Bookchapter

Sarah Theres Völkel*, Ramona Schödel, Daniel Buschek, Clemens Stachl, Quay Au, Bernd Bischl, Markus Bühner, and Heinrich Hußmann

Opportunities and Challenges of Utilizing Personality Traits for Personalization in HCI

Towards a shared perspective from HCI and Psychology

Abstract: This chapter discusses main opportunities and challenges of assessing and utilizing personality traits in personalized interactive systems and services. This unique perspective arises from our long-term collaboration on research projects involving three groups from Human-Computer Interaction (HCI), Psychology, and Statistics. Currently, personalization in HCI is often based on past user behavior, preferences, and interaction context. We argue that personality traits provide a promising additional source of information for personalization, which goes beyond context- and device-specific behavior and preferences.

We first give an overview of the well-established *Big Five* personality trait model from Psychology. We then present previous findings on the influence of personality in HCI associated with the benefits and challenges of personalization. These findings include the preference for interactive systems, filtering of information to increase personal relevance, communication behavior, and the impact on trust and acceptance. Moreover, we present first approaches of personality-based recommender systems.

We then identify several opportunities and use cases for personality-aware personalization: (1) personal communication between users, (2) recommendations upon first use, (3) persuasive technology, (4) trust and comfort in autonomous vehicles, and (5) empathic intelligent systems.

***Corresponding author: Sarah Theres Völkel, Daniel Buschek, Heinrich Hußmann,** Institute for Informatics, Media Informatics, Ludwig-Maximilians-Universität München
Ramona Schödel, Clemens Stachl, Markus Bühner, Department of Psychology, Psychological Methods and Assessment, Ludwig-Maximilians-Universität München
Quay Au, Bernd Bischl, Department for Statistics, Computational Statistics, Ludwig-Maximilians-Universität München

Furthermore, we highlight main challenges: First, we point out technological challenges of personality computing. To benefit from personality-awareness, systems need to automatically assess the user's personality. To create empathic intelligent agents (e.g., voice assistants), a consistent personality has to be synthesized.
Second, personality-aware personalization raises questions about user concerns and views, particularly privacy and data control. Another challenge is acceptance and trust in personality-aware systems due to the sensitivity of the data. Moreover, the importance of an accurate mental model for user's trust in a system was recently underlined by the right for explanations in the EU's General Data Protection Regulation. Such considerations seem particularly relevant for systems that assess and utilize personality.
Finally, we examine methodological requirements such as the need for large sample sizes and appropriate measurements. We conclude with a summary of opportunities and challenges of personality-aware personalization and discuss future research questions.

Keywords: Personalization, Personality traits, Personality-aware, HCI, Psychology

1 Introduction

The positive effects of personalization have been known to business owners since antiquity, when merchants provided different products and services to their costumers based on their individual preferences [2]. Nowadays, the rise of web technologies and ubiquitous computing has stimulated a new boost of personalization both in industry and academia [138]. However, in contrast to merchants in antiquity, who knew their customers and preferences personally, today's digital businesses face significantly bigger customer groups. Thus, they put a lot of effort into building detailed profiles of their users, for example by collecting their preferences, demographics, knowledge, previous behavior, and interests [149]. In this chapter, we argue that personality traits provide a promising additional source of information for personalization, which goes beyond context- and device-specific behavior and preferences. We think that personality traits are especially promising for building user models since they are relatively stable and cross-situational [6]. In the following section, we present the well-established *Big Five* personality trait model from Psychology [31, 50].

First of all, we give a brief overview of personalization and its benefits and challenges in general. To our knowledge there is no standard definition of personalization [8, 138]. According to Hagen, "Personalization is the ability to provide content and services tailored to individuals based on knowledge about their preferences and behavior" [52]. A more recent definition is given by Asif and Krogstie:

> "Personalization is a controlled process of adaptation of a service to achieve a particular goal by utilizing the user model and the context of use." [8]

A user model is a "(structured) data record containing user-related information [...] in contexts that are relevant to predicting and influencing future behavior" [140]. This representation of user information is built by using direct and indirect user input [91]. Direct user input refers to a user's profile, including characteristics, abilities, interests, needs, goals, and demographics, as well as preferences and ratings. While this data has the disadvantage of subjectivity and getting out of date, most personalization services rely also on indirectly and automatically recognized input, e.g., usage patterns, web logs of usage behavior, and clustering [91, 140, 149].

Personality is assumed to interact with situations [47]. For example people with certain personalities might selectively choose or avoid to be in situations (e.g., extraverts choose sociable venues). Different personalities would show different behaviors in the same situations (e.g., emotionally stable people might not panic as easily in stressful situations). Since personality traits are assumed to be relatively stable across time and situations [129], we argue that they can overcome current obstacles with direct user input. Furthermore, in section 5.1.1, we explain that there are promising approaches to predict personality traits from usage behavior.

Apart from the user model, the context of the current situation is usually used for personalization.

> "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves." [1]

Primary context types include location, identity, activity, and time. If a system uses context for personalization, it is called *context-aware* [1].

Based on the user model and the current context, personalization processes change the system's behavior [96]. Examples include the change of functionality, interface, information content, distinctiveness of a system, and aesthetic appeal [16, 91]. There are several technologies used for personalization, including cookies, pattern matching, rule-based inferencing, data mining, and machine learning [77].

The current popular trend of personalization [68] is the result of various benefits of personalization both for the user and the business. The most important advantage for the user is the reduction of information overload to increase the personal relevance of content [8, 16, 96, 131, 149]. For example, personalization allows online newspapers to show sports news only to those users, who are actually interested in sports. Hence, individual differences between users and their preferences can be addressed to improve the user experience [8, 16]. When users are looking for a nice restaurant during vacation, online tourism providers could display only specific restaurants because they know the user's preference for food, price, restaurant style, and current location [16]. This knowledge about the user could increase the fit of the provided systems and services [8, 24]. The user is delivered a pre-selection of restaurants, increasing efficiency, effectiveness and convenience of the decision making [24]. In addition, Das et al. [33] pointed out that users often do not search for specific information but want to be actively interested. For example, online streaming services show trailers, trying to interest the user in using the service.

Due to these advantages for the user, the vendor of a system or service also benefits from personalization. Users can be targeted individually on a one-to-one basis to increase user satisfaction and loyalty to the brand [24, 131]. Moreover, personalization can help businesses to target the right user groups, which benefit most from their services [8]. As a result, businesses can increase their sales revenue and make more profit [62].

However, there are also several challenges businesses have to face when employing personalization. First of all, personalization services have to ensure privacy and data control of their users' personal information [8, 24, 77]. When privacy cannot be ensured, users' acceptance of the service and their trust to use it are likely to decrease [8]. Additionally, the importance of privacy, data control and transparency was recently regulated by the European General Data Protection Regulation [133]. Since users often underestimate how much personal information is used and struggle with building appropriate mental models of personalization algorithms, intelligible interfaces are of crucial importance [58, 135]. Personalization also allows the vendor to manipulate users by showing selected contents, opinions, and products, influencing behavior [49, 131]. Finally, as discussed above, the automatic and successful recognition of user profiles has a great impact on the success of personalization [8, 91].

In this chapter, we discuss the role of personality traits for improving personalization in human-computer interaction. In a first step, we present the theoretical background of personality. Furthermore, we describe previous findings of the impact of personality traits on behavior and interaction with technology. Based on these findings, we discuss further opportunities and challenges of utilizing personality traits for personalization. Finally, we sum up our results and give suggestions for future work in our conclusion.

2 Theoretical Background

One and the same person shows relatively consistent patterns of behavior and experiencing with means of acting, thinking, and feeling. The measurement and investigation of systematic variations in human behavior, thinking and feeling have been documented and tested since 1115 (BC) [37]. These systematic, psychological patterns can be used to distinguish people from each other and are generally referred to as personality [88].

2.1 History of Personality Models in Psychology

Personality research overall aims to find ways to comprehensively describe and explain the structure of personality. The most productive and still relevant paradigm has been the traditional trait approach, which assumes that traits dispose individually specific ways of behaving and experiencing [6]. The beginnings of the modern definition of personality reach back to two models that have dominated the psychometric research scene for many years: Cattell's 16-factor model and Eysenck's three-factor model [85]. Both models are based on classification systems that reduced vast amounts of traits represented in the language of folk psychology to fewer, but meaningful dimensions. The 16-factor model provides narrower, so called primary traits. In contrast, the three-factor model describes personality in a more abstract way by using three higher-order secondary factors (extraversion, neuroticism, and psychoticism), which in turn comprise narrower, correlated traits [6, 85]. Over the years, researchers focused on further systematizing the classification of personality traits [50]. Following the psycholexical approach, it was assumed that important individual traits have entered natural language (e.g., via adjectives) and that the use of a word would attribute its importance as a psychological descriptor [35].

2.2 Big Five Model

The psycholexical approach revealed the most established personality trait model in Psychology and related research areas: the *Big Five* [31]. Currently, the *Big Five* model has been claimed to be the most useful taxonomy for personality structure [88] and therefore has represented a reference model in Psychology [85]. The *Big Five* model postulates five broad and often replicated dimensions: *extraversion*, *emotional stability*, *conscientiousness*, *agreeableness*, and *openness*. For the assessment of these five factors various self-report questionnaires have been developed, which use slightly different factor names [6]. The five global traits each comprise hierarchically organized sub-facets, which allow for describing an individual's personality in a more detailed way. As an illustration, according to the five factor model of Costa and McCrae [31], the trait facets of extraversion are *warmth*, *positive emotions*, *gregariousness*, *assertiveness*, *activity*, and *excitement-seeking*. Thus, extraverted people can be described as sociable, experiencing more positive affect, and seeking stimulating activities. In contrast, introverted people are less outgoing, reserved, shy, and prefer to spend time alone. Emotional instability, also often called neuroticism, is associated with anxiety, hostility, and experiencing negative affect. People high in emotional stability are calm and relaxed, whereas people with low emotional stability feel tense and uncertain. Conscientiousness describes how orderly, reliable, self-disciplined, and achievement-striving a person is. The level of people's willingness to help, compliance, modesty, and tolerance are inter alia known as important characteristics of agreeableness. Finally, openness describes people's tendency to be creative and to be receptive to feelings, art, ideas, and fantasy [6, 89, 35, 50, 85].

The five factor model has stimulated intensive research efforts within the last decades. Personality traits were found to be relatively stable, but they can change over a lifespan [28]. In addition, findings show that traits are stable across highly similar situations [5] and invariant across different observers, which means that self-, peer- and observer-ratings converge [89]. Finally, the five factors have been postulated to be universal as they empirically turned out to be valid for different sexes, races, cultures, and age groups [26].

2.3 Further Models

Besides the *Big Five* model, other personality trait models like the above-mentioned *Big Three* (extraversion, neuroticism, and psychoticism) by Eysenck or the *Alternative Big Five* (impulsive sensation seeking, neurotisicm-anxiety, aggression-hostility, sociability, activity) by Zuckerman have been proposed [6, 150]. In contrast to the *Big Five*, these models have a stronger focus on the psycho-biological basis of personality. As an illustration, impulsive sensation seeking is one of Zuckerman's *Alternative Big Five* factors and describes the tendency to seek and run risks to experience a certain level of arousal. Accordingly, it has been argued that the *Big Five* model is a trait concept of social interaction due to its psycholexical foundation, and therefore is not able to depict the assumed underlying true biological basis of personality [150]. However, empirical analyses revealed that the identified factors of all three models converge in large part, most of all for extraversion and neuroticism [150]. Although to date, the *Big Five* model has prevailed in psychological research, a new model, the so called *HEXACO*, has been proposed recently [7]. This psycholexical-based model assumes six dimensions (honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness to experience) and according to Asthon and Lee [7], is able to explain personality phenomena (e.g., altruism) that cannot be described within the five factor framework.

3 The Role of Personality Traits

Personality influences people's (social) behavior [31], preferences [21, 48], decision making processes, interests [102, 114] and life outcomes [106]. Hence, the role of personality traits in several domains has been investigated. Examples include work performance and intentions [100], driving behavior [30], well-being [36, 123], relationship [36, 125], and job satisfaction [69, 94], stress-coping strategies [87, 104] as well as medicine [42, 80].

In the introduction, we summed up different benefits and challenges of personalization. In the following, we present previous work regarding the relationship between personality traits and human-computer interaction, which could inform personalization and its benefits and challenges: (1) One of the main advantages of personalization is the opportunity to pre-select options for users and tailor them to their needs. Thus, in the first subsection we present previous findings on the role of personality traits for preference of interactive systems. (2) Personalization allows systems to reduce information overload. The perception of relevance of information and its link to personality is discussed in the second subsection. (3) Furthermore, we introduce research on the relationship between personality traits and communication behavior as an opportunity to improve user experience. (4) In the fourth subsection, we describe previous results on the impact of personality traits on perception of trust and acceptance, which are crucial challenges of personalization. (5) Finally, we present first approaches of using personality traits for personality-based recommender systems.

3.1 Preference for Interactive Systems

With improving technology, the choice between different systems becomes more difficult for users. For example, when two smartphones do not differ regarding technological measures, the user might have difficulties to decide which device to buy. Personalization allows to address individual needs and preferences, which might play a decisive role in the purchase decision. Previous research suggests that personality influences how people make their decisions [102]. Moreover, humans prefer to interact with personalities reflecting their own personality [19]. This preference for congruent personalities can also be transferred to humans' choice for products [127, 144] and brands [60, 95]. For example, products and brands are associated with personality traits such as activity for sports brands. Hence, we can assume that this preference also holds true for the choice of technologies, especially when intelligent systems representing humans are involved.

For example, Ehrenbrink et al. [39] suggested that personality traits influence users' choice for an intelligent personal assistant (IPA). They compared the three IPAs *Siri*, *Cortana*, and *Google Now* (predecessor of *Google Assistant*), which differ regarding their interaction with users. While Siri and Cortana act like having a personality, e.g., by telling jokes and giving emotional replies, Google Assistant shows neutral behavior. In their study they found first hints that highly conscientious individuals preferred Siri and Google Now. They attributed this effect to a more profound display of information on these devices in contrast to Cortana when users asked the IPAs questions. Probably due to a lack of prior exposure to Cortana, individuals with a low score on openness tended to dislike Cortana [39].

Rauschnabel et al. [112] reported that personality traits impact on the motivation to buy smart glasses. While extraverted users were interested in smart glasses when they expected social conformity, users with high scores in openness focused on functional benefits. However, emotional instability moderated the perceived benefits, especially when people anticipated a strong effect on their lives [112].

Summing up, previous findings suggest that personality traits can explain a preference for systems [64, 102]. This preference could help developers and companies to create systems tailored for specific personalities to stand out from others. However, this relationship has to be examined in more depth to find clearer connections between preference and personality traits and to determine the underlying reasons for this.

3.2 Providing Personalized Information

As pointed out in the introduction, a primary goal of personalization is to filter information, reducing the information overload and increasing relevance [8]. However, the amount of information perceived as relevant varies between individuals. Thus, in a first step, we present findings regarding different information seeking types. In the second subsection, we introduce previous results on how personality traits affect the way information should be presented to the user.

3.2.1 Information Seeking

Personality traits influence the way people seek for information [59]. People low in emotional stability have difficulties with evaluating the quality and relevance of a piece of information and thus tend to prefer new information which confirms previous data. Furthermore, they easily give up on information searches when they are unsuccessful in their query, especially since they perceive a lack of time to put more effort into the search. People experiencing these anxieties in combination with low levels on conscientiousness are classified as *fast surfers*, who are quickly skimming information, avoiding high effort and deep delving into the topic [59].

Individuals high in extraversion are typically active and energetic, which is also reflected by their information-seeking behavior. Due to their high social abilities, they tend to use their social contacts as information sources. People high on extraversion in combination with openness to experience and low agreeableness (competitiveness) are characterized as *broad scanners*, who are likely to be exhaustive yet unsystematic information seekers using a wide range of sources [59].

Apart from their preference for a wide range query and willingness to put effort into the search, individuals high in openness to experience tend to prefer thought-provoking new information. They are usually intellectually curious and able to judge and reflect on information critically. In contrast, conservative individuals low in openness often have a desire for confirming information and precise information, avoiding conflicting sources [59].

Individuals low in agreeableness are competitive and competent to critically analyze information. However, due to their impatient character, they tend not to put too much effort into the search. They are also more likely to be *broad scanners* of information [59].

Finally, it is not surprising that individuals high in conscientiousness are *deep divers*, hard working and trying to obtain high quality information. Apart from the immense effort they put into the search, they also pay attention to the quality of the retrieved information and follow a structured deep analysis approach [59]. They are also distinguished by information competence [128]. On the other hand, individuals low in conscientiousness are easily distracted, hasty and impulsive and thus try to retrieve information as easily as possible [59].

Tkalčič et al. [137] found a relationship between personality and preference for digital program notes of classical music concerts. Their results indicated that users high in openness, agreeableness, conscientiousness, and extraversion preferred more meta information about concerts.

3.2.2 Personal Visualizations

Apart from the amount and depth of desired information, personality traits also play a role in how this information should be presented. Green and Fisher [51] outlined the impact of personality traits on the interaction and performance in expert analytics systems and emphasized the need for real-time interface individualization. Ziemkiewicz and Kosara [148] investigated users' interactions with visual metaphors. They found out that individual differences, inter alia personality traits, determine user's ability to use different visualizations and satisfaction with representations. While they focused on expert visualizations with the primary goal to interpret information quickly, Schneider et al. [124] investigated the role of personality traits in everyday use of personal visualization. They compared plain and decorated visualizations for communicating the user's daily water intake. Their results revealed that participants high in extraversion, openness and agreeableness preferred a decorated visualization of a creature, which starts smiling with increased water intake. Since the combination of these personality traits is associated with a high need for affect, the participants might have found a cute creature more engaging than an unemotional representation. Highly conscientious participants, however, disapproved of the creature visualization due to a lack of detailed information.

Ferwerda et al. [46] identified distinct music browsing behavior based on users' personality, which could inform the design of user interfaces. For example, their findings revealed that while highly open users preferred to browse music by mood, highly conscientious users favored browsing by activity.

In summary, previous findings suggest an impact of personality traits on preference for depth and visualization of information. We assume that these findings do not only help developers to present personalized content to the user but also to give intelligible explanations on how the underlying personalization algorithms work to improve the system's transparency, which is gaining increasing importance [133]. However, users' preferences have to be analyzed in more detail and an in-depth understanding for the underlying reasons of the relationship between preferences and personality traits is necessary [124].

3.3 Communication Behavior

Several associations between individual personality trait levels and interpersonal communication behavior have been reported in previous research. Most intuitively, the personality trait of extraversion has repeatedly been related to both the frequency and duration of computer-mediated communication behaviors on smartphones [18, 93, 130]. Furthermore, extraversion has also been associated with linguistic characteristics such as higher abstractness of language [15] and specific voice features, such as higher pitch [122]. More extensive studies reported associations between several personality dimensions and word use in blogs and social networks [108, 145]. Specifically, the trait of openness was associated with higher diversity in word use, both on categorical and single word level [145].

3.4 Trust and Acceptance

When humans interact with autonomous machines and artificial intelligence, as is often the case in personalized systems, they abandon control and allow the machine to make decisions or contribute to decision-making. Hence, humans have to accept and trust the machine to perform the given task [116, 121], posing crucial challenges for personalization. Yet, not all users respond with the same trust to automation [63, 79]. Previous work suggests that some personality traits influence humans' trust in machines as well as their interaction with them [11, 53, 116, 121]. Evans and Revelle [43] showed an effect of extraversion and emotional stability on trust development in a robot. Haring et al. [55] also discovered that extraverted individuals reported higher trust in humanoid robots. In contrast, Salem et al. [120] could not detect any relationship between personality traits and robot trust development. Instead, they found that individuals high in extraversion and emotional stability anthropomorphized the robot more and felt close to it. On the other hand, Hancock et al. [54] found only little evidence of an impact of human characteristics on trust in human-robot interaction and Schaefer et al. [121] stressed that the relationship between personality traits and trust development has not been thoroughly explored yet.

These differences in perceived trust can also influence users' intention and actual usage of technology. Individuals who score low on emotional stability have in general more negative feelings towards technology and technology advances, being more cautious to use them [12]. Openness was found to positively influence the use of new technologies [146]. Moreover, conscientiousness [12] and agreeableness [126] moderate the relationship between behavioral intent and extent of use. On the other hand, personality traits can also play a role in trusting too easily and hence present a vulnerability to privacy attacks. Halevi et al. [53] suggested that highly neurotic individuals are more susceptible to phishing attacks. Moreover, a link between some personality traits and the willingness to disclose private information online was indicated, although Halevi et al. [53] found openness to be the salient component, while Bansal et al. [11] only found an effect for social components such as agreeableness, extraversion and emotional instability. First findings from a study, collecting the opinion of 5.000 participants on automated driving, revealed that individuals low in emotional stability were more anxious about data transmission in autonomous cars whereas more agreeable respondents felt more comfortable with it [79]. Furthermore, personality traits can also play a role in active security behavior to avoid attacks [75, 142].

3.5 Personality-based Recommender Systems

Today, people are confronted with seemingly endless possibilities when buying a product in online shops like *Amazon*, picking tonight's TV show on *Netflix*, or choosing an activity on *TripAdvisor*. To support the user in making the best decision, reduce information overload and engage users, recommender systems provide recommendations based on users' preferences [115]. The role of personality traits for improving recommender systems (RS) has been explored before, revealing promising results [25, 41, 44, 45, 64, 65, 71, 114, 118, 136]. An overview how personality user models can improve recommender systems can be found in [136].

There are several different approaches to implement recommender systems [103]. Content-based RSs only use the user's ratings on items and then recommend items, which have similar attributes, e.g., genre or actors, to the user's preferred items [118]. In these RSs, the user's personality serves as an additional, psychological attribute of a product [118]. Hu and Pu [65] compared a personality-based RS with a typical content-based RS using user ratings. Although they could only determine small differences regarding the perceived accuracy of the recommendations, personality based RSs were perceived to be significantly easier to use and preferred by the majority of users [65]. However, it should be noted that the evaluated RS's personality quiz is not based on solid psychological foundations.

Another possibility for giving recommendations is using the link between personality traits and entertainment preferences, for example preferences for music [114, 21, 45], film and TV show genres [23, 21], as well as book genres [21]. Based on Rentfrow and Gosling's [114] findings, Hu and Pu [66] presented a recommender system, which infers users' music preferences based on their personality traits. They used personality quizzes to build profiles for users and their friends and compared their RS with a rating-based RS but could not determine any significant differences regarding accuracy of the recommendations. However, users enjoyed using the system to find recommendations [66].

Collaborative filtering is the most popular recommender system technique, recommending items liked by other users with similar interests and preferences [103]. Each user's profile consists of items and ratings as well as previous usage history [118]. For example, user Tom is interested in science fiction books. When other users with similar preference in the past buy a new science fiction book, this book would also be presented to Tom. Roshchina et al. [118] presented a collaborative filtering RS, which automatically induced personality traits from the user's writings. In their system *TWIN*, they recommended items chosen by people with similar personality profiles (*twins*). Applying their system on the travelling application *TripAdvisor's* dataset, they were successful in predicting a user's *twin* with 10% accuracy on average.

Karumur et al. [71] suggested that recommender models using ratings from users with similar personalities can improve consumption. Elahi et al. [41] developed an active learning approach, which utilizes users' personality traits to improve the number and accuracy of their ratings. Fernández-Tobías et al. [44] could show that by incorporating users' personality for collaborative filtering, they achieved performance improvements and novelty of the recommended items for new users. Moreover, personality traits are associated with user's preference for diversification of recommendations [25].

In summary, previous research on personality-based recommender systems suggests that recommendations based on personality-traits can be accurate and improve user experience. However, several challenges have to be addressed in order to actually deploy these recommender systems in practice. These challenges include improving the accuracy of recommendations, automatically recognizing personality traits, and an in-depth analysis of users' acceptance of these recommender systems. However, personality traits cannot only be useful for improving recommender systems but there are several other opportunities for human-computer interaction. In the following section, we present these opportunities.

4 Opportunities

Several opportunities for considering personality in interactive systems arise from the literature, as reviewed in the previous section. Indeed, we find that information about a user's personality might be used at several stages of the interaction process – from motivation, choice, and a user's first contact with a system to continued use and feedback. In the following, we present diverse application opportunities which cover different parts of this range. In particular, these consider personality for: (1) informing context and content of personal communication; (2) improving recommendations upon first use; (3) supporting behavior change in persuasive technology; (4) facilitating comfortable driving in autonomous vehicles; (5) and enabling overall empathic systems.

4.1 Personal Communication

One promising use case for personality-aware personalization is personal digital communication. Here, personality could inform both *context* and *content*. Regarding context, personality information could help to address questions of *When?*, *How?*, and *Who?*. For instance, personality could be used by an intelligent contact list to help users decide *when* to contact others, similar to *ContextContacts* [105]. For each contact, this list could use both the person's context (e.g., location, time, activity, company) as well as personality to predict how likely the person would respond or feel disturbed. Similarly, such a contact list application could use personality information to predict *how* each person would like to be contacted right now (e.g., phone call vs text message). Finally, personality could support the user in deciding *whom* to contact, for example when looking for a sports partner (e.g., regarding preference for cooperation vs competition) or people to complete a team for a job. More concretely, for example, a social network might highlight friends of friends who share not only similar interests but also bring compatible skills and personality.

Regarding communication content, personality information could be used in systems which automatically generate text as reply suggestions (see e.g., Google's Smart Reply [70]). In particular, both the personality of the sender and the receiver might be considered to generate adequate content, in addition to other factors such as context and type of relationship. For example, if the receiver is highly agreeable, the system could suggest a friendly, polite, and harmonic language, even if the sender usually tends to write short and precise texts.

Moreover, personality information might also be useful to adapt common non-textual content, such as emojis or (animated) avatars. Here, the user's personality might lead to different visuals or animations, thus (subtly) communicating personal aspects of the user to others. For example, a *hooray* emoji might express joyful excitement rather differently for an extraverted user compared to a more introverted one (e.g., throwing hands into the air vs a bright smile). As a result, such digital conversations might be perceived as more personal and intimate, similar to the findings in related work on context-aware messaging (see e.g., [17, 56]).

4.2 Recommendations upon First Use

Previously, we presented first approaches from current research for personality-aware recommender systems. In addition, personality traits offer the opportunity to provide a stable foundation for recommendations, also (1) upon first use and (2) across use cases:

Accurate recommendations for new users are difficult due to the lack of behavior records [64]. A stable construct like personality might support systems in overcoming this cold start problem [136]. Regarding the integration of such user information, related work already utilized demographic information for content-based similarity [64]. Moreover, Elahi et al. [41] showed that personality traits can be used to improve the suggestions of items that users are requested to rate, avoiding the cold start problem.

Second, personality might be used across systems. For example, recommendations for movies and music are often given by separate systems. Personality traits could be used to link such different domains [64]. In contrast, specific *likes* or *ratings* might be harder to transfer adequately from one (content) type to another.

4.3 Persuasive Technology

Several applications try to persuade their users to show a specific behavior, for example continuing to play an online game, spending more time on a website, or buying recently viewed products. Furthermore, users often track their own physical activity or financial expenses in order to reach a specific goal [124]. Due to today's globalized overweight and obesity problems, mobile well-being apps are gaining increasing popularity. These fitness or nutrition apps are designed to nudge the user's behavior towards a healthier lifestyle but suitable behavior changes are very individual [13].

Users' personalities among their goals can influence how and when they should be persuaded to improve their well-being. Imagine Anna and Tom, who both want to improve their lifestyles and lose weight. Anna is an extravert, she likes to engage actively and go out with other people. A possibly successful intervention for her could involve to ask her to eat together with friends or colleagues who already foster a healthy lifestyle since she would probably appreciate the company and can easily be persuaded by social contacts. On the other hand, Tom is more introverted and highly conscientious. For him, a suitable intervention strategy could be to provide him with facts and information. For instance, a mobile app could show the calories of a burger compared to a salad for lunch and outline how much calories are left for dinner for both of the two choices. In contrast to Anna, he would not be comfortable with relying on other people's advice. Lepri et al. [83] investigated the role of personality in inducing behavioral change. They found out that individuals high in extraversion or neuroticism react positively to social comparison intervention strategies in order to increase daily physical activity. In contrast to emotionally instables, extraverts decrease their physical activity if confronted with a peer pressure social strategy.

Apart from developing suitable interventions, the visualization of the user's personal data and behavior is of significant importance to give her feedback about her behavior without evoking negative feelings [134]. However, these visualizations have to address diverse user needs and while one feedback might work for some users, it could be rejected by others [67, 124]. For instance, conscientious individuals could appreciate honest feedback while negative feedback could easily discourage neurotic users.

Another possibility to provide persuasive feedback is gamification. Gamification research has already utilized previous results from psychological theories of motivation to improve user experience and user feedback in systems [119]. In addition to theories of motivation, feedback design could be further enriched with insights from personality psychology. Most relevant findings for the design of feedback systems relate to the differential sensitivity for rewards and punishments (aversive stimuli) with regard to individual levels of extraversion and emotional stability [34, 111]. Whereas many computer games have mostly focused on the use of visual and auditory rewards (*+1*, *awesome*, *level-up*), research from the field of psychology suggests individual differences in reward dependence [29]. Therefore, rate, intensity, and the content of system feedback could be adjusted to those individual dispositions. For example, the intensity of *punishments* or negative user feedback could be adjusted to individual levels of emotional stability. Possibly, personalized feedback could then be used in persuasive systems design (e.g., to increase desired or to decrease undesired behavior) to improve the overall user experience.

4.4 Autonomous Vehicles

Using personality traits for personalization could also be a very promising approach for autonomous driving. In this context, trust in the autonomous system is especially important because the driver has to hand over the driving task to the car [116, 121]. Besides improvements of the reliability and functionality of autonomous vehicles, an approach to increase trust in autonomous vehicles could be to carefully explain actions of the car to the passenger [57]. For example, to support highly neurotic drivers in critical situations, e.g., take over requests, providing confirming and clear information can reassure the driver and prevent distraction. Individuals high in extraversion and openness to experience, in turn, could benefit from an intelligent assistant, which takes over the role of a friend or passenger and provides brief and precise explanations but simultaneously satisfies the need for social interaction and variety. It is likely that conscientious drivers prefer an indicator of the car's certainty to perform the current driving task, allowing them to maintain a sense of control. This indicator could also be useful to agreeable drivers, who might otherwise develop inappropriately high levels of trust in the system [11].

Another use case in the automotive context could refer to non-driving related activities, which will come into focus with increasing automation [110]. Using *Advanced Driver Assistance Systems* can be experienced as a reduction of driving enjoyment and fun by some drivers [38], requiring autonomous vehicles to offer alternative activities [110]. These activities are likely to be dependent on the driver's or passenger's personality and associated behavior patterns. For example, we can expect that passengers high in extraversion more often seek active and energetic activities and appreciate the possibilities to socially interact [150]. Users' preferences for specific app usage [130] could provide clues for suitable tasks, such as a focus on entertainment and communication applications for extraverted drivers or efficient task scheduling applications for organized conscientious drivers. Passengers open to new experience and therefore frequently pursuing external stimuli, could be equipped with information about points of interest on the road or latest news of the local area.

4.5 Empathic Systems

Beyond scientific literature, (popular) culture also envisions personality-aware systems. For example, empathic intelligent robots, which give humans the feeling to completely *understand* them, have had an appeal to people since Greek myths [101]. Due to this fascination empathic robots appear in recent fiction, e.g., in the movies *Her*, *Electric Dreams*, *Ex Machina*, *A.I, Artificial Intelligence*, in the TV show *Black Mirror*, and in novels such as *Origin* by Dan Brown.

Previous research suggests that – similar to human-human communication – humans automatically and unconsciously attribute a virtual humanoid character a personality [90, 113]. Hence, equipping an intelligent agent (e.g., chat bots, voice assistants, humanoid robots) with a personality will be an important requirement for successful human-robot interaction [98, 132]. Furthermore, the *Similarity Attraction Paradigm* indicates that humans feel more attracted to humans with similar personality [19]. Likewise, adapting an intelligent agent's personality to the human user was found to increase credibility, perceived competence, performance, and compliance [4, 81, 98, 132]. For example, a robot interacting with a conscientious user provides a huge amount of information, is always reliable and trustful. Agreeable users could prefer a robot, which is highly sociable, friendly and offers support to the user. On the other hand, contradicting findings also suggest a complementary attraction paradigm [4, 82].

In these scenarios, intelligent agents behave more like friends to the user. However, this opportunity also raises several research questions: When do users prefer intelligent agents to behave similarly or complementary to them or should agents sometimes just show random behavior to avoid predictability? Do users sometimes need to be pushed out of their comfort zone? For example, should an intelligent agent interacting with an introvert sometimes ask this user to be more active to set more stimuli? Do users sometimes need the intelligent agent to contradict them and if so, when and how often do users want intelligent assistants to behave differently from their personality? We will discuss further technological challenges regarding the synthesis of personality in the following section.

5 Challenges

Apart from these opportunities, personality-aware personalization also poses several challenges. With respect to technological barriers, an important technical challenge is the automatic assessment of the user's personality. To create empathic systems, a consistent personality of intelligent agents has to be synthesized. In the first subsection we present different promising approaches for personality computing. With respect to the user, personalization faces several challenges as presented in the introduction. We think that these challenges are particularly important when designing for personality. Hence, in the second subsection we discuss effects of personality-aware personalization for users and their possible views and concerns.

5.1 Personality Computing

Personality computing has gained increasing interest in the HCI community due to current interaction phenomena. On the one hand, users' personal information and behavior are available on social networking platforms and easily accessible via their smartphone use. On the other hand, current trends concern endowing machines with social and affective intelligence [141]. In their survey, Vinciarelli and Mohammadi [141] claimed three main challenges of personality computing. First, *automatic personality recognition*, which refers to ascertain an individual's *true* personality from machine-detectable cues. Second, *automatic personality perception*, which is concerned with the prediction of the personality others attribute to an individual. Third, *automatic personality synthesis*, which deals with the generation of artificial personality through intelligent agents, such as virtual assistants or embodied robots.

Since *automatic personality perception* is less related to personality-aware systems, we focus on the other two challenges in the following subsections.

5.1.1 Automatic Personality Recognition

To utilize the aforementioned opportunities of personality-awareness, systems must be able to automatically recognize the user's personality. Since personality is a latent construct, personality traits cannot be measured directly but can potentially be inferred from a set of indicators. Psychometric self-report questionnaires are currently considered the gold standard of personality assessment and are used in a wide range of academic and professional settings due to their predictive capabilities for important life outcomes [106]. Unfortunately, questionnaire approaches are also subject to a series of methodological biases, such as response styles, social desirability, and memory [139]. Furthermore, users might not be willing to fill out long questionnaires before interacting with a system.

Due to these limitations of existing approaches and due to recent technological advances, research efforts have started to focus on the observation of personality manifestations in the form of digital-footprint data. Digital footprints such as *Likes* from social media [147], app usage on smartphones [130], or records of language use [108, 145] are becoming increasingly available for researchers. Social media data in particular has shown to be predictive for individual personality [9]. Additionally, researchers have aimed at the recognition of self-reported personality traits from facial image data [22], and have reported on associations of music preferences and individual personality traits [45, 99]. In order to enable personality-aware personalization, trait-levels of personality could be directly predicted from digital footprints [9].

Despite the obvious opportunities of this new approach, it also raises questions regarding the ground truth of personality trait assessment as well as its accuracy. In a best-case scenario, personality assessment from digital footprints (in the current form) could perfectly predict self-reported personality scores, measured with conventional personality questionnaires. However, as mentioned above, self-reported personality measures are subject to a number of biases and do not necessarily constitute the most perfect measures of latent personality traits themselves.

One particular problem that remains with regard to digital footprint-based personality recognition, is the accuracy on the level of individuals. Average prediction-accuracies of personality predictions have been reported as relatively low ($r = 0.34$, 95% CI [0.27–0.34]) [9], allowing for usage in a best-guess fashion only. Still, research suggests that digital footprint-based personality predictions might be good enough for personality-based adaptions when applied on large samples [86].

However, when it comes to precise psychometric testing decisions on individual level (e.g., does person X or person Y score higher), much higher precision is needed.

Ultimately, personality assessment from digital footprints data needs to be validated based on relevant life outcomes in order to benchmark it with existing methodologies. We hypothesize that for a while, the field will need to balance the need for fast, deployable business-solutions with mapping out fine-grained manifestations of personality in digital footprint data. Finally, the automatic extraction of personality dimensions from user data also raises a series of privacy and data-ownership issues. We will discuss those in section 5.2.

5.1.2 Automatic Personality Synthesis

In subsection 4.5 we discussed the benefits of empathic intelligent agents. To achieve a realistic and natural personality, intelligent agents have to show consistent patterns of behavior [3]. For example, an agent acting reserved and shy in one situation, yet extraverted and chatty in another would be confusing for humans [74]. Hence, to achieve a successful human-agent-interaction, the personality for an intelligent agent has to be designed carefully.

Automatic personality synthesis refers to the automatic generation of behavioral cues to elicit the perception of intended personality traits [141]. These behavioral cues are perceptible externalizations of the internal and non-perceptible personality [122]. For example, humans assume that an intelligent agent which is talking fast and loud while greatly gesturing is extroverted. Thus, automatic synthesis is supposed to support agent designers to explicitly control the traits humans attribute to the intelligent agent [141].

Several researchers could show that a systematic variation of intelligent agents' synthetic behavior leads to unanimous attribution of personality traits [90]. For example, to elicit extraversion, researchers used different behavioral cues and channels, such as speech rate and pitch [98, 143], gaze [4], gestures [72, 132], and facial expressions [3, 72].

However, the relationship between Big Five personality traits and perceptible behavior is mainly researched for extraversion as it is the most observable trait [122]. However, when designing intelligent agents, e.g., for assistive or educational contexts, other traits such as conscientiousness or agreeableness are more important. Hence, further research is necessary to determine how to synthesize other personality traits apart from extraversion. Moreover, the combination of different personality traits and potentially contradicting behavioral cues still has to be researched.

5.2 User Views and Concerns

In the introduction, we presented several challenges of personalization with respect to possible user concerns: (1) privacy and data control, (2) acceptance of the service and trust in using it, (3) intelligible interfaces, and (4) the threat of manipulation. In this subsection, we discuss each of these challenges in regard to using personality traits for personalization.

5.2.1 Privacy and Data Control

Privacy concerns might arise from determining users' traits for offering personality-aware personalization. As discussed before, we assume that the most promising option is to automatically detect personality traits based on natural user data like smartphone logging data [27] or digital footprints left in social media [76, 147]. In this case, it will be indispensable to collect users' data (e.g., habits, context, or usage behavior) constantly in the background of the used device for providing personalized services. As already known from consumption research, privacy concerns depend on the type of disclosed information and are especially high for personal data [14]. Previous findings have already suggested that personality traits are perceived as sensitive data [66]. Hence, future research has to investigate users' attitude towards personality-aware personalization.

Moreover, due to the huge amount of stored data of individual and probably unique behavior, it is likely that individuals can be identified unambiguously by using these records of personality and according behavior similar to fingerprints or DNA [97]. Hence, privacy regulations to protect the user and address these new possibilities for identification have to be developed. Users might also be worried that other people see their assessed personality profiles, especially on sensitive measurements like emotional stability [66, 109]. Another problem might arise when people use other people's devices, e.g., borrowing a phone to make a quick call. If the system is adapted to the user's personality, is it then possible to determine the user's personality by using her system?

5.2.2 Acceptance and Trust

Interacting with autonomous machines and artificial intelligence often requires the user to abandon control and to allow the machine to be involved in decisions. Therefore, humans have to accept and trust the machine to perform the given task [116, 121]. Consequently, a major challenge of personality-aware personalization is whether users accept the use of personality traits as input for personalization. Therefore, one of the most important research questions is to examine users' reactions to personality-aware personalization. Furthermore, contexts, user goals, and tasks should be identified, for which users find personality-aware personalization useful. It could be particularly interesting to investigate the influence of user's self-characterization versus the system's characterization on acceptance. So far, only little research was conducted regarding the acceptance of personality-aware personalization. When comparing a personality-based with a rating-based recommender system, Hu and Pu [65] showed that users subjectively preferred the personality-based system and found it easier to use. However, they stressed the importance of system transparency and user control for user acceptance [65], which is discussed in the following section.

5.2.3 Intelligibility and Transparency

The EU's General Data Protection Regulation requires that systems reveal which information they collect about their users and how this information is used, giving users the right of explanation [133]. Hence, systems using personality traits as part of personalization algorithms have to make these procedures transparent and intelligible to their users. Moreover, intelligible explanations of the system's behavior can increase user trust, satisfaction, and efficiency among others [40, 84, 135]. Yet, this need for transparency poses several challenges to the developer.

First of all, the user has to develop an understanding of personality traits models themselves to form an accurate mental model. The accuracy of this mental model is important for users' trust [78]. On the one hand, personality as an explanation for a specific system behavior could be easier to understand for users than complex user behavior algorithms [102]. This kind of explanation refers mostly to everyday knowledge and use of personality traits. On the other hand, providing a more in-depth or scientific explanation of personality traits could prove difficult, particularly when there is only little space to provide explanations, such as in mobile applications. Furthermore, while one trait might be easy to explain ("The system did this because it thinks you are an extravert"), describing the interaction between several personality traits seems to be far more difficult. It might be necessary to combine levels of several traits to find new understandable descriptions, for example like the information seeking types *broad scanner* and *deep diver* [59].

Another challenge will be to visualize personality traits and corresponding models. Should systems provide a mere textual description or also show graphical explanations? Again, it seems easier to find graphical descriptions of one personality trait, whereas the combination of several characteristics quickly becomes more complicated. It might also prove difficult to provide a neutral or positive description of personality traits to users. Most humans associate negative or positive attributes with specific personality traits. Most users will likely disapprove of explanations like “I just did that because you have such an anxious personality”.

When transparent systems allow the user to understand the determining algorithms, they must also give their users the opportunity to give feedback to the system and to control the user model [10, 73]. For example, in rating-based recommender systems, the user has a clear understanding of the recommendations. By changing his or her ratings, the user can easily influence the recommendations. In contrast, personality-based recommender systems are less intelligible and the user might not know how to achieve a different result [65]. To improve the system’s scrutability, users should be given the possibility to tell the system that they like or dislike a recommendation despite their personality.

User feedback and control might be especially important when the system and the user disagree about the user’s personality. If the user thinks she is extraverted and conscientious but the system determines different results, the user will probably be dissatisfied with the results and lose trust in the system. However, the question remains what the ground truth of somebody’s personality should be. Should the user have the power to tell the system which personality he or she is – or is the system’s analysis more accurate than the user’s self-assessment and thus should be given higher authority?

5.2.4 Manipulation Concerns

Personality-aware personalization implies the risk of user manipulation and therefore clearly represents a challenge for users’ perception and acceptance of this concept. Ever since the international headlines about *Cambridge Analytica* [20, 117], the fear of unconscious manipulation has emerged. In early 2018, *Cambridge Analytica* has fallen into disrepute due to illegally employing Facebook users’ data for trait-related personalization of online advertisement and consequently for manipulating voters’ decisions in the US election campaign in 2016. This example illustrates that personality-aware personalization could also promote so called *filter bubbles* [107]. This term describes the isolation of a person towards information not corresponding to his or her initial point of view, which could result in intellectual restriction. It is conceivable that particularly people low in emotional stability are prone to filter bubbles as they tend to prefer information confirming their previous knowledge [59].

Due to the close link between personality traits and behavior, filter bubbles could be used to address users individually to influence their opinions, attitude, and behavior. In summary, using personality traits for personalization in HCI provides tailor-made services and applications for users' needs and preferences, which is both, a great advantage and a potential risk. Thus, from a technical and ethical point of view, it will be a major challenge in the future to develop responsible systems utilizing the right balance between comfortable but not too restrictive personalization based on personality traits.

6 Methodological Requirements

Utilizing personality traits for personalization also poses several methodological challenges. First of all, investigating the influence of personality traits usually requires large sample sizes to ensure that all personality traits expressions are represented in the sample. In the past, several studies used small sample sizes (e.g., [39]) and hence struggled with insignificant or unclear findings.

The sample sizes have to scale even more when not only considering personality traits individually but also their interactions. Until now, researchers often reported the associations of single characteristics. However, the interaction between different personality traits has to be considered, too, especially when associated intended system adaptations might contradict each other. A possible approach could be to define interesting user profiles, such as Heinstrom et al. [59] for information seeking, which consist of a specific combination of personality traits.

Furthermore, the samples have to include a representative distribution of personality traits. This requirement might prove particularly difficult since Dahlbeck and Karsvall [32] found a personality bias in volunteer-based user studies, revealing that participants are more extraverted and open than in a representative sample.

Another methodological challenge is the measurement of success of personality-based personalization. Previous researchers explained difficulties in defining a positive evaluation of these systems in contrast to control systems (e.g., [124]). Possibilities for these measurements include accuracy of recommendations, performance, and subjective satisfaction, but might be highly dependent on the use case. Moreover, these effects might only become apparent in the long term, requiring longitudinal surveys and iterative optimizations.

A possibly important measurement is not only to determine an effect of personality traits but also to examine the underlying reasons for user preferences and an effect. Often researchers reported mixed results regarding the magnitude and significance of different effects (e.g., [61]). Gaining deeper insights into user behavior could help to design more accurate experiments and clarify mixed and contradicting results.

Finally, the necessary accuracy of personality-based personalization has to be determined. Since many approaches of automatically recognizing personality are based on machine learning algorithms (e.g., [49, 130]), the guaranteed accuracy might still not be satisfying for an actual implementation. Hence, it has to be investigated which accuracy is necessary to improve systems without resulting in user's distrust. For example, only cases with a high probability of predicting personality traits could be classified. Another possibility is to present personality-aware adaptations only as initial options to user, which can easily be changed. Moreover, one must be aware of the caveats that come by using machine learning methods. These algorithms are often called black box models, because they can offer high predictive accuracy, but they do not give explanations for their predictions. In personality-based systems, however, the interpretability of algorithms is of great importance, because of the high level of transparency and intelligibility these systems require. One may have to accept a drop in accuracy in favor of higher interpretability. If the use of a black box model is essential, explanations of predictions could still be achieved by using interpretable machine learning methods (e.g., [92]).

7 Summary and Conclusion

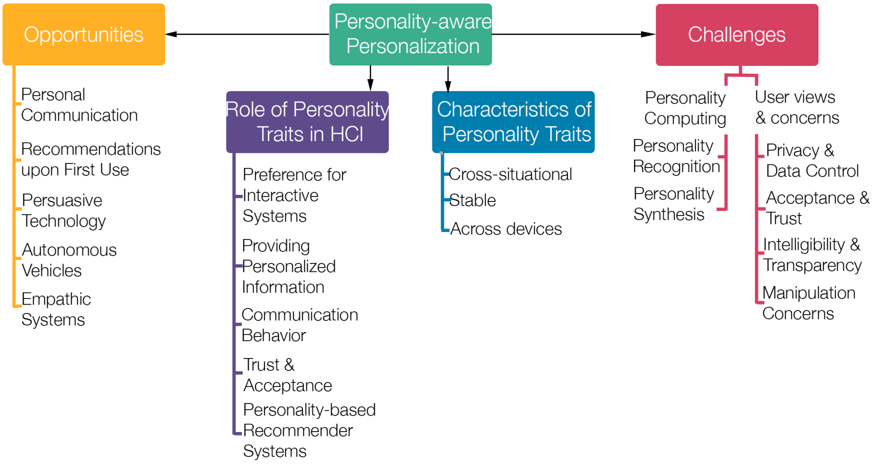

Fig. 1: Personality-aware personalization: overview of presented opportunities and challenges as well as previous findings on the role of personality traits in HCI and characteristics of personality traits.

Due to the many advantages for users and businesses, personalization is an emerging trend of the 21st century. The success of personalization highly depends on the user model, a representation of information about the user. In this chapter, we argued that personality traits provide a promising additional source of information for personalization because they are assumed to be relatively stable and cross-situational.

At first, we introduced the well-established *Big Five* personality model from Psychology. Afterwards, we presented previous findings on the role of personality traits for human-computer interaction, which could inform opportunities and challenges of personality-aware personalization. An overview of personality-aware personalization can be found in figure 1.

It was suggested that personality traits influence a preference for (intelligent) interactive systems since users prefer to interact with congruent personalities. This preference could be an opportunity to develop completely empathic intelligent systems, as imagined by popular culture for a long time. Furthermore, personality can be used to provide personalized information by addressing different preferences for the amount, depth and visualization of information. Persuasive technology could take advantage of this relationship, for example by giving adequate and engaging feedback in health applications. Another use case of personalized information is increasing comfort in autonomous vehicles. Moreover, personality traits could be used to overcome the *cold start* problem of personalization since they can inform systems before the first use. We described first approaches to develop personality-aware recommender systems. The reflection of personality in communication has been investigated both in face-to-face communication as well as in smartphone and social media use. On the one hand, this link is an opportunity to design personalized instant-messaging services regarding auto correction or emojis.

On the other hand, the relationship between personality traits and communication behavior can also be used for one of the biggest challenges of personality-aware personalization; the automatic technological assessment of personality traits. Besides, to create empathic intelligent agents, further research is necessary to synthesize consistent personalities. We also pointed out that other important challenges for utilizing personality traits for personalization are user views and concerns, particularly trust and acceptance of this sensitive data as well as transparent systems.

In conclusion, personality traits could be a promising source for personalization. However, the impact of personality traits for HCI still remains widely unexplored. In the previous sections, we presented research questions for each opportunity and challenge. We encourage researchers to address these research questions in their work to examine whether and how personality traits can improve personalization.

References

[1] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles. Towards a better understanding of context and context-awareness. In *Handheld and Ubiquitous Computing*, pages 304–307, Berlin, Heidelberg, 1999. Springer.

[2] G. Adomavicius, Z. Huang, and A. Tuzhilin. Personalization and recommender systems. *State-of-the-art decision making tools in the information-intensive age*, pages 55–100, 2008.

[3] E. André and T. Rist. Presenting through performing: on the use of multiple lifelike characters in knowledge-based presentation systems. *Knowledge-Based Systems*, 14(1):3 – 13, 2000.

[4] S. Andrist, B. Mutlu, and A. Tapus. Look like me: Matching robot personality via gaze to increase motivation. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 3603–3612, New York, NY, US, 2015. ACM.

[5] J. B. Asendorpf. Personality: Traits and situations. In P. J. Corr and G. Matthews, editors, *The Cambridge Handbook of Personality Psychology*, pages 43–53. Cambridge University Press, Cambridge, UK, 2009.

[6] J. B. Asendorpf and F. J. Neyer. *Psychologie der Persönlichkeit*. Springer-Verlag, Berlin, Heidelberg, 2012.

[7] M. C. Ashton and K. Lee. Empirical, theoretical, and practical advantages of the HEXACO model of personality structure. *Personality and Social Psychology Review*, 11(2):150–166, 2007.

[8] M. Asif and J. Krogstie. Taxonomy of personalization in mobile services. In *Proceedings of the 10th IADIS International Conference e-Society*, pages 343–350, 2012.

[9] D. Azucar, D. Marengo, and M. Settanni. Predicting the Big 5 personality traits from digital footprints on social media: A meta-analysis. *Personality and Individual Differences*, 124:150–159, 2018.

[10] F. Bakalov, M.-J. Meurs, B. König-Ries, B. Sateli, R. Witte, G. Butler, and A. Tsang. An approach to controlling user models and personalization effects in recommender systems. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces*, pages 49–56, New York, NY, US, 2013. ACM.

[11] G. Bansal, F. M. Zahedi, and D. Gefen. Do context and personality matter? Trust and privacy concerns in disclosing private information online. *Information & Management*, 53(1):1–21, 2016.

[12] T. Barnett, A. W. Pearson, R. Pearson, and F. W. Kellermanns. Five-

factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, 24(4):374–390, 2015.
[13] F. Bentley, K. Tollmar, P. Stephenson, L. Levy, B. Jones, S. Robertson, E. Price, R. Catrambone, and J. Wilson. Health mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *ACM Transactions on Computer-Human Interaction (ToCHI)*, 20(5):30, 2013.
[14] A. Bergström. Online privacy concerns: A broad approach to understanding the concerns of different groups for different uses. *Computers in Human Behavior*, 53:419–426, 2015.
[15] C. J. Beukeboom, M. Tanis, and I. E. Vermeulen. The language of extraversion: Extraverted people talk more abstractly, introverts are more concrete. *Journal of Language and Social Psychology*, 32(2):191–201, 2013.
[16] J. Blom. Personalization: a taxonomy. In *CHI'00 Extended Abstracts on Human Factors in Computing Systems*, pages 313–314, New York, NY, US, 2000. ACM.
[17] D. Buschek, A. De Luca, and F. Alt. There is more to typing than speed: Expressive mobile touch keyboards via dynamic font personalisation. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services*, MobileHCI '15, pages 125–130, New York, NY, US, 2015. ACM.
[18] S. Butt and J. G. Phillips. Personality and self reported mobile phone use. *Computers in Human Behavior*, 24(2):346–360, 2008.
[19] D. Byrne. Interpersonal attraction and attitude similarity. *The Journal of Abnormal and Social Psychology*, 62(3):713–715, 1961.
[20] C. Cadwalladr and E. Graham-Harrison. Revealed: 50 million facebook profiles harvested for cambridge analytica in major data breach, 2018. https://www.theguardian.com/news/2018/mar/17/cambridge-analytica-facebook-influence-us-election, Accessed on: 18-05-11.
[21] I. Cantador, I. Fernández-Tobías, and A. Bellogín. Relating personality types with user preferences in multiple entertainment domains. In S. Berkovsky, E. Herder, P. Lops, and O. C. Santos, editors, *UMAP 2013: Extended Proceedings Late-Breaking Results, Project Papers and Workshop Proceedings of the 21st Conference on User Modeling, Adaptation, and Personalization. CEUR Workshop Proceedings*, 2013.
[22] F. Celli, E. Bruni, and B. Lepri. Automatic personality and interaction style recognition from facebook profile pictures. In *Proceedings of the 22Nd ACM International Conference on Multimedia*, MM '14, pages 1101–1104, New York, NY, US, 2014. ACM.
[23] O. Chausson. Who watches what?: Assessing the impact of gender and

personality on film preferences. *Paper published online on the MyPersonality project website http://mypersonality.org/wiki/doku.php*, 2010.

[24] R. K. Chellappa and R. G. Sin. Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management*, 6(2-3):181–202, 2005.

[25] L. Chen, W. Wu, and L. He. Personality and recommendation diversity. In M. Tkalčič, B. De Carolis, M. de Gemmis, A. Odić, and A. Košir, editors, *Emotions and Personality in Personalized Services: Models, Evaluation and Applications*, pages 201–225. Springer International Publishing, Cham, 2016.

[26] C. M. Ching, A. T. Church, M. S. Katigbak, J. A. S. Reyes, J. Tanaka-Matsumi, S. Takaoka, H. Zhang, J. Shen, R. M. Arias, B. C. Rincon, and F. A. Ortiz. The manifestation of traits in everyday behavior and affect: A five-culture study. *Journal of Research in Personality*, 48:1–16, 2014.

[27] G. Chittaranjan, J. Blom, and D. Gatica-Perez. Mining large-scale smartphone data for personality studies. *Personal and Ubiquitous Computing*, 17(3):433–450, 2013.

[28] W. J. Chopik and S. Kitayama. Personality change across the lifespan: Insights from a cross-cultural longitudinal study. *Journal of Personality*, 70(1), 2017.

[29] C. R. Cloninger, D. M. Svrakic, and T. R. Przybeck. A psychobiological model of temperament and character. *Archives of General Psychiatry*, 50(12):975–90, 1993.

[30] E. Constantinou, G. Panayiotou, N. Konstantinou, A. Loutsiou-Ladd, and A. Kapardis. Risky and aggressive driving in young adults: Personality matters. *Accident Analysis & Prevention*, 43(4):1323–1331, 2011.

[31] P. T. Costa Jr and R. R. McCrae. Four ways five factors are basic. *Personality and Individual Differences*, 13(6):653–665, 1992.

[32] N. Dahlbäck and A. Karsvall. Personality bias in volunteer based user studies. In *Proceedings of HCI*, 2000.

[33] A. S. Das, M. Datar, A. Garg, and S. Rajaram. Google news personalization: scalable online collaborative filtering. In *Proceedings of the 16th International Conference on World Wide Web*, pages 271–280, New York, NY, US, 2007. ACM.

[34] F. De Fruyt, L. Van De Wiele, and C. Van Heeringen. Cloninger's Psychobiological Model of Temperament and Character and the Five-Factor Model of Personality. *Personality and Individual Differences*, 29(3):441–452, 2000.

[35] B. De Raad. *The Big Five Personality Factors: The Psycholexical Approach to Personality.* Hogrefe & Huber Publishers, 2000.

[36] K. M. DeNeve and H. Cooper. The happy personality: A meta-analysis

of 137 personality traits and subjective well-being. *Psychological Bulletin*, 124(2):197, 1998.

[37] P. H. DuBois. A test-dominated society: China, 1115 B.C. – 1905 A.D. *Testing Problems in Perspective*, pages 29–36, 1966.

[38] K. Eckoldt, M. Knobel, M. Hassenzahl, and J. Schumann. An experiential perspective on advanced driver assistance systems. *It-Information Technology Methoden und Innovative Anwendungen der Informatik und Informationstechnik*, 54(4):165–171, 2012.

[39] P. Ehrenbrink, S. Osman, and S. Möller. Google Now is for the extraverted, Cortana for the introverted: Investigating the influence of personality on IPA preference. In *Proceedings of the 29th Australian Conference on Human-Computer Interaction (OzCHI)*, pages 1–9, New York, NY, US, 2017. ACM.

[40] M. Eiband, H. Schneider, M. Bilandzic, J. Fazekas-Con, M. Haug, and H. Hussmann. Bringing transparency design into practice. In *23rd International Conference on Intelligent User Interfaces*, IUI '18, pages 211–223, New York, NY, UD, 2018. ACM.

[41] M. Elahi, M. Braunhofer, F. Ricci, and M. Tkalčič. Personality-based active learning for collaborative filtering recommender systems. In M. Baldoni, C. Baroglio, G. Boella, and R. Micalizio, editors, *AI*IA 2013: Advances in Artificial Intelligence*, pages 360–371, Cham, 2013. Springer International Publishing.

[42] M. Emilsson, I. Berndtsson, J. Lötvall, E. Millqvist, J. Lundgren, Å. Johansson, and E. Brink. The influence of personality traits and beliefs about medicines on adherence to asthma treatment. *Primary Care Respiratory Journal*, 20(2):141–147, 2011.

[43] A. M. Evans and W. Revelle. Survey and behavioral measurements of interpersonal trust. *Journal of Research in Personality*, 42(6):1585–1593, 2008.

[44] I. Fernández-Tobías, M. Braunhofer, M. Elahi, F. Ricci, and I. Cantador. Alleviating the new user problem in collaborative filtering by exploiting personality information. *User Modeling and User-Adapted Interaction*, 26(2):221–255, 2016.

[45] B. Ferwerda, M. Tkalčič, and M. Schedl. Personality traits and music genres: What do people prefer to listen to? In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization*, UMAP '17, pages 285–288, New York, NY, US, 2017. ACM.

[46] B. Ferwerda, E. Yang, M. Schedl, and M. Tkalčič. Personality traits predict music taxonomy preferences. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, CHI EA '15, pages 2241–2246, New York, NY, US, 2015. ACM.

[47] D. C. Funder. Persons, behaviors and situations: An agenda for personality psychology in the postwar era. *Journal of Research in Personality*, 43(2):120–126, 2009.

[48] A. Furnham and J. Walker. The influence of personality traits, previous experience of art, and demographic variables on artistic preference. *Personality and Individual Differences*, 31(6):997–1017, 2001.

[49] J. Golbeck, C. Robles, and K. Turner. Predicting personality with social media. In *CHI'11 Extended Abstracts on Human Factors in Computing Systems*, pages 253–262, New York, NY, US, 2011. ACM.

[50] L. R. Goldberg. Language and individual differences: The search for universals in personality lexicons. *Review of Personality and Social Psychology*, 2(1):141–165, 1981.

[51] T. M. Green and B. Fisher. Towards the personal equation of interaction: The impact of personality factors on visual analytics interface interaction. In *Visual Analytics Science and Technology (VAST)*, pages 203–210. IEEE, 2010.

[52] P. Hagen, H. Manning, and R. Souza. *Smart personalization.* Forrester Research, Cambridge, MA, US, 1999.

[53] T. Halevi, J. Lewis, and N. Memon. A pilot study of cyber security and privacy related behavior and personality traits. In *Proceedings of the 22nd International Conference on World Wide Web*, pages 737–744, New York, NY, USA, 2013. ACM.

[54] P. A. Hancock, D. R. Billings, K. E. Schaefer, J. Y. Chen, E. J. De Visser, and R. Parasuraman. A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors*, 53(5):517–527, 2011.

[55] K. S. Haring, Y. Matsumoto, and K. Watanabe. How do people perceive and trust a lifelike robot. In *Proceedings of the World Congress on Engineering and Computer Science*, volume 1, 2013.

[56] M. Hassib, D. Buschek, P. W. Wozniak, and F. Alt. HeartChat: Heart rate augmented mobile chat to support empathy and awareness. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, pages 2239–2251, New York, NY, US, 2017. ACM.

[57] R. Häuslschmid, M. von Buelow, B. Pfleging, and A. Butz. Supporting trust in autonomous driving. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces*, IUI '17, pages 319–329, New York, NY, US, 2017. ACM.

[58] K. Heikkinen, J. Eerola, P. Jäppinen, and J. Porras. Personalized view of personal information. *WSEAS Transactions on Information Science and Applications*, 2(4), 2004.

[59] J. Heinström. Fast surfing, broad scanning and deep diving: The influence of

personality and study approach on students' information-seeking behavior. *Journal of Documentation*, 61(2):228–247, 2005.

[60] J. G. Helgeson and M. Supphellen. A conceptual and measurement comparison of self-congruity and brand personality; the impact of socially desirable responding. *International Journal of Market Research*, 46(2):205–236, 2004.

[61] P. Y. Herzberg. Beyond "accident-proneness": Using five-factor model prototypes to predict driving behavior. *Journal of Research in Personality*, 43(6):1096–1100, 2009.

[62] S. Y. Ho and D. Bodoff. The effects of web personalization on user attitude and behavior: An integration of the elaboration likelihood model and consumer search theory. *MIS Quarterly*, 38(2):497–520, 2014.

[63] C. Hohenberger, M. Spörrle, and I. M. Welpe. How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. *Transportation Research Part A: Policy and Practice*, 94:374–385, 2016.

[64] R. Hu. Design and user issues in personality-based recommender systems. In *Proceedings of the 4th ACM Conference on Recommender Systems*, RecSys '10, pages 357–360, New York, NY, US, 2010. ACM.

[65] R. Hu and P. Pu. Acceptance issues of personality-based recommender systems. In *Proceedings of the 3rd ACM Conference on Recommender Systems*, RecSys '09, pages 221–224, New York, NY, US, 2009. ACM.

[66] R. Hu and P. Pu. A study on user perception of personality-based recommender systems. In P. De Bra, A. Kobsa, and D. Chin, editors, *International Conference on User Modeling, Adaptation, and Personalization*, UMAP 2010, pages 291–302, Berlin, Heidelberg, 2010. Springer.

[67] D. Huang, M. Tory, B. A. Aseniero, L. Bartram, S. Bateman, S. Carpendale, A. Tang, and R. Woodbury. Personal visualization and personal visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, 21(3):420–433, 2015.

[68] S. Hyken. Recommended just for you: The power of personalization, 2017. https://www.forbes.com/sites/shephyken/2017/05/13/recommended-just-for-you-the-power-of-personalization/#61403e3a6087, Accessed on: 2018-04-18.

[69] T. A. Judge, D. Heller, and M. K. Mount. Five-factor model of personality and job satisfaction: A meta-analysis. *Journal of Applied Psychology*, 87(3):530–541, 2002.

[70] A. Kannan, K. Kurach, S. Ravi, T. Kaufmann, A. Tomkins, B. Miklos, G. Corrado, L. Lukacs, M. Ganea, P. Young, and V. Ramavajjala. Smart reply: Automated response suggestion for email. In *Proceedings of the 22Nd*

ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16, pages 955–964, New York, NY, US, 2016. ACM.

[71] R. P. Karumur, T. T. Nguyen, and J. A. Konstan. Exploring the value of personality in predicting rating behaviors: A study of category preferences on movielens. In *Proceedings of the 10th ACM Conference on Recommender Systems*, RecSys '16, pages 139–142, New York, NY, US, 2016. ACM.

[72] Z. Kasap and N. Magnenat-Thalmann. Intelligent virtual humans with autonomy and personality: State-of-the-art. In N. Magnenat-Thalmann, L. C. Jain, and N. Ichalkaranje, editors, *New Advances in Virtual Humans: Artificial Intelligence Environment*, pages 43–84. Springer, Berlin, Heidelberg, 2008.

[73] J. Kay and B. Kummerfeld. Creating personalized systems that people can scrutinize and control: Drivers, principles and experience. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(4):24, 2012.

[74] H. H. Kelley. Attribution theory in social psychology. In *Nebraska Symposium on Motivation*, volume 15. University of Nebraska Press, 1967.

[75] M. L. Korzaan and K. T. Boswell. The influence of personality traits and information privacy concerns on behavioral intentions. *Journal of Computer Information Systems*, 48(4):15–24, 2008.

[76] M. Kosinski, D. Stillwell, and T. Graepel. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, 110(15):5802–5805, 2013.

[77] J. Kramer, S. Noronha, and J. Vergo. A user-centered design approach to personalization. *Communications of the ACM*, 43(8):44–48, 2000.

[78] T. Kulesza, S. Stumpf, M. Burnett, and I. Kwan. Tell me more?: The effects of mental model soundness on personalizing an intelligent agent. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '10, pages 1–10, New York, NY, US, 2012. ACM.

[79] M. Kyriakidis, R. Happee, and J. C. de Winter. Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, 32:127–140, 2015.

[80] J. LeBlanc and M. Ducharme. Influence of personality traits on plasma levels of cortisol and cholesterol. *Physiology & Behavior*, 84(5):677–680, 2005.

[81] K. M. Lee and C. Nass. Designing social presence of social actors in human computer interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '03, pages 289–296, New York, NY, US, 2003. ACM.

[82] K. M. Lee, W. Peng, S.-A. Jin, and C. Yan. Can robots manifest personality?: An empirical test of personality recognition, social responses, and social

presence in human–robot interaction. *Journal of Communication*, 56(4):754–772, 2006.

[83] B. Lepri, J. Staiano, E. Shmueli, F. Pianesi, and A. Pentland. The role of personality in shaping social networks and mediating behavioral change. *User Modeling and User-Adapted Interaction*, 26(2):143–175, Jun 2016.

[84] B. Y. Lim and A. K. Dey. Toolkit to support intelligibility in context-aware applications. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*, UbiComp '10, pages 13–22, New York, NY, US, 2010. ACM.

[85] G. Matthews, I. J. Deary, and M. C. Whiteman. *Personality Traits.* Cambridge University Press, Cambridge, UK, 2003.

[86] S. C. Matz, M. Kosinski, G. Nave, and D. J. Stillwell. Psychological targeting as an effective approach to digital mass persuasion. *Proceedings of the National Academy of Sciences of the United States of America*, 114(48):12714–12719, 2017.

[87] R. R. McCrae and P. T. Costa. Personality, coping, and coping effectiveness in an adult sample. *Journal of Personality*, 54(2):385–404, 1986.

[88] R. R. McCrae and P. T. Costa Jr. The five-factor theory of personality. In O. P. John, R. Robins, and L. A. Pervin, editors, *Handbook of Personality: Theory and Research*, pages 159–181. Guilford Press, New York, NY, US, 2008.

[89] R. R. McCrae and O. P. John. An introduction to the five-factor model and its applications. *Journal of Personality*, 60(2):175–215, 1992.

[90] M. McRorie, I. Sneddon, G. McKeown, E. Bevacqua, E. de Sevin, and C. Pelachaud. Evaluation of four designed virtual agent personalities. *IEEE Transactions on Affective Computing*, 3(3):311–322, 2012.

[91] B. Mobasher, R. Cooley, and J. Srivastava. Automatic personalization based on web usage mining. *Communications of the ACM*, 43(8):142–151, 2000.

[92] C. Molnar. *Interpretable Machine Learning.* 2018. https://christophm.github.io/interpretable-ml-book/.

[93] C. Montag, K. Błaszkiewicz, B. Lachmann, I. Andone, R. Sariyska, B. Trendafilov, M. Reuter, and A. Markowetz. Correlating personality and actual phone usage: Evidence from psychoinformatics. *Journal of Individual Differences*, 35(3):158–165, 2014.

[94] M. Mount, R. Ilies, and E. Johnson. Relationship of personality traits and counterproductive work behaviors: The mediating effects of job satisfaction. *Personnel Psychology*, 59(3):591–622, 2006.

[95] R. C. Mulyanegara, Y. Tsarenko, and A. Anderson. The big five and brand personality: Investigating the impact of consumer personality on prefer-

ences towards particular brand personality. *Journal of Brand Management*, 16(4):234–247, 2009.

[96] E. Mussi. Flexible and context-aware processes in service oriented computing. *Dipartimento di Elettronica e Informazione*, 2007.

[97] A. Narayanan and V. Shmatikov. Robust de-anonymization of large sparse datasets. In *IEEE Symposium on Security and Privacy, 2008*, SP 2008, pages 111–125. IEEE, 2008.

[98] C. Nass and S. Brave. *Wired for speech: How voice activates and advances the human-computer relationship.* MIT Press, Cambridge, MA, US, 2005.

[99] G. Nave, J. Minxha, D. M. Greenberg, M. Kosinski, D. Stillwell, and J. Rentfrow. Musical preferences predict personality: Evidence from active listening and facebook likes. *Psychological Science*, 29(7):1145–1158, 2018.

[100] J. K. H. Nga and G. Shamuganathan. The influence of personality traits and demographic factors on social entrepreneurship start up intentions. *Journal of Business Ethics*, 95(2):259–282, 2010.

[101] L. Nocks. *The Robot: The Life Story of a Technology.* Greenwood Press, Westport, CT, US, 2006.

[102] M. A. S. Nunes and R. Hu. Personality-based recommender systems: an overview. In *Proceedings of the 6th ACM Conference on Recommender Systems*, RecSys '12, pages 5–6, New York, NY, US, 2012. ACM.

[103] M. A. S. N. Nunes. Towards to psychological-based recommenders systems: a survey on recommender systems. *Scientia Plena*, 6(8), 2010.

[104] T. B. O'Brien and A. DeLongis. The interactional context of problem-, emotion-, and relationship-focused coping: The role of the Big Five personality factors. *Journal of Personality*, 64(4):775–813, 1996.

[105] A. Oulasvirta, M. Raento, and S. Tiitta. Contextcontacts: Re-designing smartphone's contact book to support mobile awareness and collaboration. In *Proceedings of the 7th International Conference on Human Computer Interaction with Mobile Devices & Services*, MobileHCI '05, pages 167–174, New York, NY, US, 2005. ACM.

[106] D. J. Ozer and V. Benet-Martínez. Personality and the Prediction of Consequential Outcomes. *Annual Review of Psychology*, 57(1):401–421, 2006.

[107] E. Pariser. *The Filter Bubble: What the Internet Is Hiding from You.* The Penguin Press, London, UK, 2011.

[108] G. Park, H. A. Schwartz, J. C. Eichstaedt, M. L. Kern, M. Kosinski, D. J. Stillwell, L. H. Ungar, and M. E. P. Seligman. Automatic personality assessment through social media language. *Journal of Personality and Social Psychology*, 108(6):934–952, 2015.

[109] E. Perik, B. De Ruyter, P. Markopoulos, and B. Eggen. The sensitivities

of user profile information in music recommender systems. *Proceedings of Private, Security, Trust*, pages 137–141, 2004.

[110] B. Pfleging, M. Rang, and N. Broy. Investigating user needs for non-driving-related activities during automated driving. In *Proceedings of the 15th International Conference on Mobile and Ubiquitous Multimedia*, MUM '16, pages 91–99, New York, NY, US, 2016. ACM.

[111] A. D. Pickering, P. J. Corr, and J. A. Gray. Interactions and reinforcement sensitivity theory: A theoretical analysis of Rusting and Larsen (1997). *Personality and Individual Differences*, 26(2):357–365, 1999.

[112] P. A. Rauschnabel, A. Brem, and B. S. Ivens. Who will buy smart glasses? Empirical results of two pre-market-entry studies on the role of personality in individual awareness and intended adoption of Google Glass wearables. *Computers in Human Behavior*, 49:635–647, 2015.

[113] B. Reeves and C. I. Nass. *The Media Equation: How People Treat Computers, Television, and New Media like Real People and Places.* Cambridge University Press, Cambridge, UK, 1996.

[114] P. J. Rentfrow and S. D. Gosling. The do re mi's of everyday life: The structure and personality correlates of music preferences. *Journal of Personality and Social Psychology*, 84(6):1236, 2003.

[115] P. Resnick and H. R. Varian. Recommender systems. *Communications of the ACM*, 40(3):56–58, 1997.

[116] C. Rödel, S. Stadler, A. Meschtscherjakov, and M. Tscheligi. Towards autonomous cars: the effect of autonomy levels on acceptance and user experience. In *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, AutoUI '14, pages 1–8, New York, NY, US, 2014. ACM.

[117] M. Rosenberg and G. J. Dance. 'You Are the Product': Targeted by Cambridge Analytica on Facebook, 2018. https://www.nytimes.com/2018/04/08/us/facebook-users-data-harvested-cambridge-analytica.html, Accessed on: 18-05-11.

[118] A. Roshchina, J. Cardiff, and P. Rosso. Twin: personality-based intelligent recommender system. *Journal of Intelligent & Fuzzy Systems*, 28(5):2059–2071, 2015.

[119] M. Sailer, J. U. Hense, S. K. Mayr, and H. Mandl. How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior*, 69:371–380, 2017.

[120] M. Salem, G. Lakatos, F. Amirabdollahian, and K. Dautenhahn. Would you trust a (faulty) robot?: Effects of error, task type and personality on human-robot cooperation and trust. In *Proceedings of the Tenth Annual ACM/IEEE*

International Conference on Human-Robot Interaction, HRI '15, pages 141–148, New York, NY, US, 2015. ACM.

[121] K. E. Schaefer, J. Y. Chen, J. L. Szalma, and P. A. Hancock. A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. *Human Factors*, 58(3):377–400, 2016.

[122] K. R. Scherer. Personality markers in speech. In K. R. Scherer and H. Giles, editors, *Social Markers in Speech*. Cambridge University Press, Cambridge, UK, 1979.

[123] U. Schimmack, P. Radhakrishnan, S. Oishi, V. Dzokoto, and S. Ahadi. Culture, personality, and subjective well-being: Integrating process models of life satisfaction. *Journal of Personality and Social Psychology*, 82(4):582, 2002.

[124] H. Schneider, K. Schauer, C. Stachl, and A. Butz. Your data, your vis: Personalizing personal data visualizations. In R. Bernhaupt, G. Dalvi, A. K. Joshi, D. Balkrishan, J. O'Neill, and M. Winckler, editors, *Human-Computer Interaction – INTERACT 2017. Lecture Notes in Computer Science*, volume 10515, pages 374–392, Cham, 2017. Springer.

[125] P. R. Shaver and K. A. Brennan. Attachment styles and the "big five" personality traits: Their connections with each other and with romantic relationship outcomes. *Personality and Social Psychology Bulletin*, 18(5):536–545, 1992.

[126] J. Shropshire, M. Warkentin, and S. Sharma. Personality, attitudes, and intentions: Predicting initial adoption of information security behavior. *Computers & Security*, 49:177–191, 2015.

[127] M. J. Sirgy. Using self-congruity and ideal congruity to predict purchase motivation. *Journal of Business Research*, 13(3):195–206, 1985.

[128] H. Song and N. Kwon. The relationship between personality traits and information competency in Korean and American students. *Social Behavior and Personality*, 40(7):1153–1162, 2012.

[129] J. Specht, B. Egloff, and S. C. Schmukle. Stability and change of personality across the life course: the impact of age and major life events on mean-level and rank-order stability of the Big Five. *Journal of Personality and Social Psychology*, 101(4):862–882, 2011.

[130] C. Stachl, S. Hilbert, J.-Q. Au, D. Buschek, A. De Luca, B. Bischl, H. Hussmann, and M. Bühner. Personality traits predict smartphone usage. *European Journal of Personality*, 31(6):701–722, 2017.

[131] K. Y. Tam and S. Y. Ho. Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, pages 865–890, 2006.

[132] A. Tapus and M. J. Mataric. Socially assistive robots: The link between personality, empathy, physiological signals, and task performance. In *AAAI Spring Symposium: Emotion, Personality, and Social Behavior*, pages 133–140, 2008.

[133] The European Parliament and Council. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). *Official Journal of the European Union*, 2016.

[134] A. Thieme, R. Comber, J. Miebach, J. Weeden, N. Kraemer, S. Lawson, and P. Olivier. "We've bin watching you": Designing for reflection and social persuasion to promote sustainable lifestyles. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '12, pages 2337–2346, New York, NY, US, 2012. ACM.

[135] N. Tintarev and J. Masthoff. A survey of explanations in recommender systems. In *2007 IEEE 23rd International Conference on Data Engineering Workshop*, pages 801–810. IEEE, 2007.

[136] M. Tkalčič and L. Chen. Personality and recommender systems. In F. Ricci, L. Rokach, and B. Shapira, editors, *Recommender Systems Handbook*, pages 715–739. Springer US, Boston, MA, US, 2015.

[137] M. Tkalčič, B. Ferwerda, D. Hauger, and M. Schedl. Personality correlates for digital concert program notes. In F. Ricci, K. Bontcheva, O. Conlan, and S. Lawless, editors, *User Modeling, Adaptation and Personalization*, pages 364–369, Cham, 2015. Springer International Publishing.

[138] A. Tuzhilin. Personalization: The state of the art and future directions. *Business Computing*, 3(3), 2009.

[139] Y. V. Vaerenbergh and T. D. Thomas. Response styles in survey research: A literature review of antecedents, consequences, and remedies. *International Journal of Public Opinion Research*, 25(2):195–217, 2013.

[140] T. Van der Geest, J. van Dijk, W. Pieterson, W. Ebbers, B. Fennis, N. Loorbach, M. Steehouder, E. Taal, and P. de Vries. *Alter Ego: State of the Art on User Profiling: An Overview of the Most Relevant Organisational and Behavioural Aspects Regarding User Profiling.* Telematica Instituut, Enschede, Netherlands, 2005.

[141] A. Vinciarelli and G. Mohammadi. A survey of personality computing. *IEEE Transactions on Affective Computing*, 5(3):273–291, 2014.

[142] M. Warkentin, M. McBride, L. Carter, and A. Johnston. The role of individual characteristics on insider abuse intentions. *AMCIS 2012 Proceedings*, 28, 2012.

[143] A. Weiss, B. van Dijk, and V. Evers. Knowing me knowing you: Exploring

effects of culture and context on perception of robot personality. In *Proceedings of the 4th International Conference on Intercultural Collaboration*, pages 133–136, New York, NY, US, 2012. ACM.

[144] R. Westfall. Psychological factors in predicting product choice. *The Journal of Marketing*, 26(2):34–40, 1962.

[145] T. Yarkoni. Personality in 100,000 Words: A large-scale analysis of personality and word use among bloggers. *Journal of Research in Personality*, 44(3):363–373, 2010.

[146] H. S. Yoon and L. M. B. Steege. Development of a quantitative model of the impact of customers' personality and perceptions on internet banking use. *Computers in Human Behavior*, 29(3):1133–1141, 2013.

[147] W. Youyou, M. Kosinski, and D. Stillwell. Computer-based personality judgments are more accurate than those made by humans. *Proceedings of the National Academy of Sciences*, 112(4):1036–1040, 2015.

[148] C. Ziemkiewicz and R. Kosara. Preconceptions and individual differences in understanding visual metaphors. *Computer Graphics Forum*, 28(3):911–918, 2009.

[149] A. Zimmermann, M. Specht, and A. Lorenz. Personalization and context management. *User Modeling and User-Adapted Interaction*, 15(3):275–302, 2005.

[150] M. Zuckerman. *Sensation Seeking: Beyond the Optimal Level of Arousal.* Lawrence Erlbaum Associates, Inc, New York,, NY, US, 1979.