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Incorporating personality in user interface design: A review

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ABSTRACT

A current topic of Human-Computer Interaction focuses on understanding and assessing user-centered design taking into account certain psychological factors related to users' thought processes, feelings and behavior into account. In particular, personality is an idiosyncratic psychological construct that captures many of such aspects from a user. It allows designers to provide a better user experience by adapting a user interface to individual characteristics. This review presents the impact of design and aesthetics on user preferences, namely considering whether certain personality traits have a preference for specific interface design features. This review also discusses the implications of personality-based user interface design, before moving on to the presentation of several research projects focused on adapted design for personality types. Finally, the review highlights trends and future directions in this domain, with particular emphasis on brain-computer interfaces.

1. Introduction

A current topic in the field of Human-Computer Interaction (HCI) focuses on understanding and assessing user-centered design, taking certain psychological factors related to users' thought processes, feelings and behavior into account (Arora and Mahajan, 2016; Deaudelin et al., 2003; Farzan et al., 2011). According to Fuchs-Frothnhofen et al. (1996), "an important aspect of human-centered system design is cognitive compatibility, which means that the structure of the human-machine interface of the computer should match the cognitive styles of the users." Psychology has been applied to HCI research in recent years (Fatahi et al., 2016; Tlili et al. 2016; Alves et al., 2018) to inform design choices and understand differences in how individuals use technology. It enables researchers to arrive at conclusions regarding design effectiveness, since successful technology development requires input from a representative set of potential users and, more precisely, the range of differences among individuals may influence technology. Some factors may include age, gender, job duties, language, culture and fundamental idiosyncratic attributes, such as personality and motivation.

With the inclusion of these factors, developers can take consumers' expectations from providers across a broad range of fields into consideration. In this review, we focus on how personality can be applied to technologies to accommodate the needs of diverse users and sustain user interest over time, since the customization of user interfaces to match personality types may lead to success (Tan and Lo, 1991). Personality is defined as the set of habitual behaviors, cognitive and emotional patterns that evolve from biological and environmental factors (Corr and Matthews, 2009). Several studies have shown that personality is correlated with job success (Barrick and Mount, 1991; Judge et al., 2006; Tett et al., 1991), attractiveness (Byrne et al., 1967), marital satisfaction (Lowell Kelly and J. Conley, 1987) and happiness (Ozer and Benet, 2006). According to Viveros et al. (2014), personality can influence how users perceive the design to be efficient. Moreover, personality has been found to have an impact on the ways in which users use technology (Kim et al., 2013a; Kosinski et al., 2014; Nov et al., 2013) and on people's acceptance of technologies (Devaraj et al., 2008; Svendsen et al., 2011).

Although it is difficult to define personality, several models have been proposed to capture its dimensions. For example, the Five-Factor Model (FFM) (McCrae and John, 1992) is a personality model that assesses personality traits and its facets, and this model has been studied within the context of technology (Barnett et al., 2015). Another important personality model is the Locus of Control (LoC) (Lefcourt, 2014), which has been studied to understand users' judgments of useful experiences (Jang et al., 2016). Therefore, design researchers should aim for cognitive compatibility, enabling the structure of the human-machine interface to match the cognitive style of the user (Fuchs-Frothnhofen et al., 1996). Even though there are multiple guidelines for different products and platforms (Apple, 2018; Brown, 1988; Marcus, 1992; Nielsen and Molich, 1990; Norman, 1983; Smith and Mosier, 1986), it has been argued that only a few adequately show

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the reasoning behind them (Johnson, 2013), and that none of them include specific guidelines for different personality types.

One of the most comprehensive definitions of design has been synthesized by Ralph and Wand as "(...) a process, executed by an agent, for the purpose of generating a specification of an object based on: the environment in which the object will exist, the goals ascribed to the object, the desired structural and behavioral properties of the object (requirements), a given set of component types (primitives), and constraints that limit the acceptable solutions" (Ralph and Wand, 2009). Within the scope of this definition, interactions with the object (an interface) appear to be omitted. If we consider users as a second object (designed by an intangible process, existing in the environment and exhibiting its own set of constraints and primitives), their personality traits and facets could be seen as part of that object's design characteristics. Modern design processes consistently refer back to design thinking, a discipline that relies on user empathy to satisfy their needs within the constraints of technological feasibility and valuable business strategies (Brown, 2008). With this definition of design, this process would be ambivalent, satisfying both object requirement and constraints. In this specific design methodology, user empathy is conducted through research and observation, however by incorporating personality profiles, a wider scope of unobserved needs might be able to surface. Personalization is already a well-established strategy that has been proven to increase revenue (Evergage, 2018), and personality adaptability is proving to be another step in this process (Sarsam and Al-Samarraie, 2018a).

Given these prospects, this study is motivated by the potential for the application of user personality as a more natural human-computer interface adaptation measure. Despite not incorporating all the dimensions of a human-computer interaction, we focus on Graphical User Interfaces (GUIs), since they are the means by which the user perceives and interacts with an interface. However, the application of user personality to HCI is limited (Sarsam and Al-Samarraie, 2018b), even though some researchers have addressed small subsets of personality traits. In particular, no facets have been studied, thus neglecting a specific and unique aspect of a broader personality trait that may provide far more detailed insights into the relationship we are addressing.

Additionally, only a small number of interface elements have been studied and only cover a limited variation of styles. Hence, we suggest an in-depth study of personality traits and facets to determine which have an influence on user preferences and which of the latter may give rise to design guidelines. We also propose an approach to the collection of personality traits and their facets based on how personality affects physiological feedback, and, more specifically, how certain personality variables may be extracted from biofeedback signatures. Although the alpha band is the most studied among the brainwaves (Gale, 1983; Klimesch, 1999; Robinson, 2001), the delta and theta bands have also been found to be related to personality traits (Schutter and Knyazev, 2012). Again, as previously mentioned for graphical user interface design, personality facets have not been studied in the biofeedback field, thus leading to a gap in this research area. There are several applications worth exploring for the relationship between personality and biofeedback, such as offering a lighter workload to both the participant and researcher, compared to having the participant fill in a personality questionnaire and the researcher calculating the personality traits.

The paper is organized as follows: In Section 2 we present the methodology used to search for papers to include in our review. Section 3 follows, with a short presentation on the fundamentals of personality and the various models that are used to capture this construct. We then move on to discuss in Section 4 how the user mental model may be incorporated in the design process of an interface and how the aesthetic design can influence user preferences, with a particular focus on user experience. To stress the importance of personality in HCI, Section 5 provides a brief overview of how personality can be incorporated in GUIs, presenting a selection of studies that have designed interfaces to match specific personality types, and examining the influence of different personality variables on those designs. Considering the incorporation of personality in user interface (UI) design, the positive and negative implications that may stem from this integration are discussed in Section 6. Finally, we conclude this review with a discussion on future directions, tackling the limitations of current approaches to the collection of users' personality types, and propose a number of possible solutions, in addition to some prospective research directions.

2. Method

We searched the EBSCO,[1] Pubmed,[2] IEEE Xplore Digital Library,[3] and ACM Digital Library[4] databases by combining different keywords [Adaptable; Adaptation; Adaptive Interfaces; Aesthetic; Agreeableness; Alpha; Beta; Biofeedback; Brainwaves; Classification; Conscientiousness; Cognition; Cognitive Styles; Critical Design; Delta; Design; EEG; Extraversion; Facets; Five-Factor Model; Graphical; GUI; Guidelines; Impact; Implications; Incorporate; Individual Differences; Locus of Control; MBTI; Mental Model; NEO PI-R; Neural Networks; Neuroticism; Openness to Experience; Personality; Personalization; Physiological Computing; Predict; Psychoanalysis; Psychophysiology; Temperament; Theta; Traits; User Interface; User Preferences] in English and with the resource to the Boolean operator "and". We did not apply publication date restrictions. Each database was searched from November 1, 2017 to September 30, 2019. We also read the reference lists of all incoming articles.

In order to select appropriate studies for inclusion in the review, the abstracts of these papers were read. Our criteria identified 294 relevant papers. We included quantitative and qualitative studies focusing on human-computer interaction, specifically GUIs, taking personality traits and their facets into account; predicting personality variables from biofeedback; and the relations among aesthetics, mental models and user preferences. We excluded articles that were not related to our theme, duplicates, and opinion articles. From the 294 papers, we chose a sub-sample of 215 important findings relevant to the incorporation of personality in user interface design.

3. Fundamentals of personality

As one begins to explore personality as a unique characteristic of the individual user and its potential for usability and experience enhancement, one must bear in mind that the human species is exceptionally differentiated. When considering biological differences, one can find variations in gender, age, neurochemistry, body build and many others. Furthermore, there is psychological variation in personality, intelligence, aptitude and emotional regulation, the study of which is the sole focus of Differential Psychology (Revelle et al., 2010).

However, personality as a singular factor has such a strong role in our real world actions, tastes and behaviors (Quercia et al., 2011) that it affects our daily personal and professional judgments and decisions regarding who to befriend, marry, trust, hire or elect as president (Wu et al., 2015). In order to easily classify people based on their personality, we need a model which enables us to define separate groups of different personality types, by applying thresholds to its metrics. There is a broad range of theories and models, each with differing perspectives on particular topics when defining personality constructs (Corr and Matthews, 2009).

Regardless of whether scholars debate over personality being a

[1] https://origin.ebsco.com/products/research-databases/academic-search .
[2] https://www.ncbi.nlm.nih.gov/pubmed/ .
[3] https://ieeexplore.ieee.org/Xplore/home.jsp .
[4] https://dl.acm.org/ .

stable or malleable construct, a whole entity or a connected system of psychological parts, or over it being innate or a product of social experience, one of the theories that has withstood the test of time is the trait theory of personality. Gordon Allport, one of the founding fathers of modern personality psychology, introduced this theory in the late 1930s to offset behaviorist and psychoanalytical views on personality that were popular at the time (Allport, 1937). He first defined personality traits as "generalized and personalized determining tendencies - consistent and stable modes of an individual's adjustment to his environment" (Allport, 1927) and built a vast lexical collection of adjectives that could be used to describe these traits. He then categorized them in a hierarchical structure with three distinct levels: cardinal, central and secondary traits. While central traits were considered to be the building blocks of an individual's personality, which remain consistent regardless of the individual's surrounding environment, he believed in the existence of secondary traits that could only become apparent in specific situations. Cardinal traits were described as rare but rather dominant. If they were ever developed in a later stage in life, they would begin to shape the entire aspect of the individual's behavior, motivation, attitude and even identity.

A number of trait theorists such as Eysenck (1963), Cattell et al. (1970) and Goldberg (1993) developed different personality models that reduced, arranged and categorized the vast collection of traits to identify the minimum required trait dimensions to predict an individual's personality. Eysenck (1963) created the PEN model, which divides personality into three dimensions, namely Psychoticism, Extraversion and Neuroticism. Cattell et al. (1970) used factor analysis from three different data sources that resulted in a model with sixteen different personality factors. Beyond trait theory, other models worthy of mentioning are the Learning Style Inventory (LSI) (Kolb and Kolb, 2013; Kolb, 2014) and the Myers–Briggs Type Indicator (MBTI) (Myers et al., 1998; O'brien et al., 1998). The LSI classifies personality types according to practical learning styles: Conversing, Accommodating, Diverging, and Assimilating. The MBTI is a type-based model, expanding on Carl Jung's theory of personality, which assesses the dichotomies, Extraversion/Introversion, Sensing/Intuition, Thinking/Feeling and Judging/Perceiving. Although it has gained significant popularity since its creation in the 1940s, this article focuses mainly on trait-based theories, as they have proven to be significantly more consistent across years of research, showing the prevalence of five basic trait dimensions. This led to the general acceptance of the FFM (Costa and R. McCrae, 2008; McCrae and John, 1992). Developed over time with the contributions of Digman (2003), Goldberg (1993), McCrae and John (1992), the FFM of personality (also known as the OCEAN model) considers the following fundamental dimensions: Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness (McCrae and John, 1992).

Despite considerable advances in recent years, personality psychology has yet to clearly articulate a comprehensive framework for understanding the whole person. McAdams (2015) views traits as underlying biologically determined dispositions; individual differences are strongly driven by genetic differences, and maturational trends follow a biologically mediated program. Personality is conceived as an individual's unique variation in the general evolutionary design of human nature, expressed as a developing pattern of dispositional traits, characteristic adaptations, and self-defining life narratives, complexly and differentially situated in culture and social context (Mcadams and L. Pals, 2006).

From a perspective that views traits as recurrent styles of self-regulation, DeYoung (2015) argues that the dispositional traits encompassed within the Big Five reflect variations in the parameters of evolved cybernetic mechanisms regarding goal-directed striving. For example, individual differences in Extraversion track variation to the extent by which individuals explore environments in order to approach rewarding goals, whereas Conscientiousness pertains more to the tendency to remain focused on long-term goals without being subject to extraneous distractions. By taking the personality variables of the aforementioned models into account, it is possible to analyze how different personality types prefer certain UI elements and styles. This allows us to tailor the interface to the personality of the user and provide a better user experience, as is discussed in the following section.

4. Aesthetics, mental models and personality

Personalization in HCI aims to improve features of the system itself and user performance. Considering that every individual has heterogeneous profiles, interests, backgrounds and specific needs, it is extremely important for websites, service providers and brands to know the psycho-demographic profiles of their users (Fonseca et al., 2012; Preece et al., 2015). Personalization may affect different aspects of the interaction, and it may address interface, content or process features by customizing them in order to better satisfy users' requirements.

Several researchers have already addressed the specific nature of users' requirements by designing GUIs for target user groups (Bergillos et al., 2017; Mitov et al., 2016; Ploderer et al., 2016; Priyam et al., 2019). In the fields of Science, Technology, Engineering, and Mathematics (STEM), Bergillos et al. (2017) created two GUIs to help undergraduate civil engineering students deal with engineering problems, and to solve the numerical methods usually applied to design maritime works without a simplification. Results showed that students were strongly motivated to solve practical engineering problems, and this motivation resulted in an improvement of their background, skills and marks (Bergillos et al., 2017). Priyam et al. (2019) designed Sequenceserver, which provides multiple highly visual and text-based output options that are hierarchically structured and mimic the requirements and work patterns of biology researchers in DNA sequencing.

Finally, Ploderer et al. (2016) focused on how therapists use upper limb movement information visualized on a dashboard to support the rehabilitation process. Their GUI presented an overview as opposed to being able to see detailed information, since therapists expressed that they would have no time to analyze individual movements or outliers in the data (Ploderer et al., 2016).

In the field of business management, Mitov et al. (2016) studied twelve GUIs of integrated software systems. Based on their analysis, the authors produced a model to improve GUI design, which includes avoiding the overlapping screens effect, using the entire working area of the screen effectively, and minimizing the use of icons. Moreover, it uses gradient mechanisms for the color design of screen forms and typography to display important information. An interesting factor to take into consideration is how these types of groups usually have typical personality demographics. For example, students with a strong investigative personality are more likely to enroll in STEM majors, while those with a strong artistic personality or enterprising personality are less likely to do so (Chen and Simpson, 2015). We may, therefore, expect these students to prefer information to be displayed hierarchically and with highly visual overviews, while students from business management, who are more likely to be extravert and perceivers (Potgieter and Coetzee, 2013), would probably prefer the minimal use of icons and gradient mechanisms for the color design of screen forms.

At a broader level, websites currently personalize their content, optimize their marketing strategies, and tailor their search results using audience profiles encompassing demographic features, such as age, gender and income (Hu et al., 2007). These user profiles can be extracted from various platforms that keep track of users' actions. As an example, Kosinski et al. (2014) showed how to predict a user's personality profile based on users' Facebook profile features and website choices. This technique may be applied to attract larger audiences with a distinct personality profile, and expand the understanding companies have of their users, thus improving the quality of service and user experience (Kosinski et al., 2014). One practical example is personality-based recommendation systems. Tkalcic et al. (2011) proposed including personality information to enhance the nearest neighbor measure when dealing with the cold-start problem. Moreover, Hu and Pu (2009) found that these types of systems are more effective in decreasing cognitive effort and increasing users' loyalty towards the system compared to other systems that do not consider personality information. Thus, incorporating user context in the design process of a product is an important milestone in the development phase. In particular, personality shapes the way people interact and perceive the outer world, which has an impact on how we create our mental model. Mental models have been described as representations of the physical world (Johnson-Laird, 1983), constructs that can explain human behavior (Wickens et al., 2015), and internal mechanisms allowing users to understand, explain, operate and predict the states of systems (Hanisch et al., 1991). Moreover, the mental model can be used to determine user preferences. The following sections discuss how researchers can integrate the mental model in the design process and assess user preferences with aesthetic design.

4.1. Incorporating the mental model in the design process

According to some researchers, design is about user experience rather than the creation of products (Buxton, 2005). In fact, the rapid adoption of HCI research by way of widely used guidelines has enabled designers to achieve their goals. One of the most important factors when designing an interface is matching users' mental models (Berrais, 1997; McTear, 2000; Sifaqui, 1999), since this enables designers to capture many features of the user and develop products tailored to his/her personality. In order to capture the mental model, firstly we have to define the users who will use the system. After they have been identified, we can define their requirements, which should consider the type of user, the tasks they perform, and the social and dynamic environment in which they interact (Jones et al., 1993).

Nonetheless, it is hard for designers to create a unified user mental model that takes all user requirements into account. Users think and process information differently, even if they are in the same field, which often leads to incomplete, inaccurate, and inconsistent mental models among individuals addressing the same subject (Sax and Clack, 2015). For instance, in the field of mobile shopping, Turumugon et al. (2018) used the mental model theory (Johnson-Laird et al., 1998), focusing on "Localization" and a content analysis method to incorporate mental models in their design process. Results showed that distinct genders led to a different mental model on the user interface for a mobile shopping app (Turumugon et al., 2018).

Recent research has focused on how different mental models are created to bridge this gap and incorporated in the design process. Revell and Stanton (2017) examined whether different design features in the context of a heating system could elicit changes in mental models. Results showed that design features contributed to differences in user mental models, intentional behavior and goal achievement. In particular, the authors conclude that a mental model approach to design can be used as a means to empower users to better fulfill their goals while interacting with the heating system (Revell and Stanton, 2017).

More recently, Ricketts and Lockton (2019) developed a kit with visual prostheses to make abstracted model landscapes that on some level represent or translate mental models of concepts. One of the most interesting applications of this kit is to explore which elements of mental models are or are not shared among group members. Once surfaced, designers can further integrate users in the design process and discuss these factors in order to gain useful insights into users' understanding constructs (Ricketts and Lockton, 2019).

Another interesting approach is a hybrid mental model which combines both human and artificial intelligence models. Du et al. (2018) focused on autonomous driving and developed a hybrid model that analyzes both user experience and interaction design influenced by human intelligence and artificial intelligence in the traditional mode, and the autonomous vehicle mode.

Finally, it is also possible to create adaptive interfaces that take the mental model of the user into account and address different individuals by providing distinct representations of information depending on their functional and psychological features. The common goal of all these approaches is to improve usability, however usability may not be one of the main focuses nowadays. Technology is now integrated in the daily lives of young adults, whether by means of digital media, video games or television (Glore, 2010). This process has led to a recent shift from a functional vision – computers as tools for cognition – towards an experiential vision – interactive systems as a medium for emotions, scalability and pleasure. Therefore, usability may no longer be the main determinant of user satisfaction (De Angeli et al., 2002; Hassenzahl, 2005; Tractinsky et al., 2000). The focus is now centered on the interface "look and feel", its potential to engage users in fulfilling interaction and creating affective responses, e.g. navigating on a "beautiful" website has been shown to be intrinsically connected to user satisfaction in several studies (Buxton, 2005; Lindgaard and Dudek, 2003; Tractinsky and Zmiri, 2006). In other words, aesthetics is now an important concept in order to understand the function of visual media in technology culture.

4.2. Aesthetic design and user preferences

Although there are various definitions for aesthetics (Hassenzahl, 2008; Lavie and Tractinsky, 2004; Lindgaard and Dudek, 2003), researchers agree that the term has something to do with pleasure and harmony that human beings are capable of experiencing. Norman (2004) claims that aesthetic design can have more influence on user preferences than traditional operational usability. In fact, the digital features of aesthetics and design are a method by which elements may be intentionally arranged to appeal to the senses or emotions of the user (David and R. Glore, 2010). If we take a closer look at products nowadays, well-established knowledge in marketing, product design and social psychology influence consumers' attitudes, and are a major determinant of their marketplace success (Bloch, 1995). This success is also related to the halo effect (Nisbett and Wilson, 1977), namely the tendency to assess a situation according to factors that are not at all related. As an example, the effect of beauty transcends the product and influences other judgments, e.g. people associate positive personality traits with attractive individuals (Dion et al., 1972) and they tend to attribute more positive dimensions to individuals in the company of a beautiful friend (Meiners and Sheposh, 1977).

Initial research suggested a correlation between the aesthetic quality of an interface, its perceived usability and overall user satisfaction with the system (Lindgaard, 2007; Lindgaard and Dudek, 2003; Tractinsky et al., 2000). However, Mahlke (2006) found that users preferred a MP3 player skin that was reasonably low in usability but very appealing over another that scored higher on usability but lower on aesthetics. More specifically, this author showed that aesthetics and design have an effect on user satisfaction – a complex construct that includes several measurable concepts and is the completion of the interactive user experience. The author concluded that people are sensitive to perceived usability problems, however they have no impact on the visual appeal, i.e. visual appeal weighs more heavily on preference judgments than usability. Thus, people may be more satisfied with a beautiful product that performs sub-optimally than with a more usable but less appealing product (Mahlke, 2006).

One example of this effect may be found in the reviews of the first iPhone™. While the phone performed in tests with less than optimal performance of the built-in system and phone network, its success was based on the beauty of the design, ease-of-use, intuitive visual interface and sharp graphics (German and Bell, 2007; PCWorldStaff, 2007). Regarding the design of websites, Fogg et al. (2003) found that over 45% of consumers made judgments about the credibility of websites based on site design. Participants paid attention to several design elements such as layout, typography, font size and color scheme. Alsudani and

Casey (2009) also found that students make these judgments about visual stimuli in a very short amount of time. In particular, Robins and Holmes (2008) found that individuals judged the credibility of the content of a website based on its appearance in 3.42 seconds.

More dimensions of the user experience have been studied besides perceived usability. Both perceived usefulness – "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis et al., 1989) – and perceived ease-of-use – "the degree to which using the technology will be free of effort" (Davis et al., 1989) – are also key determinants of individual technology adoption (Davis, 1989; Koufaris, 2002; Lin and Lu, 2000; Shin, 2009). Perceived usefulness has been shown to be an important influencing factor for the intention to use Telecare System with healthcare experts (Vadillo et al., 2017) and to be positively associated with mobile users' satisfaction (Amin et al., 2014; Hsiao et al., 2016). As for perceived ease-of-use, it has been positively associated with students' behavioral intention to accept and use e-learning in Libyan higher education (Elkaseh et al., 2016) and massive open online courses (Joo et al., 2018). Therefore, we consider both these dimensions to be important in user experience evaluation, and, more specifically, in terms of their impact on user preferences. In short, the mental model of the user has a significant effect on his/her preferences. Since personality is deeply incorporated in the mental model of a user, it affects his/her preferences given that personality dimensions change individuals' aesthetics measures[5]. As aforementioned, not only do individuals tend to prefer interfaces that have a better "look and feel" compared to others, their aesthetic taste is closely related to their personality. With this in mind, we believe that if an interface is designed according to user preferences, based on their psychology variables, we expect improved user satisfaction, in addition to more efficient interaction.

Several researchers have already tried to assess the inclusion of personality in UI design. The following section discusses how to integrate personality in UIs, by specifically focusing on GUI design with several examples of studies that have designed interfaces to match different personality types from the distinct personality constructs[6] of users.

5. Personality-based user interface design

Considering how different personality traits can have an impact on GUI design, several studies (Al-Samarraie et al., 2016; Gajos and Chauncey, 2017; Heinström et al., 2014) have shown how personality traits influence information-seeking. In particular, Kostov and Fukuda (2001) found that users performed better when they handled an interface that matched their personality type. This is an important factor to consider, since people commonly rely on their mental models to guide them through different mental and physical activities that require predictable mental representations of the information objects and different domains of knowledge (Marchionini, 1997). As an example, Al-Samarraie et al. (2016) studied three different task types: factual, exploratory and interpretive. In the factual task, the authors found that individuals high in Conscientiousness appeared to scan and decide on information faster than individuals high in other traits, thus reasoning that participants high in Conscientiousness engage in some kind of mental reflection (Mortimer, 1995). These authors also found that individuals high in Agreeableness processed eye-exploratory tasks with fewer fixations and longer durations to retrieve information, while individuals high in Extraversion required shorter durations to do so. Lastly, in the interpretive task, participants high in Conscientiousness and those high in Extraversion showed similar tendencies in their use of information-seeking strategies, such as scan-info-recognize, a strategy previously reported in research using interpretive tasks (Kim, 2008). These differences between the task types allow us to explore how we should present variations of interface features to cover the possible personality types.

In spite of these differences among personality types, all of them have some important general principles in common that already provide guidance in designing usable and engaging interfaces, namely clarity and consistency (Winograd, 1996). Regarding GUI, clarity and consistency include elements such as consistent menu names, consistent box layouts and other visual cues that make sense. Moreover, consistency implies design options always being performed in the same way. This kind of clarity in appearance and behavior allows for consistent expectations in the user, enabling him/her to work efficiently and to approach new tasks with the interface without having to expend mental energy to re-learn how the interface will behave. However, as explained in the previous section, consistency also means consistency in users' expectations (Tognazzini, 1992).

5.1. Integration of personality in user interfaces

Psychologists have studied how consistency in others helps people to predict what will happen when they engage with others (Fiske and Taylor, 2013), how it makes it easier to remember a person accurately (Cantor and Mischel, 1979), and, in most cases, how it lightens the cognitive load (Fiske and Taylor, 2013). Nevertheless, since people bring their own cultural, psycho and physiological context to interact with the interface (Norman, 2013), the designer has to take more than the internal consistency of the GUI into account. Designers should work with the set of expectations that people bring to their interaction with the artifact, creating intuitive "affordances" (Norman, 2013). Nonetheless, to have an accurate representation of how personality affects interpersonal interaction, designers must consider whether people select and prefer elements based on the match or mismatch to their own personality. There are two opposite hypotheses: the similarity-attraction hypothesis and the complementary principle. Similarity-attraction supports that people seek out and prefer to interact with others who are similar to themselves. Therefore, people will prefer those with similar personalities to their own (Nass et al., 1995). On the contrary, complementarity holds that people tend to behave in complementary ways in their interpersonal interactions, and will seek out and prefer others that elicit complementary behavior from them. The idea is that people will pursue a balance in the power relations in an interaction, i.e. one person will be more dominant than the other, otherwise there is imbalance and tension. Both hypotheses have experimental confirmation in the literature, yet only the similarity-attraction has been studied in the field of HCI (Moon and Nass, 1996).

As far as Extraversion is concerned, several studies (Isbister and Nass, 2000; Nass and Lee, 2001; 2000) have examined how it influences computer interface users' preferences in various circumstances. More precisely, individuals were presented computer-animated characters and text-to-speech interfaces that either mimicked introvert or extravert human behavior. The objective was to identify whether individuals preferred a character that was similar to them. Nass et al. (1995) discerned dominant and submissive individuals and matched them with dominant and submissive computers. The computer's personality was created by manipulating the computer's verbal style, confidence level, name and choice of font. Results show that participants correctly identified dominant and submissive computers. Moreover, they preferred to interact with a computer that was similar to themselves and found the interaction more fun, useful and satisfying (Nass et al., 1995). Based on these human-computer findings, we believe that a similarity-

[5] Personality has been found to be correlated with music (Cattell and Saunders, 1954; Dollinger, 1993), painting (Feist and R. Brady, 2004; Rawlings et al., 2000), entertainment (Schierman and Rowland, 1985), and video and film (Zuckerman and Litle, 1986) preferences, aesthetic activities (Mcmanus and Furnham, 2006) and creativity (Barron and Harrington, 2003)

[6] There are already studies mapping different personality models, such as the FFM, the Hans Eysenck's Model and the MBTI (Acton, 2001; Furnham, 1996; McCrae and Costa, 1989).

attraction effect should be pursued in the development of interfaces capable of adapting to the personality style of the user. Adaptability can be created with two different alternatives. There is a debate (Shneiderman and Maes, 1997) in the HCI community between those who promote "comprehensible, predictable, and controlled interfaces that give users the sense of power, mastery, control and accomplishment" (Shneiderman and Maes, 1997) – adaptable interfaces – and those who "adapt their layout and elements to the needs of the user or context" (Schneider-Hufschmidt et al., 1993) – adaptive interfaces. While adaptable interfaces keep the user in control by providing mechanisms to personalize according to user needs (Fischer, 1993), adaptive design relies on artificial intelligence to automatically adjust in a way that is expected to better suit the needs of each individual user. Moreover, an adaptive mechanism provides more efficient communication between the interface and the user, increases overall performance and satisfaction, and minimizes the frustration experienced by users (Greenberg and Witten, 1985).

5.2. Graphical user interface adaptation

In the case of GUIs, several elements may be adapted, e.g. structure (Chae and Kim, 2004), navigation (Fleming and Koman, 1998), layout (Basu, 2013), font style attributes (Evett and Brown, 2005), font size (Lee et al., 2008), buttons (Kane et al., 2008), color (Reinecke and Bernstein, 2013), list (Ribeiro and Carvalhais, 2012), information density (Reinecke and Bernstein, 2013), support (Reinecke and Bernstein, 2013), and alignment (GeiBler et al., 1999). The following studies address subsets of this list.

In their examination of the research on cognitive styles, Mampadi et al. (2011) created Adaptive Hypermedia Learning Systems that varied in structure, buttons and layouts according to the Holistic/Serialist dimension, as identified by Pask (1976). In this dichotomy, an individual's approaches to learning a range of complex academic topics is monitored by overseeing his/her path between the related subjects of said topics. Holistic learners prefer breadth-first paths, make global connections and prefer non-linear navigation. Serialists thrive on more sequential and structured navigation of the topic, and tend towards depth-first paths. In this between-subjects study, learners who used adaptive systems displayed improved learning performance and perception of structure clarity and logical sequence in the system compared to those who used an ordinary interface with dual interface components to suit both Holistic and Serialist students. Focusing on the more consensual trait theories, Karsvall (2002) addressed the Extraversion trait specifically. The author developed three alternative interfaces (introvert, extravert and neutral), as depicted in Fig. 1. The *neutral* design is in-between when compared to the other two designs. It displays variations of saturated hues in greens, blues, reds, black, and white, and uses both rounded and squared shapes. The *extravert* and *introvert* prototypes were simplified by firstly reducing the number of hues and increasing brightness levels. The *extravert* prototype has higher contrasts between interactive elements and more saturated red, yellow, and blue hues. The background was turned from blue-green hues to red-orange, and windows were given bolder lines and all squared shapes. It also provides visual clues to users to actively direct them in the interaction, e.g. by darkened inactive areas. The *introvert* design was accordingly given lower contrasts and desaturated colors in white, green and gray hues. It has a white-green background and thinner rounded frames, and directs users to a lesser extent, through the use of fewer and subtler visual keys (Karsvall, 2002).

With regard to MBTI dichotomies, Su et al. (2013) developed two interface designs focusing on the Sensing/Intuition and Thinking/Feeling pairs. Fig. 2 shows both interfaces designed for sensing-thinking (ST) and intuitive-thinking (NT) individuals. Since sensing types prefer to see the differences between concepts and to disassociate processes from goals, the authors designed a scrolling interface with a global view to enable sensing types to establish a complete mental model. In contrast, intuitive people connect processes with goals and see the integration. Therefore, the authors created a switching interface to decrease unnecessary searching. As for the display of information alongside, intuitive types have a red color warning as they prefer to view things globally and may not detect small changes. Finally, sensing types learn experimentally, therefore the user prompt area displays possible reasons and solutions for a problem. Conversely, the user prompt area for intuitives shows possible solutions since they learn from theory and may over-think when they are handling a situation. Results showed that reaction times were reduced in some critical situations and the number of mistakes was reduced (Su et al., 2013).

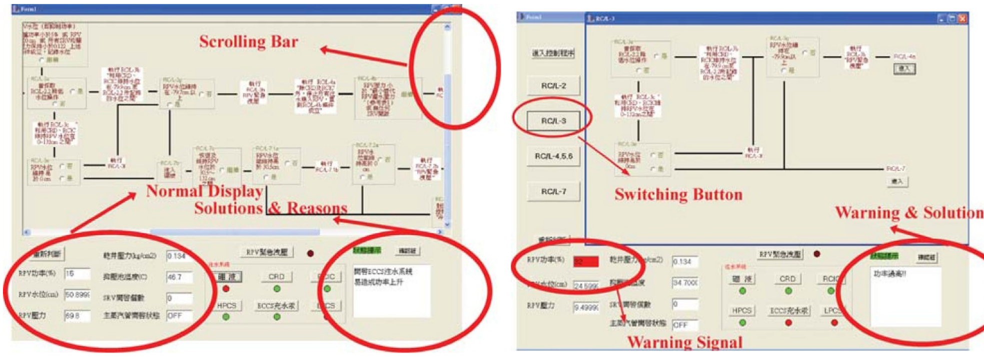
In the education field, Abrahamian et al. (2004) found that interfaces designed based on students' Extraversion/Introversion and Sensing/Intuition traits from the MBTI depicts two of the four interface examples where students had to learn about binary trees. The most notable difference is that while introverted intuitive types are able to understand concepts that are presented in an implicit non-structured manner, extraverted intuitives prefer a well-structured display of information. Kim et al. (2013b) also studied Extraversion/Introversion using interfaces to offer depth-first or breadth-first structured learning. The depth-first strategy was designed for the introverts, since it employs a bottom-up approach, starting with low-level details and then proceeding to teach more abstract concepts. In comparison, the breadth-first approach begins by establishing an overview of the concepts before

(a) The introvert interface.

(b) The extravert interface.

(c) The neutral interface.

Fig. 1. Three different interface designs of Karsvall (2002).



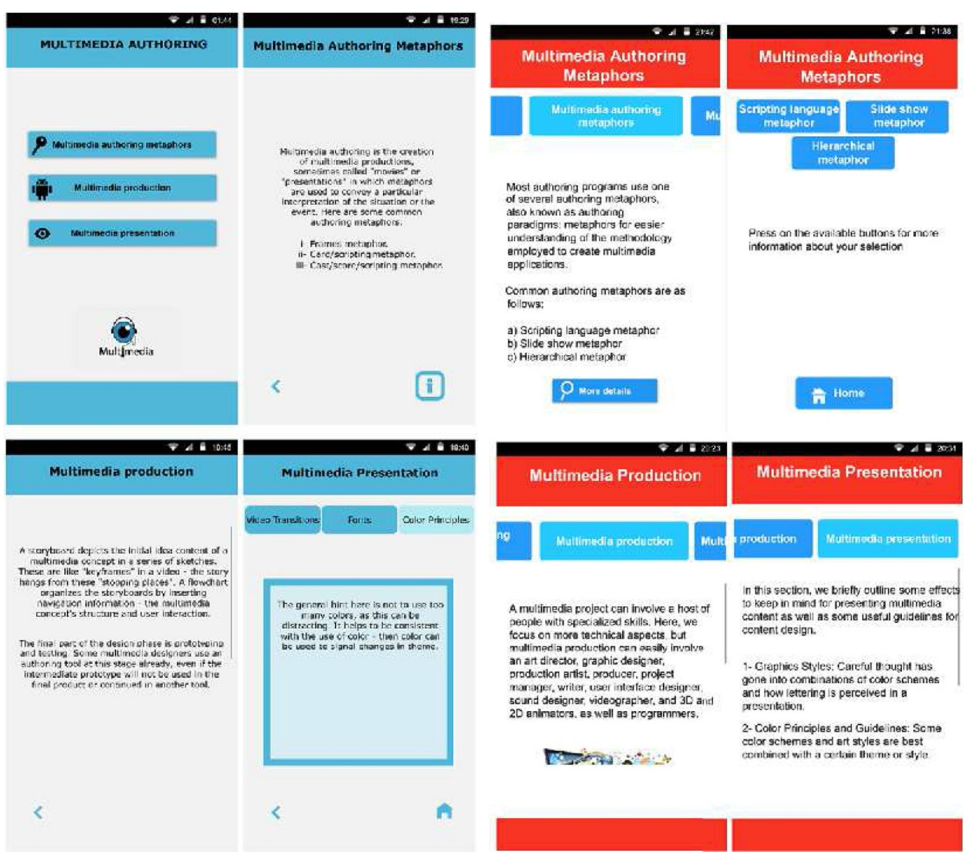
(a) Interface for sensing type. (b) Interface for intuitive type.

Fig. 2. Two different interface designs of Su et al. (2013).

moving on to further details, since extravert learners prefer the big picture before addressing the detailed content (Abrahamian et al., 2004).

Lawrence and Charles Selvaraj (2013) also found that personality based on the Eysenck Personality Inventory questionnaire can affect learners' preferred design parameters of a learning interface. In particular, some learners found a designed interface with a particular color and font more efficient and easier for the recollection of information than others. For example, extravert learners can easily recollect information presented in blue with a "Times" font style, while neurotic learners can easily recollect information presented in green with a "Times" font style (Lawrence and Charles Selvaraj, 2013). More recently, Sarsam and Al-Samarraie (2018b) created two different trait-based interfaces, one addressing Neuroticism and the other Extraversion and Conscientiousness, as depicted in Fig. 3. As may be observed, there are several differences between both prototypes, e.g. font size, button placement, icon usage, and theme.

Condenço et al. (2018) studied whether there is a relationship between color and the personality trait, Extraversion. Although they did not achieve statistically significant results, they found trends in the influence of personality on color preference. In particular, they observed that extraverts and ambiverts like a larger amount of colors than introverts, and that extraverts tend to have a higher score in likeness of a color compared to introverts. Regarding different colors, the authors found that assertiveness was positively correlated with a person liking white and his/her degree of activity was negatively correlated with the



(a) Portion of a neuroticism-based user interface. (b) Portion of a extraversion-conscientiousness-based user interface.

Fig. 3. Two different interface designs of Sarsam and Al-Samarraie (2018b).

extent to which the person liked black. Moreover, extraverts tend to prefer orange and grey, which are the least liked colors of introverts, and the contrary happens with brown. Nevertheless, cyan is the most liked color by introverts, and is not disliked by extraverts. The same applies to black, which is the second favorite color of extraverts and introverts do not dislike it either. Therefore, there is no strong preference in colors which states that people with opposite scores in Extraversion like and dislike opposite colors. However, we can deduce that introverts and extraverts do not share the same favorite colors and that their favorite colors (cyan for introverts and orange for extraverts) are opposite on the color wheel (Condenço et al., 2018)).

In a comparable study, we looked into the relationship between personality and decision-making competences. This study was conducted with the objective of creating design guidelines for interfaces that could adapt to cognitive biases in a way that rewarded users' intuition by turning their mistakes into positive outcomes. Having found positive correlations between facets of Conscientiousness and Openness to Experience and resistance to the sunk cost fallacy, we attempted to create a set of guidelines on how to design for individuals with susceptibility to this bias. We created two separate designs: a standard control interface and a susceptibility-adapted interface. Both interfaces emulated an academic learning platform where students could access lessons to practice for tests and improve their grades. Each lesson had its content separated into modules. When conceptualizing the learning environment, students were likely to opt for one of three learning strategies: breadth-first (exploring as many modules possible), depth-first (completing as many modules possible) or mixed. The tests students had to complete were designed to favor a breadth-first learning strategy.

We used GUI elements, such as scoreboards and bonus systems, to create a choice architecture to guarantee a controlled decision-making environment. Bonus systems rewarded module completion and were created to encourage more impulsive individuals to maintain focus. The scoreboard added a concept of value that enabled more practical individuals to become aware of their progress. These particular elements trigger the sunk cost fallacy, compelling students to subconsciously opt for a depth-first strategy. Despite promoting a sub-optimal learning strategy, the underlying hypothesis for these design choices defended that allowing users to engage in their more intuitive heuristics (biased or not) within a controlled environment guaranteed increased user performance.

Results suggested that, given an initial baseline score, students with high susceptibility to the sunk cost fallacy tended to have a slightly higher improvement rate after practicing with the adapted design when compared to the results after practicing with a standard platform design. Thus, evidence showed that adapting to less open to experience and conscientious individuals could enhance their learning experiences. As may be observed, the potential of GUI design based on personal characteristics has been studied by customizing the display to meet certain demands (Karanam et al., 2014), but this has only been studied by a few researchers. Table 1 pinpoints the personality traits that influenced some interface features. Of the contributors, only Lawrence and Charles Selvaraj (2013) provide design guidelines for extravert and neurotic learners in terms of Font Family and Theme (Text Color). Moreover, only a subset of the aforementioned interface elements have been studied and not all of them have defined design guidelines. Thus, there is still limited evidence of the usefulness of designing GUIs based on individuals' personality traits and a solid set of design guidelines for these psychological variables.

Nonetheless, designing interfaces based on personality has several implications. So far, we have delved into modern views on graphical interface design and personalization, building an argument for the importance of more accurate user models and individuated user experiences. We believe that personality-adapted interfaces can have social effects. Under the hypothesis that personality-based designs become mainstream, the need to look into the technological and humanistic implications of such a feat is imperative. The next section considers how personality and adaptability would affect interface design as a process, and the long term effects of such interfaces on their users and society as a whole.

6. Implications of personality-based user interface design

Digital-era technology has already caused an unprecedented impact on humanity (Adele and Brangier, 2013). It has influenced the way we learn (Hsin et al., 2014), the way we communicate (Misra et al., 2016), and even the way we think (Loh and Kanai, 2015). The nature of this influence is widely recognized and has been proposed as the sole subject of the blooming field of digital anthropology – the study of the mutual relations between humans and the computer-generated world (Horst and Miller, 2013; Libin and Libin, 2005). Seeking to address the role of psychological culture in human-computer interaction and its associated moral dilemmas, Libin and Renata's proposal reflects the need to understand the individual differences in people's interaction with the digital world as the very basis of the field's endeavor (Libin and Libin, 2005).

Moreover, it has been argued that technology has had an active role in human evolution (Osiurak et al., 2018). One could say the methods used to design tech today retroactively design the humans of tomorrow. Lumbreras et al. (2015) argued that if the manner in which one thinks is a necessary component of one's personality, any design that is adaptive to personality will have a consequent impact on cognitive processes. The Internet alone has been the propeller of drastic changes in our cognitive landscape (Loh and Kanai, 2015). Prensky was one of the first to comment on how his students' profiles had shifted throughout his teaching career – "Our students have changed radically. Today's students are no longer the people our educational system was designed to teach." (Prensky, 2001). To fully describe this dichotomy, he created the terms "digital native" - referring to those born into our modern digital environment, never having to experience a world without digital media - and "digital immigrant" - referring to those who adopted the use of ubiquitous digital media later in life. The cognitive profiles of

Table 1
Collection of examples of interface features influenced by personality traits.

Feature	Personality Trait	Contributors
Buttons	Conscientiousness, Extraversion, Neuroticism	Sarsam and Al-Samarraie (2018b)
Element Style	Extraversion	Karsvall (2002)
Font Family	Extraversion, Neuroticism	Lawrence and Charles Selvaraj (2013)
Font Size	Conscientiousness, Extraversion, Neuroticism	Sarsam and Al-Samarraie (2018b)
Icons	Conscientiousness, Extraversion, Neuroticism	Sarsam and Al-Samarraie (2018b)
Information Density	Extraversion, Sensing/Intuition, Thinking/Feeling	Abrahamian et al. (2004); Su et al. (2013)
Menu Structure	Conscientiousness, Extraversion, Neuroticism	Kim et al. (2013b); Sarsam and Al-Samarraie (2018b)
Navigation	Sensing/Intuition, Thinking/Feeling	Su et al. (2013)
Theme	Conscientiousness, Extraversion, Neuroticism	Condenço et al. (2018); Karsvall (2002); Lawrence and Charles Selvaraj (2013); Sarsam and Al-Samarraie (2018b)

both groups differed quite drastically, and consistently, from the way the brain manages memory for its information processing strategies (Carr, 2011). The moral nature of this change cannot, however, be linearly determined as good or bad for the human species.

Up to this point, this review has only focused on the creation of products that match user preferences to have a greater appeal in the market. However, this direction has several sociocultural implications that must be addressed through Critical Design (CD). CD looks beyond concerns about usability and professional support tools, to steadily increase the focus on issues such as user experience, social justice and activism, and values-oriented design. More specifically, CD is a response to *mainstream design*, which is a slave to the market. One example is the design line of phone chargers: the development of phone chargers focuses solely on the products and, when the phone becomes obsolete, so does the charger. Therefore, *mainstream design* does not focus on the functional design, it tries to sell the product taking all local price, time, balance and resources constraints, among others, into account.

In order to critically analyze our work, we have paid particular attention to the *progress dogma* oblique constraint[7] presented by Auger et al. (2017), since up to now we have assumed that cognitive style-based adaptability will provide only positive outcomes. *Progress dogma* addresses the belief that technology is simply good and that, when we put it in the world, it makes the world a better place. While some technologies, such as the steam engine and the mechanical typewriter, have positively altered the course of contemporary civilization, others are more ambivalent. One example is nuclear power. On the one hand, it is recognized as a practical, inexpensive and clean (emission-free) source of energy, while on the other, it can be extremely dangerous in the wrong hands, or if there is any disruption in the nuclear reactor. This is the main point of this constraint: designers should always be encouraged to extrapolate what could go wrong with the emergence of a new technology. Thus, *progress dogma* tries to add a space for discussion on the negative impact of a design before the product is made available to a wider public. In the end, it creates a layer of responsibility and allows designers to test and act accordingly on their products, rather than dealing with problems that arise from launching the product.

In this case, we must address both the positive and negative sides of creating interfaces that adapt to the cognitive style. Artificial worlds and agents already come with certain moral dilemmas, such as defining the line between virtual presence and reality absence, using digital products to cope with hardship versus escaping from the reality of said hardship, and keeping technology as a human-supportive medium instead of a substitutive one (Libin and Libin, 2005). Hence, there is an added layer of implications when we discuss the hypothetical side of personality adapted interfaces. As already mentioned, we expect them to enable users to be more efficient and satisfied when they perform certain tasks, given that the interface will be similar to their preferences based on their personality. We may also expect individuals who continuously interact with agents that have a similar personality to lose their sensitivity to interact with opposite personality traits, since they use their dominant traits more often. Moreover, if we continuously shape the interactions to our image, users may no longer feel the need to improve, as the level of discomfort will progressively descend. Thus, the individual will stagnate and may potentially lose cognitive power, which can be explained by the means and ends oblique constraint (Auger et al., 2017).

This constraint focuses on how technology substitutes our senses and turns us into spectators. When we deal with technology, we should make conscious decisions and have an active role in the interaction, so that we can have an understanding of how the system works. Therefore, it is important to differentiate things that are inseparable from the environment and devices that hide in the environment. Nevertheless, we believe that, although we wish to provide the most comprehensive personality representation, there will always exist a residual discomfort in the user as we are unable to capture every single aspect of a complex structure such as personality (Johnson, 1997). Thus, we assume that the result of incorporating personality in the design of a product is a responsible artifact that integrates the commercial market while taking a reasonable product evolution into account.

7. Future directions

As previously described, there is no set of complete UI design guidelines to explain preferences regarding certain interface design features. The studies presented in Section 5 address only interfaces designed for specific combinations of personality traits, varying a small subset of design elements. For instance, we found no interface adaptation study addressing Openness to Experience, Conscientiousness and Agreeableness, and, in particular, no personality facets were studied, which are a specific and unique aspect of a broader personality trait that may explain intrinsic differences between personality types. The lack of research in this area should drive future studies to further investigate how each personality trait and facet affect the way users interact with interfaces, and to ascertain whether such physiological variables have any preferences for specific design elements. Results will allow for the creation of guidelines for the design of personalized interfaces that depend on the psychological variables of the user. There are several applications for these results. One interesting commercial application of our results in the future is their integration in IBM's Watson Personality Insights project (IBM, 2018). Since Watson Personality Insights easily collects information on personality traits, our results may improve IBM's software by adapting it to the user's personality and, thus, provide a better user experience. Another application is to help designers identify the audiences their GUIs will appeal to or to understand whether they are developing their UIs for the correct target audience, by following our design guidelines.

Another interesting topic is related to how all the aforementioned approaches require users to fill in questionnaires in order to determine their cognitive styles. It is our aim to extend their detection without user conscious input. One way to do so is by using the biofeedback of the user, such as capturing the brain activity with a Bitalino[8] (see Fig. 4). Electroencephalography (EEG) allows researchers to observe the human brain's oscillatory phenomenon. According to the brain area, the experimental procedure, and the associated behavior, these rhythms are generally confined within a frequency band (Traub et al., 1999) and arise through the synchronization of neurons (Maex and De Schutter, 2003). According to Chi et al. (2005), it is reasonable to assume that features of the intrinsic oscillatory phenomena are associated with the structures and functions of the corresponding neural generators. Moreover, the authors believe that different features in EEG bands may predict individual differences in brain function and structures. Nonetheless, it is also possible that features in this frequency domain do not represent individual differences reliably, due to the highly complex nature of the brain network. Therefore, researchers need to study the relationship between EEG and personality in addition to its reliability.

As far as brainwaves are concerned, the alpha band brainwave is the most studied in relation to personality (Gale, 1983; Klimesch, 1999; Robinson, 2001). Broadhurst and Glass (1969) showed that introverts have both larger alpha amplitudes and a higher percentage of alpha waves than extraverts. Moreover, Johannisson (2016) found that alpha waves from different individuals can be categorized into three main

[7] An oblique constraint is a type of constraint that keeps us "to a limited path or trajectory, and in some cases condemns us to repeating the same mistakes over and over again" (Auger et al., 2017).

[8] www.bitalino.com/en/hardware.

Fig. 4. User from Alves et al. (2017) with a front head sensors of Bitalino to measure brain activity.

groups where the frequencies are around 8, 10, and 12 Hz. In particular, the middle group appears to have a bimodal distribution, such that subdivision produces a total of four alpha groups. These groups comprise four personality profiles that are similar to the four classic temperaments[9]

Although the alpha band is the most studied brainwave length, other bands have also been correlated with certain personality traits. For instance, researchers have found that mid-frontal theta power covaries with Extraversion (Knyazev, 2009; Wacker et al., 2010). Knyazev (2006) studied the differences between overcontrollers, undercontrollers and resilients (Herzberg and Roth, 2006). The author found that overcontrolled individuals have a relative prevalence of alpha oscillations, particularly in the parietal zone, while undercontrolled individuals have a relative prevalence of delta oscillations, mostly in the frontal region, and resilients are characterized by a balanced activity of alpha and delta oscillations. Additionally, negative relationships between power in lower (delta and theta) and higher (alpha and beta) frequency bands were also related to individual differences (Schutter and Knyazev, 2012).

All these findings lead us to believe that it is important to further study how personality traits and facets are represented in brainwaves, and whether they have a specific signature that can be used for automatic UI adaptation. There are many possibilities for using this adaptive UI. For example, the constant rise of ubiquitous computing promises the ability to acquire users' personality profiles by means of a swift technique without conscious input on the part of the user. Imagine how interesting it would be to buy a product that on its first usage could adapt itself to your personality, or for services available to you on the Internet to be all focused on satisfying your specific personality. Those are the kind of possibilities that this technology could offer.

8. Conclusions

From this gathering of research and experiments, it is evident that personality is a differentiating factor when it comes to designing user interfaces. However, the precise mechanisms and groundwork on how and why it is such a differentiator are still being pinned down. As decades of personality researchers did in the past when consolidating major theories on such a complex and dynamic concept, the scientific community should now strive to combine all these findings into a comprehensible and consistent compendium of guidelines to ensure the future of adaptive design initiatives.

These guidelines have several applications. In the industrial field, they may be integrated in IBM's Watson Personality Insights project, since the latter collects information on personality traits from the user, to adapt IBM's software to personality. New software may increase user satisfaction and efficiency in the workplace, besides helping users in the learning process, since it is adapted to how users perceive and create their thought processes. Moreover, a physiological signals-based framework improves the integration of user models with ubiquitous computing. Personality classification, based on biofeedback, dramatically changes the process of collection of personality constructs, since it implicitly acquires the variables without investing time in questionnaires as is the case nowadays. Finally, another application is to provide designers with a tool to identify the audiences their GUIs will appeal to or to understand whether they are correctly developing their GUIs for the target audience by following the design guidelines. With an appropriate interface design, technologies can properly display information to users and efficiently and accurately solicit information from them.

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[9] The four temperament theory suggests that there are four fundamental personality types: sanguine, choleric, melancholic, and phlegmatic (Merenda, 1987).

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