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.

1. Introduction

Much of the motivation behind the Human-Computer Interaction field is the creation of systems whose interaction with people is as harmonious as possible. 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[8]. 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 individuals[2]. Motivated by this premise, researchers have been investigating how to optimise user experience by creating systems that take into account individual user characteristics [5]. Among several psychological elements, personality has shown promising results [5].

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. 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 [9].

A few studies on the topic of personality have already uncovered some findings relating to conscientiousness [10] in a mobile and GUI context. However,to the best of our knowledge, there is no research that found significant results in the domain of information visualisation[10] regarding this trait. In the light of this, we extend prior work[2] 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. 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, that could possibly be attributed to the additional importance high conscientiousness users give to detail.

2. Related Work

The impact of individual user differences on technology is a topic that can be approached in several ways. Some of these include cognitive abilities, user performance, perceived usability and personality. Several scopes [12] already link personality to user interaction with technology. Butt et al. [4] observed that it is possible to correlate certain patterns of mobile phone use to specific personality traits. They found out that disagreeable extraverts report spending more time than others using their mobile phones performing a variety of actions from receiving calls to changing their phone's appearance. Another study relating to that same theme, but using a different context, was conducted by Braun et al. [3] investigation on the link between different visualizations and user personality. They found that in car dashboards extraverted users enjoyed the proactive ones the most, such as notifications, while Neurotic users preferred having a constant display of their state. Conati et al. [5] also explored those same traits in other two studies and found confirmation of the relevance of the impact of cognitive abilities in the effectiveness of visualisations. Lallé et al. [8] explored PS, visual WM, Visual scanning, visualization literacy, Locus of Control (LOC) and proposed a set of design guidelines for GUIs based on those characteristics.

Ottley et al. [11] presented another study that focused on user search strategies and the LOC. 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 (an indented tree or a dendrogram). 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.

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. achieved some results when studying the impact of personality traits on users' information-seeking behaviour [1]. 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 [14].

Another study by Sarsam et al. [12] explored how personality can be used to shape interfaces that better suit user preferences. 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 again 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.

Nunes et al. [6] 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.

The above-mentioned studies show us systematically that there is a link between personality and user behaviour towards a system [8]. There also seems to be evidence that the link between personality and behaviour is relevant to the research of user differentiation and their interaction with technology [1]. Users seem to consistently respond more positively to systems that are tailored to their individual characteristics compared to others that were not. This seems to be true in different contexts, including in the domain of data visualisation [13].

Overall, we conclude that understanding the impact of individual user difference is a valuable asset that is being subject to several studies. Yet, it is still hard to pinpoint which characteristics are the most impactful. Studies seem to indicate that personality is a good characteristic to base these systems on, but there is still little research that understands what components of personality are the most relevant and what system features are associated with them. Conscientiousness is a trait that still does not have many results to show, but there seems to be evidence that it is a trait worth exploring more in-depth. Some of the mentioned studies were in the scope of information visualisation, but most of them were instead in the context of GUIs, while we want to specifically explore the role of Conscientiousness in the domain of Information Visualisation. Our research can be relevant to understand whether this trait has an impact on visualisation design and what system features it can have an impact on taking into account user preference.

3. Data Collection

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.

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.

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

I- Competence: To perform a task effectively.

II- Order: To need structure and neatness in one's environment.

III- Dutifulness: To take rules seriously, be obedient and fulfill obligations.

IV- Achievement-Striving: To work hard towards reaching goals.

V- Self-Discipline: To have the self-control to be rigorous and persistent.

VI- 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.

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 [1] we selected some design features that are relevant to the domain of InfoVis (font size, button style, information density, menu bar positioning and idioms).

I- Font style: It refers to the font family used in the dashboard. The types tested were:

II- 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).

III- 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.

IV- 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.

V- 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 a particularly 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[10]. 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 house-

Table 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

hold'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 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.

3.1. 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 ANOVAS we found that neither of those factors affected their answers.

4. Data Analysis

This section describes how we extract the design guidelines from the user personality and preference data. We did this by identifying clusters of conscientiousness, and then using the Apriori algorithm and the Association Rules Technique (ART) to compute preference guidelines for every cluster.

4.1. Clustering Personality

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, 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 1 describes our results with the median and standard deviation for each cluster.

Table 2: Association Rules for each Cluster

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

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 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.

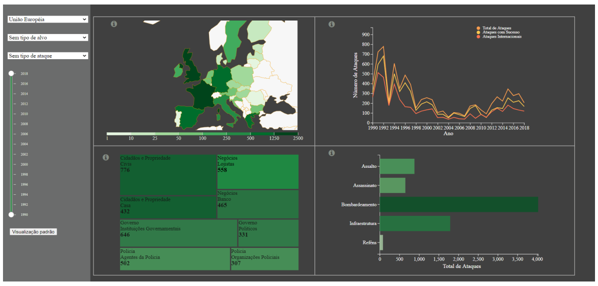
4.2. Extracting Association Rules

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

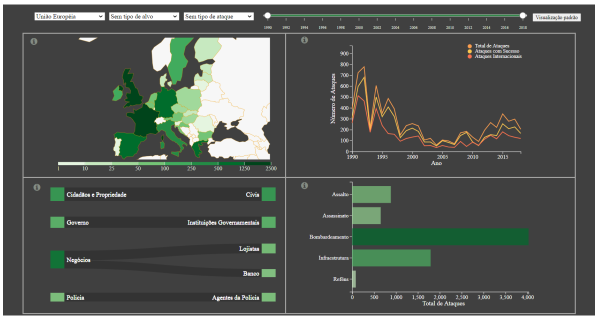
Table 3: Features and design styles for each cluster. Bold styles were derived from the association rules.

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**

(a) High conscientiousness cluster visualisation



(b) Medium conscientiousness cluster visualisation



(c) Low conscientiousness cluster visualisation

Figure 1: Visualisations created from the design guidelines extracted from the Apriori and Association Rules

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*.

4.3. User preferences for each cluster

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 2 show the selected rules for each cluster, while Table 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:

- 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 it 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 it 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 it is a line chart without points and for ranking it is a horizontal bar chart.

5. 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 [4, 7].

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 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 [7].

H2: Conscientiousness has an effect on the errors while completing tasks.

textbfH2a: Users make less errors when interaction with visualisations adapted to their conscientiousness.

H3 to H5 refer to the evaluation of perceived usefulness, perceived ease-of-use and preference users attribute to each visualisation [1]. 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.

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.

5.1. 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, where the researcher screen-shared a browser with the three visualisations (Figure 1) 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.

For each visualisation users were asked 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.

6. Results

Following the user tests, we performed statistical data analysis in order to arrive at the results. The first step was to verify the normality of the collected data, where we found that none of the data collected followed a normal distribution, leading us to only use non-parametric tests. 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.

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 both **H1** and **H1a**. Indeed, taking a closer look into the estimated marginal means (EMM), 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 ($M = 107; SD = 88.6; SE = 24.6$) had 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 EMM is the lowest for the visualisation with the conscientiousness level it was designed for, which supports **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 of the infovis systems, $F(2, 84) = 0.069, p = .933$, partial $\eta^2 = 0.002$, and 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 the EMMs, 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, which manifests in the similar interquartile ranges between clusters. 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 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, since C1 made the most amount of errors in V2 (and less in V1 and V3), while C3 made the most amount of errors in V1 and V3 (and less in V2).

H3: Conscientiousness has an effect on perceived usefulness.

H3a: Perceived usefulness is higher in information visualization systems designed for the 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 and estimated marginal means 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 interquartile range 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 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 $\eta^2 = 0.0.089$, 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 have to refute both **H4** and **H4a**. Taking a closer look into the differences of estimated marginal means 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 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 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 both **H5** and **H5a**. Indeed, taking a closer look into the differences of and estimated marginal means 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 results, 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.

The 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 alto tell that the strength of association is not very strong.

Finally, we can go back and answer our research question. **RQ1**: Is conscientiousness relevant for

personality-based adaptive information visualization systems?

Considering our results, we believe that there is some influence on conscientiousness level and information 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 obtain on time could be good hints on what elements to explore later. We did not however obtain significant results for errors and perceived usefulness.

6.1. 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 revealed by the EMMs for task efficiency, each cluster scored a lower average time completing tasks 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 [13]. This observation supports our belief that conscientiousness is an important factor in user differentiation for visualisation design.

There was no significant result for H2, but we can still point out some interesting considerations. Looking at the EMMs for task errors, 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.

The same argument could apply to the trend observed in the EMMs for task usefulness 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. However the same cannot be said for C1, which rates V1 lower.

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. That 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 EMMs 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. V2 was attributed lower scored than V3 according to all the clusters, again possibly because of the treemap and menu bar. Although in the EMMs for task usefulness C1 had the same mean values for V2 and V3, It differentiated them in the EMMS for ease-of-use. 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. Be 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 the results from the EMMs for preference 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.

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.

7. Conclusions

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. But does not show any 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 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 haven't identified what factors are the most relevant.

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