Examining User Preferences based on Personality Factors in Graphical User Interface Design

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***Abstract*—Individual differences play a major role in human-computer interaction. In particular, personality shapes how we process and act on the world, and how users perceive and accept technology. Nevertheless, there is limited evidence on the effect of different personality types in graphical user interface design preferences. Weighting how personality affects perception, we leverage in-depth synergies between personality variables and design preferences for graphical user interface elements to study whether it is possible to formulate a novel set of design guidelines that allow the creation of user interfaces customized to psychological variables. A clustering approach of the subjects (N=65) yielded three different personality profiles based on the personality variables of the Five-Factor Model. Then, an association rules algorithm produced a set of rules from which we created a set of design guidelines. We discuss the study implications and future work opportunities.**

***Index Terms*—personality, user preferences, design guidelines, user study, graphical user interfaces**

I. Introduction

Psychology principles have been notably applied as a core piece of Human-Computer Interaction (HCI) research. In particular, recent work has focused on informing design choices and understand differences regarding how individuals use technology (e.g., [1]). It enables researchers to take conclusions regarding design effectiveness, since successful technology development needs input from a representative set of potential users and, more precisely, the range of differences among individuals may influence technology [2]. Some factors may include age, gender, job function, language culture or fundamental idiosyncratic attributes, such as personality and motivation. The inclusion of these factors empowers developers to take into account not only how individual characteristics of the user impact the user experience (UX), but also consumers' expectations from providers across a large range of fields. However, there is limited evidence of the usefulness of designing a graphical user interface (GUI) based on individual psychological variables [3].

Weighting how personality affects perception [4] and design efficiency [5], we focus on how in-depth synergies between personality variables and graphical user interface preferences can be applied to graphical user interface design to accommodate the preferences of diverse users. The potential of GUI design based on personal characteristics has been studied by customizing the display to meet certain demands [6]. Sarsam and Al-Samarraie [7] focused on how differences in personality traits can stimulate individuals' information processing capabilities according to their display preferences. The authors focused on the Five-Factor Model (FFM) [8], which categorizes personality with five traits: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. In particular, the authors grouped individuals with common personality profiles in two clusters – one addressing neuroticism, and the other extraversion and conscientiousness – and continued with an association rules technique to find which design elements were preferred for each group of subjects. Results showed how the visual experience improves when subjects interacted with the interface designed based on their personality characteristics. However, there is no set of complete GUI design guidelines to explain the preferences regarding certain interface design features. Additionally, only a small number of interface elements that cover a limited variation of styles have been studied.

In this light, our research goal is **to create a set of design guidelines based on a match between user preferences for GUI feature styles and personality factors.** In particular, we extend prior state-of-the-art research of Alves et al. [3] and Sarsam and Al-Samarraie [9] by studying in-depth personality variables from the FFM, since other current research only applies personality at a superficial trait level, thus neglecting facets, a specific and unique aspect of a broader personality trait, that may provide far more detailed insights into the relationship we are addressing. Our contribution adds new key pieces of knowledge to the field of HCI through the applied methodology. To the best of our knowledge, our work is the first to replicate the personality profiling and GUIs creation based on Sarsam and Al-Samarraie [9] in the website layout context. Although we do not intend to validate personality profiling, our results provide more insights regarding how this methodology is relevant for the introduction of personality in the design process.

II. Related Work

Recent research leverages individual characteristics to personalize user interface (UI)s and improve user experience [7], [10]. In particular, GUIs designed in accordance to user personality have been shown to affect both information-seeking performance and behavior [11], [12], as well as user preference [13]. There is a wide variety of graphical elements that can be customized such as structure [14], navigation [15], layout [16], font style attributes [17], font size [15], [18], buttons [19], color [20], [21], list [22], information density [20], support [20], and alignment [23]. As such, it is of utmost importance to consider in-depth how the designers should draft the GUI, since personality factors affect information-seeking behaviors and, in particular, how one builds their mental model to interact with a piece of technology [11], [12]. However, we believe that there is limited evidence of the effect of designing GUIs based on individual psychological variables [3]. In particular, although the potential of GUI design based on personal characteristics has been studied by customizing the display to meet specific demands [6], there is little empirical data to provide solid guidelines for practitioners to leverage personality variables in this domain.

Table I pinpoints the state-of-the-art research regarding the targeted personality traits, graphical features, and metrics used to study the effect of personality-based GUIs. As we mentioned at the beginning of this section, researchers only addressed an interface elements subset, and not all elements have defined design guidelines. Of the contributors, only Arockiam and Selvaraj [24] provide design guidelines for extravert and neurotic learners in terms of Font Family and Theme (Text Color). As such, there is a considerable lack of research. Although there are several quality dimensions like perceived usability and performance, user preference has been the most studied dimension. In particular, Karsvall [25] and Abrahamian et al. [26] found that participants preferred an interface designed for their personality type. Nevertheless, both studies fall on the mentioned pitfall of designing interfaces beforehand without any input from a sample of participants. As we have already discussed, this may lead to biased results due to the choice of the researchers.

Most studies that found measurable effects with personality traits focus on extraversion. Moreover, a smaller percentage leveraged neuroticism, conscientiousness, and dichotomies from the Myers-Briggs Type Indicator (MBTI). Although Sarsam and Al-Samarraie [7] use the openness to experience and agreeableness traits, these factors were not relevant to differentiate the subjects. As such, there are no studies regarding the effect of these last two traits on user preferences in the context of GUIs. Additionally, the majority of the studies (66.67%) in Table I focuses on personality profiles composed of a unique trait. In contrast, Abrahamian et al. [26], Su et al. [28], and Sarsam and Al-Samarraie [7] leverage more than one personality factor to differentiate users. All the mentioned research gaps allow us to conclude that the state-of-the-art presents several open challenges. In this work, we want to contribute to the state-of-the-art and, at the same time, study the different personality profile compositions for user preference assessment. The following two sections present our work regarding this topic, including personality profiles with a unique factor and multiple factors, as well as how designing GUIs based on user preferences from different personality profiles influences how users perceive those interfaces.

III. Data Collection

As we mentioned in the previous section, our work focuses on studying and incorporating personality traits in GUI design, in particular to extend the current methods of design research and commercial communities, contributing to the HCI research field. Thus, we formulate our research question as: *Are personality-based user preferences a relevant factor to the design of GUIs?* In order to study this effect, we started by choosing which features and their styles we want to address.

A. Design Elements

The core of graphical features we target in this study is similar to Sarsam and Al-Samarraie [9]. In particular, both our work and Sarsam and Al-Samarraie [9] cover information structure, layout type, font style attributes, text size, buttons, color, information density, support, and alignment. While Sarsam and Al-Samarraie [9] asked participants to assess each component of the HSB color model and a set of hues individually, we provide a set of color palettes that we created based on the work of Condeço [21]. We believe that providing the user with optional full color palettes provides a clearer, more rational choice since the user has full information about the final set of colors. This design decision is in contrast to Sarsam and Al-Samarraie [9], where the authors derived the interface color theme from the preference rates of each hue and how much saturated and bright subjects like to see colors. The major limitation of this approach is that the subject cannot see beforehand how the final color palette will look like. This means that there may be some interaction effects between colors in the derived design guidelines that were overlooked by the participants and may have an effect on their interaction.

Sarsam and Al-Samarraie [9] also addressed navigation and list elements. Nevertheless, we do not cover them in this study, since we believe that these graphical elements are better suited for a mobile setting rather than a website desktop-based layout. Regarding navigation, our website desktop-based setting does not have the limited screen size of the typical mobile setting paired with the nonexistence of actions such as hover events. Website desktop-based GUIs have larger screen sizes that allow designers to focus on other design features, as well as support pointer events that would overlap with the design proposals of Sarsam and Al-Samarraie [9]. A similar case can be made for listing elements since its importance is exacerbated by the small screen size that is common in mobile devices. In the webpage desktop-based setting, lists are relegated to an importance similar to other graphical elements, such as images or tables, given that usually the screen size is larger and able to display a larger volume of information. In this case, we decided not to cover this type of design elements as a means to control the complexity of the data analysis.

Besides the nine graphical features that our work shares with Sarsam and Al-Samarraie [9], we decided to also approach three other design elements: body margin, menu structure, and text highlights. Regarding body margin, we believe it is important to assess in the website desktop-based context; it allows us to explore and manipulate more in depth information

TABLE I: Collection of studies focused on user preferences for GUI features influenced by personality traits. The rightmost group includes the quality dimensions used to test the effect of the personality traits.

	Personality Traits							**Graphical Features**												**Quality Metrics**			
	Neuroticism	Extraversion	Openness to Experience	Agreeableness	Conscientiousness	Sensing/Intuition	Thinking/Feeling	Buttons	Element Style	Font Family	Icons	Information Density	Layout	Menu Structure	Navigation	Text Alignment	Text Size	Theme	Mental workload	Perceived usability	User Preference	Performance
Karsvall [25]		x							x									x			x	
Abrahamian et al. [26]		x				x						x									x	
Arockiam and Selvaraj [24]	x	x								x								x				x
Kim et al. [27]		x												x							x	x
Su et al. [28]						x	x					x			x							x
Condeço [21]		x																x			x	
Sarsam and Al-Samarraie [7]	x	x			x			x			x		x	x		x	x	x			x	
Xavier [15]	x														x	x	x		x	x	x	

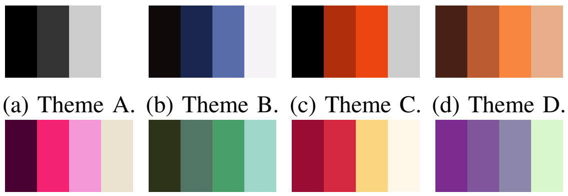
density on the screen, given that the body margin supports the use of white space on the outer border of the main content to change the volume of information on the screen. Menu structure is also an important feature, since it has already shown significant interaction effects with a personality trait in Kim et al. [27]. Since Kim et al. [27] only focused on extraversion, we believe that we can extend their work by including all personality traits from the FFM. Finally, text highlights are common in website desktop-based settings to showcase important information. Alas, we found no study in our research field that leverages this design element. Again, we believe that we can extend the state-of-the-art by including this graphical feature in our study.

Overall, we address low-level text properties (font size, font family, highlights, and text alignment), webpage-level content organization (layout, information density, body margins, and theme), webpage-level organization (menu and information structures) and, finally, other elements such as buttons and support. We believe that these elements include the GUI features more frequently mentioned in the literature as well as the most relevant levels of context granularity in webpage-based GUIs. Although some of these features are less abstract, such as font size or family, elements such as information density and structure have different styles that are harder to visually exemplify. In order to bridge this gap, we include with this kind of features a brief explanation regarding what is their meaning and how they are present in a website layout. The elements are described as follows:

- **Body margins**: It addresses the space between the main content and the limits of the GUI. We tested for small, medium, and large margins.
- **Buttons**: A graphical element that can be clicked to prompt an action. Our study focuses on three types of buttons: buttons with a name, buttons with an icon, and buttons with a name and an icon.
- **Information density**: It denotes the volume of graphical and textual elements in the display. We presented three different amounts of information density: low, medium, and high information density.
- **Information structure**: It refers to the organization of data in the GUI. We decided to focus on four different settings: linear structure, hierarchical structure, network structure, and matrix structure [9].
- **Layout type**: It refers to the arrangement of the GUI components. Similar to Sarsam and Al-Samarraie [9], we focus on linear, relative, and web view layouts.
- **Menu structure**: We focus on the depth and breadth dimensions in the menu structure design.
- **Support**: It provides hints to the user that are embedded usually within the design of GUIs. Likewise Sarsam and Al-Samarraie [9], we test support items based on icons and text.
- **Text alignment**: It refers to how information is arranged within compartments. We study justified, left, and center alignments.
- **Text font**: It refers to the font family of the text. We study several font families, namely Arial, Courier, Georgia, Handwritten, Times New Roman, and Verdana.
- **Text highlights**: It establishes how relevant information is highlighted. We use background color, bold, and underline styles.
- **Text size**: It refers to the size of the text compared to the size of the GUI. We tested for small, medium, and large font sizes.
- **Theme**: The theme of the GUI has a set of colors to use on the drawing of the elements. Based on Condeço [21], the selection of colors was in accordance to hue, saturation, and brightness (Figure 1).

B. Personality Data

Regarding personality variables, we use the personality traits and their facets from the Five-Factor Model (FFM). The FFM is the most widespread and generally accepted model of personality [8], [29], [30], since it provides a nomenclature and a conceptual framework that unifies much of the research



(a) Theme A. (b) Theme B. (c) Theme C. (d) Theme D.

(e) Theme E. (f) Theme F. (g) Theme G. (h) Theme H.

Fig. 1: The different styles for the theme feature.

findings in the psychology of individual differences[1]. This model consists of five general traits to describe personality and 30 facets of personality as follows:

- **Neuroticism** (*Anxiety* (N1), *Anger* (N2), *Depression* (N3), *Self-consciousness* (N4), *Immoderation* (N5), *Vulnerability* (N6)): distinguishes the stability of emotions and even-temperedness from negative emotionality, which can be described as feeling nervous, sad, and tense [32]. It is often referred to as emotional instability, addressing the tendency to experience mood swings and negative emotions such as anxiety, worry, fear, anger, frustration, envy, jealousy, guilt, depressed mood, and loneliness [33].
- **Extraversion** (*Friendliness* (E1), *Gregariousness* (E2), *Assertiveness* (E3), *Activity level* (E4), *Excitement-seeking* (E5), *Cheerfulness* (E6)): suggests a lively approach toward the social and material world [32]. It measures a person's tendency to seek stimulation in the external world, the company of others, and to express positive emotions.
- **Openness to experience** (*Imagination* (O1), *Artistic interests* (O2), *Emotionality* (O3), *Adventurousness* (O4), *Intellect* (O5), *Liberalism* (O6)): describes the wholeness and complexity of an individual's psychological and experiential life [32]. It measures a person's imagination, curiosity, seeking of new experiences, and interest in culture, ideas, and aesthetics. It is related to emotional sensitivity, tolerance, and political liberalism.
- **Agreeableness** (*Trust* (A1), *Morality* (A2), *Altruism* (A3), *Cooperation* (A4), *Modesty* (A5), *Sympathy* (A6)): distinguishes pro-social and communal orientation toward others from antagonism [32]. It measures the extent to which a person is focused on maintaining positive social relations.
- **Conscientiousness** (*Self-efficacy* (C1), *Orderliness* (C2), *Dutifulness* (C3), *Achievement-striving* (C4), *Self-discipline* (C5), *Cautiousness* (C6)): suggests self-use of socially prescribed restraints that facilitate goal completion, following norms and rules, and prioritizing tasks [32]. It measures the preference for an organized approach to life as opposed to a spontaneous one.

[1]Several personality researchers agree that these five personality traits are representative of cross-cultural individual differences in normal behavior and studies have replicated this taxonomy in a diversity of samples [31].

C. Apparatus

The native version of the Revised NEO Personality Inventory (NEO PI-R) [34] was developed by Lima and Simões [35] to assess personality variables from the FFM. The NEO PI-R has a high internal consistency with values ranging from 0.79 to 0.86 [35]. It has 240 items and allows researchers to assess the FFM five personality traits and their 30 facets. The questionnaire identifies the intensity of each personality trait of a person using high-score and low-score features. The questionnaire has 30 different subscales (one for each facet), with eight items for each subscale. Thus, every trait has 48 different items. Additional experimental setup included an online questionnaire with the features and their different styles to assess user preferences[2]. Each style was accompanied by an illustrative image and an explanation.

D. Procedure

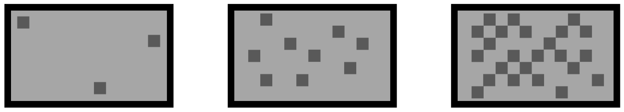
We recruited subjects through standard convenience sampling procedures by direct contact and word of mouth. Subjects included any native interested in participating with at least 18 years old. Our data set comprises 65 participants (31 males, 34 females) between 18 and 60 years old ($M = 24.03; SD = 6.81$). All participants had a normal or corrected-to-normal vision, and there were no color blind subjects as assessed by a validated simplified version of the Ishihara test [36]. Additionally, we found that the apparatus (mobile, desktop, or tablet) through which participants assessed their design preferences did not lead to statistically significant differences in their ratings.

Before the experiment, participants were informed about the experience and invited to agree with a compulsory consent form. We also informed them that they could quit the experiment at any time. Beforehand, participants filled in the NEO PI-R in an online platform to collect the personality traits and their facets from the FFM. Afterward, we invited participants to fill in the online questionnaire that presented all features and visual examples of the styles in a fixed order to assess user preference for each arrangement. In particular, each participant assessed their preference for a style of a feature by completing a seven-point Likert scale ranging from *Low Preference* (1) to *High Preference* (7). As an example, Figure 2 presents the set of possible styles for the information density feature (see the supplemental material for the full questionnaire). Finally, participants received their compensation.

IV. Data Analysis

This section describes how we created the design guidelines for the different personality profiles. It starts by analysing how to cluster personality characteristics, and continues by exploring association rules from patterns regarding user preferences. In particular, we conducted a mixed analysis, where the within-subjects variables are the ratings that each participant

[2]https://drive.google.com/file/d/14jgCLIRCcixXT_Dn1gTRaC_EEXuCCZaL/view?usp=sharing (Last access: September 30, 2022).



(a) Low density. (b) Medium density. (c) High density.

Fig. 2: The different styles for the information density feature (adapted from Sarsam and Al-Samarraie [7]).

attributed to the styles and the between-subjects variables are the personality traits and their facets from the FFM.

A. *Clustering Personality Characteristics*

There are several ways to understand how personality models design choice preferences. One approach is to first convert each personality variable to categorical values following either the quartile distributions of the sample or the native population [35], and then analyse each personality variable separately using ANOVAs to explore main and interaction effects with the features and its styles according to user preferences. The other approach is by clustering users according to their personality characteristics and find whether participants with similar personality profiles share preferences for certain GUI elements. In our work, we focus on the second approach. Although it is also possible to categorize personality variables as aforementioned and then cluster users, we decided to work with integers, as they allow a finer granularity compared to data binning. In particular, we use the 30 facets from the FFM as input variables for the clustering algorithms.

We started by applying hierarchical clustering [37] to find the most appropriate number of clusters to work with. In particular, we allow the algorithm to choose the minimal cluster size (the smallest size grouping that we wish to consider a cluster) and how conservative the algorithm should be while clustering (the number of points that are declared as noise) according to the best silhouette and Davies–Bouldin index scores [38]. Additionally, we use the euclidean distance as the clustering metric since we are working with integer values. This approach allows the algorithm to search in a given set of parameter values which combination of arguments generates the best clustering solution according to the silhouette and Davies–Bouldin index scores. Following this approach, hierarchical density-based clustering [39] yielded three clusters. We followed up with the k-means clustering algorithm [40] as a way to avoid the noise labels that hierarchical density-based clustering produces. By fixing the number of clusters to three, we normalized the data and allowed k-means to run 100 times with different centroid seeds using Euclidean distance. The final result contained the best output of 100 consecutive runs in terms of inertia.

The distributions of personality variables from the clusters are presented in Figure 3. The first cluster ($N = 20$) notably has participants with the highest levels of extraversion ($M = 124.10; SD = 14.46$) and openness to experience ($M = 136.20; SD = 16.17$), followed by medium levels of neuroticism ($M = 96.15; SD = 17.36$) and conscientiousness ($M = 119.05; SD = 16.04$), and low levels of agreeableness ($M = 119.05; SD = 18.87$). For simplicity, we labeled this cluster as "Extraversion-Openness" (C-EO), as those traits present the highest means compared with other clusters. In contrast, the second cluster ($N = 19$) shows high neuroticism ($M = 121.47; SD = 16.76$), and low extraversion ($M = 95.74; SD = 17.46$), openness to experience ($M = 118.79; SD = 16.65$), agreeableness ($M = 125.42; SD = 12.99$), and conscientiousness ($M = 108.84; SD = 19.89$). Therefore, we labeled this cluster as "Neuroticism" (C-N). Finally, the third cluster ($N = 26$) includes participants with high agreeableness ($M = 132.38; SD = 16.29$) and conscientiousness ($M = 135.54; SD = 16.18$), medium levels of extraversion ($M = 107.38; SD = 16.99$), and low levels of neuroticism ($M = 80.12; SD = 12.94$) and openness to experience ($M = 115.04; SD = 16.30$). We labeled it as "Agreeableness-Conscientiousness" (C-AC) since this cluster shows higher scores for agreeableness and conscientiousness. Although most traits follow the native distribution [35], the dimensions of openness to experience and conscientiousness show higher and lower medians, respectively. These differences may be due to the sampling of our study being composed of young adults (from 18 to 24 years old) and adults (older than 24) from a university setting. Nevertheless, the interquartile range (IQR) shows a well-balanced distribution for these cases.

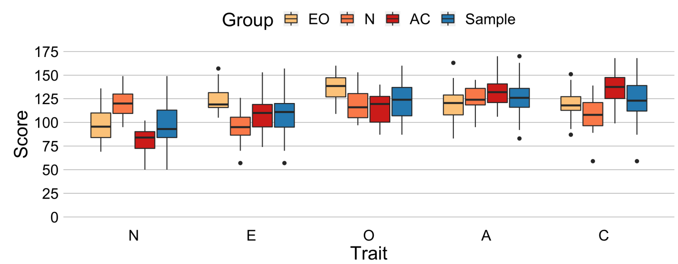


Fig. 3: Boxplots of the distribution of traits between clusters and the sample.

Additionally, we conducted an ANOVA to validate whether the clusters are interdependent regarding personality traits. We found a significant difference in neuroticism ($F(2, 62) = 38.938, p < .001$), extraversion ($F(2, 62) = 14.812, p < .001$), openness to experience ($F(2, 62) = 10.198, p < .001$), agreeableness ($F(2, 62) = 3.823, p = .027$), and conscientiousness ($F(2, 62) = 13.7, p < .001$) across the three clusters. There were also significant differences in 17 personality facets out of 30. These results show that clusters differ in many personality scores, notably at a trait level. Therefore, each of the three clusters contains a different stable and valid user group than the other clusters. In particular, C-EO contains people that are outgoing, talkative, and show an energetic behavior open to new experiences. In contrast, C-N depicts people that are not emotionally stable and have a tendency to experience mood swings. Finally, C-AC includes pro-social people that focus on maintaining positive social relations while following socially prescribed restraints to have an organized approach to life. After identifying the different personality groups, our next objective is to extract design guidelines among individuals of those three clusters. We used an association rules method to identify the design preferences for each personality profile.

B. Extracting Association Rules

We used the Apriori algorithm [41] to find common patterns between the preferred styles of each participant. We started by creating an array containing the style preferred the most for each feature per user. In case of ties in the preference rate between styles, we included all arrangements tied together. For instance, if the subject rated their preference for "medium" and "high" information density with 6 and the "low" with 4, we included both the "medium" and "high" styles in the array. Next, we divided users by their cluster labels and used the Apriori in each cluster. Each run was performed with lower bound minimal values of 0.15 for support, 0.9 for confidence, and 6 for lift. We empirically tested these values to reach a core of rules as robust as possible. The algorithm yielded 74 rules for the C-EO, 282 for the C-N, and 6 for the C-AC.

C. Finding Preferences for Clusters

We continued our analysis by choosing which rules to use on the design guidelines according to the frequency of each rule. We started by choosing the rule with the highest frequency value and then continued by picking rules with lower frequency that share a design style and do not conflict with a design style previously selected for a feature. In addition, we focused on maximizing the number of design elements that could be derived from the association rules. When a feature did not have a style associated with it at the end of our analysis, we chose the most frequent preferred style for that feature among participants of the cluster. Table II illustrates the final rule sets for each cluster. Based on the final set of rules for each cluster, we were able to derive which styles to apply to the different GUI elements (Table III). There are several features that have different styles across versions: font family and size, information density, layout, text align, and theme. Nevertheless, we were not able to derive styles for certain features.

As we mentioned, we address this issue by choosing the most frequent style among cluster participants. Regarding the C-EO, only the styles of *Highlights* and *Information Structure* features were not derived from the association rules. The most common styles were "bold" and "hierarchy", respectively. Moreover, both the "bold" highlights (M = 5.90; SD = 1.07) and the "hierarchy" information structure (M = 5.85; SD = 0.88) were favored by the participants. For the C-N, *Information Structure* was the only feature assessed by the post-analysis based on the frequency of styles, resulting in the "hierarchy" style that also yielded positive ratings in design preference (M = 5.95; SD = 0.78). Finally, we derived five features' styles from them though the C-AC had only three defined rules. The remaining features were *Font Size*, *Help*, *Highlights*, *Information Density*, *Information Structure*, *Menu*, and *Theme*, which yielded the positively rated styles of "medium" (M = 5.65; SD = 1.26), "icon" (M = 5.46; SD = 1.07), "bold" (M = 5.85; SD = 0.92), "medium" (M = 4.96; SD = 1.31), "hierarchy" (M = 5.73; SD = 0.96), "breadth" (M = 5.81; SD = 0.90), and the mono-chromatic blue theme (M = 5.31; SD = 1.32), respectively.

TABLE II: Association rules chosen for each cluster. An association rule from the Apriori algorithm is often represented as $styleA \rightarrow styleB$, which translates into $styleB$ being frequently present in a set of preferences that also contains $styleA$.

Rules for the C-EO	**Frequency**	**Support**	**Confidence**	**Lift**
themeB → layoutRelative	13	0.150	1.00	6.667
layoutRelative → menuBreadth	7	0.150	1.00	6.667
buttonIconText → menuBreadth	6	0.150	1.00	6.667
themeB → menuBreadth	5	0.150	1.00	6.667
marginSmall → menuBreadth	4	0.150	1.00	6.667
marginSmall → alignJustified	3	0.150	1.00	6.667
buttonIconText → alignJustified	2	0.150	1.00	6.667
densityMedium → layoutRelative	2	0.150	1.00	6.667
buttonIconText → densityMedium	2	0.150	1.00	6.667
themeB → buttonIconText	2	0.150	1.00	6.667
densityMedium → buttonIconText	1	0.150	1.00	6.667
layoutRelative → sizeLarge	1	0.150	1.00	6.667
menuBreadth → sizeLarge	1	0.150	1.00	6.667
themeB → sizeLarge	1	0.150	1.00	6.667
marginSmall → helpIcon	1	0.150	1.00	6.667
buttonIconText → marginSmall	1	0.150	1.00	6.667
Rules for the C-N	**Frequency**	**Support**	**Confidence**	**Lift**
themeA → marginSmall	29	0.158	1.00	6.333
themeA → buttonIconText	15	0.158	1.00	6.333
densityLow → themeA	9	0.158	1.00	6.333
layoutLinear → themeA	4	0.158	1.00	6.333
themeA → menuBreadth	3	0.158	1.00	6.333
marginSmall → densityLow	2	0.158	1.00	6.333
marginSmall → layoutLinear	1	0.158	1.00	6.333
layoutLinear → highlightBold	1	0.158	1.00	6.333
themeA → helpIcon	1	0.158	1.00	6.333
Rules for the C-AC	**Frequency**	**Support**	**Confidence**	**Lift**
alignLeft → marginSmall	4	0.160	1.00	6.250
alignLeft → buttonIconText	1	0.160	1.00	6.250
layoutRelative → fontGeorgia	1	0.160	1.00	6.250

With the features and their styles defined for each cluster, we can create personality-based GUI design guidelines for different elements. In particular, we were able to derive the following guidelines:

- *People high on extraversion and openness to experience prefer GUIs with large Arial font, medium information density, relative layout, justified text, and a monochromatic blue theme.*
- *People high on neuroticism prefer GUIs with medium Arial font, low information density, linear layout, justified text, and a gray-scale theme.*
- *People high on agreeableness and conscientiousness prefer GUIs with medium Georgia font, medium information density, relative layout, left-align text, and a monochromatic blue theme.*

As our findings show similar preferences for button, help, highlights, menu, and structure types, in addition to the size of the margins in a GUI, preferences regarding these design features may be independent of personality traits. Indeed,

TABLE III: Features and preferred styles for each cluster. The percentage represents the amount of times the design style was chosen compared to the other styles for a feature in each cluster. Bold styles were derived from the association rules. Highlighted rows present differences in styles among distinct personality groups.

Feature	C-EO	C-N	C-AC
Buttons	**IconText** (48%)	**IconText** (43%)	**IconText** (48%)
Font Family	**Arial** (34%)	**Arial** (45%)	**Georgia** (13%)
Font Size	**Large** (38%)	**Medium** (50%)	Medium (69%)
Help	**Icon** (71%)	**Icon** (75%)	Icon (63%)
Highlights	Bold (59%)	**Bold** (61%)	Bold (57%)
Information Density	**Medium** (57%)	**Low** (23%)	Medium (55%)
Information Structure	Hierarchy (41%)	Hierarchy (71%)	Hierarchy (43%)
Layout	**Relative** (42%)	**Linear** (48%)	**Relative** (48%)
Margin	**Small** (63%)	**Small** (50%)	**Small** (65%)
Menu	**Breadth** (86%)	**Breadth** (76%)	Breadth (81%)
Text Align	**Justified** (87%)	**Justified** (85%)	**Left** (24%)
Theme	**B** (34%)	**A** (20%)	B (29%)

a closer look at Table III shows that the three personality profiles often preferred the same style for the GUI features, thus suggesting that the groups may not have differed much regarding those elements.

V. Discussion and Future Work

Our findings add to prior work by Alves et al. [3], who found that there is a strong need for personality-based GUI design research, and to the work of Sarsam and Al-Samarraie [9], who addressed a subtopic of GUI design by focusing on mobile applications. Similar to Arockiam and Selvaraj [24], we found that extraversion and neuroticism have an effect on the font family, since users with high values on both traits prefer Arial font, while people with lower values tend to prefer Georgia. We also found that conscientiousness, extraversion, and neuroticism have an effect on how people prefer the size of the text on the screen [7], [15], since people with high extraversion prefer large fonts, while the remaining would rather have medium font size. Information density also showed differences between personality profiles [26], with people with high neuroticism preferring lower densities. Additionally, we found that people with high neuroticism prefer themes in a gray scale, and people with on the other traits would rather have a monochromatic blue theme varying in value, according to the HSV color scheme. In particular, we found contradictory results compared to the work of Condeço [21] by showing that introverts prefer gray-scale themes and extraverts blue tones. We also found contrary results compared to Sarsam and Al-Samarraie [7] and Kim et al. [27], since there were no differences regarding buttons and menu structure. The next step in our research is to validate the design guidelines. In particular, we want to design GUIs according to the preferences of each group and then examine how the different personality profiles interact with those interfaces.

Some relevant factors may explain the lack of significance observed in some results. First, the number of participants in this experiment could have been higher, as a higher number of participants would allow conclusions with a better impact. Our results are limited to native users and may not transfer to other populations. Both factors are relevant when considering a personality profile with a level of complexity based on five personality traits. Although this variation may lead to different preferences from each cluster, our methodology is sound to differentiate people based on personality factors since each group was interdependent from others for all personality traits. Another common point to the previous study is that we could show more styles to participants that may have revealed other preferences. However, we chose the most common styles for the features. In addition, basing our approach on association rules and shared patterns of design preferences may hinder design styles that are most frequently chosen as the preferred one independently of their relationship with the remaining features. In other words, although an association rule may be relatively more frequent, it does not mean that it applies to the cluster as a whole. Thirdly, the images used to illustrate the different styles may have affected how people perceived them. Given its abstract nature, people may have over-fitted their preference regarding certain element styles and, therefore, assess their choice based on one particular experience instead of assuming a general scenario. Further, the design guidelines assume that the personality of users must be known beforehand. Although some studies have already been able to predict personality characteristics without questionnaires [42], further research is needed. Finally, the design guidelines were not validated. Future studies should include a validation of the guidelines in specific design contexts to understand how they can be applied to develop better user interfaces in practice.

VI. Conclusion

Our objective was to assess how personality variables model user preferences. We focused on the FFM to represent people and used the NEO PI-R to model their personality variables. Moreover, we addressed the most used GUI elements of the state-of-the-art and based their style variations on past research. Our approaches aggregated users based on their personality variables to then extract design preferences from various personality profiles. On the basis of an association rules technique, results showed that different personality profiles have distinct preferences for certain GUI element styles. Notably, although our objective is not to validate the personality profiling, we were able to identify the design preferences of three different personality profiles that are well-suited to separate the population according to the five personality traits of the FFM. Additionally, we identified which features are independently modelled by user preferences.

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