a visualisation, and is inherently linked to its functionality, we speculate that it could have had some impact on the usefulness, ease-of-use and preference scores. Returning to ease-of-use, V2 was attributed lower scored than V3 according to all the clusters, again possibly because of the treemap and menu bar. Although in Figure 5.6 C1 had the same mean values for V2 and V3, It differentiated them in Figure 5.8. It is possible that users with high conscientiousness perceived the treemap and sankey diagram of visualisations V2 and V3 as equally useful, while at the same time perceiving the treemap as harder to use. Out of those metrics, perceived ease-of-use was also the only one to show a significance dependence on eye correction. We believe this could have affected the ratings of C1, since V1 was made with a *medium* font size, and V2 and V3 were built with *Large* and that could account for the overall lower values of ease-of-use in that visualisation.

For H5 we found that there was a main effect for the InfoVis system, and it is visible in Figure 5.10 that for every cluster, V3 was the preferred choice. Once again we can observe that V2 did not have a favourable vote in general, and that much like with the case of usefulness and ease-of-use, C2 and C3 follow a similar trend in their votes while C1 stands out for behaving in a different manner. Although the preference scores refute our hypothesis, they are not particularly surprising considering our overall results. It makes sense that C1 would chose V3 as its preferred visualisation, as it was the visualisation where users from this cluster made the least task mistakes, and gave it the best score for ease-of-use. The results for C2 and C3 do not come as surprising either, since they follow the trend seen in the

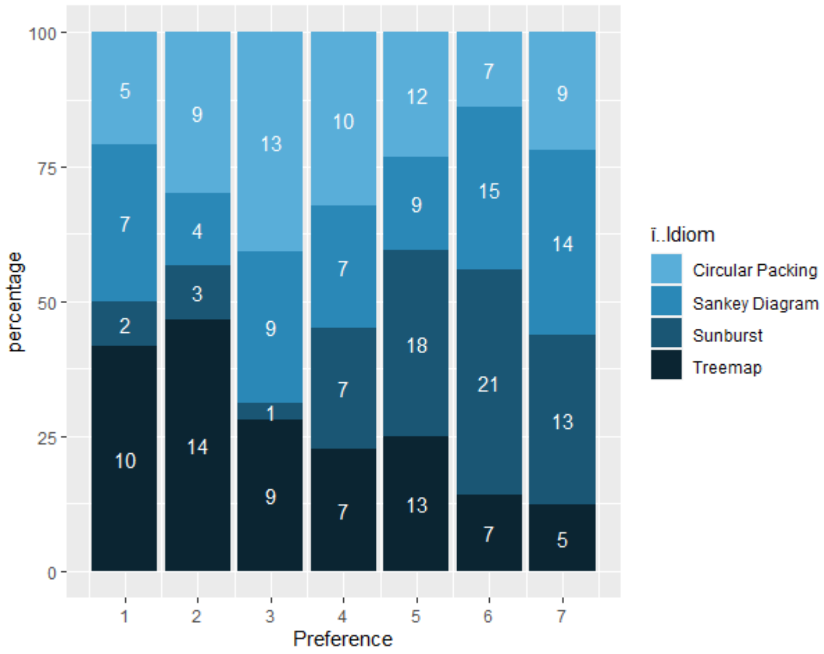


Figure 5.12: Stacked frequency bar chart for user preferences of hierarchical idioms.

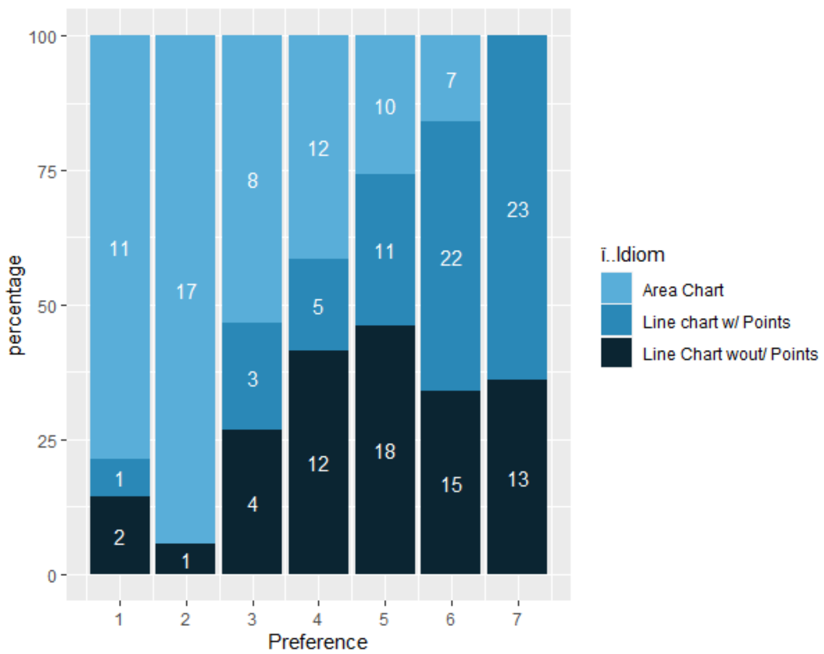


Figure 5.13: Stacked Frequency Bar Chart for user preferences on evolution idioms.

usefulness and ease-of-use charts. Indeed it seems like our user sample did not enjoy V2 in general and that C1, contrary to our expectations, did not enjoy V1.

Figures 5.12, 5.13, and 5.14, display the preference scores for users in the preferences question-

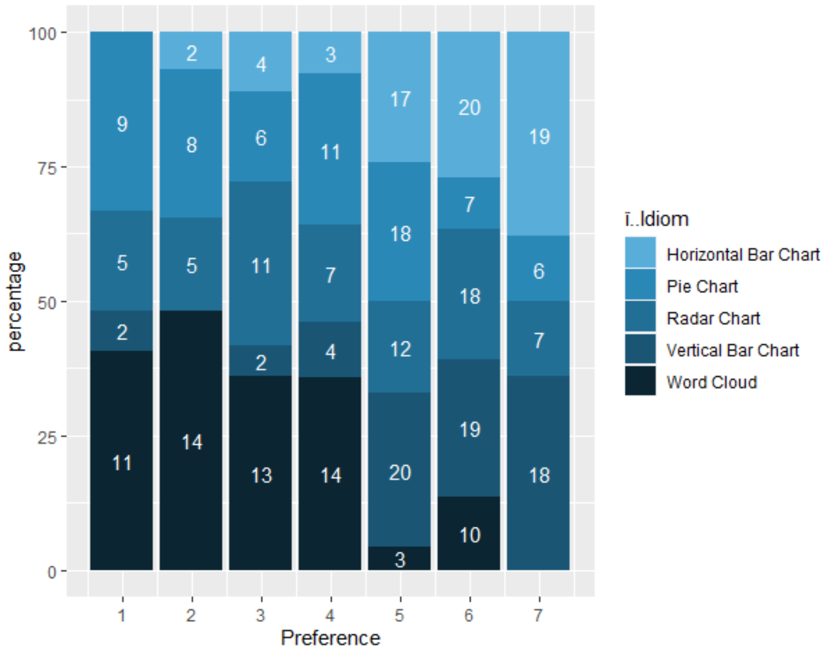


Figure 5.14: Stacked frequency bar chart for user preferences of ranking idioms.

naire, according to the different idiom categories. From Figure 5.12 we can tell that the treemap had a low preference, having mainly been attributed scores of 1 and 2. The sankey diagram scores better, having even been the idiom with the most 7 scores. From Figure 5.13, we can tell that line charts with points were mostly preferred for the evolution idioms, and that the line chart without points was more mid-range. Figure 5.14 shows us that the vertical and horizontal bar charts were the generally preferred options from all the idioms of of the preference questionnaire.

In light of this, our study showed support for the effect of conscientiousness on task efficiency, perceived ease-of-use and preference in information visualisations contexts while rejecting the effects of perceived usefulness, and task effectiveness. This leads us to believe that conscientiousness does have some effect on users in visualisation contexts, although we still haven't been able to pin point what design characteristics have implications in this matter and what metrics are affected.

5.8 Research Implications

The nature of research involving psychology often has social implications revolving around the people affected by the research process or findings. In this analysis it is important to consider the effects of creating design guidelines for users' personality.

The impact of our findings on society would be best considered in accordance to what usage they are given. One possible outcome, would be improved systems with an overall better user experience that would consist of a positive societal implication on Human-Computer Interaction Systems. On the other hand, the question of data privacy arises. In order to create systems based on personality, it is first necessary to collect that data. Such private data can be extremely sensitive, as it could easily be used for manipulation if steered outside of its original well meaning goal. Users should always give consent before data collection, and it should always be anatomised, but the ever present risk of corruption should not be ignored.

Another thing to consider is the possibility of annoying users by trying to anticipate their preferences based on isolated characteristics. This means that even if a set of optimal personality based guidelines is achieved, it is worth considering that user preference might change according to other factors such as the goal of the user, other cognitive abilities, or their default mental model of the system.

It is also worth considering that we used clustering to divide users into three conscientiousness groups, but this could also have been done by diving users according to the portuguese norma. However that approach would have not created equal sized clusters. Since there would be a large number of initial users with high conscientiousness $(N = 34)$, a lower number of users with medium conscientiousness $(N = 20)$, and a low number of people with low conscientiousness $(N = 10)$. This implies that our results are skewed towards a population of people with higher conscientiousness, and is not representative of the whole portuguese population.

5.9 Limitations

There were some limitations to this study that should be considered in the future. One possible limitation in this experiment was the familiarity of people with interactive visualisations. We tested for the familiarity towards each idioms, but did not address the effect of familiarity towards the idioms and dependent variables. We performed Spearman's correlations tests and found significant effects in the dependency between bubble chart and preference $(Rs = 0.216; p = 0.012)$, bubble charts and usefulness $(Rs = 0.194; p = 0.024)$, treemaps and preference $(Rs = 0.218; p = 0.110)$, and sankey diagrams and usefulness $(Rs = -0.173; p = 0.045)$. As seen in Figure 5.11, there were observable differences in the familiarity scores between idioms that probably had an effect on the results.

In order to make a distinction between the levels of information density of the visualisations, we added a bubble chart to the first visualisation. This chart was meant only to cater to the high information density preference we obtained in the design guidelines for C1, and was not associated with any task. However, some people commented that although they preferred the first visualisation overall, the extra chart with no purpose had a negative effect on their evaluation of the interface.

Similarly, as pointed out previously, the menu bar positioning extracted from the preference questionnaires seemed to not entirely correspond to the users expectations. One way of correcting these limitations would be to redesign the preference questionnaire and include each element in a generic visualisation, instead of isolated. This could help users make the connection between their preferred elements in a visualisation context, and more in line with their mental models.

Another limitation for this study was the number of users in our sample. In order to obtain more solid results we should repeat the experiment with a larger population, given that we validated the experiment with 45 users which is a relatively small number to give solid conclusions.

6

Conclusion

Contents

6.1 Conclusions and Future Work

This study was conducted with the goal of better understanding user differences in their interaction with visualisations. Towards that objective we aimed at investigating how conscientiousness shapes the way users interact with visualisations.

We created five hypothesis that related conscientiousness to task efficiency, task effectiveness, perceived usefulness, perceived ease-of-use and preference. In order to validate the hypotheses we collected data on users personality and preferences, which led us to create design guidelines for users within three different levels of conscientiousness. Then we proceeded to the validation of the guidelines through user testing.

Our results show difference in users behaviour towards the visualisations in task efficiency, ease-of-use and preference. Nevertheless, we found no relevant results for usefulness and task efficacy. Our results show that that users with higher conscientiousness, generally perform tasks faster than users with lower conscientiousness. We also found that users with lower conscientiousness attributed higher ease of use scores to every InfoVis in general. We also found that C1 often had different behaviour than C2 and C3, which could stem from the fact that users with higher conscientiousness are more aware and sensitive by design details in visualisations. We also speculated on some design guidelines that should be further investigated such as a general dislike for treemap visualisations in favour of sankey diagrams, and a general preference for top menu bars. We conclude that it is possible that conscientiousness is linked to user interaction with visualisations, but we still have not been able to figure out what factors are the most relevant.

In the future we can attempt to perform the experiment with a larger sample of users in order to obtain more accurate results. We should also give more consideration to the effects of familiarity, create preference questionnaires more directed to InfoVis context, and explore other InfoVis features that can have implications for users depending on their conscientiousness.

Bibliography

[1] T. M. Green and B. Fisher, "Impact of personality factors on interface interaction and the development of user profiles: Next steps in the personal equation of interaction," *Information Visualization*, vol. 11, no. 3, pp. 205–221, 2012. [Online]. Available: https://doi.org/10.1177/1473871612441542

[2] A. Ottley, H. Yang, and R. Chang, "Personality as a predictor of user strategy: How locus of control affects search strategies on tree visualizations," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 2015, pp. 3251–3254.

[3] S. M. Sarsam and H. Al-Samarraie, "A first look at the effectiveness of personality dimensions in promoting users' satisfaction with the system," *SAGE Open*, vol. 8, no. 2, p. 2158244018769125, 2018. [Online]. Available: https://doi.org/10.1177/2158244018769125

[4] S. Lallé and C. Conati, "The role of user differences in customization: A case study in personalization for infovis-based content," in *Proceedings of the 24th International Conference on Intelligent User Interfaces*, ser. IUI '19. New York, NY, USA: ACM, 2019, pp. 329–339. [Online]. Available: http://doi.acm.org/10.1145/3301275.3302283

[5] L. Wang, G. Wang, and C. A. Alexander, "Big data and visualization: methods, challenges and technology progress," *Digital Technologies*, vol. 1, no. 1, pp. 33–38, 2015.

[6] J.-D. Fekete, "The infovis toolkit," in *IEEE Symposium on Information Visualization*. IEEE, 2004, pp. 167–174.

[7] J.-D. Fekete, J. J. van Wijk, J. T. Stasko, and C. North, *The Value of Information Visualization*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2008, pp. 1–18. [Online]. Available: https://doi.org/10.1007/978-3-540-70956-5_1

[8] R. Kosara and S. Miksch, "Visualization methods for data analysis and planning in medical applications," *International journal of medical informatics*, vol. 68, no. 1-3, pp. 141–153, 2002.

[9] L. Chittaro, “Information visualization and its application to medicine,” *Artificial intelligence in medicine*, vol. 22, no. 2, pp. 81–88, 2001.

[10] D. Fisher, R. DeLine, M. Czerwinski, and S. Drucker, “Interactions with big data analytics,” *interactions*, vol. 19, no. 3, pp. 50–59, 2012.

[11] U. Hinrichs, S. Forlini, and B. Moynihan, “Speculative practices: Utilizing infovis to explore untapped literary collections,” *IEEE transactions on visualization and computer graphics*, vol. 22, no. 1, pp. 429–438, 2015.

[12] Y. Mejova, A. X. Zhang, N. Diakopoulos, and C. Castillo, “Controversy and sentiment in online news,” *arXiv preprint arXiv:1409.8152*, 2014.

[13] H. Wickham, D. Cook, H. Hofmann, and A. Buja, “Graphical inference for infovis,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 16, no. 6, pp. 973–979, 2010.

[14] C. Ware, *Information Visualization: Perception for Design: Second Edition*, 04 2004.

[15] M. Braun, R. Chadowitz, and F. Alt, “User experience of driver state visualizations: A look at demographics and personalities,” in *Human-Computer Interaction – INTERACT 2019*, D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, and P. Zaphiris, Eds. Cham: Springer International Publishing, 2019, pp. 158–176.

[16] C. Conati, G. Carenini, E. Hoque, B. Steichen, and D. Toker, “Evaluating the impact of user characteristics and different layouts on an interactive visualization for decision making,” in *Computer Graphics Forum*, vol. 33, no. 3. Wiley Online Library, 2014, pp. 371–380.

[17] T. Alves, S. Gama, and F. S. Melo, “Flow adaptation in serious games for health,” in *2018 IEEE 6th International Conference on Serious Games and Applications for Health (SeGAH)*. IEEE, 2018, pp. 1–8.

[18] 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. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S019188691930649X

[19] Z. Liu, R. Crouser, and A. Ottley, “Survey on individual differences in visualization,” *Computer Graphics Forum*, vol. 39, pp. 693–712, 06 2020.

[20] T. Alves, B. Ramalho, J. Henriques-Calado, D. Gonçalves, and S. Gama, “Exploring how personality models information visualization preferences,” *arXiv preprint arXiv:2008.13133*, 2020.

[21] C. Conati and H. Maclaren, “Exploring the role of individual differences in information visualization,” in *Proceedings of the Working Conference on Advanced Visual Interfaces*, ser. AVI ’08. New York, NY, USA: ACM, 2008, pp. 199–206. [Online]. Available: http://doi.acm.org/10.1145/1385569.1385602

[22] S. Butt and J. G. Phillips, “Personality and self reported mobile phone use,” *Computers in Human Behavior*, vol. 24, no. 2, pp. 346 – 360, 2008, part Special Issue: Cognition and Exploratory Learning in Digital Age. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0747563207000295

[23] D. Toker, C. Conati, B. Steichen, and G. Carenini, “Individual user characteristics and information visualization: Connecting the dots through eye tracking,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ser. CHI ’13. New York, NY, USA: ACM, 2013, pp. 295–304. [Online]. Available: http://doi.acm.org/10.1145/2470654.2470696

[24] K. J. Vicente, B. C. Hayes, and R. C. Williges, “Assaying and isolating individual differences in searching a hierarchical file system,” *Human Factors*, vol. 29, no. 3, pp. 349–359, 1987, pMID: 3623569. [Online]. Available: https://doi.org/10.1177/001872088702900308

[25] C. Chen and M. Czerwinski, “Spatial ability and visual navigation: an empirical study,” *New Review of Hypermedia and Multimedia*, vol. 3, no. 1, pp. 67–89, 1997. [Online]. Available: https://doi.org/10.1080/13614569708914684

[26] C. Chen, “Individual differences in a spatial-semantic virtual environment,” *Journal of the Association for Information Science and Technology*, vol. 51, no. 6, pp. 529–542, 2000, copyright: Copyright 2007 Elsevier B.V., All rights reserved.

[27] B. Allen, “Individual differences and the conundrums of user-centered design: Two experiments,” *JASIS*, vol. 51, pp. 508–520, 01 2000.

[28] M. Tremaine, M. C. Velez, and D. Silver, “Understanding visualization through spatial ability differences,” in *Visualization Conference, IEEE*. Los Alamitos, CA, USA: IEEE Computer Society, oct 2005, p. 65. [Online]. Available: https://doi.ieeecomputersociety.org/10.1109/VIS.2005.108

[29] C. A. Cohen and M. Hegarty, “Individual differences in use of external visualisations to perform an internal visualisation task,” *Applied Cognitive Psychology*, vol. 21, no. 6, pp. 701–711, 2007. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/acp.1344

[30] 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.

[31] J. J. Jackson, D. Wood, T. Bogg, K. E. Walton, P. D. Harms, and B. W. Roberts, "What do conscientious people do? development and validation of the behavioral indicators of conscientiousness (bic)," *Journal of Research in Personality*, vol. 44, no. 4, pp. 501–511, 2010.

[32] R. R. McCrae, "The place of the ffm in personality psychology," *Psychological Inquiry*, vol. 21, no. 1, pp. 57–64, 2010. [Online]. Available: https://doi.org/10.1080/10478401003648773

[33] K. Lee and M. Ashton, "Psychometric properties of the hexaco personality inventory," *Multivariate Behavioral Research - MULTIVARIATE BEHAV RES*, vol. 39, pp. 329–358, 04 2004.

[34] G. M. Philip J. Corr, Ed., *The Cambridge Handbook of Personality Psychology*, 2nd ed., ser. Cambridge Handbooks in Psychology. Cambridge University Press, 2020.

[35] H. Al-Samarraie, A. Eldenfria, and H. Dawoud, "The impact of personality traits on users' information-seeking behavior," *Information Processing and Management*, vol. 18, pp. 17–18, 10 2016.

[36] S. 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*, 02 2018.

[37] E. Abrahamian, J. Weinberg, M. Grady, and C. M. Stanton, "The effect of personality-aware computer-human interfaces on learning," *Journal of universal computer science*, vol. 10, no. 1, pp. 27–37, 2004.

[38] T. A. Daniel Tavares Nunes, Sandra Pereira Gama, "Relevância da conscienciosidade para desenho de interfaces gráficas," 11 2019, Master's Thesis, pp. 1–78.

[39] B. Saati, M. Salem, and W.-P. Brinkman, "Towards customized user interface skins: investigating user personality and skin colour," *Proceedings of HCI 2005*, vol. 2, pp. 89–93, 2005.

[40] M. W. Miller, "Personality and the etiology and expression of ptsd: A three-factor model perspective," *Clinical Psychology: Science and Practice*, vol. 10, no. 4, pp. 373–393, 2003.

[41] J. R. Hall, S. D. Benning, and C. J. Patrick, "Criterion-related validity of the three-factor model of psychopathy: Personality, behavior, and adaptive functioning," *Assessment*, vol. 11, no. 1, pp. 4–16, 2004, pMID: 14994949. [Online]. Available: https://doi.org/10.1177/1073191103261466

[42] M. C. Ashton and K. Lee, "The hexaco–60: A short measure of the major dimensions of personality," *Journal of personality assessment*, vol. 91, no. 4, pp. 340–345, 2009.

[43] 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.

[44] J. S. Wiggins, *The five-factor model of personality: Theoretical perspectives*. Guilford Press, 1996.

[45] B. W. Roberts, J. J. Jackson, J. V. Fayard, G. Edmonds, and J. Meints, “Conscientiousness.” *Handbook of individual differences in social behavior*, p. 369–381, 2009.

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

[48] P. T. Costa and R. R. McCrae, *The NEO personality inventory*. Psychological Assessment Resources Odessa, FL, 1985.

[49] L. Gou, J. Mahmud, E. Haber, and M. Zhou, “Personalityviz: A visualization tool to analyze people’s personality with social media,” in *Proceedings of the Companion Publication of the 2013 International Conference on Intelligent User Interfaces Companion*, ser. IUI ’13 Companion. New York, NY, USA: ACM, 2013, pp. 45–46. [Online]. Available: http://doi.acm.org/10.1145/2451176.2451191

[50] N. Capuano, G. D’Aniello, A. Gaeta, and S. Miranda, “A personality based adaptive approach for information systems,” *Computers in Human Behavior*, vol. 44, pp. 156 – 165, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0747563214006463

[51] A. Ottley, R. Crouser, C. Ziemkiewicz, and R. Chang, “Manipulating and controlling for personality effects on visualization tasks,” *Information Visualization*, vol. 14, 12 2013.

[52] T. M. Green and B. Fisher, “The personal equation of complex individual cognition during visual interface interaction,” in *Workshop on Human-Computer Interaction and Visualization*. Springer, 2009, pp. 38–57.

[53] J. Sheidin, J. Lanir, C. Conati, D. Toker, and T. Kuflik, “The effect of user characteristics in time series visualizations,” in *Proceedings of the 25th International Conference on Intelligent User Interfaces*, ser. IUI ’20. New York, NY, USA: Association for Computing Machinery, 2020, p. 380–389. [Online]. Available: https://doi.org/10.1145/3377325.3377502

[54] M. Millecamp, N. N. Htun, C. Conati, and K. Verbert, “To explain or not to explain: The effects of personal characteristics when explaining music recommendations,” in *Proceedings of the 24th International Conference on Intelligent User Interfaces*, ser. IUI ’19. New York, NY, USA: Association for Computing Machinery, 2019, p. 397–407. [Online]. Available: https://doi.org/10.1145/3301275.3302313

[55] I. Ajzen, “Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1,” *Journal of applied social psychology*, vol. 32, no. 4, pp. 665–683, 2002.

[56] D. Toker, C. Conati, G. Carenini, and M. Haraty, “Towards adaptive information visualization: On the influence of user characteristics,” in *User Modeling, Adaptation, and Personalization*, J. Masthoff, B. Mobasher, M. C. Desmarais, and R. Nkambou, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 274–285.

[57] E. Haapalainen, S. Kim, J. F. Forlizzi, and A. K. Dey, “Psycho-physiological measures for assessing cognitive load,” in *Proceedings of the 12th ACM international conference on Ubiquitous computing*, 2010, pp. 301–310.

[58] K. van Dun and P. Mariën, “Chapter 6 - cerebellar-induced aphasia and related language disorders,” in *The Linguistic Cerebellum*, P. Mariën and M. Manto, Eds. San Diego: Academic Press, 2016, pp. 107 – 133. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B9780128016084000062

[59] G. J. Hitch, S. Halliday, A. M. Schaafstal, and J. M. C. Schraagen, “Visual working memory in young children,” *Memory & cognition*, vol. 16, no. 2, pp. 120–132, 1988.

[60] C. J. Sadowski and H. E. Cogburn, “Need for cognition in the big-five factor structure,” *The Journal of Psychology*, vol. 131, no. 3, pp. 307–312, 1997. [Online]. Available: https://doi.org/10.1080/00223989709603517

[61] J. T. Cacioppo and R. E. Petty, “The need for cognition.” *Journal of personality and social psychology*, vol. 42, no. 1, p. 116, 1982.

[62] J. Cacioppo, R. Petty, J. Feinstein, and W. Jarvis, “Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition,” *Psychological Bulletin*, vol. 119, pp. 197–253, 03 1996.

[63] C. Ziemkiewicz and R. Kosara, “Preconceptions and individual differences in understanding visual metaphors,” *Computer Graphics Forum*, vol. 28, no. 3, pp. 911–918, 2009. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8659.2009.01442.x

[64] E. Brown, A. Ottley, H. Zhao, Q. Lin, R. Souvenir, A. Endert, and R. Chang, “Finding waldo: Learning about users from their interactions,” *Visualization and Computer Graphics, IEEE Transactions on*, vol. 20, pp. 1663–1672, 12 2014.

[65] J. Chin, V. Diehl, and K. Norman, “Development of an instrument measuring user satisfaction of the human-computer interface,” *ACM CHIi’*, 01 1988.

[66] M. Pedroso-Lima, E. Magalhães, A. Salgueira, A.-J. Gonzalez, J. J. Costa, M. J. Costa, and P. Costa, "A versão portuguesa do neo-ffi: Caracterização em função da idade, género e escolaridade," *Psicologia*, vol. 28, no. 2, pp. 01–10, 2014.

[67] C. Ziemkiewicz, A. Ottley, R. Crouser, A. Yauilla, S. 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, pp. 1109–21, 07 2013.

[68] V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decision Sciences*, vol. 39, no. 2, pp. 273–315, 2008. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5915.2008.00192.x

A

Preference Questionnaire

Questionário de Preferências

Bem-vindo(a)!

Foi convidado(a) para participar no seguinte estudo de investigação: Criação de Design Guidelines para Visualizações de Informação Baseadas em Conscienciosidade. Desde já agradecemos a sua colaboração.

As pessoas envolvidas neste estudo são a Bárbara Ramalho (barbara.ramalho@tecnico.ulisboa.pt), o Tomás Alves (tomas.alves@tecnico.ulisboa.pt) e a Prof.ª Dr.ª Sandra Gama (sandra.gama@tecnico.ulisboa.pt).

Neste estudo estamos a procurar relacionar a Conscienciosidade, uma variável de personalidade do Modelo dos Cinco Fatores, com preferências por estilos de diferentes elementos numa visualização de informação. Assim, o presente questionário serve para recolher as suas preferências por elementos gráficos apresentando diversos estilos ilustrativos.

Primeiro, recolhemos o seu identificador e o contexto no qual está a preencher este questionário. De seguida, ser-lhe-ão apresentados diversos aspetos de design gráfico. Pedimos que analise todos os estilos diferentes apresentados e que responda a todas as escalas com as suas preferências.

Este questionário demora cerca de 10 minutos. Não existem respostas certas ou erradas.

Todos os dados serão tratados de forma anónima. Os riscos esperados de participar são mínimos, não excedendo os da vida quotidiana.

Se acredita que existe algo de errado com o conteúdo deste questionário, entre em contato com o(s) investigador(es) e / ou a Comissão de Ética do Instituto Superior Técnico (comissaoetica@tecnico.ulisboa.pt).

Custos: Não existem custos associados à participação neste estudo.

Compensação: Estará inscrito(a) num sorteio de um de cinco bilhetes de cinema por participar neste estudo.

Se consentir com as condições apresentadas, por favor, continue para a próxima secção. Caso contrário, saia desta página web.

* Required

Contexto do Utilizador

Nesta secção, irá responder a perguntas que nos ajudam a perceber o seu contexto. Novamente, não existem perguntas certas ou erradas, pelo que as suas respostas irão ajudar-nos a perceber se o seu contexto afeta as suas respostas nas secções seguintes.

(b) Interface personalized for the neuroticism group

1. Qual o identificador que lhe foi enviado? *

2. Em que dispositivo está a preencher este questionário? *

Mark only one oval.

- Computador Pessoal
- Tablet
- Telemóvel
- Other: ______

3. Está a usar lentes ou óculos corretivos neste momento? *

Mark only one oval.

- Sim
- Não

Preferências de Design

De seguida, ser-lhe-ão apresentados diversos elementos gráficos com diferentes estilos de design. Pedimos que analise todos os estilos diferentes apresentados e que responda a todas as escalas com as suas preferências. Note que as opções não são mutuamente exclusivas, isto é pode gostar de igual forma de vários estilos, não sendo preciso estabelecer uma ordem entre eles.

Tipo de Letra

Avalie cada um dos seguintes tipos de letra de acordo com a sua preferência.

4. Arial *

This is Arial

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

5. Calibri *

This is Calibri

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

6. Calibri Light *

This is Calibri Light

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

7. Times New Roman *

This is Times New Roman

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

8. Lucinda Handwriting *

This is Lucida Handwriting

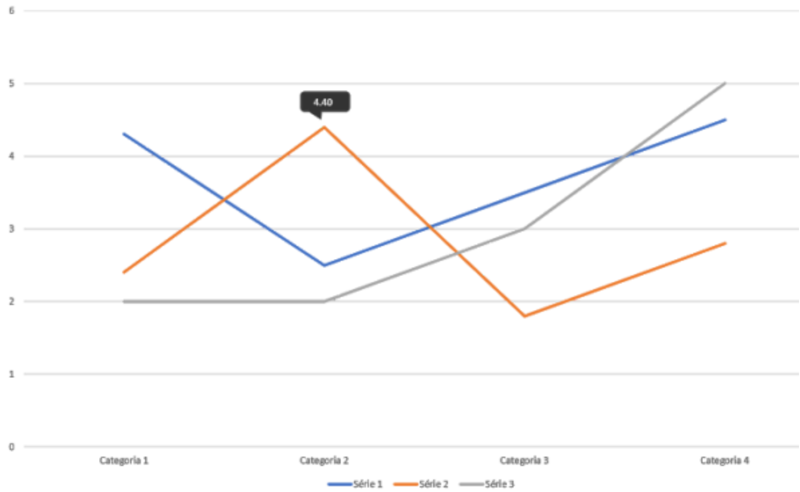
Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

Tamanho de letra

Avalie cada um dos seguintes gráficos de acordo com a sua preferência do tamanho de letra em relação ao gráfico.

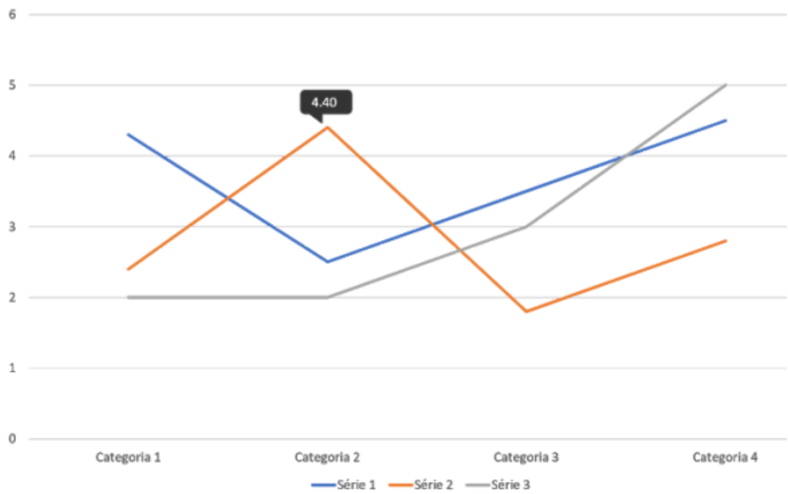
9. Tamanho de letra pequeno *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

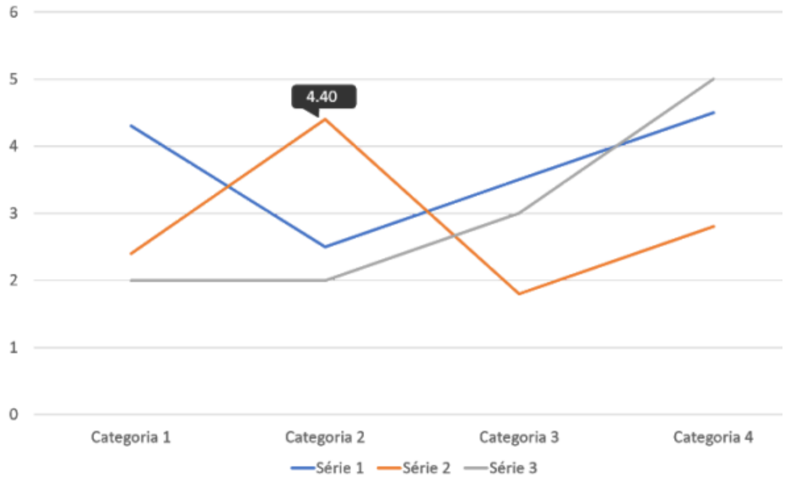
10. Letra de tamanho médio *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

11. Letra de tamanho grande *



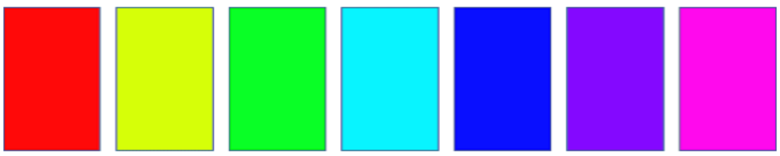
Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

Cores

Avalie cada uma das seguintes paletes de acordo com a sua preferência de cor.

12. Avalie cada uma das tonalidades de acordo com a sua preferência. Considere que 1 é referente a preferência baixa e 7 é referente a preferência alta. *



Mark only one oval per row.

	1	2	3	4	5	6	7
Vermelho							
Amarelo							
Verde							
Azul Claro							
Azul Escuro							
Roxo							
Cor-de Rosa							

13. Avalie a sua preferência do nível de saturação de cor. *

Mark only one oval.

	1	2	3	4	5	6	7	
Saturação alta	◯	◯	◯	◯	◯	◯	◯	Saturação baixa

14. Avalie a sua preferência do nível de luminosidade de cor. *

Mark only one oval.

	1	2	3	4	5	6	7	
Luminosidade baixa	◯	◯	◯	◯	◯	◯	◯	Luminosidade alta

15. Botão apenas com ícone. *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

16. Botão apenas com texto.

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

17. Botão com ícone e com texto. *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

17. Botão com ícone e com texto. *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

18. Densidade baixa *

Mark only one oval.

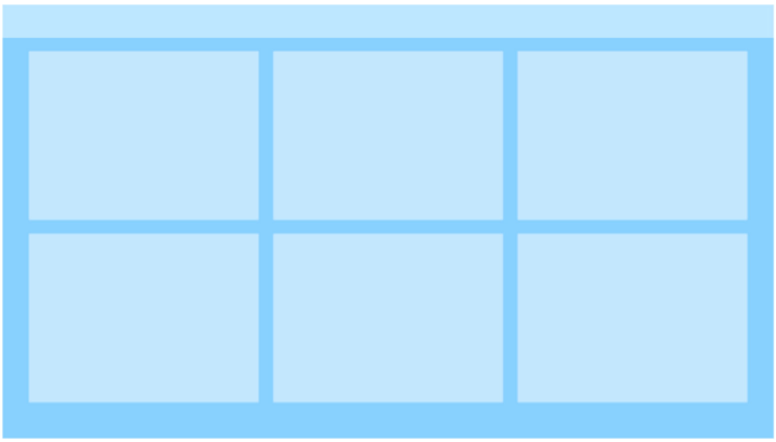
	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

19. Densidade média *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

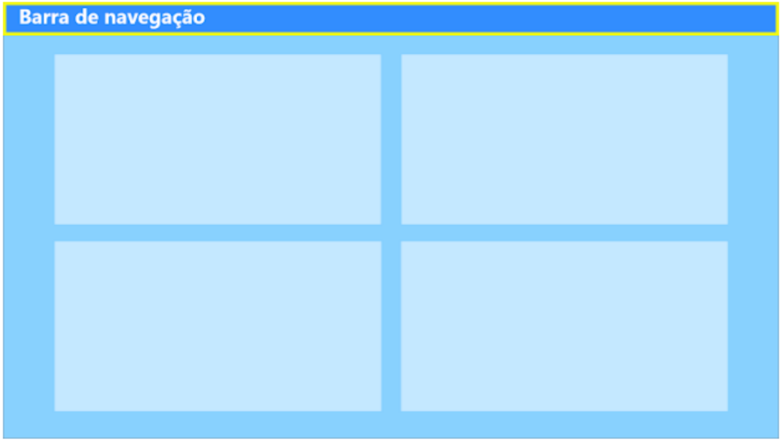
20. Densidade alta *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

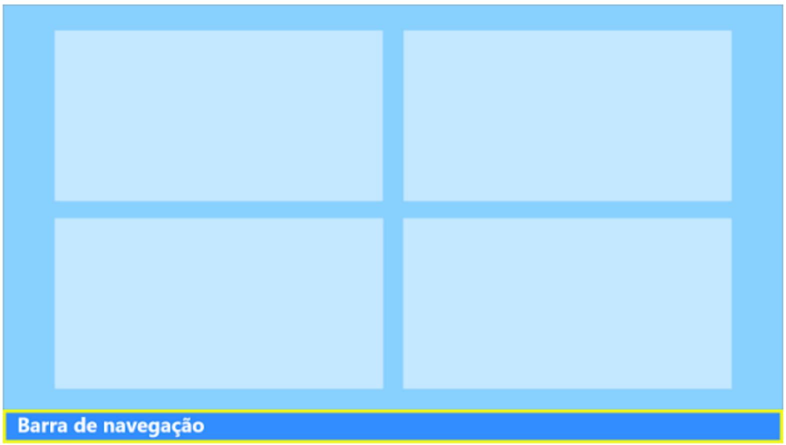
21. Posicionamento superior da barra de navegação. *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

22. Posicionamento inferior da barra de navegação. *



Mark only one oval.

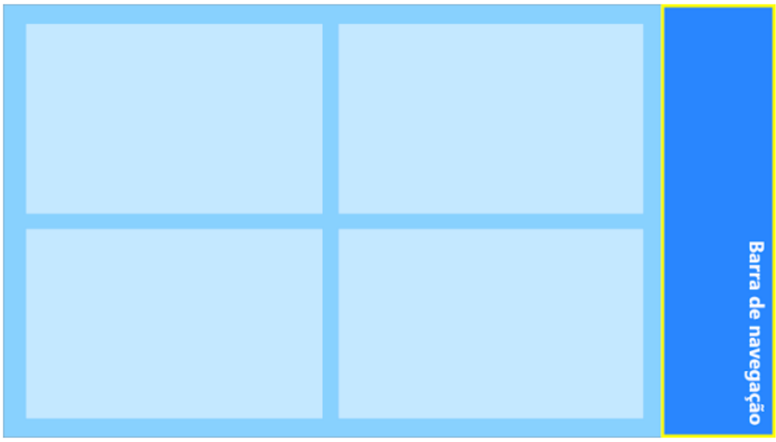
	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

23. Posicionamento lateral esquerdo da barra de navegação. *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

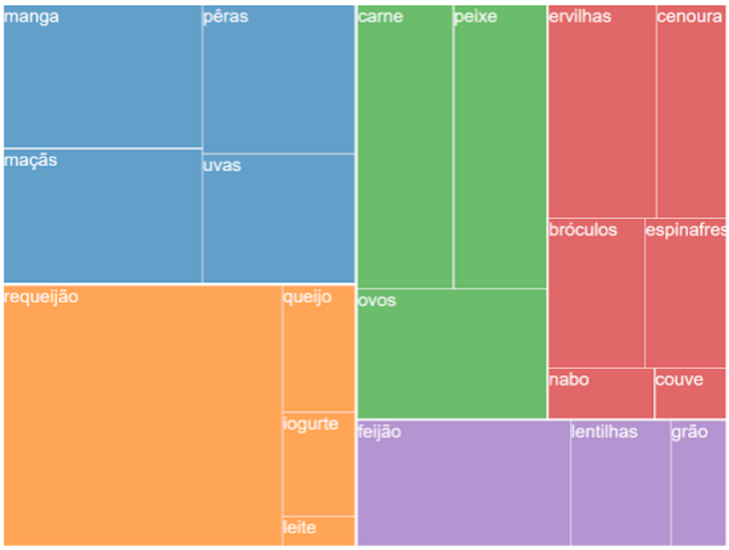
24. Posicionamento lateral direito da barra de navegação. *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

25. Representação através de um Treemap. *



Mark only one oval.

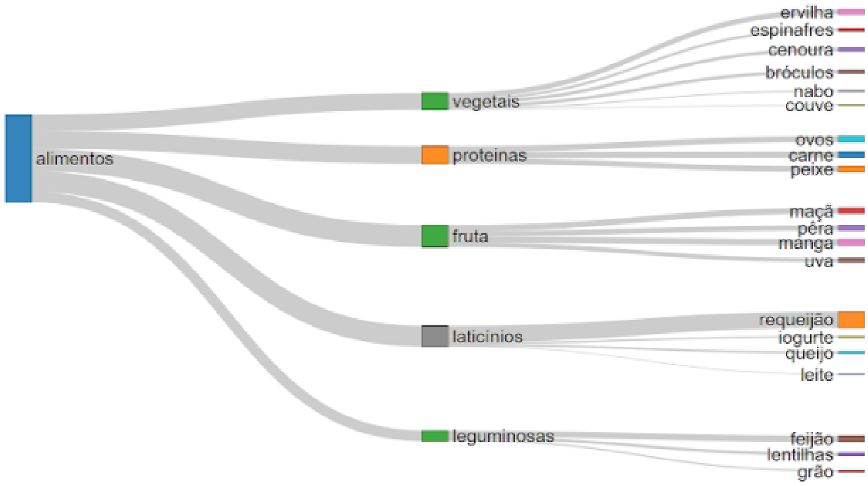
	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

27. Representação através de um Sunburst. *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

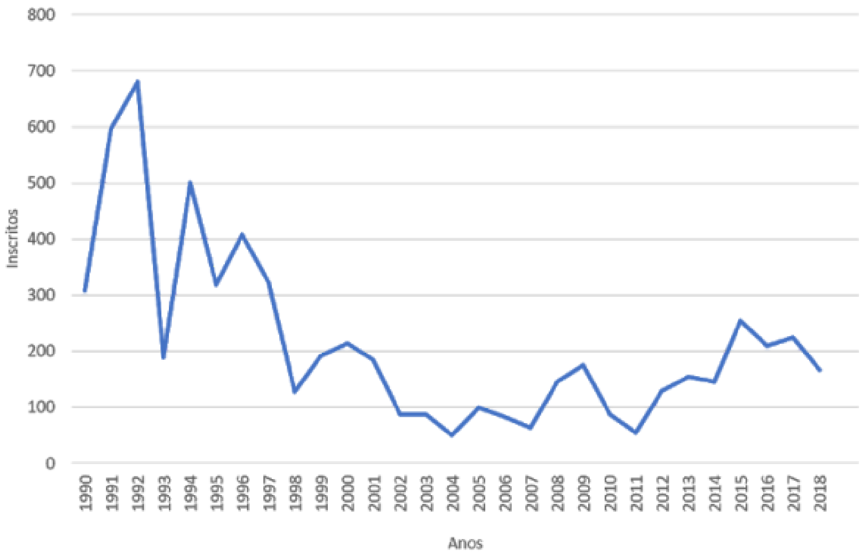
28. Representação através de um Sankey diagram. *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

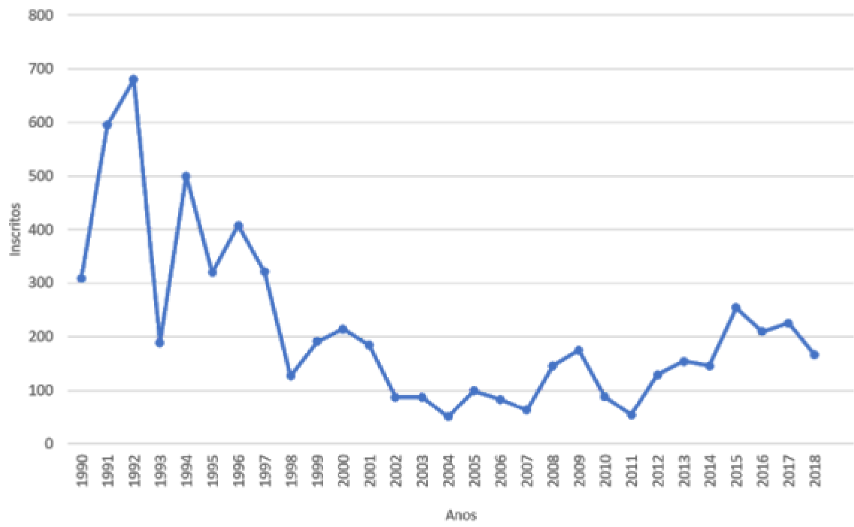
29. Representação através de um Linechart. *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

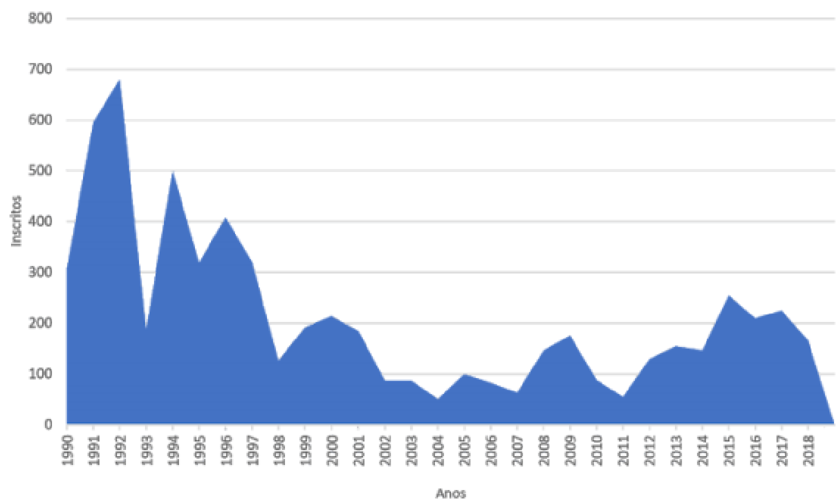
30. Representação através de um Linechart, com pontos. *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

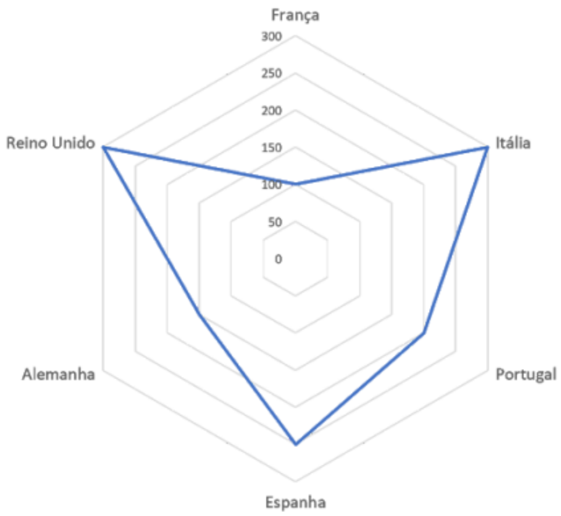
31. Representação através de um Area chart *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa								Preferência alta

32. Representação através de um Radar chart *



Mark only one oval.

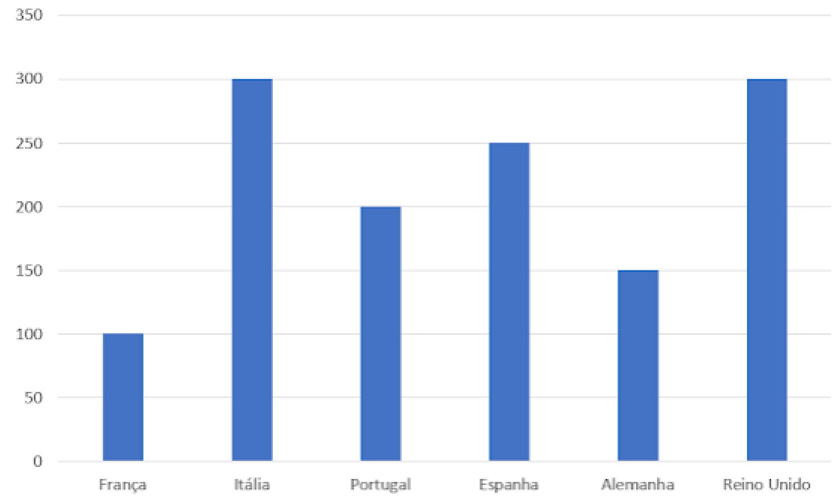
	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

33. Representação através de um Word Cloud *

Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

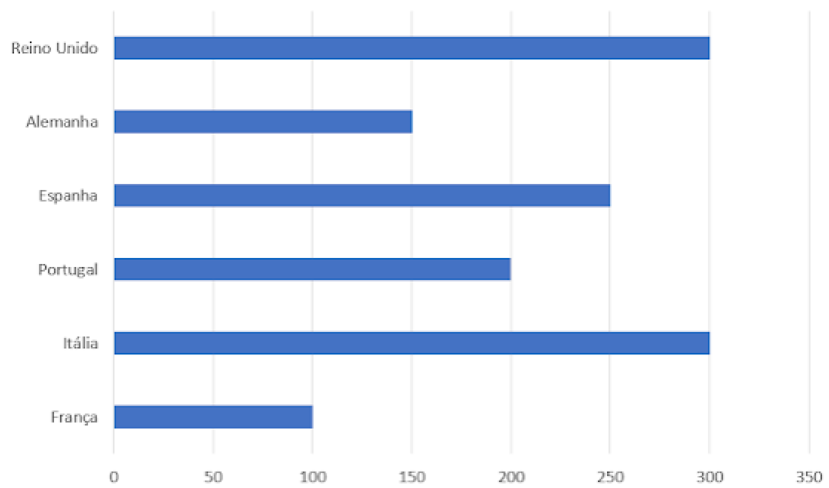
34. Representação através de um Bar chart vertical



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

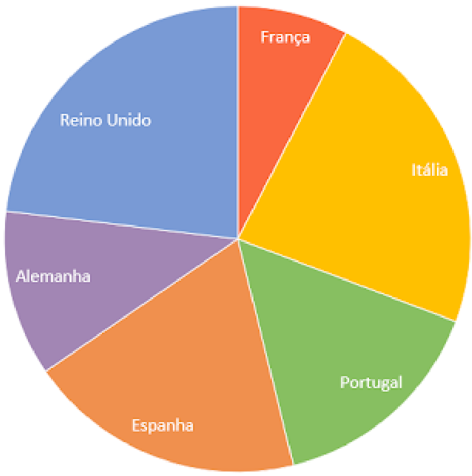
35. Representação através de um Bar chart horizontal *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	◯	◯	◯	◯	◯	◯	◯	Preferência alta

36. Representação através de um Pie chart *



Mark only one oval.

	1	2	3	4	5	6	7	
Preferência baixa	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Preferência alta