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Abstract:

Personalization is an effective means for accommodating differences between individuals. Therefore, the personalization of a system's user interface (UI) features can enhance usability. To date, UI personalization approaches have been largely divorced from psychological theories of personality, and the user profiles constructed by extant personalization techniques do not map directly onto the fundamental personality traits examined in the psychology literature. In line with recent calls to ground the design of information systems in behavioral theory, we maintain that personalization that is informed by psychology literature is advantageous. More specifically, we advocate an approach termed "personalityzation", where UI features are adapted to an explicit model of a user's personality. We demonstrate the proposed personalityzation approach through a proof-of-concept in the context of social recommender systems. We identify two key contributions to information systems research. First, extending prior works on adaptive interfaces, we introduce a UI personalization framework that is grounded in psychology theory of personality. Second, we reflect on how our proposed personalityzation framework could inform the discourse in design research regarding the theoretical grounding of system's design.

Keywords: Personalityzation, Human-Computer Interaction (HCI), User Interface (UI), Adaptive Interfaces, Personality, Personalization, Design Research.

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1 Introduction

In the early days of the information systems discipline, a steady stream of research studied individual differences (especially in the area of cognitive style) and their effect on information system success (Benbasat and Taylor, 1978; Zmud, 1979). However, at that period it was impractical to employ knowledge of these individual differences to inform system design due to the difficulty of customizing computerized systems (Huber 1983).[1] With recent technological advancements coupled with the exploding amounts of information captured about users, interest in personalized user interfaces has surged in the human-computer interaction (HCI) community (Grudin, 2009; Jameson, 2009). The fundamental idea behind this trend rests on the notion that, if a system can gather key information about the user, generate a relevant user model, and apply it appropriately, it would be possible to adapt the behavior of a system and its interface to the user at the individual level (Findlater & Gajos, 2009; Jameson, 2008; Hirsh, et al., 2012). Today most systems have built-in capability for personalizing many aspects of a user's experience, including look and feel, search recommendations, and other functionality.

With this paper, we primarily contribute to HCI research by introducing a novel personality-based approach to designing personalized user interfaces (UI), which we term "personalityzation" (personality-zation). Despite the long tradition in HCI research of grounding design in theoretical frameworks from the field of psychology, extant research on personalization has been largely disconnected from psychological research on personality. Existing approaches to personalization often construct a user profile that is suited for a particular task such that the profile is based on a user's consumption history or topics of interest relevant for the particular task at hand. As a consequence, profiles are restricted to a particular online application. Moreover, these profiles are quite malleable and are updated frequently, such that personalized UI may also need to adapt repeatedly, resulting in unpredictability (Jameson, 2008). Users of such systems struggle to continually adapt their mental maps and learn to navigate the ever-changing interfaces. Taking these potential shortfalls of personalized UIs in mind, we propose to construct the user model around personality traits, which are more fundamental and relatively stable attributes of the user (for example, extroversion or conscientiousness). We argue that such personality-based personalization (or personalityzation) would ameliorate some of the challenges facing research on personalized UI, namely by offering a personalization approach that is more durable and applicable across a wider range of tasks and contexts.

With recent technological advances, personalityzation is now achievable. While users could be asked to explicitly describe their personality (using psychometric survey instruments), it is now increasingly possible to automatically and unobtrusively construct a model of users' personality. Recent years have seen an explosion of information available about individuals in a variety of contexts. This data is being collected by a multitude of companies in the information aggregation industry and is also being bought and sold in market-like commodity exchanges (Angwin, 2010). This preponderance of personal data online in conjunction with advances in data-mining technologies has opened up new opportunities for personalization. In particular, one can now automatically construct a profile of users' key personality traits based on their online behavior (Chittaranjan, Blom, & Gatica-Perez, 2012; Golbeck, Robles, Edmondson, & Turner, 2011; Park et al., 2014).

To provide a proof-of-concept for our proposed personalityzation framework, we report two empirical studies that test how the interaction between users' personality and UI design features affect participation in social recommender systems. Specifically, we focus on the application of the personality profiles in the context of personalized UI. The first study reported in this paper explores the personality trait of emotional stability and its interaction with a UI feature of social anchoring; the second study investigates how people with varying conscientiousness levels respond differently to UI cues regarding the number of active participants. The contribution of our work to HCI research is in proposing a novel framework for personalized UI—personalityzation—where interface features are adapted to users' personality profile.

With this paper, we secondarily contribute to the ongoing discourse in the design research (DR) field regarding the role of theory in grounding system's design (Arazy, Kumar, & Shapira, 2010; Gregor & Jones, 2007; Kuechler & Vaishnavi, 2012). Personalityzation calls for grounding UI adaptation practices in the theory of personality; similarly, theory could play a role in guiding the design of other system components. Design research seeks to develop prescriptive design knowledge (often referred to as "design principles")

[1] At the time, Robey (1983) responded to Huber's criticism arguing that impacts of individual differences were important and striking, but not all systems had to be designed for individual differences.

through building and evaluating innovative IT artifacts (Hevner, March, Park, & Ram, 2004). There is a stream in DR that emphasizes the role of explanatory and predictive theories from the natural and behavioral sciences (i.e. "kernel theories") in directing design (Walls, Widmeyer, & El Sawy, 1992). However, there are several key challenges in bridging kernel theories and design principles, and the DR literature provides little guidance on how to address these challenges (Arazy et al., 2010). In recent years, there have been preliminary attempts to guide the process of theory-directed design by prescribing the use of an intermediate model between kernel theories and design (Arazy et al., 2010; Kuechler & Vaishnavi, 2012). Nonetheless, in developing our personalityzation framework, we found that we could ground UI design in the theory of personality without requiring such an intermediate model. Reflecting on the lessons learned from our research, we seek to contribute to the ongoing conversation in DR regarding ways for addressing the challenges associated with theory-directed design.

The paper proceeds as follows: In Section 2, we review relevant works on personalization in HCI. In Section 3, we present our proposed theory-driven personality-targeted UI approach and illustrate it through two studies. In Section 4, we discuss the contribution of our work to HCI research. In Section 5, we discuss the implications of our work on personalityzation to the discourse on theoretical grounding in design research, and, in Section 6, we conclude by discussing the promise of our approach and offering pointers to possible future research directions.

2 Personalized User Interfaces

In the past, personalization research in HCI has been studied under various labels such as adaptive UI, user modeling (UM), and intelligent user interfaces (IUIs). Maybury and Wahlster (1998) define these adaptive UIs as "human-machine interfaces that aim to improve the efficiency, effectiveness and naturalness of human-machine interaction by representing, reasoning and acting on models of the user, domain, task, discourse and media (e.g. graphics, natural language, gesture)" (p. 3).

A well-designed personalized interface can help improve a user's effectiveness by taking over parts of routine tasks (as in Gmail's feature that automatically sorts emails into broad categories such as promotions and social updates), changing the appearance of the interface so that it fits better with a user's way of working with the system (e.g., smart menus on Microsoft software products), offering advice on the task at hand (e.g., Microsoft Intelligent Help feature), and even mediating the interaction of a user with the real world based on the user's emotional and cognitive state (Begole, Matsakis, & Tang, 2004; Findlater & Gajos, 2009; Jameson, 2008). It can also help a user manage information overload by filtering relevant information and customize information presentation appropriately (Jameson, 2008; Maes, 1994). Recent research in online shopping shows that personality-based personalization can be effective in helping consumers understand product information better and lead to increased purchase intentions (Bosnjak, Galesic, & Tuten, 2007; Hirsh, Kang, & Bodenhausen, 2012; Woo & Shirmohammadi, 2008).

However, users do not always respond positively to UI personalization. For example, Mitchell and Shneiderman (1989) adapted the UI (namely, menu design) based on users' frequency of usage and found that the adaptive interfaces fared poorly when compared to standard non-personalized UI. Several problems and unintended side effects have been noted in the design and use of adaptive interfaces (Höök, 2000; Jameson, 2009; Mitchell & Shneiderman, 1989; Shneiderman & Maes, 1997). In his survey of the field, Jameson (2008) identified five major usability challenges for adaptive interfaces: diminished predictability and comprehensibility, diminished controllability, obtrusiveness, infringement of privacy, and diminished breadth of experience. Research on adaptive UI has been trying to address these usability issues by proposing a diverse range of strategies (Cockburn, Gutwin, & Greenberg, 2007; Findlater & Gajos, 2009; Gajos, Czerwinski, Tan, & Weld, 2006; Mitchell & Shneiderman, 1989). One approach has proposed to hand users' some control over the adaptation procedure (Bunt, Conati, & McGrenere, 2010). Another approach argued for minimizing adaptation only to situations where the personalized approach is expected to be most effective by automatically analyzing factors such as users' prior familiarity with interfaces, length of usage, and complexity of tasks (Cockburn et al., 2007; Findlater & Gajos, 2009; Gajos et al., 2006; Tsandilas & Schraefel, 2005).

In this paper, we propose a different approach for addressing the usability issues associated with personalized UI; namely, in basing the adaptation on factors that change less frequently. Personality traits are more durable aspects of individuals' background (Costa & McCrae, 1996) and, hence, can serve as a useful foil for the more transient contextual data collected about these individuals. Thus, personality-based adaptation—or personalityzation—has the potential to alleviate the concerns for diminished predictability, comprehensibility, and controllability. For example, prior studies have demonstrated that personality-based design can mitigate usability concerns and reduce users' cognitive load (Goren-Bar, Graziola, Pianesi, & Zancanaro, 2006; Jahng, Jain, Ramamurthy, & Jahng, 2002; McGrenere, Baecher, & Booth, 2002). Note that our proposed approach for personalization does not seek to replace existing strategies for adapting the UI; in fact, our approach could *complement* existing adaptive UI strategies (e.g., taking into consideration a user's prior behavior with the UI). We believe that personality traits—when paired with contextual data—can not only help better anticipate how individuals might react to variations introduced by adaptive interfaces (one of the critical factors that affected performance), but also provide useful signposts for incorporating appropriate design elements into the interface, thus boosting performance and satisfaction with the interfaces.

3 Personalityzation: Grounding UI Personalization in the Psychology of Personality

Our personalityzation approach to HCI design is informed by psychology research. A fundamental factor that distinguishes individuals from one another is personality: the dispositions and interpersonal strategies that explain people's behavior and the unique and relatively stable patterns of behaviors that individuals exhibit (Zweig & Webster 2004). In line with the interactionist approach in psychology (Endler & Parker, 1992; Swann & Seyle, 2005) and its application in the field of informatics (Oreg & Nov, 2008), we propose that HCI design be adapted to users' personality, such that specific UI features are presented to users with a particular personality profile (and not to others). Given that personality traits are relatively stable, personalityzation could alleviate the concerns for diminished predictability, comprehensibility, and controllability that are associated with personalized UI design (Jameson, 2008) to potentially yield higher levels of flow, performance, user satisfaction, and engagement. As a practical matter, surveying new users about their personality traits as a part of their enrollment process could provide a minimally intrusive way to learn about users' personal attributes. As an alternative, personality attributes could be automatically extracted by analyzing users' online behavior (Chittaranjan et al., 2012).

In the sections that follow, we offer a proof-of-concept for our personalityzation approach through two studies. Building on our argument that personality-based user models are more stable and are, thus, less likely to suffer from usability issues, we demonstrate that the proposed personalityzation framework is effective. Namely, we aim to show that there are noticeable differences between users of dissimilar personalities in terms of their response to UI design manipulations. Given that prior studies have showed the feasibility of automatically constructing users' personality profiles based on their online behavior (Chittaranjan et al., 2012; Golbeck et al., 2011), our proof-of-concept employs a simple survey-based method for measuring users' personality.

In the two studies reported below, we investigated whether differences in users' enduring personal attributes could explain the effects of design interventions on users' online behavior. Building on prior studies that have used a social movie recommender system as a live laboratory setting for investigating the effects of design on user behavior (Fugelstad et al.. 2012; Ling et al., 2005), we performed our studies in the context of social recommender systems (although, in principle, our proposed approach is applicable in a variety of online settings). Recommender systems are a class of social participation systems (Kraut et al., 2010) and, thus, our outcome variable is online participation (i.e., providing a recommendation online). We investigate UI design manipulations that enact social influence processes and are expected to affect online participation. In our studies, personality traits moderate the relationships between the effect of UI manipulations (i.e., independent variables) and online participation (dependent variable).

The following section elucidates two studies we conducted to examine the interaction between personality traits and UI design interventions. The studies provide two independent examples of personalityzation. Each explores one distinct UI feature and its interaction with particular personality attribute. Note that we chose simple examples to demonstrate the principle. For example, one of the UI design manipulations we investigate is social anchoring, which, in the context of social recommender system, entails presenting to the user the community's rating of the item under consideration. An example of a personality trait we investigate is emotional stability. Different design features may call for personalityzation around a different trait. The most relevant personality trait for a particular problem could be selected based on both theoretical considerations and empirical explorations. We note that there are various ways in which personality traits and design interventions could be categorized and operationalized (e.g., as nominal or ordinal categories).

For simplicity, here we assume ordinality along a single personality trait and design intervention. Table 1 illustrates the 2x2 experimental design for our personalityzation framework.

Table 1. Experimental Design: Traits X Interventions

	Experimental UI design interventions	
Individual trait	*Design intervention: low level*	*Design intervention: high level*
Low level of individual trait	Outcome for: low trait X low intervention	Outcome for: low trait X high intervention
High level of individual trait	Outcome for: high trait X low intervention	Outcome for: high trait X high intervention
	Experimental outcomes	

For both studies, we drew on the big five model of personality (Goldberg, 1981). This model of personality traits consists of five high-level factors, which represent personality at the broadest level of abstraction. Each bipolar factor (e.g., extraversion vs. introversion) summarizes several more specific facets, which, in turn, subsume a large number of even more specific traits (Gosling, Rentfrow, & Swann, 2003). The big-five framework has been widely used and extensively researched in a variety of research domains (John & Srivastava, 1999). In particular, scholars have found the "big five" personality factors to be useful predictors of Internet use (McElroy, Hendrickson, Townsend, & DeMarie, 2007), online shopping (Bosnjak et al., 2007; Hirsh et al., 2012; Jahng et al., 2002), perceived and actual usage of technology (Barnett, Pearson, Pearson, & Kellermanns, 2014) and participation in social media sites (Buffardi & Campbell, 2008; Chen & Caropreso, 2004; Correa, Hinsley, & De Zuniga, 2010). For our personalityzation project, we focused on three of the five personality traits that we believed to be most relevant for the context of UI design: emotional stability, conscientiousness, and extraversion. In the first study reported here, we focused on the personality trait of emotional stability, while, in the second study, we investigated the role of conscientiousness (more on the rationale for the choice of these traits below). We based the operationalization of these personality traits on the ten item personality instrument (Gosling et al., 2003), which includes two items per each of the five personality constructs (this scale has been validated and tested numerous times in prior studies (Ehrhart et al., 2009)). In both studies, we surveyed participants for emotional stability, conscientiousness, and extraversion; the results of a confirmatory factor analyses (CFA, using Varimax rotation with Kaiser Normalization) showed that item loadings on relevant constructs were in the 0.73-0.90 range, while cross loadings were below 0.30. Please see results of CFA in Tables 2 and 3 (loadings under 0.3 suppressed).

Table 2. Results of CFA (Study 1)

	Component		
Scale item	**1**	**2**	**3**
Emotional_Stability1	0.871		
Emotional_Stability2	0.846		
Extraversion1		0.869	
Extraversion2		0.896	
Conscientiousness1			0.729
Conscientiousness2			0.873

The setting for both these studies was a simulated online recommender system called PetLink, which we developed as an experimental platform. PetLink is presented as a research project involving the development of a technique to match users' personality traits with pets that are most suitable for them. PetLink's landing page invites participants to answer a very short personality questionnaire. Given this setting, users had an incentive to answer the questionnaire items candidly. After answering the personality questions, respondents were presented with their purported "best match": an image of an animal based on the responses to the survey questions, such that each combination of responses was associated with a specific pet image. Unbeknown to the respondents, the system arbitrarily paired images with personality profiles, with no attempt to match images to personalities. At this stage, respondents were presented with additional, experimentally manipulated UI cues about prior participation by other users and were requested to rate the quality of the match on a five-star scale. Social recommender systems rely on users to provide their assessment of items (e.g., ratings) and, thus, the UI design experimental manipulations we explored were intended to induce users to contribute by providing their ratings. These two studies demonstrate the effectiveness of a personality-based UI adaptation (or personalityzation). We provide details for both studies in the sections that follow.

Table 3. Results of CFA (Study 2)

	Component		
Scale item	**1**	**2**	**3**
Emotional_Stability1	0.874		
Emotional_Stability2	0.862		
Extraversion1		0.878	
Extraversion2		0.902	
Conscientiousness1			0.848
Conscientiousness2			0.862

3.1 Study #1: Emotional Stability, Social Anchoring, and Online Participation

In this study, we investigated how user participation is affected by the interaction between the personality trait of emotional stability and a design intervention of social anchoring (Nov, Arazy, López, & Brusilovsky, 2013a). In Sections 3.1.1 to 3.1.5, we briefly review the theoretical grounding guiding the design (in terms of the choices regarding the relevant personal attributes and the appropriate UI design interventions), describe the research methodology, present the study's findings, and discuss their implications for HCI research.

3.1.1 Related Studies

Human judgment tends to be influenced by anchoring: when asked to make a quantitative judgment, people are often influenced by externally presented information when such information is available to them (McElroy & Dowd, 2007). Anchoring is seen as one of three basic heuristics in intuitive judgment (Kahneman, Slovic, & Tversky, 1982). Extant psychology research demonstrates that, in asking people to make a judgment, the experimental manipulation of initial values, or anchors, leads to estimates that are biased toward that anchor (Englich, Mussweiler, & Strack, 2006; Galinsky & Mussweiler, 2001). As a result, studies of the effects of anchoring on human behavior have been carried out in a variety of fields, including finance (Johnson, Schnytzer, & Liu, 2009), law (Guthrie, Rachlinski, & Wistrich, 2007) and marketing (Adaval & Wyer, 2011). Some of the psychological mechanisms underlying anchoring are confirmatory hypothesis testing, numeric or magnitude priming, and insufficient adjustment. Recent studies, focusing on the social context in which anchors arise, have taken a broader view of anchoring and adopted an attitudes and persuasion perspective (Wegener, Petty, Blankenship, & Detweiler-Bedell, 2010). We use the term social anchoring to refer to an anchoring effect where the social context and, in particular, the anchor's source elicit processes of persuasion and social influence and affect judgment (Epley & Gilovich, 2010).

In the context of UI design, anchors could be used as design features, prompting users to make a particular action. Generally speaking, HCI research on the effects of anchoring has been relatively scarce, with the notable exception of Cosley, Lam, Albert, Konstan, and Riedl (2003), who found that, when users of a movie recommender system were asked to re-rate movies while (experimentally manipulated) being presented with "predicted" ratings, they tended to change their rating toward the "prediction" anchor. More recently, Adomavicius, Bockstedt, Curley, and Zhang (2011) showed that users' ratings can be influenced by a recommender system's (experimentally manipulated) anchors, and that the effects of anchoring can be separated from the effects of the system's perceived reliability. Our example study builds on this prior work and extends it to explore whether some people are more sensitive to anchoring than others.

3.1.2 Theoretical Context

The interaction between personality traits and anchoring has been the subject of recent research in psychology. For example, McElroy and Dowd (2007) found that individuals who were high in the openness-to-experience personality trait were significantly more influenced by anchoring cues relative to participants low in this trait, and Eroglu and Croxton (2010) found that those high on agreeableness and conscientiousness but low on extroversion were more susceptible to anchoring. In contrast, Furnham et al. (2012) found no significant interaction between anchoring cues and the personality traits of openness-to-experience. In this study, we focus on the personality trait of emotional stability, sometimes known as the opposite of neuroticism (Mobbs, Hagan, Azim, Menon, & Reiss, 2005; Vittersų, 2001). Emotional stability is highly relevant for the anchoring context because it affects people's likelihood of being influenced by others.

3.1.3 Hypothesis Development

The main hypothesis of this study was that emotional stability has the potential to explain user behavior in the presence of anchoring. Since individuals who are high on emotional stability tend to be more secure and self-assured (Costa & McCrae, 1992), we expected that they would be less susceptible to the influence of social anchoring cues. Individuals who are low on emotional stability, on the other hand, tend to be insecure and self-doubting (Diefendorff & Richard, 2003) and they often exhibit an external control of reinforcement (Judge, Erez, Bono, & Thoresen, 2002; Judge, 2009) (i.e., they believe events in their life are outside of their control (Rotter, 1975; Rotter, 1990)). Hence, because those high in neuroticism tend to be externally focused, we anticipated that they would be more susceptible to the influence of others and, in particular, to anchors representing the opinions of others. In sum, this study hypothesized that the effect of social anchoring cues on users' rating will be weaker among high-emotional stability participants compared to low-emotional stability participants. Formally stated:

Hypothesis #1: A participant's emotional stability will moderate the effect of social anchoring cues on the participant's rating score, such that people low on the emotional stability scale will react more strongly (when compared to those with high emotional stability) as a response to the cue, increasing their rating score.

Figure 1 illustrates this study's hypothesis.

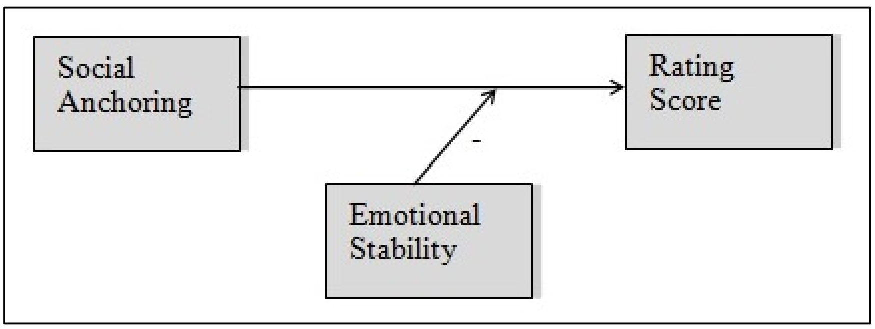

Figure 1. Hypothesis: Emotional Stability Moderates (Negatively) the Relationship between Social Anchoring and Participants' Rating Score

3.1.4 Research Method

We tested the study's hypothesis using PetLink (the simulated online recommender system). We recruited participants in the study via Amazon Mechanical Turk. They received $0.05 and took part in the study only once. PetLink's landing page invited participants to answer a very short questionnaire to measure emotional stability using two items (on a 7-point Likert scale) that we adapted from the ten item personality instrument (Gosling et al., 2003): "I see myself as calm, emotionally stable" and "I see myself as anxious, easily upset" (reversed code). In line with the experimental design presented in Table 1, we performed a median split to classify respondents as high or low on emotional stability.

The experimental manipulation consisted of high and low social anchor level, whereby respondents were presented with information about the community's average rating for the particular pet image presented to them (along the lines of UI design common on popular recommender systems such as Amazon or Netflix). We experimentally manipulated this "average rating" value, representing the social anchor, and randomly assigned it either a high level (4.5 stars) or a low level (1 star) (see Figure 2). After we presented the respondents with their purported "best match" and the social anchor, we requested them to rate the quality of the match on a five-star scale. The outcome variable was the average rating (ranging between 1-5 stars) that the participants provided.

Figure 2. Experimental Manipulation: Two Anchor Values

3.1.5 Results

Two hundred and forty-nine participants (66% of those who answered the personality survey) rated the quality of the match. Cronbach's alpha value for emotional stability was 0.74, above the 0.70 threshold, demonstrating good composite reliability (Hair, Anderson, Tatham, & Black, 1998). The average variance extracted (AVE) for emotional stability was 0.737, well above the 0.50 threshold measure (Fornell & Larcker, 1981), and the square root of AVE (0.859) was higher than the correlation with other factors; inter-construct correlations were well below the threshold (the highest, 0.223, for social anchoring—rating score pair); together, these results demonstrate discriminant and convergent validity (Straub, Boudreau, & Gefen, 2004). Each user was assigned to one of the four cells Table 1 based on the UI manipulation (i.e., the type of anchor) and emotional stability level (based on the median split). The average rating among participants in all experimental conditions was 3.04. Consistent with prior research, ratings were biased toward the anchors, with mean rating = 3.36 among high-anchor participants and 2.71 and among low anchor participants. The results of an ANOVA comparing the four experimental bins (high and low emotional stability X two experimental interventions) revealed an insignificant main effect of emotional stability on participants' rating score and a significant effect for the social anchor ($p < 0.01$). Therefore, the study's primary hypothesis was supported because the interaction effect between the independent variables was significant ($p < 0.01$) (see Figure 3). The results suggest that, while anchoring may be a universal phenomenon, its magnitude is moderated by the personality trait of emotional stability. In order to gain a deeper insight into the interaction between emotional stability and social anchoring, we performed a Bonferroni post-hoc analysis (Holm, 1979). The analysis revealed that, for people with below-average emotional stability, changes in the social anchor make a significant difference in participation ($p < 0.01$); on the other hand, for people with above average emotional stability, the effect of social anchors was insignificant. From a HCI design perspective, using anchors as a way to influence behavior is more effective among some users and less for others. Taking our study's findings into consideration, the UI should be adapted to present the social anchoring cues to people with low emotional stability.

Figure 3. Social Anchoring UI Manipulation Moderates the Relationship between Emotional Stability (ES) and Participants' Ratings

3.2 Study #2: Conscientiousness, Perceived Critical Mass, and Online Participation

In this study, we focused on providing personalized UI design intended to increase online participation in social recommender systems. Particularly, the goal of this study was to use UI indicators of the community size as a means to entice incoming users to provide their own rating (Nov & Arazy, 2013). We investigated how user participation is affected by the interaction between the personality trait of conscientiousness and a design intervention of perceived critical mass. In Sections 3.2.1 to 3.2.3, we briefly review the theoretical grounding guiding the design (in terms of the choices regarding the relevant personal attributes and the appropriate UI design interventions), describe the research methodology, present the study's findings, and discuss their implications for HCI research.

3.2.1 Related Studies

Extant organizational literature provides a complex view regarding the effects of group size in collective action: although larger groups are able to draw on the expertise and skills of a broader membership base, group size can negatively affect members' motivation to contribute to the collective action (Oliver, Marwell, & Teixeira, 1985). Research shows that the higher the number of people present in a situation or taking part in a collective effort, the higher likelihood of social loafing (Karau & Williams, 1993) and diffusion of responsibility (Darley & Latane, 1968; Garcia, Weaver, Moskowitz, & Darley, 2002), such that each one of the users present feels less personal responsibility and less compelled to help. This phenomenon applies to online settings as well (Alnuaimi, Robert, & Maruping, 2010; Butler, 2001; Counts, 2007). Prior studies have tried to reconcile these conflicting views by focusing on intervening factors, such as group homogeneity (Oliver & Marwell, 1988) and group interaction (Esteban & Ray, 2001).

Within the context of online participation, studies have shown that "perceived critical mass"—a user's subjective belief that there is a large number of other users who participate in a community or adopt a new technology—has a positive effect on the user's own participation behavior (Markus, 1987; Raban, Moldovan, & Jones, 2010; Van Slyke, Ilie, Lou, & Stafford, 2007). Our second study builds on this prior work and extends it to explore whether some people are more sensitive to perceived critical mass than others.

3.2.2 Theoretical context

In this study, we focused on the personality trait of conscientiousness, (being responsible, dependable, planful, organized, and persistent, (Barrick, Mount, & Strauss, 1993)). Prior studies of personality and social behavior have showed the important role the conscientiousness trait plays in explaining helping behavior that is relevant to the present study. Specifically, researchers have found that organizational citizenship behavior (OCB), a discretionary behavior that promotes the effective functioning of an organization but is not part of the formal reward system (Organ, 1988; Podsakoff, MacKenzie, Paine, & Bachrach, 2000), was highly affected by conscientiousness (Hoon & Tan, 2008; Organ, 1994). Other studies have shown that conscientiousness was negatively related to social loafing (Hoon & Tan, 2008). Participation in social recommender systems could be perceived as an act of citizenship behavior, and, thus, we expect a user's conscientiousness level to influence his online participation.

3.2.3 Hypothesis Development

The main hypothesis of this study was that conscientiousness has the potential to explain user response to critical mass UI indicators. In particular, we hypothesized that perceived low level of critical mass will discourage diffusion of responsibility among participants characterized by high conscientiousness, resulting in increased participation; in contrast, we expect that one's perception of the existence of critical mass will decrease the participation of highly conscientiousness users. We reasoned that people characterized by high conscientiousness tend to be responsible and self-disciplined (Costa & McCrae, 1992; Renn, Allen, & Huning, 2011) and, therefore, we expected them to act more responsibly in the face of a request for help (e.g., the researchers' request to rate users' pet match as part of a research project) when they see that there are fewer others who may be available to do so (i.e., low critical mass experimental condition). When facing a situation in which there is an indication that others have already provided help (i.e., high critical mass condition), the need for help would seem less important, and we expected highly conscientious people to feel less obliged to help, leading to decreased participation. We expected participants characterized by low conscientiousness, on the other hand, to be more likely to exert effort when there is social pressure on them from others to do so (Bolino, Turnley, Gilstrap, & Suazo, 2010; Grant, 2008). Therefore, we hypothesized that they would be more likely to participate when faced with an indication of a large number of other participants who already rated (i.e., high critical mass indicator) but less likely to participate in the absence of such indication (i.e., low critical mass indicator). Formally stated:

Hypothesis #2: A participant's conscientiousness will moderate the effect of critical mass cues on the participant's likelihood of rating, such that people low on the conscientiousness scale will react more strongly (when compared to those with high conscientious) as a response to the cue, increasing their likelihood of rating.

Figure 4 illustrates this study's hypothesis.

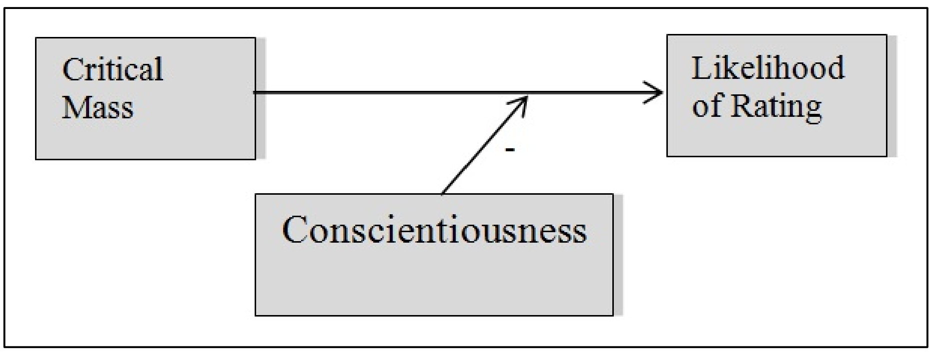

Figure 4. Hypothesis: Conscientiousness Moderates (Negatively) the Relationship between Critical Mass and Participants' Likelihood of Rating

3.2.4 Research Method

We tested the study's hypothesis using PetLink (the simulated online recommender system). We recruited participants in the authors' universities among undergraduate and graduate students. In addition, we asked students to share the invitation to participate in the study with their friends and family, and many of them shared the PetLink link with their contacts via social media. We did not compensate participants for their participation. PetLink's landing page invited participants to answer a very short questionnaire to measure conscientiousness using two items (on a 7-point Likert scale) that we adapted from the ten item personality instrument (Gosling et al., 2003): "I see myself as dependable, self-disciplined" and "I see myself as disorganized, careless" (reversed code). In line with the experimental design presented in Table 1, we performed a median split to classify respondents as high or low on conscientiousness.

The experimental manipulation consisted of high and low critical mass levels. In addition to the image, we also presented respondents with information about the number of previously reported ratings for the particular pet image presented to them (along the lines of UI design common on popular recommender systems such as Amazon or Netflix). Perceived critical mass is a subjective and context-specific concept

(Lou, Lou, & Strong, 2000; Van Slyke et al., 2007), and, therefore, we set two levels of critical mass in the study, assigned randomly to participants: a high value of prior ratings (2,127) represented a high level of critical mass and a low value (26 ratings) represented a low level of critical mass.

To validate the low and high values in the experiment, we administered an additional experiment using Amazon Mechanical Turk. In this experiment, participants were directed to a webpage describing a simple scenario that is fairly similar to PetLink (i.e. a hypothetical customer heard about a website where users rate movies, visited the website, and checked out a movie). The participant then finds that the movie received a rating of 3.5 stars out of 5 based on X reviews (where X is manipulated by the researchers and is randomly assigned the values of either 2,127 or 26 ratings, corresponding to the low and high critical mass values in PetLink). Having seen this rating, the participant is asked to what extent they agree with a statement that the movie reviews website has reached a critical mass of users. Responses range from 1 to 7 on a Likert scale (1 = strongly disagree; 4 = neutral; 7 = strongly agree). Seventy-eight people took part in this validation experiment. The low critical mass anchor (26 ratings) received an average score of 2.44 out of 7, while the high critical mass anchor (2,127 ratings) received an average score of 5.11. We used a t-test to compare the means and found the difference between them to be statistically significant ($p < 0.001$). Moreover, both scores were significantly ($p < 0.001$) lower and higher (respectively) than a "neutral" perceived critical mass value. These results corroborate our assumption that the two anchors represent high and low anchors for perceived critical mass.

In addition to the image indicators described, respondents were presented with two participation opportunities: (1) a request to rate the quality of the match on a five-star scale and (2) a request to provide verbal feedback: a comment or a link to a better match. Respondents' decision on whether to perform these actions or not served as a measure of the participation outcome variables.

3.2.5 Results

Four hundred and fifty-nine people used PetLink: 46.8 percent provided ratings and 21.7 percent provided verbal feedback.

Cronbach's alpha value for conscientiousness was 0.72, above the 0.70 threshold, demonstrating good composite reliability (Hair et al., 1998). The average variance extracted (AVE) for conscientiousness was 0.740, well above the 0.50 threshold measure (Fornell & Larcker, 1981), and the square root of AVE (0.860) was higher than the correlation with other factors; inter-construct correlations were extremely low (the highest was 0.009); together, these results demonstrate discriminant and convergent validity (Straub et al. 2004). In order to test the hypothesis, we studied two metrics of participation as our dependent variables: (1) whether respondents rated or not (rated = 1, not rated = 0), and (2) whether they provided verbal feedback (feedback = 1, no feedback = 0). The independent variables were conscientiousness level (high and low—above and below the median, respectively) and perceived critical mass (high and low). We created an interaction variable (UI intervention x personal attribute) to analyze the moderating effect of the personal attribute on the relationship between the intervention and the outcome. Since the outcome variable is binary (whether or not the user provided rating), we analyzed the data using logistic regression. We performed regression analyses to test a full model including independent variables, interaction between them, and control variables (age and gender). Table 4 presents the regression results (outcome variable whether users rated or not).

Table 4. Logistic Regression Result for Experiment #2

Independent variables	Beta	S.E.	Wald χ^2	P value	Odds ratio
Age	.012	.011	1.165	.281	1.012
Gender	-.280	.246	1.292	.256	0.756
Conscientiousness	1.023	.383	7.131	.008	2.781
Critical mass	.518	.395	1.716	.190	1.679
Conscientiousness X Critical mass	-1.115	.506	4.860	.027	0.328

As hypothesized, the interaction (see Figure 5) was such that participants characterized by high conscientiousness were more likely to rate when there was perceived low critical mass (i.e., when participants perceived that few others were available to rate). Low conscientiousness participants, on the other hand, were more likely to rate when faced with an indication of a large number of other participants (i.e., perceived high critical mass). Table 4 lists the odds ratios for the corresponding beta coefficients. We obtained similar results for the alternative outcome variable: the decision on whether to provide verbal feedback.

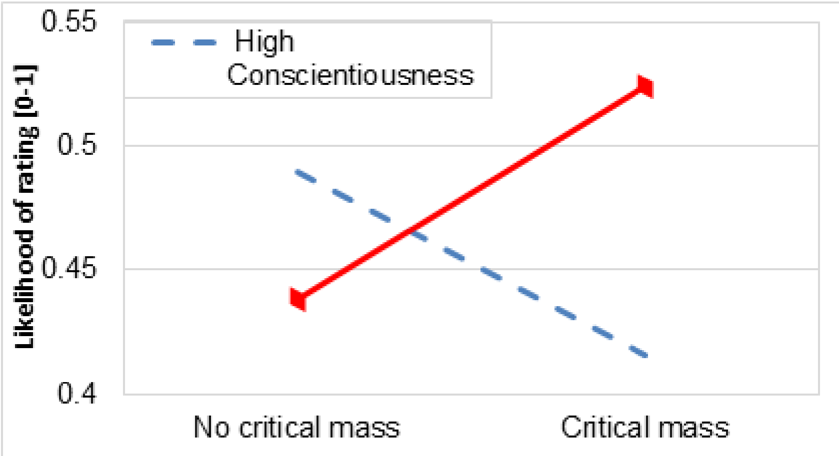

Figure 5. Critical Mass UI Manipulation Moderates the Relationship between Conscientiousness and The Likelihood of Rating

4 Implications for Research on HCI Design

In recent years, several studies have investigated the effects of users' personal traits on HCI design. Studies on persuasion strategies have shown how personality determines people's reaction to persuasive messages (Kaptein & Eckles 2012) and have suggested that this approach is applicable to the design of system interfaces (Halko & Kientz, 2010). The personalized UI field has established that contextual data about the user (and task) is invaluable for their successful implementation. This contextual information comes from a variety of unconventional and unrelated sources aggregated together using sophisticated algorithms to form a profile of the user. The Gartner Group (Clark & Lapkin, 2008) has identified four salient categories of contextual information: business process (information about the user through direct interactions with the user), environment (such as location, directional orientation, possible distractions, mood, network and device capabilities/constraints among others), community (information from social media), and identity (reputation, privacy preferences, personal preferences and traits among others). Our work focuses on contextual information that could be used for learning about a user's personality traits. Given that personality traits are relatively stable, personalityzation could alleviate the concerns for diminished predictability, comprehensibility, and controllability that are associated with adaptive UI design (Jameson, 2008), which prior studies on personality-based design illustrate (Goren-Bar et al., 2006; McGrenere et al., 2002). Our work builds on and extends such prior research and shows that personalityzation is also an effective design strategy, such that variations in personality result in different responses to UI designs.

In the studies described here, we provide a proof-of-concept for the effectiveness of personalityzation as a way to influence users' online behavior. Specifically, we show that the social anchoring and critical mass UI design cues had a differential effect on participants with different levels of emotional stability and consciousness (respectively). For example, results from study 1 show that people with below-average emotional stability reacted differently to social anchoring cues than those higher on the emotional stability scale (i.e., anchoring cues significantly increase participation for the former group, but, for the latter group, the effect is not as strong), which suggests that this design feature is effective for only a subset of the population. The results from study 2 provide an even stronger justification for personalityzation by showing that the effect of a particular design feature (i.e., critical mass) can have contradicting effects: people low on the conscientiousness scale reacted positively to indicators of the community's size, while those highly conscientious reacted negatively to this same indicator. Beyond the particular implications to the relevant literatures for each of the studies, a more general implication from our recent experimentation is that we cannot necessarily expect UI design features (such as indicators of community's activity) to equally affect all participants; instead, a more nuanced, personalized approach to HCI design is needed, where design features are catered to users' particular personality traits.

The contribution of this work to HCI is that it informs research on UI design by demonstrating how insights from psychology research can guide the design of more effective interfaces of social technologies. For example, we demonstrate how an understanding of personal differences in terms of emotional stability could guide the design of a personalized interface, which helps to increase participation in recommender systems. Note that personalityzation could be used in a variety of contexts beyond that of social recommender systems. Consider the effect of anchoring, for instance, where designers of Web-based systems can encourage users to take a particular course of action (say, follow certain hyperlinks) by providing indications that this particular path is popular amongst prior visitors to the website. Our results suggest that such designs are more effective for particular personalities. Personalityzation could be applied to personality traits beyond those investigated in the current paper. Table 5 explores some possible future research directions with personalityzation in HCI by providing examples for conceivable adaptations of UI design elements around the big five personality traits. Beyond personality traits, additional personal characteristics (for instance, motivation) could be employed in the design of adaptive UI (Nov, Arazy, Lotts, & Naberhaus, 2013b). A second contribution of our work is in showing how HCI design can serve as a large-scale experimental tool for testing hypotheses from psychology (e.g., the interaction between personality and social anchoring; see (Eroglu & Croxton, 2010; Furnham, Boo, & McClelland, 2012)).

Table 5. Possible Future Research Directions for Personalityzation

Big five personality traits	Sample HCI research possibilities
Openness to experience (inventive/curious vs. consistent/cautious)	Given the potential negative relationship between personalization and predictability (Jameson, 2008), HCI research could investigate the impact of contextual menus such as those used by software programs (for example, Microsoft Office 2013). For example, one potential research direction might investigate whether individuals who are high on openness to experience prefer more personalized (and hence less predictable) contextual menus when compared to those low on this trait.
Conscientiousness (efficient/organized vs. easy-going/careless)	Past research in HCI has looked at the impact of persuasive technologies through the theoretical prism of Elaboration Likelihood Model (Petty & Cacioppo, 1986) (for example in studying web site credibility (Fogg et al., 2003)). One potential direction is to explore whether individuals who are very conscientious are more susceptible to persuasion through the central rather than peripheral route.
Extraversion (outgoing/energetic vs. solitary/reserved)	Individuals who are introverted tend to be less social (but not anti-social) than extroverts. Hence, HCI research might explore whether interface cues that stimulate the senses (for example, use of specific color patterns, immersive multimedia) might specifically get the introverts more socially engaged in cases where that is the desired outcome.
Agreeableness (friendly/compassionate vs. analytical/detached)	In community participation sites (bulletin boards, comments section), individuals may need to be shown different sets of interface features to reduce trolling behavior. For example, empirical research could be conducted to test whether the "thumbs down" (or down-vote) button should not be shown to those who are disagreeable (whereas other individuals might be shown both "up-vote" and "down-vote" buttons).
Neuroticism (sensitive/nervous vs. secure/confident)	Individuals who are emotionally stable (not neurotic) tend to be less susceptible to others' influence. Hence, social networking websites such as Facebook can measure the impact of the UI features such as sponsored posts (while being mindful of the ethical implications) for different personalities. For example, HCI research could attempt to measure the differential effectiveness of advertisements endorsed by friends on these websites by individuals high and low on neuroticism.

A more practical implication of our results concerns the survey-based method for extracting and modeling users' personality (to be used for personalityzation). Such an approach has already become popular in the area of e-learning (Ford & Chen, 2000). The advantage of this approach is that the user model maps directly to constructs from psychology theory. To reduce users' burden of answering long personality questionnaire, designers may survey new users as part of their joining the system or make it part of a game-like activity (such as PetLink). If one can successfully elicit this information via explicit feedback (for example, by following gamification design principles), it has the potential to significantly improve the quality of the underlying intervention.

An alternative approach is to automatically (and unobtrusively) detect aspects of users' personality based on their online behavior. A partial combination of personal data outlined in these four categories—both online and offline—is already being collected by an extensive ecosystem of companies in the information aggregation industry. While some of this information is collected by explicitly asking users for information (for example, personal preferences on Facebook page), most of this information is being collected implicitly and automatically. A report by Wall Street Journal found that the top 50 websites in the US installed about 64 distinct pieces of tracking technology on average on visitors' computers (Angwin, 2010). These tracking technologies can aggregate users' browsing behavior over time and can develop in-depth profiles of individuals that can be bought and sold on market exchanges. Such methods may help infer traits and dispositions by creating a user profile. They may also capture users' transient preferences and attitudes such that the UI is not only personalized across users but also tailored to a users' particular attitude at particular points in time. Prior research has demonstrated the feasibility of recognizing user traits in "rich" multi-modal and dialog interfaces (Goren-Bar et al.. 2006; Lepri, Mana, Cappelletti, Pianesi, & Zancanaro, 2009; Mairesse, Walker, Mehl, & Moore, 2007) and in Web and mobile phone interfaces (Chittaranjan et al., 2012; Golbeck et al., 2011). Such techniques could possibly be employed in building a profile of users' personal traits to be used as part of personalityzation.

Once designers are able to profile users based on their personality, they could adapt the interfaces such that users with dissimilar personalities are exposed to different UI features. For example, to encourage participation in recommender systems, only people low on conscientiousness should be presented with UI features indicating the size of the community. Similarly, social anchoring cues need to be emphasized for individuals with low emotional stability.

5 Implications for Design Research

With this paper, we also inform the discussion on theoretical grounding in design research (DR) in information systems (IS). Previously, we explain that extant personalization approaches are largely divorced from psychology research on personality and argue for constructing a user model that is grounded in the theory of personality. Now, we seek to generalize the lessons learned through the development of our personalityzation framework and advance the discourse on theoretical grounding in the design of information systems. We note that a broader discussion regarding the relation between HCI and DR is beyond the scope of the current paper.

5.1 Theoretical Grounding in Information Systems Design Research

Design research seeks to develop prescriptive design principles through building and evaluating innovative IT artifacts (Hevner et al., 2004). HCI research, on the other hand, is concerned with the ways humans interact with information, technologies, and tasks, especially in business, managerial, organizational, and cultural contexts (Zhang & Li, 2004). Carroll (1997) argues that research in the field of human-computer interaction (HCI), too, could be viewed as a "science of design". Despite the similarity in goals and methods, design research in IS and HCI proceeded as two almost independent research streams[2]. However, in recent years, we are witnessing a move towards convergence. For example, Hevner and Zhang (2011) argue that design research and HCI "are inherently related and highly overlapping" (p. 56) and provide an initial attempt at mapping HCI research to DR conceptualization (Hevner, 2007).

We focus here on one aspect of information system design—theoretical grounding—that is a salient feature of HCI research but that has not received sufficient attention in the DR community (Iivari, 2007a). Research in HCI is deeply rooted in behavioral theory, primarily from the fields of cognitive psychology, social psychology and industrial and organizational psychology (Carroll, 1997; Shneiderman, 1998)[3]. The rationale for employing cognitive and social science theories as sources of principles for innovation is that it yields superior designs (Ling et al., 2005). Such strong emphasis on theoretical grounding is not a common feature of DR in IS, and the explication of the theoretical basis for making the design effective is often absent in DR studies (Arazy et al., 2010; Gregor & Hevner, 2011; Iivari, 2007b; Kuechler & Vaishnavi, 2008; Venable, 2006). Nonetheless, there is a growing recognition in DR for the importance of theoretical grounding, and we argue that this stream of design research could benefit by drawing insights from our work in the area of HCI.

The theory-directed design approach in DR is best explicated by the early conceptualization of Walls et al. (1992), who introduced the IS design theory as a prescriptive statement of how to develop design paths that rigorously derive their rationale from more fundamental research in the natural or social sciences (referred

[2] We note that there is an active research stream on HCI in the IS field, but this research has been primarily concerned with the "soft" aspects of HCI (namely, impact of artifacts) rather than with the design of human-computer interfaces (Zhang & Li, 2004).
[3] The disconnect between psychology theory on personality and personalization research within HCI is the exception to the norm.

to as kernel theories). Some DR scholars have adopted (and further developed) Walls et al.'s ideas and argued that grounding systems design in behavioral theory not only increases the designer's understanding of the problem domain, but also helps formulate high-level design principles that are independent of technological constraints and specific implementation details (Arazy et al., 2010; Gregor & Jones, 2007; Kuechler & Vaishnavi, 2008; Kuechler & Vaishnavi, 2012; Sein, Henfridsson, Purao, Rossi, & Lindgren, 2011).

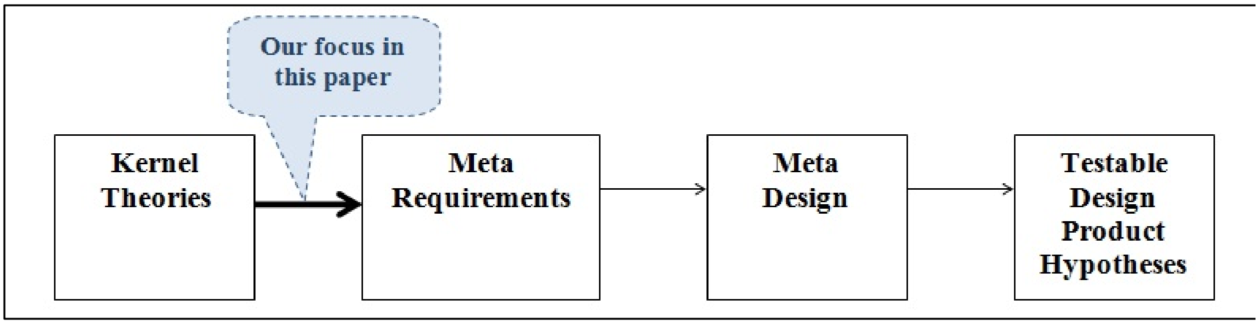

Figure 6. An Illustration of IS Design Theory (Adapted from Walls et al., 1992)

A key challenge for theory-directed design in both IS and HCI is in creating the linkage between theoretical foundations and system design. Walls et al.'s (1992) formulation provided little direction on how the linkage between kernel theory and design could be achieved. Kernel theories are at such a high level of abstraction that their relationship to design are frequently difficult to discern; thus, kernel theories provide insufficient prescriptions for artifact construction (Kuechler & Vaishnavi, 2008; Kuechler & Vaishnavi, 2012). As a result, when system design is informed by theory, the deduction from kernel theories to design is often not a process of logical derivation; instead, theories are only used as sources for inspiration (Goldkuhl, 2004).

Two approaches have been proposed for guiding the transition from kernel theories to design principles in DR, and both of these approaches rely on the introduction of an intermediate model or a "midrange theory"; that is, explanatory theories of a restricted scope that could more readily suggest actions (Merton, 1968). In the context of IS design, mid-range theories can provide a conceptual bridge between high-level explanatory kernel theories and highly prescriptive design theories construction (Arazy et al., 2010; Kuechler & Vaishnavi, 2008; Kuechler & Vaishnavi, 2012). Mid-range theories in IS design are informed by both kernel theories and design. In moving from kernel to mid-range theories, we descend a level of abstraction, arriving at a more concrete model. With the first approach for bridging kernel and design theories, the intermediate model lies within the domain of kernel theories (Arazy et al., 2010), while the second approach suggests that the newly introduced mid-range theory lies in the realm of design (Kuechler & Vaishnavi, 2012). Although the solutions recently proposed in DR offer a possible solution for bridging theory and design, these solutions are very complex and require complicated procedures. To date, there is little evidence to indicate whether the approaches for the introduction of an intermediary model could generalize and help guide the transition from kernel theory and design in design problems other than the examples in (Arazy et al., 2010; Kuechler & Vaishnavi, 2008; Kuechler & Vaishnavi, 2012).

5.2 Personalityzation: Insights for Design Research

As illustrated through the example studies presented in Section 3, our proposed approach advocates applying theory from psychology to guide HCI design[4]. A reflection on our experiences offers some insights regarding how to tightly link theory to design. Interestingly, the way in which we have grounded UI design in theory did *not* require the development of an intermediary mid-range theory (as proposed by Card in his early works on HCI (Card, 1989; Card, Moran, & Newell, 1983) and prescribed by recent DR conceptualizations (Arazy et al., 2010; Kuechler & Vaishnavi, 2012)). Below, we recap the challenges for theory-directed design highlighted by Arazy et al. (2010) and discuss how we address them in our research on personalityzation.

Challenge 1: "it is not easy to find relevant kernel theories for a specific design problem at hand". Our personal experience has taught us that identifying a relevant kernel theory for HCI design problems is often

[4] Our personalityzation framework is in line with recent DR works on 'user-centeredness' (Iivari & Iivari, 2011).

less challenging than when designing the internal workings of an IS. In particular, our interest in adapting systems' UI to users' personality points directly to the relevant theoretical foundation: theories of personality. In addition, we had to identify a relevant theoretical basis for the particular UI design feature under investigation (e.g., in the first example study, social anchoring). This, of course, is not straightforward; yet, given our experimental design and the narrow focus of the design problem (only one UI feature at a time), the search for a theoretical basis is quite constrained, and our experience shows that the challenge of identifying a relevant kernel theory for a particular set of UI features is surmountable. Take, for example, our study in which we experimentally manipulated the UI indicator of the number of prior raters; in order to explain the effect of this UI design feature, we considered framing this manipulation in terms of "group size", but we eventually turned to the theory of critical mass (Lou et al., 2000; Van Slyke et al., 2007). We note that identifying relevant theoretical foundations for directing the design of non-UI components may be more challenging as the scope of the search is less constrained. For example, designers of artificial intelligence algorithms have sought inspiration in areas as diverse as neurology (e.g., neural networks) and evolutionary biology (e.g., genetic algorithms).

Challenge 2: "the scope of the existing kernel theories is often too narrow". Our experimental design was able to mitigate this concern. In our case, the design problem involved an interaction between a personalization and a UI feature. Thus, we sought prior behavioral studies that investigated the combination of the relevant personality trait and the UI design feature under investigation. For example, in study 1, we searched for prior work on the interaction between emotional stability and social anchoring. Interestingly, we were able to identify relevant prior studies on the anchoring effect that considered personality (Furnham et al., 2012; McElroy & Dowd, 2007); such studies directly informed our design. More broadly, we suspect that concerns for the scope of kernel theories may not be a critical issue for research on personalityzation since personality is a well-established scholarly field offering a breadth of theories for consideration.

Challenge 3: "the theoretical model guiding the design should employ a level of abstraction that is suited to the design problem at hand". Here, too, our experimental design allowed us to sidestep the challenge concerning abstraction level. For the personality constructs, our current method relies on existing survey instruments for estimating users' personality; thus, the abstraction level for theory directly matches that of the design (this, of course, may be a bit more problematic when employing automatic data mining methods for constructing users' personality profile). For the UI feature, it may be more difficult to associate a design feature with a behavioral construct, but our experience shows that, if a behavioral theory is considered during the design process, it is often possible to design the UI feature such that it maps to a behavioral construct (at the appropriate level of abstraction). For example, in study 1, we operationalized the anchoring effect through a presentation of the community's average rating (illustrated using stars).

Challenge 4: "kernel theories are not adequate for guiding design because they commonly specify only the direction of effects, whereas making design choices requires that we also consider the effects' magnitude". In the context of our work, we notice that kernel theories of personality often do include information about effect size. In addition, in the particular context of personalityzation, the magnitude of effect is of lesser importance, and, often, the direction of effect is sufficient to guide design. For instance, it is sufficient to know that extroverts respond differently from introverts to a UI feature (e.g., presenting others' ratings); the direction of effect would allow HCI designers to decide on whether to display the feature under consideration for a particular person. The magnitude of effect (e.g., how much this is likely to impact the average extrovert), however, is less critical for designing the user interface.

Table 6 lists the four primary areas of concern for theory-directed design that Arazy et al. (2010) identified and summarizes the way in which we mitigated these concerns in our research on personalityzation.

In sum, there is a long tradition of theory-directed design in HCI research that demonstrates that a tight linkage between theory and design is feasible (and extremely useful). In line with this tradition, we sought to ground the design of personalized UI in theory of personality. In our studies of personalityzation, we were able to sidestep many of the challenges associated with theory-directed design. Previously, we reflect on how we alleviated the concerns for theory-directed design described by Arazy et al. (2010). We stress that the lessons drawn from our experience in personalityzation may not necessarily apply to other UI design problems.

Table 6. Theory-directed Design

Challenge (Arazy et al., 2010)	Examples in social recommender systems: associating a recommendation recipient with a source (Arazy et al., 2010)	Addressing the challenges—Our experience in personalityzation

1. It is not easy to find relevant kernel theories for a specific design problem at hand.	There may be several potential relevant theoretical streams: theory of interpersonal attraction (social psychology); reinforcement theories (social psychology); word-of-mouth influence theories (marketing, social psychology); the tie strength theory (sociology); social influence theories (social psychology, marketing and knowledge sharing).	The design problem (personalizing the UI) points directly to the relevant theoretical foundation: theories of personality. Relevant theoretical basis for the UI design features (social anchoring, critical mass): Given the narrow focus of the design problem (only one UI feature at a time), identifying a relevant kernel theory did not present a real challenge.
2. The scope of the existing kernel theories is often too narrow.	Various types of data regarding users' online interaction could be used to associate a recipient with recommenders; each type of relationship data points to a different theoretical basis; e.g., interaction frequency data point to tie strength theory, while social network data point to word-of-mouth theories. Thus, there is no one single kernel theory that maps to the full design problem.	We were able to identify few prior studies that have integrated the two theoretical foundations relevant for our study: (a) theory of the particular personality trait and (b) frameworks linked to the design feature. The breadth of prior research on personality offered us a large range of theoretical frameworks to choose from.
3. The theoretical model guiding the design should employ a level of abstraction that is suited to the design problem at hand.	Tie strength theory treats interaction frequency, tie duration, and closeness as indicators of a single tie strength construct. However, each of these indicators is associated with a distinct metric that could be extracted from online data. Thus, in order to direct design, we require a kernel theory that treats interaction frequency, tie duration, and closeness as distinct constructs and that provides predictions regarding the effects of each of these constructs.	Our experimental design allowed us to sidestep this challenge. For the personality constructs, our current method relies on existing survey instruments for estimating users' personality; thus, the abstraction level for theory directly matches that of the design. For the UI feature, although more challenging, we found that, if a behavioral theory is considered during the design process, it is often possible to design the UI feature such that it maps to a behavioral construct at the appropriate level of abstraction.
4. Kernel theories are not adequate for guiding design because they commonly specify only the direction of effects, whereas making design choices requires that we also consider the effects' magnitude	Tie strength theory predicts that strong ties are not useful for advice seeking, and word-of-mouth theories suggests that trust in the recommender is an antecedent the recipient willingness to take advice. However, given distinct metrics—some linked to tie strength while others to trust—it is not clear how they should be combined for optimal recipient-source matching.	Kernel theories of personality often do include information about effect size. In addition, in our particular context of personalityzation, the magnitude of effect is of lesser importance, and, often, the direction of effect is sufficient to guide design.

Nonetheless, we suspect that some of our lessons apply more broadly to HCI research. Notably, in line with our work on personalityzation, we observe that research in HCI is often able to ground the design without requiring the introduction of an intermediate model. We can offer possible explanations for how the HCI field is able to mitigate the four areas of concern discussed previously and employ theoretical frameworks to guide the design. First, the search for relevant kernel theories is more constrained in HCI (addressing challenge 1). The design of human-computer interaction (user interfaces, user experience) lends itself naturally to theories from psychology. The HCI field is inherently interested in human information processing and (cognitive, social, organizational) psychology has served as the primary theoretical basis for directing design in HCI (Grudin, 2006). Second, HCI design is often modular such that the design of UI features is not tightly coupled, and, thus, the concern surrounding the restricted scope of kernel theories (challenge 2) is less critical in the case of HCI. Third, HCI researchers are often interested in discrete (rather than continuous) levels in UI design features and frequently employ A/B testing methods; in these situations, the direction of effect is most important (addressing challenge 4). For example, knowing that users prefer one design over another may be sufficient for UI designers (how much one is superior to the other may be of lesser importance). Finally, the close synergy between psychologists and designers that characterizes many HCI research teams helps in mitigating the concerns around theory-directed design. While HCI researchers face similar challenges to DR scholars in overcoming the mismatch between design problems and the corresponding theoretical frameworks (primarily issues of scope and abstraction level) (Card, 1989; Carroll & Kellogg, 1989; Ling et al., 2005), a close interaction between theorists and designers allows moving between theory and design with less effort, finding creative ways for bridging the gap (addressing challenges 2 and 3). As others have argued (Arazy et al., 2010; Kuechler & Vaishnavi, 2008; Kuechler & Vaishnavi, 2012; Nunamaker, Chen, & Purdin, 1991; Orlikowski & Barley, 2001), we believe that a close synergy between the behavioral and the design science research communities—such as the one often observed in HCI research teams—is essential for DR researchers seeking to ground their design in theoretical foundations.

The contribution of our work to design science research is, thus, in highlighting some techniques for alleviating the concerns that plagued prior efforts to derive design principles from theory. Theoretical grounding of IS design is imperative because it: (a) leads to the construction of better artifacts and thus to more valuable prescriptive knowledge (Arazy et al., 2010; Goldkuhl, 2004) and (b) furthermore distinguishes DR from what practitioners do (Gregor, 2006). We believe that bridging the gap between theory and design could contribute to our field's constant search for identity (Benbasat & Zmud, 2003), and could potentially create synergies and help overcome the problems associated with two distinct bodies of knowledge in the IS field (i.e., "theoretical knowledge" and "design knowledge"). While few recent studies in DR have proposed ways for bridging theory and design through constructing an intermediate model, our experience with theory-directed design in HCI suggests that such an intermediate model may not always be warranted and that alternative solutions are possible. We acknowledge that not all design problems lend themselves to theory-directed design and we are *not* implying that DR should always seek a tight linkage between kernel theories and design. Rather, we propose that, for those design problems that could benefit from theoretical grounding, lessons drawn from our personalityzation studies can offer insights on how to bridge the gap between theories from the natural and behavioral sciences and design principles.

6 Conclusion

In this paper, we introduce our personalityzation approach to HCI design and provide a proof-of-concept through two distinct studies. In these studies, we applied personalityzation to different personality traits and design features. We stress that different design features may call for personalityzation around a different trait. The most relevant personality trait for the problem at hand is selected primarily based on theoretical considerations. In the absent of theoretical guidance, a researcher may start by surveying subjects on an array of personality traits—using proven measurement instruments for the Big 5 or Big 10 personality traits—and test which traits interact with the UI design; findings could then help direct the search for theoretical explanations.

Our personality-based UI design framework addresses many of the limitations facing the design of personalized interfaces. Since personality traits are relatively stable, personalityzation can help users cope with the sense of reduced control and diminished predictability that plague personalized systems. The cumulative evidence brought here suggests that not only does personality help users cope with UI adaptability, but also that this approach is effective in influencing online behavior. Our primary contribution is, thus, to HCI research. IS scholars have traditionally focused their efforts on analyzing the impacts of IT artifacts, and less effort has been put into innovative design contributions (Te'eni, Carey, & Zhang, 2007; Zhang & Li, 2004; Zhang & Li, 2005; Zhang, Li, Scialdone, & Carey, 2009). Recently, there is a move within the IS HCI community to place greater emphasis on design (Benbasat, 2010; Hevner & Zhang, 2011; Lyytinen, 2010). Thus, there is a particular value in bringing novelties in UI personalization to the IS audience interested in human-computer interaction.

In addition, the proposed approach to UI design also informs research in the area of design science. Hevner and Zhang (2011) discuss the relation between HCI and design research and suggest that "it is important to encourage active research efforts to make progress and research contributions at the intersection of these two streams" (p. 56). We follow up on their suggestion and show how our proposed HCI framework informs DR conceptualizations. While the DR literature stresses the difficulty in theory-directed design, the two studies described here demonstrates the feasibility of grounding design in theories from the behavioral sciences. In particular, we show that, under certain conditions (simple interface design decisions that focus on one UI feature at a time), it is possible to forego reliance on mid-range theories entirely and rely instead on granular theories to direct UI design. To that end, we contribute to the ongoing debate in the DR community regarding theory's role in guiding design.

Our exploration of personalityzation suffers from many limitations that future research could address. In terms of the contribution to HCI research, first, we plan to extend our framework by employing other theoretical frameworks of personality (beyond the big five) and by considering other types of enduring individual traits, such as dispositions. Second, we intend to extend our investigation beyond social participation systems by focusing on design interventions that enact mechanisms other than social influence and testing alternative outcome variables (e.g., flow, engagement, satisfaction). Third, in terms of research methodology, future research could extend our work by assessing users' personality at multiple points in time and using alternative data collection methods especially for contextual data (using industry practices outlined in an earlier section). For example, recent work has demonstrated that some of the profile information—especially information posted on Facebook—can also be used to make algorithmic predictions about users' personality characteristics (Alam, Stepanov, & Riccardi, 2013). We believe that it is crucial to use personality characteristics as the basis for UI design—either on their own or in conjunction with other contextual data—because they help improve performance, as demonstrated in our work. Finally, we hope to be able to generalize our findings to different settings and to multiple types of devices and interfaces (e.g., mobile and haptic interfaces). In terms of design research, extending our work in HCI would allow us to draw new insights regarding the relationship between HCI and DR. For example, we are interested if the lessons discussed here regarding the linkage between theory and design would still be applicable when designing complex, multi-feature user interfaces.

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References

Adaval, R., & Wyer, R. S., Jr. (2011). Conscious and nonconscious comparisons with price anchors: Effects on willingness to pay for related and unrelated products. *Journal of Marketing Research, 48*(2), 355-365.

Adomavicius, G., Bockstedt, J., Curley, S., & Zhang, J. (2011). *Recommender systems, consumer preferences, and anchoring effects*. In Proceedings of the RecSys 2011 Workshop on Human Decision Making in Recommender Systems (pp. 35-42).

Alam, F., Stepanov, E. A., & Riccardi, G. (2013). *Personality traits recognition on social network—Facebook.* Paper presented at the The 7th International AAAI Conference on Weblogs and Social Media, Boston.

Alnuaimi, O. A., Robert, L. P., & Maruping, L. M. (2010). Team size, dispersion, and social loafing in technology-supported teams: A perspective on the theory of moral disengagement. *Journal of Management Information Systems*, *27*(1), 203-230.

Angwin, J. (2010, July 30) The Web's new gold mine: Your secrets. *Wall Street Journal*.

Arazy, O., Kumar, N., & Shapira, B. (2010). A theory-driven design framework for social recommender systems. *Journal of the Association for Information Systems*, *11*(9), 455-490.

Barnett, T., Pearson, A. W., Pearson, R., & Kellermanns, F. W. (2014). Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*.

Barrick, M. R., Mount, M. K., & Strauss, J. P. (1993). Conscientiousness and performance of sales representatives: Test of the mediating effects of goal setting. *Journal of Applied Psychology, 78*(5), 715.

Begole, J. B., Matsakis, N. E., & Tang, J. C. (2004). Lilsys: Sensing unavailability. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work*. New York, New York: ACM Press.

Benbasat, I. (2010). HCI research: Future challenges and directions. *AIS Transactions on Human-Computer Interaction*, *2*(2), 16-21.

Benbasat, I., and Taylor, R. N. (1978). The impact of cognitive styles on information system design. *MIS Quarterly*, 1(1), 43-54.

Benbasat, I., & Zmud, R. W. (2003). The identity crisis within the IS discipline: Defining and communicating the discipline's core properties. *MIS Quarterly, 27*(2), 183-194.

Bolino, M. C., Turnley, W. H., Gilstrap, J. B., & Suazo, M. M. (2010). Citizenship under pressure: What's a "good soldier" to do? *Journal of Organizational Behavior, 31*(6), 835-855.

Bosnjak, M., Galesic, M., & Tuten, T. (2007). Personality determinants of online shopping: Explaining online purchase intentions using a hierarchical approach. *Journal of Business Research, 60*(6), 597-605.

Buffardi, L. E., & Campbell, W. K. (2008). Narcissism and social networking web sites. *Personality and Social Psychology Bulletin*, *34*(10), 1303-1314.

Bunt, A., Conati, C., & McGrenere, J. (2010). Mixed-initiative interface personalization as a case study in usable AI. *AI Magazine, 30*, 58-64.

Butler, B. (2001). Membership size, communication activity, and sustainability: A resource-based model of online social structures. *Information Systems Research*, *12*(4), 346-362.

Card, S. K. (1989). Theory-driven design research. In G. R. McMillan, D. Beevis, E. Salas, M. H. Strub, R. Sutton, & L. van Breda (Eds.), *Applications of human performance models to system design* (pp. 501-509). New York: Springer.

Card, S. K., Moran, T. P., & Newell, A. (1983). *The psychology of human-computer interaction*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Carroll, J. M. (1997). Human-computer interaction: Psychology as a science of design. *Annual review of psychology, 48*(1), 61-83.

Carroll, J. M., & Kellogg, W. A. (1989). *Artifact as theory-nexus: Hermeneutics meets theory-based design.* Paper presented at the SIGCHI Conference on Human Factors in Computing Systems.

Chen, S.-J., & Caropreso, E. J. (2004). Influence of personality on online discussion. *Journal of Interactive Online Learning, 3*(2), 1-17.

Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2012). Mining large-scale smartphone data for personality studies. *Personal and Ubiquitous Computing*, 1-18.

Clark, W., & Lapkin, A. (2008). Fundamentals of context delivery architecture: Introduction and definitions. In G. Research (Ed.).

Cockburn, A., Gutwin, C., & Greenberg, S. (2007). A predictive model of menu performance. *Proceedings of the 2007 SIGCHI Conference on Human Factors in Computing Systems*. New York, New York: ACM Press.

Correa, T., Hinsley, A. W., & De Zuniga, H. G. (2010). Who interacts on the Web?: The intersection of users' personality and social media use. *Computers in Human Behavior, 26*(2), 247-253.

Cosley, D., Lam, S. K., Albert, I., Konstan, J. A., & Riedl, J. (2003). *Is seeing believing?: How recommender system interfaces affect users' opinions.* Paper presented at the SIGCHI Conference on Human Factors in Computing Systems, Ft. Lauderdale, FL.

Costa, P., & McCrae, R. (1992). *NEO personality inventory–revised (NEO-PI-R) and NEO five-factor inventory (NEO-FFI) professional manual.* Odessa, FL: Psychological Assessment Resources.

Costa, P., & McCrae, R. (1996). Toward a new generation of personality theories: Theoretical contexts for the five-factor model. In J. S. Wiggins (Ed.), *The five factor model of personality: Theoretical perspectives* (pp. 51-87). New York, NY: Guilford Press.

Counts, S. (2007). Group-based mobile messaging in support of the social side of leisure. *Computer Supported Cooperative Work, 16*(1), 75-97.

Darley, J. M., & Latane, B. (1968). Bystander intervention in emergencies: diffusion of responsibility. *Journal of personality and social psychology, 8*(4p1), 377.

Diefendorff, J. M., & Richard, E. M. (2003). Antecedents and consequences of emotional display rule perceptions. *Journal of Applied Psychology, 88*(2), 284.

Ehrhart, M. G., Ehrhart, K. H., Roesch, S. C., Chung-Herrera, B. G., Nadler, K., & Bradshaw, K. (2009). Testing the latent factor structure and construct validity of the ten-item personality inventory. *Personality and Individual Differences, 47*(8), 900-905.

Endler, N., & Parker, J. (1992). Interactionism revisited: Reflections on the continuing crisis in the personality area. *European Journal of Personality, 6*(3), 177-198.

Englich, B., Mussweiler, T., & Strack, F. (2006). Playing dice with criminal sentences: The influence of irrelevant anchors on experts’ judicial decision making. *Personality and Social Psychology Bulletin, 32*(2), 188-200.

Epley, N., & Gilovich, T. (2010). Anchoring unbound. *Journal of Consumer Psychology, 20*, 20-24.

Eroglu, C., & Croxton, K. L. (2010). Biases in judgmental adjustments of statistical forecasts: The role of individual differences. *International Journal of Forecasting, 26*(1), 116-133.

Esteban, J., & Ray, D. (2001). Collective action and the group size paradox. *American Political Science Review, 95*(3), 663-672.

Findlater, L., & Gajos, K. Z. (2009). Design space and evaluation challenges of adaptive graphical user interfaces. *AI Magazine, 30*, 68-73.

Fogg, B., Soohoo, C., Danielson, D. R., Marable, L., Stanford, J., & Tauber, E. R. (2003). *How do users evaluate the credibility of Web sites?: a study with over 2,500 participants.* Paper presented at the Proceedings of the 2003 Conference on Designing for User Experiences.

Ford, N., & Chen, S. Y. (2000). Individual differences, hypermedia navigation, and learning: An empirical study. *Journal of Educational Multimedia and Hypermedia, 9*(4), 281-311.

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Fugelstad, P., Dwyer, P., Filson Moses, J., Kim, J., Mannino, C. A., Terveen, L., & Snyder, M. (2012). *What makes users rate (share, tag, edit...)?: predicting patterns of participation in online communities.* Paper presented at the ACM 2012 Conference on Computer Supported Cooperative Work.

Furnham, A., Boo, H. C., & McClelland, A. (2012). Individual differences and the susceptibility to the influence of anchoring cues. *Journal of Individual Differences, 33*(2), 89.

Gajos, K. Z., Czerwinski, M., Tan, D. S., & Weld, D. S. (2006). Exploring the design space for adaptive graphical user interfaces. In *Proceedings of the Working Conference on Advanced Visual Interfaces* (pp. 201-208).

Galinsky, A. D., & Mussweiler, T. (2001). First offers as anchors: The role of perspective-taking and negotiator focus. *Journal of Personality and Social Psychology, 81*(4), 657.

Garcia, S. M., Weaver, K., Moskowitz, G. B., & Darley, J. M. (2002). Crowded minds: The implicit bystander effect. *Journal of Personality and Social Psychology, 83*(4), 843.

Golbeck, J., Robles, C., Edmondson, M., & Turner, K. (2011). *Predicting personality from twitter.* Paper presented at the IEEE International Conference on Privacy, Security, Risk and Trust.

Goldberg, L. R. (1981). Language and individual differences: The search for universals in personality lexicons. In L. Wheeler (Ed.), *Review of personality and social psychology* (Vol. 2, pp. 141-165). Beverly Hills, CA: Sage.

Goldkuhl, G. (2004). Design theories in information systems-a need for multi-grounding. *Journal of Information Technology Theory and Application,, 6*(2), 59-72.

Goren-Bar, D., Graziola, I., Pianesi, F., & Zancanaro, M. (2006). The influence of personality factors on visitor attitudes towards adaptivity dimensions for mobile museum guides. *User Modeling and User-Adapted Interaction*, *16*, 31-62.

Gosling, S., Rentfrow, P., & Swann, W. (2003). A very brief measure of the big-five personality domains. *Journal of Research in Personality, 37*(6), 504-528.

Grant, A. M. (2008). The significance of task significance: Job performance effects, relational mechanisms, and boundary conditions. *Journal of Applied Psychology, 93*(1), 108.

Gregor, S. (2006). The nature of theory in information systems. *MIS Quarterly, 30*(3), 611-642.

Gregor, S., & Hevner, A. R. (2011). Introduction to the special issue on design science. *Information Systems and e-Business Management*, *9*(1), 1-9.

Gregor, S., & Jones, D. (2007). The anatomy of a design theory. *Journal of the Association for Information Systems, 8*(5), 312-335.

Grudin, J. (2006). Is HCI homeless?: In search of inter-disciplinary status. *Interactions, 13*(1), 54-59.

Grudin, J. (2009). AI and HCI: Two fields divided by a common focus. *AI Magazine*, *30*, 48-57.

Guthrie, C., Rachlinski, J., & Wistrich, A. (2007). Blinking on the bench: How judges decide cases. *Cornell Law Review, 93*, 1.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. (1998). Multivariate data analysis, 1998. *Upper Saddle River*.

Halko, S., & Kientz, J. (2010). Personality and persuasive technology: An exploratory study on health-promoting mobile applications. *Persuasive technology, 6137*, 150-161.

Hevner, A., & Zhang, P. (2011). Introduction to the AIS *THCI* special issue on design research in human-computer interaction. *AIS Transactions on Human-Computer Interaction*, *3*(2), 56-61.

Hevner, A. R. (2007). The three cycle view of design science research. *Scandinavian Journal of Information Systems, 19*(2), 87-92.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly, 28*(1), 75-105.

Hirsh, J. B., Kang, S. K., & Bodenhausen, G. V. (2012). Personalized persuasion tailoring persuasive appeals to recipients' personality traits. *Psychological Science*, *23*(6), 578-581.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 65-70.

Höök, K. (2000). Steps to take before intelligent user interfaces become real. *Interacting with Computers, 12*, 409-426.

Hoon, H., & Tan, T. M. L. (2008). Organizational citizenship behavior and social loafing: The role of personality, motives, and contextual factors. *The Journal of Psychology, 142*(1), 89-108.

Huber, G. P. (1983). Cognitive style as a basis for MIS and DSS designs: Much ado about nothing?. *Management Science*, 29(5), 567-579.

Iivari, J. (2007). A paradigmatic analysis of information systems as a design science. *Scandinavian Journal of Information Systems, 19*(2), 39-64.

Iivari, J., & Iivari, N. (2011). Design science research for user-centeredness *Reframing Humans in Information Systems Development* (pp. 173-180). New York: Springer.

Jahng, J., Jain, H., Ramamurthy, K., & Jahng, C. D. J. (2002). Personality traits and effectiveness of presentation of product information in e-business systems. *European Journal of Information Systems, 11*(3), 181-195.

Jameson, A. (2008). Adaptive interfaces and agents. In J.A. Jacko & A. Sears (Eds.), *The human-computer interaction handbook: Fundamentals, evolving technologies and emerging applications* (pp. 433-458). Boca Raton, FL: CRC Press.

Jameson, A. (2009). Understanding and dealing with usability side effects of intelligent processing. *AI Magazine, 30*, 23-40.

John, O. P., & Srivastava, S. (1999). The big five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (pp. 102-138). New York: Guilford Press.

Johnson, J. E. V., Schnytzer, A., & Liu, S. (2009). To what extent do investors in a financial market anchor their judgments excessively? Evidence from the Hong Kong horserace betting market. *Journal of Behavioral Decision Making, 22*(4), 410-434.

Judge, T., Erez, A., Bono, J., & Thoresen, C. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self-efficacy indicators of a common core construct? *Journal of Personality and Social Psychology, 83*(3), 693-710.

Judge, T. A. (2009). Core self-evaluations and work success. *Current Directions in Psychological Science, 18*(1), 58-62.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge: Cambridge University Press.

Kaptein, M., & Eckles, D. (2012). Heterogeneity in the effects of online persuasion. *Journal of Interactive Marketing, 26*, 176-188.

Karau, S. J., & Williams, K. D. (1993). Social loafing: A meta-analytic review and theoretical integration. *Journal of Personality & Social Psychology, 65*(4), 681-706.

Kraut, R., Maher, M. L., Olson, J., Malone, T. W., Pirolli, P., & Thomas, J. C. (2010). Scientific foundations: A case for technology-mediated social-participation theory. *IEEE Computer, 43*(11), 22-28.

Kuechler, B., & Vaishnavi, V. (2008). On theory development in design science research: Anatomy of a research project. *European Journal of Information Systems, 17*(5), 489-504.

Kuechler, W., & Vaishnavi, V. (2012). A framework for theory development in design science research: Multiple perspectives. *Journal of the Association for Information Systems*, *13*(6), 395-423.

Lepri, B., Mana, N., Cappelletti, A., Pianesi, F., & Zancanaro, M. (2009). Modeling the personality of participants during group interactions. *User Modeling, Adaptation, and Personalization*, 114-125.

Ling, K., Beenen, G., Ludford, P., Wang, X., Chang, K., Li, X., Cosley, D., Frankowski, D., Terveen, L., Rashin, A. M., Resnick, R., & Kraut, R. (2005). Using social psychology to motivate contributions to online communities. *Journal of Computer-Mediated Communication, 10*(4).

Lou, H., Luo, W., & Strong, D. (2000). Perceived critical mass effect on groupware acceptance. *European Journal of Information Systems, 9*(2), 91-103.

Lyytinen, K. (2010). HCI research: Future directions that matter. *AIS Transactions on Human-Computer Interaction, 2*(2), 22-25.

Maes, P. (1994). Agents that reduce work and information overload. *Communications of the ACM (CACM), 37*(7), 30-40.

Mairesse, F., Walker, M., Mehl, M., & Moore, R. (2007). Using linguistic cues for the automatic recognition of personality in conversation and text. *Journal of Artificial Intelligence Research, 30*(1), 457-500.

Markus, M. L. (1987). Toward a "critical mass" theory of interactive media universal access, interdependence and diffusion. *Communication Research*, *14*(5), 491-511.

Maybury, M. T., & Wahlster, W. (1998). Intelligent user interfaces: An introduction. In M.T. Maybury, & W. Wahlster (Eds.), *Readings in intelligent user interfaces* (pp. 1-13). San Francisco, CA: Morgan Kaufmann Publishers.

McElroy, J. C., Hendrickson, A. R., Townsend, A. M., & DeMarie, S. M. (2007). Dispositional factors in internet use: Personality versus cognitive style. *MIS Quarterly, 31*(4), 809-820.

McElroy, T., & Dowd, K. (2007). Susceptibility to anchoring effects: How openness-to-experience influences responses to anchoring cues. *Judgment and Decision Making*, *2*(1), 48-53.

McGrenere, J., Baecker, R. M., & Booth, K. S. (2002). *An evaluation of a multiple interface design solution for bloated software.* Paper presented at the 2002 SIGCHI Conference on Human Factors in Computing Systems.

Merton, R. K. (1968). *Social theory and social structure*. New York: Free Press.

Mitchell, J., & Shneiderman, B. (1989). Dynamic versus static menus: an exploratory comparison. *ACM SIGCHI Bulletin*, *20*(4), 33-37.

Mobbs, D., Hagan, C. C., Azim, E., Menon, V., & Reiss, A. L. (2005). Personality predicts activity in reward and emotional regions associated with humor. *Proceedings of the National Academy of Sciences of the United States of America*, *102*(45), 16502.

Nov, O., & Arazy, O. (2013). *Personality-targeted design: Theory, experimental procedure, and preliminary results.* Paper presented at the 2013 Proceedings of Computer Supported Cooperative Work, San Antonio, Texas, USA.

Nov, O., Arazy, O., López, C., & Brusilovsky, P. (2013). *Exploring personality-targeted UI design in online social participation systems.* Paper presented at the 2013 SIGCHI Conference on Human Factors in Computing Systems.

Nov, O., Arazy, O., Lotts, K., & Naberhaus, T. (2013). *Motivation-targeted personalized UI design: A novel approach to enhancing citizen science participation.* Paper presented at the 13th European Conference on Computer Supported Cooperative Work, Paphos, Cyprus.

Nunamaker, J. F., Chen, M., & Purdin, T. (1991). Systems development in information systems research. *Journal of Management Information Systems*, *7*(3), 89-106.

Oliver, P., Marwell, G., & Teixeira, R. (1985). A theory of the critical mass. I. Interdependence, group heterogeneity, and the production of collective action. *American Journal of Sociology, 91*(3), 522-556.

Oliver, P. E., & Marwell, G. (1988). The paradox of group size in collective action: A theory of the critical mass. II. *American Sociological Review*, *53*, 1-8.

Oreg, S., & Nov, O. (2008). Exploring motivations for contributing to open source initiatives: The roles of contribution context and personal values. *Computers in Human Behavior, 24*(5), 2055-2073.

Organ, D. W. (1988). *Organizational citizenship behavior: The good soldier syndrome*. Lexington, MA: Lexington Books.

Organ, D. W. (1994). Personality and organizational citizenship behavior. *Journal of Management*, *20*(2), 465-478.

Orlikowski, W. J., & Barley, S. R. (2001). Technology and institutions: What can research on information technology and research on organizations learn from each other? *MIS Quarterly, 25*(2), 145-165.

Park, G., Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Kosinski, M., Stillwell, D. J., Ungar, L. H., & Seligman, M. E. (2014). Automatic personality assessment through social media language. *Journal of Personality and Social Psychology, 108(6), 934-52*

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 19, pp. 123-205). New York: Academic Press.

Podsakoff, P. M., MacKenzie, S. B., Paine, J. B., & Bachrach, D. G. (2000). Organizational citizenship behaviors: A critical review of the theoretical and empirical literature and suggestions for future research. *Journal of Management, 26*(3), 513-563.

Raban, D. R., Moldovan, M., & Jones, Q. (2010). *An empirical study of critical mass and online community survival.* Paper presented at the ACM 2011 Conference on Computer Supported Cooperative Work, Savannah, GA.

Renn, R. W., Allen, D. G., & Huning, T. M. (2011). Empirical examination of the individual-level personality-based theory of self-management failure. *Journal of Organizational Behavior, 32*(1), 25-43.

Robey, D. (1983). Cognitive style and DSS design: A comment on Huber's paper. *Management Science* , 29(5): 580-582.

Rotter, J. B. (1975). Some problems and misconceptions related to the construct of internal versus external control of reinforcement. *Journal of Consulting and Clinical Psychology, 43*(1), 56-67.

Rotter, J. B. (1990). Internal versus external control of reinforcement: A case history of a variable. *American Psychologist, 45*(4), 489-493.

Sein, M., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. *MIS Quarterly, 35*(1), 37-56.

Shneiderman, B. (1998). *Designing the user interface: Strategies for effective human-computer interaction*. Reading, MA: Addison-Wesley.

Shneiderman, B., & Maes, P. (1997). Direct manipulation vs. interface agents. *Interactions, 4*, 42-61.

Straub, D., Boudreau, M., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems, 13*(24), 380-427.

Swann, W. B., & Seyle, C. (2005). Personality psychology’s comeback and its emerging symbiosis with social psychology. *Personality and Social Psychology Bulletin, 31*(2), 155-165.

Te'eni, D., Carey, J. M., & Zhang, P. (2007). *Human-computer interaction: Developing effective organizational information systems*. Hoboken, NJ: John Wiley & Sons.

Tsandilas, T., & Schraefel, M. C. (2005). *An empirical assessment of adaptation techniques.* Paper presented at the 2005 Human Factors in Computing Systems, New York, New York, USA.

Van Slyke, C., Ilie, V., Lou, H., & Stafford, T. (2007). Perceived critical mass and the adoption of a communication technology. *European Journal of Information Systems, 16*(3), 270-283.

Venable, J. (2006). *The role of theory and theorising in design science research.* Paper presented at the 1st International Conference on Design Science in Information Systems and Technology.

Vittersų, J. (2001). Personality traits and subjective well-being: Emotional stability, not extraversion, is probably the important predictor. *Personality and Individual Differences, 31*(6), 903-914.

Walls, J. G., Widmeyer, G. R., & El Sawy, O. A. (1992). Building an information system design theory for vigilant EIS. *Information Systems Research, 3*(1), 36-59.

Wegener, D., Petty, R., Blankenship, K., & Detweiler-Bedell, B. (2010). Elaboration and numerical anchoring: Implications of attitude theories for consumer judgment and decision making. *Journal of Consumer Psychology, 20*(1), 5-16.

Woo, N. H., & Shirmohammadi, S. (2008). *Modeling and measurement of personality for e-commerce systems.* Paper presented at the 2008 Instrumentation and Measurement Technology Conference.

Zhang, P., & Li, N. (2004). An assessment of human-computer interaction research in management information systems: topics and methods. *Computers in Human Behavior, 20*(2), 125-147.

Zhang, P., & Li, N. (2005). The intellectual development of human-computer interaction research: A critical assessment of the MIS literature (1990-2002). *Journal of the Association for Information Systems, 6*(11), 227-292.

Zhang, P., Li, N., Scialdone, M., & Carey, J. (2009). The intellectual advancement of human-computer interaction research: A critical assessment of the MIS literature (1990-2008). *AIS Transactions on Human-Computer Interaction*, *1*(3), 55-107.

Zmud, R. W. (1979). Individual differences and MIS success: A review of the empirical literature. *Management Science*, 25(10), 966–979.

Zweig, D., & Webster, J. (2004). What are we measuring? An examination of the relationships between the big-five personality traits, goal orientation, and performance intentions. *Personality and Individual Differences, 36*(7), 1693-1708.

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