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PERSONALIZATION SYSTEMS FOR DECISIONS INVOLVING RISK: THE INTERACTIVE EFFECTS OF USER PERSONALITY AND SUGGESTIVE GUIDANCE

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ABSTRACT

This study designs and tests a personalization system that considers the interactive effects of user personality and suggestive guidance in a decision-making situation involving risk. The system suggests a specific course of action that varies in congruency with the users' natural risk taking tendencies. Findings suggest that when the system suggests a risk-seeking course of action, both high and low propensity users assume greater risks, with high risk propensity users taking significantly greater risks than low risk propensity users. Regardless of risk propensity, however, all users make conservative decisions when the system suggests a risk-averse course of action. Providing mismatched offerings to risk-seeking users nullifies the effects of risk propensity. The modality of suggestive guidance embedded in a personalization system influences the decisions of different personality types in unique ways. Theoretical and practical implications are discussed.

Keywords: decision-making, human-computer interaction, personalization systems, personality, risk taking, risk propensity, personality matching, suggestive guidance

INTRODUCTION

Human-computer interaction (HCI) involves communication between two types of information processors – the human and the computer. These interactions typically necessitate a deviation from innate human-to-human communication toward more contrived human-computer dialogues. Given the artificial nature of HCI, the frontiers of research seek new ways to implement interfaces that offer more human-like ways for computers to deliver information to humans [67, 79]. Ultimately, progress in this area depends on the ability to design computing technologies that emulate the characteristics of human-to-human communication [58].

The emergence of personalization systems, which can deliver information tailored to particular users [16, 21, 74], hold promise for providing a closer approximation to the personalized nature of human-to-human discourse [13]. Although personalization systems have recently garnered a great deal of attention, most of the research in this area has focused on user preferences and behaviors [2, 73]. Relatively little is understood about the potential effects of personalization based on user personality traits, which are known to systematically affect individual behavior [48] and, in particular, use of information systems [47].

Equally important, despite a few notable exceptions [e.g., 74], studies have tended to marginalize the impact of personalization systems on decision outcomes. Most studied generally assume that the design features embedded within personalization systems influence all types of users in a similar way. However, design features interact with user characteristics to influence decision making processes [34, 36, 77], resulting in beneficial or detrimental outcomes [41]. For instance, personalization systems research has focused on providing offerings (e.g., product recommendations) that are *matched* to user preferences and behaviors [16, 35, 73]. There is reason to believe that delivering *mismatched* offerings can facilitate particular decision outcomes. As Benbasat [8] points out, understanding how such designs influence users toward particular objectives constitutes an important issue for HCI research. In essence, advancing our knowledge further requires an understanding of the intended and unintended consequences that can arise at the intersection of design features and specific types of users.

Given the theoretical and practical importance of the topic, this study addresses the research question of *how do personality traits and the matching of offerings embedded within a personalization system influence decision outcomes?* Although there are many potential personality traits to consider, this study concentrates on one important facet of personality, *risk propensity*, which refers to an individual's tendency to take risks [68]. Since many decisions involve risk and uncertainty [72], predispositions toward risk are likely to affect such decisions [71]. Therefore, the personalization system studied herein first captures a specific aspect of user personality, risk propensity, and subsequently delivers suggestive guidance that is matched [or mismatched] to the user's personality. In doing so, we can understand how personality matching interacts with user personality to affect decision outcomes.

The remainder of this paper is structured as follows. In the next section, we provide a brief review of the personalization systems literature, as well as an overview of a framework for understanding the process of personalization. The research model and hypotheses are then presented. This is followed by a description of the experimental methods and results. The paper concludes with a discussion of the findings, as well as implications for research and practice.

LITERATURE REVIEW

The benefits of personalizing human-to-human business communications in commercial settings have long been recognized [81]. In order to maintain relationships with customers over the long term and differentiate themselves from the competition, companies seek to create enduring value for their customers through personalizing service offerings [16, 46, 56, 64]. Creating value requires organizations to understand each customer's "deeply held beliefs, psychological predispositions, life stages, moods and modes, aspirations and fears" because each person will have a "unique set of experiences, expectations, and unconscious preferences in his relationship with the company" [56, p. 40]. As a result, companies strive to utilize detailed knowledge about customers to target personalized offerings (e.g., one-to-one marketing).

Higher levels of personalization have been shown to offer firms a competitive advantage [5]. These benefits can be achieved by treating the customer as an individual rather than one instance of a generic set of customers to be serviced. The challenge for designing personalization systems involves determining the appropriate mix of personal attributes for the system to utilize when communicating with a user [29]. Therefore, from a theoretical and practical point of view, it is essential to understand the specific personal characteristics to capture, as well as the features to embed into personalization systems in order to realize the benefits of personalization via human-computer dialogues.

Technology-Enabled Personalization

Specific to information systems, personalization can be defined as "a process that changes the functionality, interface, information access and content, or distinctiveness of a system to increase its personal relevance to an individual or category of individuals" [21, p. 183]. Through technologies, such as the World Wide Web (Web), personalization can be performed on a broader scale and accomplished more quickly, effectively, and ubiquitously than was ever possible before [16; 17]. Technologies make the personalization process more efficient, as users can be segmented more accurately based on accumulated data, such as transactional history, click stream activity, or personal profiles [21]. Personalization systems are seen as a promising way to close the communications gap between humans and computers through improved interface designs [15, 29, 66]. Such systems can potentially achieve many benefits, including 1) helping users reduce information overload and increase user satisfaction, 2)using technologies and user information to provide offerings (e.g., content, recommendations, services) tailored to specific user needs, and 3) supporting the development of meaningful one-to-one relationships between systems and users [2, 17, 21, 38, 74, 37].

As depicted in Figure 1, information systems can be viewed along a personalization continuum ranging from low personalization, where the system offers generic information (i.e., not specific to a particular user), to high personalization, where the system generates tailored information based on a rich set of knowledge about the user [3]. For example, e-mails offerings, such as generic solicitations to refinance a mortgage, tend to be lower in personalization, as these types of messages are broadcast to a group of individuals regardless of whether they own a home. However, if the e-mail addresses the receiver by name, discloses the current loan balance, and identifies the address of the property, this detailed knowledge about the user enables the system to achieve higher levels of personalization. In essence, the more a system knows about the user, the more personalized the human-computer interaction can become.

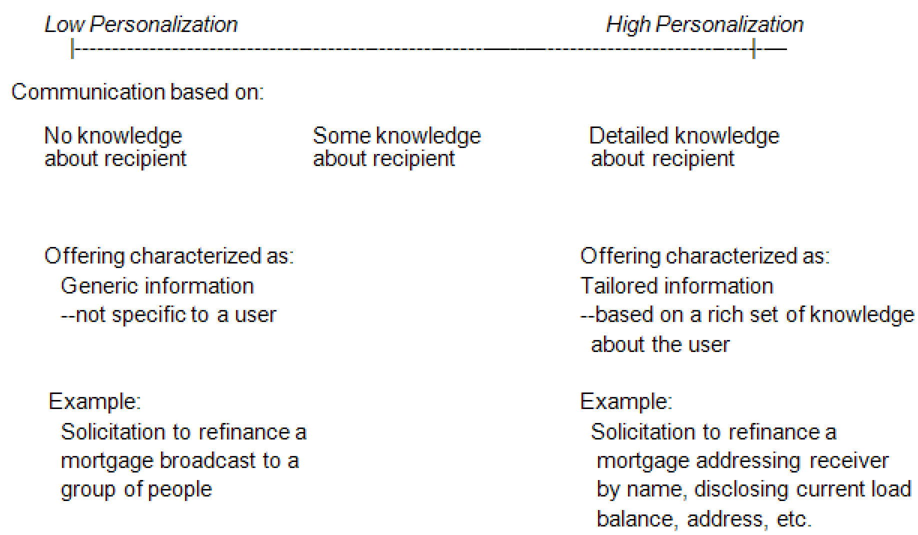

Figure 1: Personalization Scale

Personalization research has examined applications of personalization technology, philosophical issues, such as privacy regulations and ethics regarding user profiles, and technologies for analyzing massive amounts of user information and deriving efficient rules to generate personalized content [28]. Research has shown that people choose to use personalization features based on their level of involvement with the task, whether the information provided is useful, and whether the System adequately addresses privacy concerns [28]. Furthermore, personalization appears to be more helpful when users are looking for knowledge about a certain topic rather than for general browsing [38]. Finally, research has examined how to create user profiles, including explicit methods to collect user data such as asking users to express their preferences, and implicit methods such as monitoring users' behaviors [i.e., capturing keystrokes] to infer user preferences [38].

Although researchers in computer science and information systems study personalization systems, each discipline examines the context using different perspectives. Typically, computer scientists attempt to determine how personalization technologies can be optimally designed and adapted to help users achieve their goals [e.g., 28, 32, 39, 52, 63]. Information systems scholars, in contrast, tend to focus on how to effectively manage customer relationships by delivering benefits unique to each customer using Web-based features that are congruent with a user's characteristics [e.g., 17, 28, 39, 62, 73].

The Personalization Process

Personalization systems gather knowledge about specific users and leverage this knowledge to deliver tailored offerings in order to achieve a particular set of goals [16, 17]. To understand the process by which personalization systems accomplish these objectives, we utilize the stages of the personalization process identified by Adomavicius and Tuzhilin [2], as shown in Figure 2. The figure also shows contributions of this study, as well as the specific factors addressed.

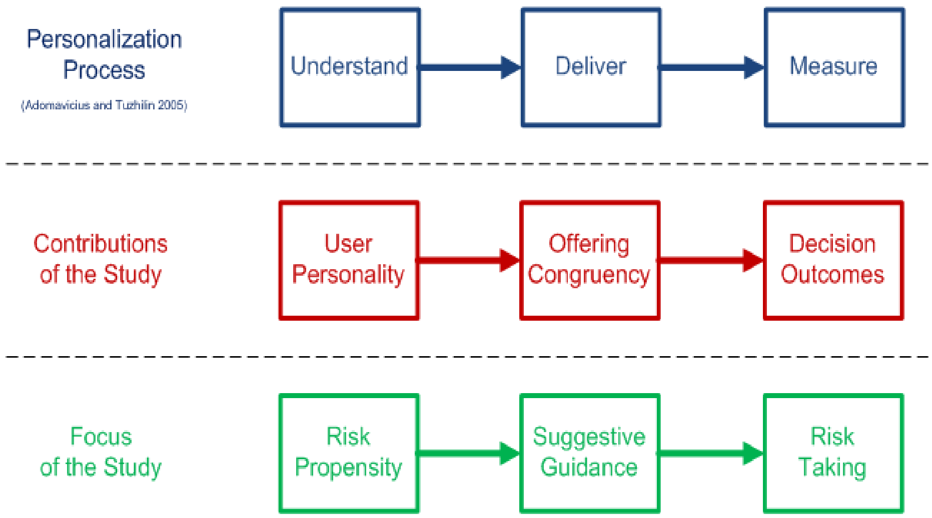

Figure 2: Personalization Process, Contributions, and Focus of the Study

The first stage in the personalization process, *understand*, gathers information about the user and converts it into a user profile. To achieve this objective, the system can explicitly ask questions about the user's preferences [17, 23, 24, 28, 32, 38, 52, 74], or implicitly observe behaviors through click streams or purchase patterns [21]. These data can be used to determine the relative importance of system features, as well as the strengths and weaknesses of the design [27, 38, 44, 57].

To date, most research focusing on the understand stage has been limited to explicitly soliciting user preferences or to implicitly tracking user behaviors. In order to gain additional knowledge about the users and achieve higher levels of personalization, additional factors beyond preferences and behaviors must be considered. Although research has examined user characteristics, such as need for cognition [73], the effect of personalization based on user personality remains an open empirical issue. The personality of a user has been shown to be an important predictor of technology adoption and use [47]. Therefore, this study contributes to the literature by considering user personality, which should enhance the capabilities of a designer to deliver highly personalized content.

The next stage, *deliver*, utilizes the knowledge gathered about the user and subsequently delivers a personalized offering. Traditionally, delivery has focused on providing offerings that match a user's profile [39, 44, 52, 57, 70, 73, 74]. The goal involves providing the optimal set of online content that match particular users' needs [1, 10, 28, 27, 38]. Consistent with Tam and Ho [74], this form of delivery as *matched*, as the designer aligns content with a user's profile. As we will argue in the following section, there is reason to believe that *mismatched* offerings may also produce interesting effects. However, no study to date has examined the impact of delivering personalized offerings that are mismatched with a user's profile. As a result, this study contributes to our accumulated knowledge of personalization systems by addressing this gap.

The next stage, *measure*, assesses the impact of the personalization systems on user experiences. Studies have largely focused on determining the effectiveness of personalized information in terms of user satisfaction [28, 38, 70]. Research addressing this stage has been relatively sparse. The few studies that have focused on the measure stage have surveyed whether users chose to use systems that offer personalized content over those that do not [17]. Studies have evaluated users' perceptions, such as satisfaction, time savings, importance of functionality, information recall, and content acceptance [28, 38, 70], examined usage patterns of personalization features to determine their importance to users [44], and gathered user opinions about information relevance [39]. However, making the interaction more efficient and satisfying are only pieces of a larger puzzle. A transaction may be completed very quickly and the user can be satisfied [3], but the decision made by the user may be sub-optimal. Therefore, efficiency and satisfaction are not the only outcomes that need to be considered. In fact, there are numerous ways to achieve system success [19], such as the quality of the decision outcomes [36, 77, 74]. Therefore, this study examines how design features, such as those embedded within a personalization system, can transform decision making.

In terms of the *understand* stage, our system captures the risk propensity of the user to create a user profile. For the *deliver* facet, the system subsequently delivers personalized offerings in the form of suggestive guidance, which proposes a particular course of action to the user [53, 67]. Because relatively little is understood about the effects of mismatched offerings, the system delivers either matched or mismatched suggestive guidance based on the user's risk propensity. Finally, we *measure* the effectiveness of the personalization system in terms of altering the level or risk a user is willing to accept in a decision-making context. As evidenced in our review of prior work, none of these variables has been previously addressed in the personalization systems literature.

RESEARCH MODEL AND HYPOTHESES

The proposed research model below (Figure 3) represents an initial step toward understanding how a user's risk propensity combines with the various modalities of suggestive guidance to influence the level of risk a decision maker is willing to accept.

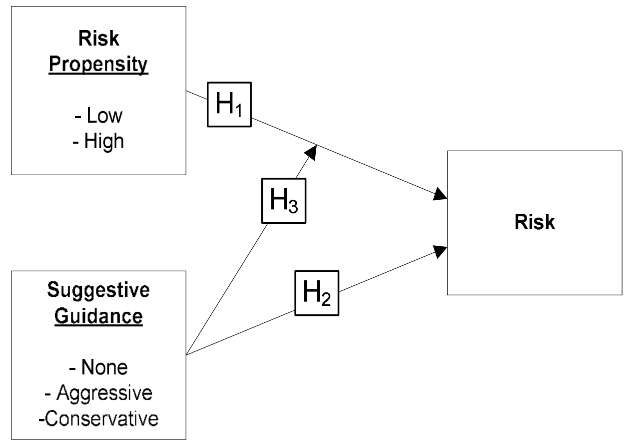

Figure 3: Research Model

Risk Propensity

Because investing inherently involves uncertainty and risk, risk psychology represents an important and relevant variable that will plausibly play a key role in one's decision to take risks. This variable, *risk propensity*, refers to "an individual's current tendency to take or avoid risks" [68, p. 1575]. The rational perspective of classic decision theory conceptualizes risk as a calculation of the probabilities and magnitudes associated with incurring a loss [45]. Observations, however, indicate that purely rational perspectives fail to capture individual behavior [43]. Rather than basing decisions purely on rational calculations, some scholars argue that risk-taking behaviors are partially determined by an individual's perception of the risk [68]. In particular to technology use, risk perceptions influence a user's willingness to engage in online transactions involving risk [54].

While this line of logic views risk perceptions as situational, other studies suggest that risk-taking behavior is heavily influenced by predispositions toward risk [14]. In other words, stable personality traits contribute toward an individual's willingness to take risks. This predispositional perspective is consistent with Big Five Personality Theory [48], which views an individual's tendency toward taking risks (i.e., risk propensity) as a facet of one of the five major personality traits, namely extroversion [51]. For instance, individuals who have high levels of risk propensity tend to be attracted to situations involving risk [71]. Thus, we surmise that, under conditions of risk and uncertainty, risk propensity will influence a user's willingness to take risks when utilizing a personalization system. In essence, risk-seeking individuals (i.e., high risk propensity) will tend to take greater risks than risk-averse individuals (i.e., low risk propensity).

> *H_1: Risk will be significantly higher for high risk propensity users than for low risk propensity users.*

Suggestive Guidance

Decisional guidance, defined as "how a decision support system enlightens or sways its users as they structure and execute their decision-making processes - that is, as they choose among and use the system's functional compatibility" [67 p. 107], constitutes one design feature that can potentially be embedded within a personalization system. Decisional guidance can be delivered in two forms – suggestive and informative. Whereas informative guidance provides relevant information that enlightens the user about the decision, suggestive guidance recommends a course of action. In other words, suggestive guidance directs the user toward a particular problem solving approach while informative guidance does not inform the user how to behave [67, 50]. The type of decisional guidance deployed in the personalization systems described herein is suggestive guidance, as the system intends to steer the user towards a particular decision outcome.

According to classic decision theory, when outcomes are certain, the decision maker should always choose the alternative providing the maximum utility [72]. However, most decisions involve some degree of uncertainty and, therefore, are inherently risky. To reduce uncertainty and risk, decision makers tend to gather information from different sources, including the advice of others. As Looney and Hardin [40] point out, suggestive guidance can be viewed as a form of advice, as the intent involves pointing the user toward a particular solution. Individuals decide how to utilize advice based on their beliefs about their own capabilities, as well as their judgments about the expertise the advice source [11, 61]. People are more likely to seek advice when they have limited knowledge about the topic. When the risks associated with making a poor decision are high, decision makers leverage advice to make better decisions and share responsibility for the outcome [26]. These notions are consistent with Silver [67], which stated that building suggestive guidance into a system should prove especially persuasive in situations involving risk. Like human advisors, suggestive guidance provided by a personalization system is likely to help reduce the apparent uncertainty and risk endemic to most decisions [6, 50, 53, 67].

All forms of suggestive guidance, however, are not created equal. Technologies can influence user behavior in beneficial and detrimental ways [41] and, therefore, it is essential to understand how different forms of suggestive guidance influence decision outcomes. To this end, this study compares three suggestive guidance modalities – conservative, none, and aggressive. Whereas the conservative form suggests a risk-averse course of action, the aggressive form recommends a risk-seeking approach. The no guidance modality is included to understand how suggestive guidance induces deviations from the user's natural risk-taking tendencies. When risk and uncertainty prevail, the literature suggests that users should rely on suggestive guidance and adjust their risk-taking behaviors accordingly [40]. Specifically, aggressive guidance should propel risk-taking, whereas conservative guidance should curtail it. Therefore, we propose the following hypotheses:

> *H_2: Suggestive guidance will have a significant influence on risk such that:*
> *a) Risk will be significantly higher when suggestive guidance recommends an aggressive course of action than when suggestive guidance is not available.*
> *b) Risk will be significantly lower when suggestive guidance recommends a conservative course of action than when suggestive guidance is not available.*

Risk Propensity and Suggestive Guidance

Regret theory suggests that risk propensity and suggestive guidance will interact. According to regret theory [7], regret is a negative emotion that people experience when realizing or imagining that their present situation would have been better had they previously chosen an alternative course of action [81]. Regret can be experienced in two ways: 1) by choosing an alternative that leads to a less desirable result than if a different alternative had been selected, or 2) by avoiding action and subsequently missing out on a more desirable state [81]. For regret to surface, individuals must first anticipate regret by contemplating potentially negative outcomes. Knowing the result of the foregone alternative, a common characteristic of many decisions, is therefore a key factor underlying the emergence of regret [7, 31]. Regret theory posits that negative or unpleasant information concerning a potential outcome influences individuals to a greater extent than does positive or pleasant information [75]. Losses are felt more profoundly than gains of a similar magnitude [78]. As a result, when forming impressions about decision alternatives, the anticipation of negative outcomes is given more emphasis than potentially positive outcomes [34, 69].

These notions suggest that personality matching might affect different types of users in unique ways. We propose that suggestive guidance provides inputs to the user about prospective decisional outcomes and, thus, can create the anticipation of regret. Specifically, conservative guidance, which recommends a risk-averse course of action, is likely to induce the sense that the decision may result in negative consequences. Because negative information is weighed more heavily than positive information, conservative guidance is likely to be more persuasive than aggressive guidance. However, this effect may not be robust across each level of risk propensity. Low risk propensity individuals are predisposed to making risk-averse choices, meaning that conservative guidance is congruent with their natural tendencies. Therefore, conservative guidance is likely to have a diminished effect on these individuals. In contrast, conservative guidance should have a profound effect on high risk propensity individuals, who tend to be risk-seeking. In essence, we expect that, regardless of users' natural risk-taking tendencies, all users will act in a risk-averse manner when given conservative guidance.

H3: Risk propensity and suggestive guidance will interact such that:

a) When suggestive guidance is not available, risk will be significantly higher for high risk propensity users than low risk propensity users.

b) When suggestive guidance recommends an aggressive course of action, risk will be significantly higher for high risk propensity users than low risk propensity users.

c) When suggestive guidance recommends a conservative course of action, risk will not significantly differ between high risk propensity users and low risk propensity users.

RESEARCH METHOD

A laboratory experiment was conducted using an experimental retirement portfolio management website. A 2 × 3 factorial design was utilized, crossing risk propensity (low risk propensity vs. high risk propensity) and suggestive guidance (none, aggressive, vs. conservative).

Given the desire to understand the effects of risk propensity and suggestive guidance in decisions involving risk and uncertainty, an online retirement portfolio management setting was utilized. The context was chosen for three primary reasons. First, investment decisions are fraught with risk and uncertainty. Investors must forecast and weigh the risks and rewards across investment alternatives [12]. Second, online investing constitutes an area with substantial practical importance. Over 55 million U.S. employees directly manage over $3.2 trillion in retirement plan assets [18]. Third, personalization systems are viewed as a critical aspect of financial services [21]. Financial and retail firms deploy roughly half of all commercial personalization systems [59]. Finally, many retirement plan participants are not sophisticated in financial matters [42]. Suggestive guidance (i.e., advice) is particularly well-suited for users who question their abilities [61].

Participants

As part of an online retirement planning study sponsored by three U.S. universities, 98 individuals volunteered to participate in the study. Student participants were utilized. In return for their participation, students were offered course credit and a chance to win small prizes ranging in value from $10 to $100. Prizes were awarded to the top five performers who accumulated the highest portfolio balances at the end of a simulated 30-year retirement planning period. On average, participants were 23.19 years old (SD = 5.84) and 60.2% were male. Participants reported an average of 3.33 years (SD = 6.71) investing experience, 11.37 years (SD = 4.13) computing experience, and 7.00 years (SD = 5.29) work experience.

Procedure

Prior to engaging in the experiment, participants were assigned a unique account identifier and password, which would be used to access the experimental website. Participants were asked to logon to the website to complete a demographic questionnaire, which included the risk propensity measure. After these data were collected, accounts were flagged as belonging to one of two risk propensity groups. Following Tam and Ho [73], a median split was utilized to classify an account as belonging to either a low or high risk propensity user.

The experiment was conducting in a controlled laboratory setting. Upon entering the laboratory, participants used their assigned account/password combination to logon to the website. The website randomly assigned each participant to one of the three suggestive guidance conditions. Participants then engaged in the experimental task (see below). Afterward, participants completed a set of post-task questionnaires and were dismissed. Prior to recruiting volunteers, pilot tests were conducted to ensure the instructions were understandable, to test the interface, and to confirm the efficacy of the suggestive guidance manipulations. Minor improvements were made based on the pilot study results.

Experimental Task

Participants were introduced to the experimental task via instructions, which were delivered through the website. Participants were informed that they had been provided with an online retirement account containing a hypothetical sum of $100,000. They were asked to use the application to manage a portfolio of retirement investments, with the goal of maximizing their wealth over a simulated 30-year period. In each year, the application presented financial information associated with two mutual fund investments: a relatively aggressive (i.e., risky) stock fund and a conservative bill (i.e., money market) fund. Participants evaluated this information and made decisions as to how to allocate their money among the alternatives.

Participants navigated the website by clicking on one of four tabs at the top of the screen – *Instructions*, *Portfolio*, *Research*, and *Allocations*. Although the core instructions were consistent across conditions, specific aspects were tailored to reflect whether suggestive guidance was available. Specifically, participants receiving suggestive guidance were told that the system would offer recommendations about their investment decisions. The *Portfolio* screen provided participants with the current value of their portfolio and the percentage gain/loss from the previous year, broken down by each investment. The *Research* screen displayed a list containing the names of the two mutual funds. To preclude familiarity and ordering effects, the funds were displayed to participants as Fund A and B. Each fund was randomly assigned as Fund A or B 50% of the time. To view financial information associated with a particular fund, participants clicked on the desired fund name. The application displayed a list of available information cues (see Table 1).

Table 1: Investment Information by Mutual Fund

Information (Annualized)	Stock Fund	Bill Fund
Average Return	12.98%	3.86%
Standard Deviation	20.17%	3.18%
Best Return	53.99%	14.71%
Worst Return	-43.34%	-0.02%
% of Years w/ Loss	28.00%	1.33%

Because prior theory and results imply that decision processes are shaped by perceived effort–accuracy tradeoffs [55, 77], the goal of the experimental design was to create a situation in which subjects would not be constrained by their limited cognitive resources [49]. Thus, the number of information cues was intentionally limited to five. The same investments and information cues were available to all participants.

After conducting their research, participants made an investment decision using the *Allocations* tab. Participants allocated a percentage, representing a specific portion of the current portfolio value, to each fund. The application ensured entries totaled 100%. In each year, participants were required to reallocate the entire value of their portfolio, meaning that the value of a particular investment was not automatically reinvested in the subsequent year. Following each decision, the application calculated the gain (or loss) associated with each investment, proceeded to the next year, and displayed the Portfolio screen where participants evaluated the performance of their portfolios.

To maximize external validity, a simulated set of mutual fund investments was created using historical market data. Two types of funds were included in the simulation – a stock fund and a bill fund. Simulated return data for these funds were generated using historical market returns spanning a 75-year time period (1926-2000). Annual return data for the Standard & Poors 500 Index, and U.S. Treasury Bills Index served as proxies for the construction of the stock and bill funds, respectively [30]. Table 1 presents the historical return data associated with the two funds.

Because retirement portfolio management involves decision making over an extended period of time, consistent with prior research [9, 40], the experimental task involved managing a portfolio of mutual fund investments over the course of a 30-year retirement planning period. Thus, 30 years of simulated return data were generated for each fund. To replicate the distributional properties of historical return data [30], a bivariate lognormal distribution containing 30 observations per variable was generated using the means, standard deviations, and correlations obtained from the historical record. Returns for the two funds were then derived from the output, with each observation representing one of 30 simulated years. To confirm the validity of the derived returns, means, standard deviations, and correlations were compared against those observed in the historical record. No significant discrepancies were discovered. To preclude ordering effects, simulated years were randomly assigned such that each year had an equal probability of being presented anywhere within the simulated 30-year period.

Variables

Independent Variables

Two independent variables were utilized in the study – risk propensity and suggestive guidance. Risk propensity was operationalized at two levels – low (i.e., risk-averse) and high (i.e., risk-seeking). Risk propensity was captured in the demographic questionnaire, as mentioned in the procedure above. Specifically, a four-item measure, adapted from a previous study [68], was utilized. Participants were asked to respond to questions, such as *"I enjoy gambling and taking chances"*, using Likert-type scales ranging from (1) *Strongly Disagree* to (8) *Strongly Agree*. The four items were summated, providing a risk propensity score for each individual. As a reminder, low and high risk propensity groups were operationalized using a median split, following Tam and Ho [73].

Suggestive guidance was manipulated at three levels – none, aggressive, or conservative. The no suggestive guidance condition was included as a control, enabling the examination of risk taking in an un-manipulated state. As a result, the natural decision making tendencies of participants could be captured and compared to the manipulated levels of suggestive guidance. In addition to the control, suggestive guidance either recommended a risk-seeking (i.e., aggressive) or a risk-averse (i.e., conservative) course of action. Specifically, in the aggressive guidance manipulation, the system suggested that participants allocate 80% of their money to the riskier stock fund. In contrast, the system suggested an 80% allocation to the safer bill fund in the conservative guidance manipulation. When available, suggestive guidance was delivered through a fifth tab, *Guidance*, positioned at the top of the screen. Participants could click on the tab to reveal the guidance.

Dependent Variable

The dependent variable, risk taking was measured by the level of risk in a participant's portfolio. Specifically, portfolio risk was calculated using Sharpe ratios [65], which is the standard for computing the level of risk in an investment portfolio [12]. Based on annual historical return data (1926-2000), a Sharpe ratio of 0.445 was calculated for the stock fund. Given that the bill fund carried negligible risk, the Sharpe ratio was calculated at 0.000. After participants entered their allocations, the application determined portfolio risk by multiplying each allocation percentage by the corresponding Sharpe ratio. The products were then totaled, yielding an overall indicator of portfolio risk ranging from 0.000 to 0.445, with higher values reflecting greater risk taking.

As a reminder, participants made a total of 30 investment decisions, one during each year of the simulation. Following prior studies employing similar designs [24, 40, 76], aggregate means were calculated for the entire simulation, resulting in a single measure of risk taking for each participant.

RESULTS

Prior to testing the hypotheses, a Chi-square (χ^2) test was conducted to ensure that the randomization process distributed the levels of risk propensity and gender across treatment cells equally. According to the results, no significant differences emerged across the treatment cells for risk propensity ($\chi^2(5,92) = 0.763$, *ns*) or gender ($\chi^2(5,92) = 0.727$, *ns*), verifying the robustness of the randomization process. The hypotheses were tested using a 2 × 3 ANOVA with planned comparisons. Table 2 presents the means, standard errors, and ANOVA results. The control variables were examined prior to evaluating the hypothesized relationships. Gender ($F(1,89) = 4.238$, $p = 0.042$, $\eta^2 = 0.043$) has a significant influence on risk, with males exhibiting greater risk than females. Neither age ($F(1,89) = 0.007$, *ns*) nor investing experience ($F(1,89) = 0.391$, *ns*) alters risk to a significant degree.

Turning to the hypotheses, Hypothesis H_1 proposed that risk would be significantly higher for high propensity users than low risk propensity users. The main effect for risk propensity was significant ($F(1,89) = 4.976$, $p = 0.028$, $\eta^2 = 0.053$). Examining the means, high risk propensity users (0.281) exhibited higher risk taking than low risk propensity users (0.248), as expected. Thus, hypothesis H_1 was supported.

Table 2: Means, Standard Errors, and Between-Subjects ANOVA Results for Risk

Independent Variable	*N*	*Risk* *M*	*SE*		*Between-Subjects ANOVA Results* *df*	*F*	*p*	η^2
Risk Propensity (RP)					1,89	4.976	0.028	0.053
Risk-averse	50	0.248	0.010					
Risk-seeking	48	0.281	0.011					
Suggestive Guidance (SG)					2,89	18.961	0.000	0.299
None	33	0.260	0.013					
Aggressive	33	0.325	0.013					
Conservative	32	0.209	0.013					
RP × SG					2,89	4.104	0.020	0.084
Risk-averse/None	17	0.224	0.018					
Risk-averse/Aggressive	15	0.299	0.019					
Risk-averse/Conservative	18	0.223	0.017					
Risk-seeking/None	16	0.296	0.018					
Risk-seeking/Aggressive	18	0.352	0.017					
Risk-seeking/Conservative	14	0.196	0.020					
Covariate	*N*	*Estimate*			*df*	*F*	*P*	η^2
Gender	98	0.58			1,89	4.238	0.042	0.045
Age	98	23.19			1,89	0.007	0.931	0.000
Investing Experience (years)	98	3.33			1,89	0.391	0.533	0.004

Hypotheses H_2 suggested that suggestive guidance provided by the personalization system would exhibit a significant influence on risk taking. A significant main effect for suggestive guidance ($F(2,89) = 18.961$, $p < 0.001$, $\eta^2 = 0.299$) provides overall support for this assertion. As depicted in Table 3, pairwise comparisons (Sidak adjustments) were used to assess hypotheses H_{2a} and H_{2b}. Hypothesis H_{2a} suggested that a personalization system providing aggressive guidance would lead to greater risk taking compared to a system that provided no guidance. The statistical comparison indicated that risk taking was significantly higher ($M_{\text{dif}} = 0.065$, $p = 0.002$) when users were provided with aggressive advice (0.325) than when the personalization system did not provide guidance (0.260). Similarly, hypothesis H_{2b} suggested that risk taking would be significantly lower when the personalization system provided conservative guidance than when no guidance was available. The result revealed that risk taking was significantly lower ($M_{\text{dif}} = -0.051$, $p < 0.001$) when users were provided with conservative advice (0.209) compared to users who received no guidance (0.260). Hypotheses H_{2a} and H_{2b} were, therefore, supported.

Table 3: Pairwise Comparisons Associated with Hypotheses H_2

Hypothesis	*Suggestive Guidance Comparison*			*Mean Difference in Risk (M_{dif})*	*SE*	*p*
H_{2a}	Aggressive	to	None	0.065	0.019	0.002
H_{2b}	Conservative	to	None	-0.051	0.018	0.000

Hypothesis H_3 predicted an interaction effect between risk propensity and suggestive guidance whereby both risk propensity groups would make risk-averse decisions when provided conservative guidance. The risk propensity × suggestive guidance interaction was significant ($F(2,89) = 4.104$, $p = 0.020$, $\eta^2 = 0.084$), provide initial support for hypothesis H_3. Figure 4 depicts the interaction.

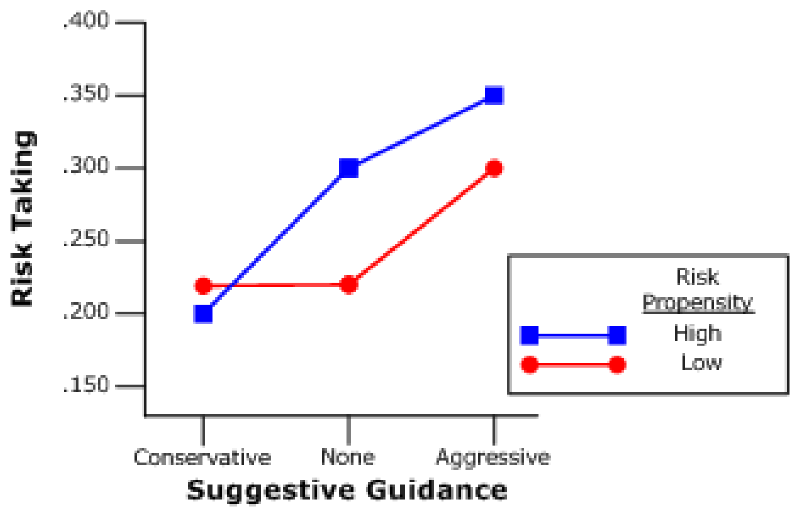

Figure 4: Risk Propensity ➨ Suggestive Guidance Interaction

To support the hypothesis, significant differences in portfolio risk between high risk propensity and low risk propensity users needed to emerge in the control (i.e., no guidance) and aggressive guidance conditions, but not in the conservative guidance condition. As indicated in Table 4, pairwise comparisons (Sidak adjustments) were used to compare risk taking between high risk propensity and low risk propensity users across the three levels of suggestive guidance. In the control condition, risk taking was significantly greater ($M_{dif} = 0.072$, $p = 0.006$) for high risk propensity (0.296) than low risk propensity (0.224) users, supporting hypothesis H_{3a}. Similarly, hypothesis H_{3b} received support. Aggressive guidance produced a significant difference in risk taking ($M_{dif} = 0.053$, $p = 0.039$). Portfolio risk was significantly greater for high risk propensity (0.352) than for low risk propensity (0.299) individuals. However, no significant difference emerged in the conservative guidance cells. Risk taking was statistically similar ($M_{dif} = 0.026$, *ns*) for high risk propensity (0.196) and low risk propensity (0.223) users, supporting hypothesis H_{3b}. Given the expected pattern of results, hypothesis H_3 received overall support.

Table 4: Pairwise Comparisons Associated with Hypothesis H_3

Hypothesis	***Suggestive Guidance***	***Risk Propensity Comparison***			***Mean Difference in Risk (M_{dif})***	***SE***	***p***
H_{3a}	None	Risk-seeking	to	Risk-averse	0.072	0.025	0.006
H_{3b}	Aggressive	Risk-seeking	to	Risk-averse	0.053	0.025	0.039
H_{3c}	Conservative	Risk-seeking	to	Risk-averse	0.026	0.026	0.315

DISCUSSION

The purpose of this study was to understand how a personalization system that delivers offerings varying in congruency with user personality trait affects decision outcomes. By crossing risk propensity with the modality of suggestive guidance, an important interaction was uncovered. As such, the results provide a more refined picture of how system design features and user characteristics independently and cumulatively influence decision making behavior. To date, personalization has primarily been accomplished through capturing user preferences and behaviors [2], ignoring the influence of user personality traits. Consistent with prior studies [47], the results attest that user personality traits can and do affect the utilization of personalization systems. Interestingly, however, the effect of personality depends on the features embedded within a personalization system. The combination of user and system characteristics interact to influence decisions in unique ways.

Specifically, individuals who naturally gravitate toward taking risks (i.e., high risk propensity) make more aggressive decisions when using personalization systems. However, this pattern of results is qualified by the type of suggestive guidance embedded within a personalization system. Users who receive aggressive guidance tend to take more risks than users who receive conservative or no guidance. However, when the personalization system delivers conservative guidance, risk propensity no longer constitutes an influential factor. Both high and low risk propensity groups react to conservative guidance in a similar, risk-averse fashion, regardless of their innate tendencies toward taking risks. As a result, the data provide strong support for the notion that personality matching has the potential to influence different types of users in distinct ways. In the context of the present study, incongruent offerings nullify the effect of personality by inducing risk-averse behaviors in high risk propensity individuals.

Therefore, rather than simply personalizing systems according to user characteristics, our results suggest that it is important for designers to consider the outcomes the system intends to achieve. Regardless of risk propensity, aggressive guidance accelerates risk taking. Under this condition, the decrease increased the risk-taking behavior of both high and low risk propensity users, with high risk propensity individuals taking significantly greater risks. In contrast, all users exhibit risk-averse behaviors when the system delivers conservative guidance. Risk-averse recommendations, which are incongruent with high risk propensity individuals (and congruent with low risk propensity individuals), induce all users to behave in a similar, conservative fashion. Therefore, systems that attempt to minimize risk taking can be configured in such a way to inform users of the negative consequences that could arise from a particular decision. Such a design is likely to minimize risk taking across all user groups. This may be particularly useful in other settings involving substantial risks, such as decisions related to health care and disaster planning.

Implications for Research

Designing personalization systems based on user personality traits, delivering matched and mismatched guidance, and understanding their independent and cumulative effects on decision outcomes had yet to receive sufficient empirical attention. This study contributes to the personalization systems literature by providing a fundamental understanding of how and why user personality traits and personality matching interact to influence decision making. The findings advance our understanding through providing evidence that the manner in which personalization systems present information affect different types of users in distinct ways. Specifically, research suggested that all users would make risk-averse decisions when the personalization systems delivered conservative guidance. The findings support this prediction. Consistent with Todd and Benbasat [77], it appears that influence of technological designs not only depend on the features embedded within a system, but also on the characteristics of its users. These variables interact in complex ways. Thus, we encourage researchers to consider other design features and user characteristics, leading to deeper knowledge about HCI and personalization systems in particular.

Contributing back to the psychology-based advice literature, advice has been traditionally treated as consistently affecting all individuals [26, 80]. The findings, however, suggest that differences based on personalities do exist and, therefore, might be present in other advice taking scenarios. The accuracy of recommendations influences user satisfaction [38]. The advice in this study, operationalized as suggestive guidance, did not fluctuate throughout the course of the simulated retirement portfolio management period. Given the present study's design, we could not ascertain whether users will eventually ignore suggestive guidance that is a poor predictor of decision quality. In future studies, the accuracy of suggestive guidance should be varied to tease out whether such configurations affect particular groups of individuals in unique ways.

Implications for Practice

In addition to its theoretical importance, this study carries implications for practice. As the results attest, system designers not only need to consider the design features to deploy, but also account for user personalities in order to achieve higher levels of personalization. Designers need to be aware that system- and user-related factors combine to have a considerable impact on user behavior and decision outcomes. In commercial settings, firms are more likely to prosper when they implement systems that enable individuals to make quality decisions. However, simply implementing personalization systems does not necessarily translate into better decisions. Certain designs can produce unanticipated or undesirable side effects [41]. Consequently, firms need to thoroughly test applications prior to deploying them in the field.

Moreover, as the results point out, design features, such as suggestive guidance, can affect different segments of the population (e.g., risk-seeking vs. risk-averse individuals) in unique ways. Thus, designers need to take into account the types of individuals who will be using their systems and which tools are likely to be most beneficial for these people. This study suggests that personalization, which has been growing in popularity, may hold the key [13, 73]. For instance, systems can now tailor advice based on particular user needs and preferences, but also need to consider user personalities to achieve higher levels of personalization. This suggests that additional user characteristics need to be determined in order to develop systems appropriate for various types of users. The findings herein provide a solid foundation for making progress in this direction.

Limitations

Every research study is limited in certain respects. The methodology employed a laboratory experiment using a simulated environment. The use of an experimental website moves away from a natural setting in which users make decisions. The design features incorporated into the system were limited compared to the vast assortment of features available in a designer's toolbox. In addition, even though the investment data were derived from the historical record, the number of investment alternatives does not reflect the wide array of products available to retirement plan investors [20]. Although this restriction enabled a precise test of the underlying theory, it is an oversimplification of reality. In addition, user behavior is partially determined by task demands [77]. The task represents a limitation due to its imprecise reflection of a 30-year retirement planning period. Although it would have been impractical to carry out the study over 30 years, the design does not precisely capture the timing of decisions that retirement plan participants make.

In terms of our participants, it might seem intuitive that sampling active retirement plan participants would be a better choice than using student participants. However, evidence demonstrates that experienced investors are more susceptible to decision making fallacies than students [25], meaning that student participants provide a more conservative test of the underlying theory. As such, we anticipate that the effects would have been even more robust if we had recruited actual retirement plan participants. While we may not be able to generalize our findings to all forms of personalization systems, various tasks, and all types of individuals, we can probably generalize the results to users asked to make decisions involving risk and uncertainty. Nonetheless, additional research is needed to understand the extent to which these findings may generalize to different systems, tasks, and users.

CONCLUSION

There are many factors that can influence the usability of personalization systems. Among them, user personality traits, offering congruency and strategies for enhancing the effectiveness of personalization systems in decision making contexts has been some of the least studied. This paper investigated whether the independent and cumulative effects of personalization systems based on user personality and offering congruency affected decision outcomes. The results indicate the risk propensity (a facet of user personality) and suggestive guidance (congruent or incongruent advice) interact such that the influence of risk propensity is nullified when the system suggests a conservative course of action. While the implications of these findings to other types of personalization systems, tasks, and users are not yet fully understood, the findings are encouraging.

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