Involvement and Decision-Making Performance with a Decision Aid: The Influence of Social Multimedia, Gender, and Playfulness

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ABSTRACT: This research explores how multimedia vividness and the use of computer-based social cues can influence involvement with technology and decision-making outcomes. An experiment is conducted that examines the effect that increased levels of vividness (text, voice, and animation) and decision aid personality have on decision-making involvement. In addition, the influence of two individual differences, gender and computer playfulness, on decision aid involvement are investigated. The cost–benefit framework of decision making and related research on consumer information processing provide the theoretical foundation for the study and suggest how increased involvement may influence decision making. Several decision-making outcomes are measured, including decision effort, decision quality, satisfaction with the decision aid, and understanding of the decision aid. Findings indicate that personality similarity (between the user and the decision aid) and computer playfulness result in increased involvement with the decision aid. In addition, women report higher levels of involvement with the decision aid. Increased levels of multimedia vividness are found to have a contradictory effect, with animation actually reducing involvement

Journal of Management Information Systems / Winter 2005–6, Vol. 22, No. 3, pp. 15–54.

0742–1222 / 2006 $9.50 + 0.00.

with the decision aid. The findings are discussed in terms of theoretical contributions and practical interface design implications.

KEY WORDS AND PHRASES: computer-based social cues, computer playfulness, decision aids, decision making, decision performance, multimedia in computing.

ADVANCEMENTS IN INTERFACE DESIGN have provided end users with media-rich, interactive computing environments. Multimedia technology, the simultaneous presentation of information in various formats (text, audio, animation, etc.), has been applied to many types of information systems (IS) [39], including computer-based training [35, 55], Web sites [21, 24, 27, 34, 63], and communication environments [5, 13, 37, 38, 75]. IS are also being endowed with social cues that convey human-like attributes through technology [5, 48]. Designers assume that this richer, social technology will attract and engage users, yet research on how this technology affects decision making has not kept pace with these advancements. The effect of these more engaging interfaces on decision-making performance warrants more focused exploration [28, 39].

Prior to these advancements in interface design, researchers had investigated and advanced the use of technology to support decision-making activities. Applications referred to as decision aids, or decision support systems (DSS), were developed and tested in various experimental settings and provided functionality to support individuals in decision making [56, 71]. Spreadsheet-like features and built-in functions were incorporated into decision aids to encourage users to employ better decision-making strategies [25, 56, 68, 69, 70, 71]. Today, this decision-making support is readily visible in the comparison matrices of numerous shopping Web sites, search engines, office automation systems, and DSS. Designers now have the guidelines and the tools for developing technology that support decision-making tasks. Guidelines do not exist, however, for the use of multimedia and social cues in decision aids.

Existing research on the use of multimedia has focused on the use of rich media in computer-mediated person-to-person communication and in person-to-computer interaction. The first category of research used media richness theory to explain media choice in person-to-person organizational communication [10, 11, 52, 58, 73]. Contradictory findings and a focus on organizational media choice limited the applicability of this research stream. The second category of research, multimedia in person-to-computer interaction, has begun to identify the specific attributes of multimedia that may affect user perceptions of technology. From this research and from earlier work on media in consumer decision making, vividness has emerged as a key concept. Vividness, defined as "the representational richness of a mediated environment as defined by its formal features" [64, p. 81], has been shown to affect the human experience with technology [21, 24, 27, 29, 75]. More vivid media may use more information cues (e.g., more sensory channels, such as visual and auditory, to convey the same information) and may use greater resolution within a single channel (e.g., using pictures and animation instead of just text in the visual channel) to increase the user's sensory experience. It is believed that the increased sensory experience will increase the user's involvement with media [21, 24], but there has been only limited testing of the relationship between multimedia vividness and involvement.

A related stream of research on human–computer interaction (HCI), the Computers as Social Actors (CSA) Paradigm, has focused on how users respond to computing applications that exhibit social cues through multimedia. Nass and colleagues conducted a series of experiments in which users exhibited social responses to computing applications despite knowing that the applications were not in any way human [48]. Users demonstrated a preference for a computer-based personality that matched their own (e.g., extroverted/introverted) and made more positive attributions toward the computer when it exhibited a similar personality [5, 44, 45, 47, 51]. Gender stereotyping [36, 49, 50] and social categorization [49] were also exhibited by users in response to social cues from computing applications. Exploration of the decision-making effects of these computer-based social cues, however, has been limited.

The purpose of this study is to investigate how multimedia and computer-based social cues affect decision aid involvement and decision-making performance. Our research model was developed from the cost–benefit framework of decision making [56] and incorporates two technology characteristics and two individual characteristics, along with several decision-making outcomes. The technology characteristics are (1) multimedia vividness (text, voice, and animation) and (2) personality similarity between the user and the decision aid. The individual characteristics, gender and computer playfulness, were essential in our study, as empirical research has demonstrated that these characteristics are strongly related to involvement and technology perceptions. Research on multimedia has stressed the importance of individual differences in understanding the affect of using this technology, as interpretation of a mediated environment varies across individuals [64]. In addition, gender has become an increasingly relevant issue in computer use as evidenced by the growing number of female technology users [8] and the empirical findings of recent gender-based management information systems (MIS) studies [14, 23, 74].

This study differs from previous research by providing a theoretical framework for understanding how multimedia vividness, social cues in the form of computer personality, and related individual differences influence involvement with a decision aid. In addition, this research extends previous decision-making research by exploring how user involvement with the decision aid affects decision-making outcomes. An analyzable, unequivocal task used in prior in decision-making experiments [56, 68, 69, 70, 71] was purposely selected for this study to provide insight as to how multimedia affects user involvement and decision-making outcomes in less complex (baseline) scenarios.

Theoretical Framework

GIVEN OUR FOCUS ON DECISION-MAKING PERFORMANCE, we applied a decision-making lens to our study of multimedia, and used the cost–benefit (effort–accuracy) framework from the decision-making and information processing literature as our core theoretical foundation (see [56] for a review). The major premises of this framework are that different decision strategies are available to decision makers, and different levels of effort and accuracy characterize these strategies. Decision makers decide which strategy to use based upon their desire to maximize accuracy and minimize effort. In this framework and in the information processing literature, a strategy in which the decision maker utilizes all the information and expends the most effort and time is believed to result in the best accuracy. Thus, decision makers are faced with a trade-off in that they wish to maximize accuracy, but doing so will also maximize their effort. This framework has been applied in many empirical studies of consumer decision making [4, 7, 32, 43, 56, 57] and in many studies on decision aids [25, 68, 69, 70, 71].

The concept of involvement plays an important role in decision making, as higher levels of involvement are believed to positively affect effort and accuracy, central components of the cost–benefit framework. In the context of consumer decision making, involvement with the task and with marketing media (e.g., advertisements) has been studied [7, 40, 43, 57]. As technology has been developed to support decision-making tasks, researchers have begun to focus on user involvement with these tools and how it affects perceptions of the tool and performance [24, 60]. Just as task and print media characteristics have been shown to influence task involvement and decision performance, the technology characteristics visible to the user (e.g., the interface) are believed to influence involvement with decision aids, and thus decision-making performance.

In the following sections, we describe our research model (shown in Figure 1) and present our hypotheses. First, *involvement with the decision aid* is described in more detail. The potential antecedents of involvement with a multimedia decision aid are then discussed (*gender, computer playfulness,* and *personality similarity* between the decision aid and the decision maker, and *multimedia vividness).* Hypotheses for each are presented as the relevant literature is reviewed. The effect of involvement on decision-making outcomes is then described and related hypotheses are presented.

Involvement

Researchers in consumer information processing have long recognized the importance of involvement, or focused attention, on decision-making outcomes [7, 43, 56, 57]. Involvement affects information processing at a fundamental level, as increased involvement can lead to greater information acquisition, improved understanding, and increased effort. In this context, involvement has been defined as the degree to which the person is engaged with a task or object [43]. Involvement is believed to come from two broad sources: (1) *intrinsic* or stable sources due to individual differences and (2) *situational* sources, those that may be manipulated within the environment [7]. The interface elements of IS, such as multimedia and social cues, are expected to affect the *situational* form of involvement. In our study, *involvement with a decision aid* is investigated and is defined as the degree to which a person is engaged with a decision aid.

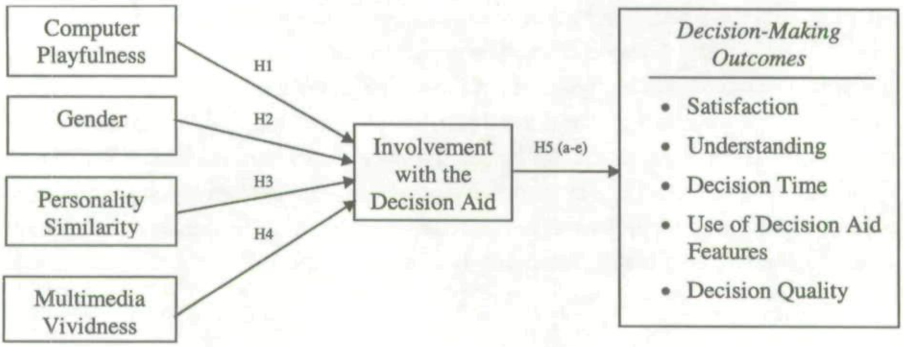

Figure 1. Research Model: The Effect of Computer Playfulness, Gender, Personality Similarity, and Vividness on Involvement and Decision-Making Outcomes

Recent MIS research has investigated involvement-related constructs in the context of technology acceptance. Agarwal and Karahanna note that current IS often employ rich media that provide an "increasingly riveting and engaging experience" [1, p. 667]. They advanced the cognitive absorption construct to explain the affect of an engaging IS experience on technology acceptance. Similarly, Koufaris has applied the state of flow concept from the psychology literature to e-commerce in the context of technology acceptance [33]. A state of flow occurs when an individual is absorbed in a task and acts with complete involvement [9]. In another e-commerce study, higher levels of interface involvement were found to influence user attitudes toward the interface and the information conveyed via the interface [24]. Involvement and related constructs are of interest to MIS researchers because interface design may affect user involvement and performance with an IS.

Although research has shown that involvement with technology may affect user attitudes and acceptance of IS, the effect of decision aid involvement on decision-making outcomes has received little attention. One communication study investigated involvement, decision quality, and communication measures in an experimental communication task [5], but the sample size was limited. IS researchers have noted that the effect of multimedia on decision-making outcomes and user involvement is still largely unknown [28, 37, 38, 39, 75]. Additional research is needed to establish the antecedents of involvement, their relative importance in predicting involvement, as well as the downstream effect of involvement on decision-making outcomes.

Computer Playfulness

In studying involvement-related constructs in the context of IS, researchers have noted the importance of an individual trait, *computer playfulness,* in understanding an individual's involvement with a system [75, 76]. Webster and Martochhio defined computer playfulness as "the degree of cognitive spontaneity in microcomputer interactions" [76, p. 204]. Several studies have found that higher levels of general computer playfulness lead to higher levels of flow or absorption with an IS [1, 75, 76, 77]. Given that computer playfulness has been found to be a significant antecedent to involvement-related constructs in MIS, it follows that this individual trait would be a significant antecedent to decision aid involvement. We would expect an increase in computer playfulness to positively affect user involvement, thus, as computer playfulness increases, user involvement will increase. Therefore,

H1: Computer playfulness will have a positive effect on user involvement with a computer-based decision aid.

Gender and Technology

In consumer information processing, gender differences have been investigated for decades due to the common practice of gender-based market segmentation. Differences in how males and females process information in the form of advertisements and product labels have been found across a variety of tasks [42]. The Selectivity Model was advanced in this domain to explain the different information processing strategies exhibited by men and women [41, 42]. According to the Selectivity Model, females are more comprehensive processors, respond to more subtle cues in messages, and have a lower threshold for elaborative processing. Empirical studies of this model have supported these findings [12, 41, 42].

Gender researchers in social behavior [61], communication [14, 62], and IS acceptance [23, 74] have noted differences in how men and women interact with each other and technology. Compared to men, women are perceived to be more socially focused, more aware of other's feelings, and more concerned with group harmony, consensus building, and interrelationships. Men, on the other hand, are viewed as being more independent, assertive, and unemotional.

In the context of technology acceptance, this more socially focused view of women has been empirically supported. Gefen and Straub found that women perceived a higher level of social presence in e-mail than did men [23]. Dennis et al. found support for the premise that women were more sensitive to, or aware of, nonverbal social cues in computer-mediated conditions [14]. Greater awareness of nonverbal social cues and perceptions of greater social presence suggest that women may be more involved or attentive in social interactions. Although gender research has found differences between men and women in their communication patterns and initial beliefs or expectations with regard to technology, there has been less support for gender-based differences in actual performance with technology.

These findings suggest that women are more detailed information processors than men. Women also appear to be more socially focused than men and more observant of social cues in general. In addition, women have been found to perceive a greater social presence in electronic communication [23]. Therefore,

H2: Women will be more involved than men with a computer-based decision aid.

Personality Similarity with a Computer-Based Decision Aid

As mentioned previously, HCI and communications researchers from the CSA paradigm have demonstrated that users respond in a human-like manner to social cues exhibited by computing applications [5, 45, 47, 48]. This paradigm asserts that users respond to social cues from computers with social behaviors, but that this conditioned response occurs despite the user knowing that the computer is not human. One important finding of this research is that users can accurately assess personality traits in computing applications and respond differently to the computer-based personality depending upon their own personality. The multimedia used in many of these studies was not advanced and sometimes included just text. As an example, in one such experiment, the subjects completed a problem-solving task and were provided with feedback on their initial solution from a computer program. The program provided this feedback using only text, and the personality of the program was manipulated primarily by changing the phrasing of the text (dominant/submissive) [51]. No animation, graphics, or voice were used in the study; text was sufficient to convey the desired social cues and computer-based personality.

Similarity-attraction theory offers an explanation for these responses [6]. This theory posits that individuals will be more attracted to other individuals that exhibit similar characteristics. This theory has been extended to interactions with friends and colleagues in business settings [2, 59, 65]. In the early stages of an interaction or relationship, personality traits are easy markers for assessing similarity and reducing the uncertainty of a new interaction. Simply stated, we are more comfortable with people that exhibit traits that are familiar (e.g., like our own). In HCI, we would expect users to be more comfortable with computer-based interactions that are similar to their everyday interactions with other humans [44, 45, 48, 51]. In addition, when these computer-based interactions exhibit personality traits similar to the user's traits, this attraction should increase. Several studies have examined how computing applications may exhibit personality traits (extrovert/introvert, dominant/submissive) and have found support for similarity-attraction theory [5, 44, 45, 47, 51]. These studies, however, did not address involvement and decision-making performance with a multimedia decision aid.

The psychology literature and CSA studies provide support for the relationship between personality similarity and user attraction to the decision aid. Greater attraction to a computer-based decision aid should affect a user's involvement or attention to the decision aid. Therefore,

> *H3: The personality similarity between the decision maker and the computer-based decision aid will have a positive effect on user involvement with the decision aid.*

Multimedia Vividness

Research on vividness from the decision-making literature provides a foundation for understanding how multimedia vividness may affect involvement with a decision aid.

Prior to the use of multimedia technology, the vividness of message information was studied in consumer information processing for its effect on attention in decision-making [30, 31, 40, 53, 66, 67]. Vivid information (e.g., easily imagined, image provoking) was described as being "likely to attract and hold our attention and to excite the imagination" [53, p. 45]. The basic premise of these studies was that vivid information would be more persuasive and salient and thus would have a greater influence on attitudes and alternative evaluation. Results from these studies were largely mixed with some studies finding an effect for vividness while others did not. Possible explanations for these results were that vividness only produces an effect when there is competition for attention among vivid and nonvivid information [66, 67], and vividness only has an effect when observers are encouraged to elaborate and not just passively observe [30, 31, 40].

Multimedia vividness "refers to the ability of a technology to produce a sensorially rich mediated environment" [64, p. 80] and is believed to affect involvement with the mediated environment [21, 24, 27]. Vividness can be achieved through *depth* and through *breadth,* where breadth represents the number of different sensory channels utilized (visual, auditory, smell, etc.) and depth represents the resolution or detail of a particular sensory channel [64]. Vividness is distinct from the concept of multimedia interactivity, which refers to the "extent to which users can participate in modifying the form and content of a mediated environment in real time" [64, p. 84]. In studies of multimedia presentations, results have indicated that users were more engaged in presentations that were more vivid. In one such study, two different presentation software packages were used to develop presentations with the same information content, but one package provided animation and sound [75]. This study found that individuals were more engaged in the presentation that had more stimulus variety, or greater breadth of multimedia. In a similar presentation study, individuals were more attentive to presentations that included color and to animated slides than to nonanimated slides or transparencies [46].

In studies that utilize video as a form of multimedia, empirical results showed that first impression bias can be reduced with multimedia, but not with text-based presentations [38]. Similarly, multimedia presentations, but not text-based presentations, were found to reduce perceived equivocality in less-analyzable tasks [37]. An analyzable task is one in which there is general understanding of the steps needed to complete the task. No differences were found in the dependent variable, perceived equivocality, between multimedia and text-based presentations for analyzable tasks [37], whereas differences were found with less-analyzable tasks. In recent studies of multimedia used in Web sites and DSS, vividness was found to increase interface involvement [24] and browsing behavior [28].

Norman's principle of visibility in technology design [54] supports the findings of these multimedia studies and is in keeping with the vividness concept. The visibility principle is simply to make technology features visible. And when visibility is not possible, the designer should add sound and make features audible [54]. The addition of sound and viewable properties makes it easier for the user to see and understand technology features.

While most of the studies discussed above focused on multimedia represented through video and presentation software, the findings are applicable to the implementation of multimedia in the current study (text, voice, and animation). Given that the task used in our study is analyzable and relatively unambiguous, we would not expect any direct impact from increased vividness on decision-making outcomes such as decision quality, time, or effort. Based upon the concept of vividness advanced in the literature, which aligns with Norman's principle of visibility, the additional sensory channels of information provided in more vivid media should increase user involvement with a decision aid. Therefore,

H4: Multimedia vividness will have a positive effect on involvement with the computer-based decision aid.

Involvement and Decision Performance

The cost–benefit framework and the consumer information processing literature [7, 43, 56] provide theoretical support for the influence of involvement on decision-making outcomes. Recent MIS and HCI research has extended this support to involvement with technology. Multiple decision-making outcomes were investigated in this study to provide a more comprehensive understanding of how involvement can influence decision making. In keeping with more recent studies on decision making [13], several measures of decision-making outcomes were included to increase the relevance of the results.

Many empirical studies in consumer information processing have found a positive relationship between involvement with a task or object and attitudes toward this task or object [43, 57]. These results have been found with regard to involvement with advertisements, decision-making tasks, and, more recently, with interfaces [24]. An individual that finds something, such as a decision aid, to be engaging and stimulating, is also likely to have positive perceptions of that decision aid. Therefore,

H5a: User involvement with the computer-based decision aid will have a positive effect on satisfaction with the decision aid.

The cost–benefit framework suggests that decision makers that are more involved in a decision-making task will gain a better understanding of the task and task information [56]. Empirical results have supported this premise and have shown that decision makers have greater comprehension of decision-making information when they are more involved with the decision [7]. Similarly, an individual that is more involved with a decision aid should gain a better understanding of the decision aid. Therefore,

H5b: User involvement with the computer-based decision aid will have a positive effect on understanding of the decision aid.

The cost–benefit framework predicts that an individual who is more involved with a decision-making task is more likely to devote increased information processing effort to decision-making activities. More recent research on involvement suggests that an engaging system interface will increase user involvement with the system and with the information and task supported by the system [5, 24, 60]. In addition, users that are more involved with a system tend to spend more time using the system [1, 33]. Given the difficulties in directly evaluating decision-maker effort, previous decision-making studies have evaluated effort through decision-making time and decision-maker use of the decision aid [56]. The features of a decision aid provide support for the cognitive processes of decision making by allowing the user to sort alternatives and reorganize attribute information. Thus, a decision maker that is involved in making a decision should use more decision aid features. Therefore,

> *H5c: User involvement with the computer-based decision aid will have a positive effect on decision time.*

> *H5d: User involvement with the computer-based decision aid will have a positive effect on the use of decision aid features.*

Involvement with a decision aid may also translate into improved decision quality. In the cost–benefit framework and information processing literature, decision quality is viewed as the accuracy of the decision compared to a normative solution for that individual [56]. The decision alternative with the highest weighted additive value, as calculated from a user's weighted preferences, would be considered the best solution for a decision maker [25, 56]. If a decision maker is more involved with a decision aid that supports the user in selecting a high-quality alternative, then the decision maker is more likely to make a more accurate, high-quality decision. Therefore,

> *H5e: User involvement with the computer-based decision aid will have a positive effect on decision quality.*

Research Methodology

A 2×3, BETWEEN-SUBJECTS RESEARCH DESIGN was used, varying the level of multimedia vividness (text only—T; text and voice—TV; text, voice, and animation—TVA) and the personality of the decision aid (extroverted, introverted). Subjects were randomly assigned to one of the six treatment conditions. The decision task and the interactivity of the decision aid in each treatment were identical. This study was conducted after multiple pretests and two extensive pilot studies were performed to refine the experimental manipulations.

Participants

Participants were 259 undergraduate students recruited from a sophomore-level business course with a research study participation requirement. The experiment was conducted in a controlled, heavily monitored laboratory environment, and the subjects received credit for this scheduled assignment only if they completed the study in a

Table 1. Apartment Attributes and Values

Apartment attributes	Attribute values
Rent	\$460–\$900
Size	Compact, moderate, spacious
Laundry	Washer/dryer in unit, on-site, off-site
Distance from campus	< 0.5 miles, 0.5–1 mile, 1–5 miles, ≥ 5 miles
High-speed Internet access	Yes, no
Age of facility	1–5 years, 5–15 years, > 15 years
Parking	Reserved spot on-site, open on-site, off-site
Noise	Very quiet, quiet, somewhat quiet

diligent and responsible manner. No additional incentives were provided for performance. The average age of the subjects was 20.6, with 164 males and 95 females participating. The subjects participated in the experiment after completing three months of training on several office automation applications and thus had a moderate level of competency in using computing applications.

Task

The subjects performed an apartment selection task similar to that employed in prior decision-making studies [56, 71]. This task was chosen as it is believed to be a personally relevant choice problem for most college students, and it has been successfully employed in other decision-making experiments using college age subjects. The subjects were presented with ten apartment alternatives that varied by the eight attributes shown in Table 1. Apartment alternatives were specified so that all of the alternatives were *nondominated.* If an alternative is dominated, then at least one other alternative has better attribute values across all attributes [25, 32, 56]. A dominated apartment alternative would have higher rent, less space, off-site laundry, and so on, and thus would be a bad selection for any decision maker, regardless of their preferences. A decision-making task with nondominated alternatives is thus more cognitively demanding than one with dominated alternatives.

Treatment Conditions

The different levels of vividness, or information cues (T, TV, TVA), were developed using the Microsoft Agent Technology. In the T treatment, the decision aid provided subjects with instructions through text displayed in text balloons. In the TV treatment, instructions were provided through the text balloons along with a computer-generated voice that read the text in the balloons as it was displayed. In the TVA treatment, an animation provided instructions through text balloons and voice. An animated bird was selected over a male or female animation to avoid the gender biases found in other studies [36, 49, 50]. The animation was able to gesture and change

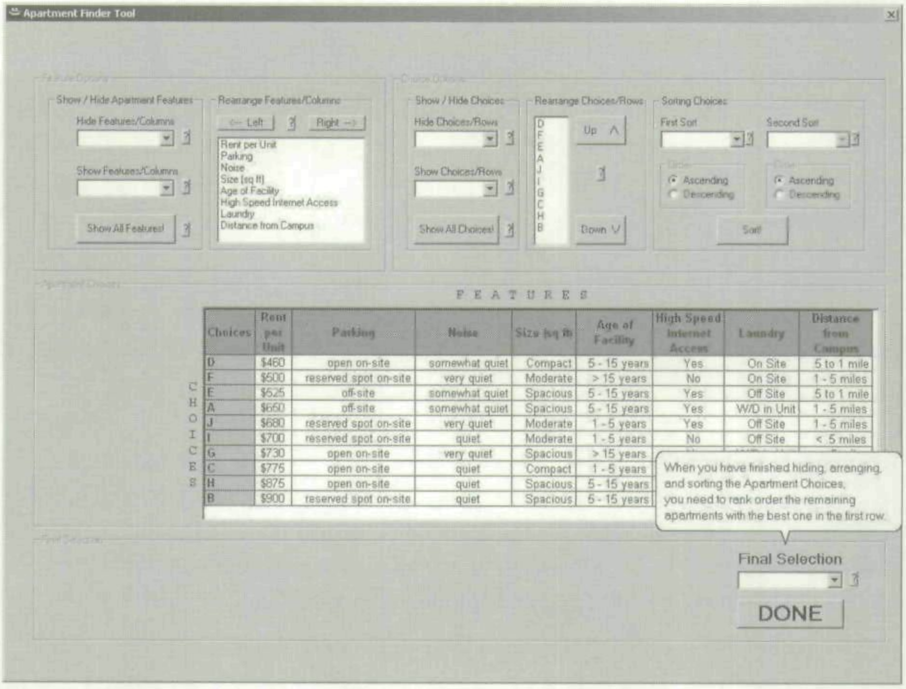

Figure 2. Screenshot of the T, Extroverted Treatments of the Decision Aid

facial expressions as it provided instructions. Figures 2 and 3 provide screenshots of the T and TVA treatment interfaces, respectively. A screenshot of the TV treatment is not provided as it has the same visual appearance as the T treatment.

The extroverted dimension from the circumplex model of interpersonal behavior [72, 78] was used to assess the effect of personality similarity. This dimension represents the degree to which an individual is outgoing in social situations and was selected because it can be easily represented and accurately assessed in a short interaction period. This personality trait was manifested in the treatments by varying communication style and voice characteristics in keeping with the personality literature and similar experiments on personality traits [5, 19, 22, 47, 48]. The same information content was used in all treatments, but consistent with past research on personality, the manner in which the information was conveyed was altered. For example, the script used in the extroverted treatment included more outgoing, assertive statements (e.g., "After you have reviewed the various alternatives, you should select the apartment that best meets your needs!"), whereas the introverted script used more timid, unassuming statements (e.g., "After you have reviewed the various alternatives, you will be asked to select the most suitable apartment").

In the TV treatment, the extroverted script included the same assertive statements, and the frequency, range, and speed of the computer-generated voice was increased to be in keeping with the vocal traits of an extroverted personality [19, 47]. In the TVA treatments, the extroverted script included the same assertive statements and

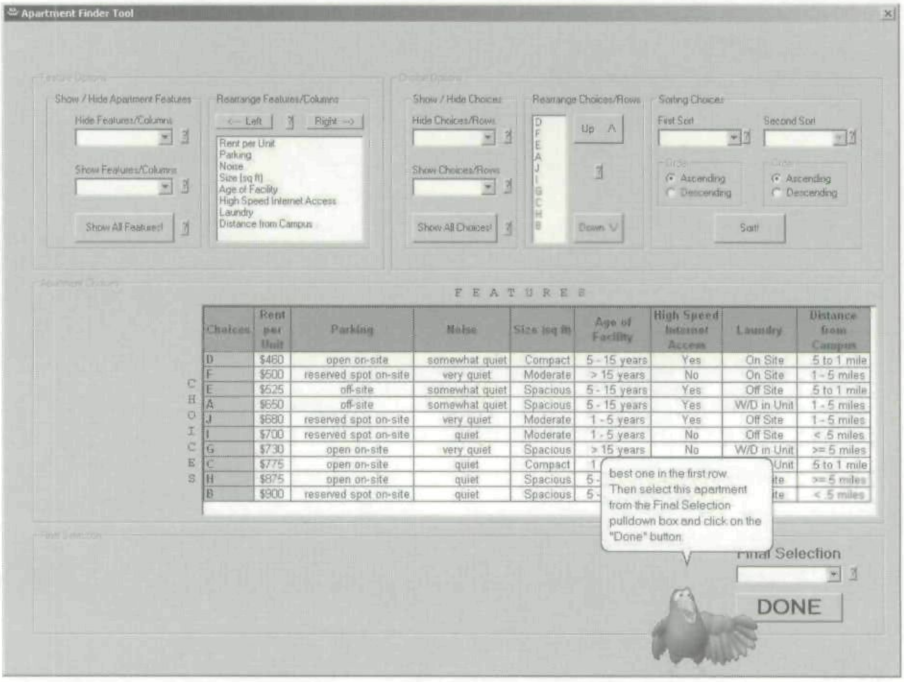

Figure 3. Screenshot of the TVA, Extroverted Treatment of the Decision Aid

vocal cues, and was allowed to make more extroverted gestures. For example, in the extroverted treatment, the animation was programmed to gesture toward features of the decision aid with arm movements, whereas in the introverted treatment, the animation simply nodded toward the decision aid features. The same number of gestures was programmed for both the extroverted and introverted treatments, only the type of gesture differed. The scripts for the extroverted and introverted treatments are included in Appendix A. These scripts include both the text and the animations used in the treatments.

Procedure

A preexperiment survey was first administered to ascertain the subjects' perceptions of their own personality trait (extroversion). Empirical studies of personality similarity typically administer personality assessments of the subject and the subject's perceptions of another individual or object at different times to avoid any recency effects [44, 47, 51]. For example, a subject that assesses their own personality and the personality of others at the same time may be more likely to assess these personalities as being similar. In our study, the subjects completed the survey assessing their own personality seven weeks prior to the experiment and the survey assessing the decision aid personality to avoid any recency effects. The subjects were randomly assigned to one of the six treatments (extroverted T, TV, TVA; introverted T, TV, TVA).

The computer-based decision aid first provided a description of the decision task and then guided the user through the use of the tool for decision-making purposes (selecting an apartment). The delivery of information was in keeping with the subjects' assigned treatment condition. During the tutorial portion of the experiment, the users were unable to use the decision aid and were unable to bypass the tutorial. Upon completion of the tutorial, the users were presented with the feature weighting form and asked to specify their preference for each apartment feature by allocating 100 points among the features as shown in Figure 4. The users were required to allocate all 100 points before they could proceed. The decision aid then provided a spreadsheet-based interface with several functions to facilitate the subject's selection of an apartment, as shown in Figures 2 and 3. These functions included hiding and showing apartment alternatives (rows) and features (columns), changing the order of the apartments (rows) and features (columns), and sorting by one or two of the apartment features. The subjects were asked to rank order the apartments according to their preference and select their preferred apartment. After the subjects selected an apartment, a postexperiment survey was administered to assess perceptions of the decision aid and decision-making performance.

Measures

The scales used in the pre- and postsurveys are included in Appendix B. The measurement of the subject's personality and the personality of the decision aid on the extroversion dimension was obtained using five items from the Interpersonal Adjectives Scale [72, 78]. Personality difference scores were calculated by taking the absolute value of the difference between the subject's assessment of their own personality and their assessment of the personality of the decision aid on these five items measuring extroversion. Smaller difference scores represent personality similarity, whereas larger difference scores indicate that the perceptions of the personality of the subject and the decision aid differed on the extroversion trait. Because of known methodological problems with the use of difference scores [17], alternative procedures were also conducted as shown in Appendix C (using polynomial regression components in place of difference scores), and similar results were obtained.

The *involvement* scale was developed from an existing five-item scale that measures a user's focused attention (immersion) with an IS [1]. This scale was comparable to marketing scales used to measure involvement or attention in non-IS settings and was more reliable than similar scales in the communication literature [5]. The measures for computer playfulness were taken from the scale developed by Webster and Martocchio [76].

Decision-making performance was measured by several common decision-making outcomes. The subjects' *satisfaction* with the decision aid was measured with a three-item scale adapted from other IS satisfaction scales [15]. The subjects' *understanding* of the decision aid was measured with a four-item scale adapted from the decision-making literature. Decision *quality,* or accuracy, was measured by comparing the subjects' final selections to their *normative choice* using a weighted-additive calcula-

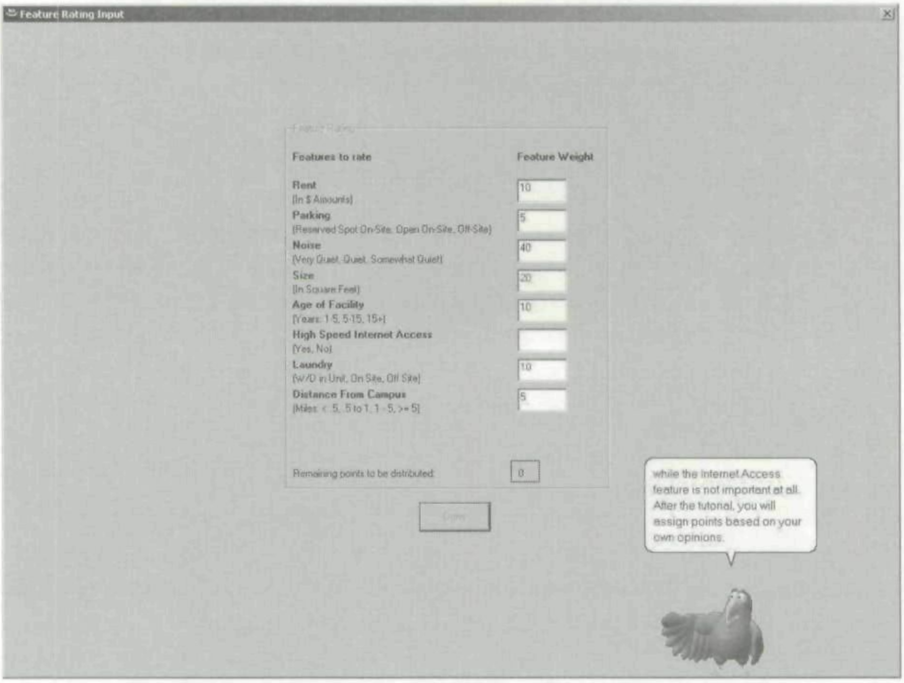

Figure 4. Screenshot of Feature Rating Form for the TVA Extroverted Treatment

tion. If a subject selected the normative apartment based upon the weights that he or she specified for each apartment attribute, then quality was recorded as a zero, otherwise decision quality was coded as a one.

In past decision-making studies, decision-making effort has been measured by both the amount of time spent making a decision and the number of decision aid features used by the decision maker [56]. In our study, the amount of time spent using the decision aid was measured by the experimental application. This time period corresponds to the time spent evaluating the decision alternatives and making the final selection, as the decision aid supported the entire decision-making process. We also measured the number of decision aid features used by the decision maker, as tracked by the experimental application. The number of decision aid features used provides a good surrogate for effort, in addition to time spent using the decision aid, as time may vary based on user characteristics other than effort, such as technology experience, task or context experience, problem-solving ability, and so on. Other decision support studies have similarly measured decision aid feature use to represent user effort [56, 68, 71].

Results

IN THIS SECTION, DESCRIPTIVE DATA FOR ALL VARIABLES is provided, a manipulation check of the experimental treatments is conducted, confirmatory factor analysis and structural regression model results are presented, and supplementary statistical procedures are described. Means and standard deviations for all measured variables, by treatment condition, are shown in Table 2.

Manipulation Check

The subjects' perception of the decision aid personality was used to verify that the treatment personality was adequately manipulated. The more extroverted computer personality treatment was perceived to be more extroverted overall (F (1, 257) = 27.17, $p < 0.000$) and across the three forms of information cues as shown in Table 3. Means for all treatment conditions (extroverted T, TV, TVA; introverted T, TV, TVA) are shown in Table 3. Thus, the manipulation appeared to be successful.

Measurement Model

Measurement model results are presented in Table 4. The standardized loadings obtained through confirmatory factor analysis were sufficient (> 0.7, as recommended by [20]) for most of the scales used in the study. Exceptions include the fourth item in the involvement scale (taken from [1]), which had a loading of 0.42. This item was negatively worded and research has shown that negatively worded items can reduce scale unidimensionality [26]. Two of the difference score items measuring personality similarity also had lower loadings. The original items used to create these differences (subject and decision aid extroversion), however, had overall reliabilities > 0.8 and factor loadings > 0.62. Given the fit of the model and the lack of high modification indices, which would indicate cross-loadings with other constructs, these items were retained in the model.

Structural Regression Model

Analysis of the full model initially shown in Figure 1 was performed using AMOS 4.0 for structural equation modeling (SEM) with maximum likelihood estimation. Figure 5 provides the results for each hypothesis and the fit statistics for the model. Standardized regression weights are displayed along each relationship in the model, and the squared multiple correlations shown within each of the endogenous variables represent the variance accounted for in the model.

With regard to the hypotheses related to the determinants of involvement, H1, H2, and H3 were supported, whereas H4 was not supported. Computer playfulness (H1) increased user involvement, and women were more involved with the decision aid than men (H2). When the personalities of the user and the decision aid were more similar (lower difference scores), users were more involved with the decision aid (H3). The vividness of the multimedia did significantly affect involvement but not in the hypothesized direction (H4). The addition of animation appeared to reduce user involvement with the decision aid.

Table 2. Means and Standard Deviations for Measured Variables

	Treatments											
	Extroverted T		Extroverted TV		Extroverted TVA		Introverted T		Introverted TV		Introverted TVA	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Subject extroversion												
Male	5.39	0.91	5.65	0.89	5.26	1.03	5.19	1.01	5.02	1.03	5.42	1.01
Female	5.81	1.17	5.71	0.94	5.84	0.86	5.92	1.39	5.55	0.89	5.74	0.87
Decision aid extroversion												
Male	4.72	0.89	4.35	0.64	4.97	1.00	4.16	1.06	3.87	1.29	4.30	1.04
Female	5.13	1.16	4.99	0.97	5.43	1.09	4.60	1.75	3.73	1.55	4.81	1.29
Involvement												
Male	4.24	1.34	4.13	1.03	3.68	1.37	4.07	1.27	4.19	1.34	3.61	1.39
Female	4.49	1.23	4.56	1.02	4.43	1.06	4.56	1.24	4.69	0.98	3.58	1.53
Computer playfulness												
Male	4.38	1.22	4.77	0.94	4.93	1.02	4.58	1.02	4.69	1.32	4.59	1.32
Female	4.72	0.85	4.81	0.98	5.17	1.08	4.54	0.72	4.73	0.71	5.10	1.13
Decision effort												
Male	14.20	7.37	16.48	13.47	17.00	10.32	12.90	13.01	13.76	11.56	8.52	9.56
Female	17.13	14.07	15.18	9.56	17.92	10.32	17.57	18.38	11.14	10.84	11.18	8.13
Decision time												
Male	206.00	89.50	208.30	131.70	212.50	88.10	178.20	178.20	185.60	135.40	116.80	74.20
Female	197.00	99.50	218.30	109.70	225.90	98.70	242.40	242.40	163.50	72.50	177.40	104.00
Satisfaction												
Male	5.44	1.18	4.83	1.49	4.72	1.35	4.59	1.72	5.15	1.40	4.67	1.35
Female	5.37	1.67	5.46	1.17	6.19	1.27	5.36	1.65	5.46	1.56	5.26	1.27
Understanding												
Male	5.84	1.24	5.66	1.25	5.70	1.05	5.11	1.66	5.47	1.24	5.34	1.60
Female	6.03	1.26	5.81	0.93	6.04	0.93	5.78	1.05	6.01	1.17	5.56	1.22

Table 3. Manipulation Check—Mean Decision Aid Extroversion Score

Treatment	T	TV	TVA	All levels
Extroverted	4.920	4.671	5.201	4.931
Introverted	4.380	3.802	4.557	4.246
p-value	0.044	0.001	0.011	0.000

Table 4. Items, Standardized Loadings (All Loadings $p < 0.0001$), and Fit Statistics

Items	Standardized loadings	Items	Standardized loadings
Involvement1	0.790	Satisfaction3	0.811
Involvement2	0.930	Understanding1	0.862
Involvement3	0.887	Understanding2	0.913
Involvement4	–0.416	Understanding3	0.893
Involvement5	0.737	Understanding4	0.902
Computer playfulness1	0.693	Personality similarity1	0.510
Computer playfulness2	0.720	Personality similarity2	0.456
Computer playfulness3	0.874	Personality similarity3	0.755
Computer playfulness4	0.874	Personality similarity4	0.829
Satisfaction1	0.946	Personality similarity5	0.678
Satisfaction2	0.967		

Fit statistics

Comparative fit index (CFI) = 0.986
Normed fit index (NFI) = 0.926
Goodness-of-fit index (GFI) = 0.921
Adjusted goodness-of-fit index (AGFI) = 0.893
Root mean square error of approximation (RMSEA) = 0.028 (0.014–0.039)
χ^2/df = 1.205

For the hypotheses relating to the effect of involvement on decision performance, H5a, H5b, and H5c, were fully supported, whereas H5d and H5e were not supported. Involvement positively affected user satisfaction (H5a) and understanding (H5b) with the decision aid. Users that were more involved with the decision aid also spent more time using the decision aid (H5c), but involvement did not significantly affect the number of decision aid features used (H5d). User involvement also did not significantly affect decision quality/accuracy (H5e). A summary of the hypotheses results is provided in Table 5.

Additional paths between some of the dependent variables were included in the final model, but were not hypothesized, as these relationships were incidental to the purpose of the study. Past experimental studies involving similar dependent variables have typically included less complex research models and were tested with multivariate analysis of variance (MANOVA) or simple correlations, with the assumption that

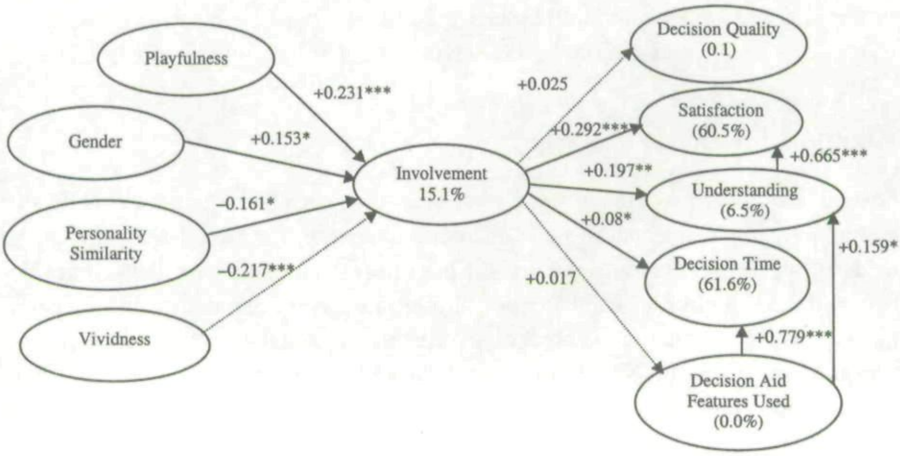

Figure 5. Structural Regression Model Results.
Fit statistics: CFI = 0.979; NFI = 0.912; GFI = 0.906; AGFI = 0.885; RMSEA = 0.33 (0.22–0.42); χ^2/df = 1.279; *** significant at 0.001; ** significant at 0.01; * significant at 0.05; the solid line indicates the hypothesis is supported; the dotted line indicates the hypothesis is not supported.

Table 5. Summary of Hypotheses Results

Hypotheses	Findings
H1. Computer playfulness ⇑ involvement	Supported
H2. Gender ⇒ involvement, women > men	Supported
H3. Personality similarity ⇑ involvement	Supported
H4. Multimedia vividness ⇑ involvement	Not supported
H5a. Involvement ⇑ satisfaction	Supported
H5b. Involvement ⇑ understanding	Supported
H5c. Involvement ⇑ decision time	Supported
H5c. Involvement ⇑ use of decision aid features	Not supported
H5d. Involvement ⇑ decision quality/accuracy	Not supported

the dependent variables were correlated [5, 13, 14]. In our study, SEM was needed to fully analyze the more explanatory and complex research model. With SEM, it is necessary to formally specify the relationships between the dependent variables, whereas with other statistical techniques, such relationships are assumed.

Prior research has shown dependent variables such as *understanding* and *satisfaction* to be strongly related [5, 13, 14]. This relationship was confirmed in our study, with a standardized weight of 0.665. The number of *decision aid features used* would logically be related to *decision time,* as it would take more time to use more decision aid features. The relationship between these two dependent variables was significant in our study, with a standardized weight of 0.779. Similarly, the number of *decision aid features used* should improve the users' *understanding* of the decision aid features, as confirmed with the standardized weight of 0.159. No variance was explained in the measure of decision aid features used, as the hypothesized relationship between *involvement* and the number of *decision aid features used* was insignificant.

Additional Analysis Procedures

Several additional procedures were performed to ensure that alternative models or additional paths would not provide a better explanation for the relationships in the data set. While the literature supports the use of involvement in a mediation capacity between the technology characteristics of multimedia and social cues and decision-making outcomes, alternative procedures were conducted to evaluate partial mediation and poor model fit. No modification indices greater than 8.5 were observed with the exception of two indices related to computer playfulness and understanding. These two indices, 22.25 and 19.95, were observed for the regression path between these two constructs (playfulness ⇒ understanding) and the covariance between the computer playfulness construct and the residual for understanding. Additional analysis was performed on the apparent relationship between playfulness and understanding as described below.

In order to eliminate subject extroversion and treatment extroversion as alternative antecedents to involvement (in addition to personality similarity), these two additional constructs were temporarily added to the model shown in Figure 5. The purpose of this additional procedure was to determine if the components of personality similarity (subject and treatment extroversion) significantly affected involvement. The regression weights for these two constructs were not significant.

Multiple linear regression was conducted, as suggested by Baron and Kenny [3], to determine whether any of the antecedents of involvement directly affected any of the decision-making outcomes (with the involvement construct excluded from the analysis), and whether any such relationships were fully or partially mediated by involvement. Prior to performing regression analysis, all measures were standardized to address the different levels of some scales (seven-point and eight-point scales). Results from this analysis are shown in Table 6. Only two of the antecedents, computer playfulness and gender, directly affected any of the decision-making outcomes when involvement was excluded from the analysis. Computer playfulness was significantly related to both satisfaction and understanding, whereas gender was only significantly related to satisfaction. These regressions were then rerun with involvement included, and the standardized regression coefficients were still found to be significant. When these three additional relationships were added to the structural regression model shown in Figure 5, however, only one of these paths was found to be significant (playfulness ⇒ understanding).

Thus, involvement was found to only partially mediate the relationship between computer playfulness and understanding. Adding this relationship increased the variance accounted for in the understanding construct from 6.5 to 14.0. The regression weight for the path from involvement to understanding was lowered slightly but was still significant. No other significant changes would result from the addition of this path to the model. Based upon the results of the mediation tests, the review of the

Table 6. Tests for Mediating Effect of Involvement

	Satisfaction		Understanding		Satisfaction with involvement		Understanding with involvement	
	β	p-value	β	p-value	β	p-value	β	p-value
Playfulness	0.314	0.000	0.336	0.000	0.250	0.000	0.321	0.000
Gender	0.173	0.003			0.121	0.029		

modification indices, and the analysis of the personality similarity components, the model shown in Figure 5 appears to be appropriate for this data set.

Discussion

In this section, additional discussion of the study results is provided and practical implications of the empirical findings are discussed. The unsupported hypotheses are also reviewed and possible explanations for the lack of results are offered.

Practical Implications of Findings

The findings of this study have important implications for interface designers. Previous findings on the relationship between computer playfulness and involvement-related constructs in a presentation context were confirmed in a new context, decision aid/support, and remained significant when gender, vividness, and personality constructs were also measured (H1). Women expressed higher levels of involvement across all treatments, in keeping with the premise of the Selectivity Model [41, 42]. The lower level of involvement from males was expected given that they are typically less comprehensive processors than females (H2). Marketing segmentation could be utilized to provide more involving interfaces to users based on characteristics such as computer playfulness and gender. Empirical studies from marketing suggest that situational factors in advertisements and product information can be altered to increase comprehensive and detailed message elaboration among males [12]. For example, by creating cue incongruity or by providing more objective claims (preferred by males), gender information processing differences can be eliminated. These same practices could be applied in interface design to ensure that both males and females are equally involved or engaged. Similarly, user involvement could be enhanced for users that exhibit low computer playfulness by manipulating the personality traits exhibited through the interface as described below.

The findings on personality similarity (H3) also have practical implications for interface designers, as interfaces could be more extensively tailored to suit the user. Interface designers with some general understanding of user demographics and characteristics could develop interfaces that exhibit social cues, creating perceptions of

Table 7. Involvement by Treatment

	T	TV	TVA
Extroverted	4.325	4.343	3.918
Introverted	4.223	4.369	3.575
Overall	4.274	4.355	3.747

similarity between users and the interface. Traits as simple as extroversion and introversion can be easily exhibited in an interface and matched to user groups to increase user involvement and downstream decision performance.

Multimedia Vividness and Involvement

Multimedia vividness did not positively affect user involvement with the decision aid (H4), as hypothesized. Instead, there was a significant negative relationship between vividness and involvement. Analysis of variance (ANOVA) results ($F(2, 256) = 5.895$, $p < 0.003$) indicate that there were significant differences in involvement among the vividness treatments. Post hoc tests (Tukey's) indicated that involvement was significantly different between the animation treatment (TVA) and the two unanimated treatments (T, TV). The means by treatment are shown in Table 7. There were no significant differences between the T and TV treatments, thus the negative relationship found in the overall model is attributed to the effect of animation.

The lack of vividness effects between the T and TV treatments may be explained by earlier research on message information vividness in decision making that took place before multimedia technology became available. Mixed results were obtained in studies that investigated the effect of vividness on involvement and attitudes. One of the explanations offered for these results was that vividness only produces an effect when there is competition for attention among vivid and nonvivid information [66, 67]. These explanations are applicable to the current study, as vividness was a between-subjects effect, and different levels of vividness were not compared within-subjects. As suggested in these prior studies, "the non-vivid version of the message is given as much attention as the vivid version when each is presented separately," and no other task effects are varied [40, p. 188]. In other multimedia studies in which vividness effects were found, there were substantial changes in the information display, such as the use of overheads as compared to presentation software and the use of video as compared to just text. In our study, the addition of computer-generated voice, one sensory channel, to a computer-based decision aid that was otherwise unchanged, did not increase involvement with the decision aid.

In further evaluating the effect of animation (TVA) on involvement, we first considered whether the animation selected could have annoyed the subjects by analyzing two affective measures of the decision aid (enjoyment and satisfaction). A four-item scale from a study of cognitive absorption [1] was used to measure enjoyment of the decision aid. ANOVA results for both satisfaction and enjoyment with the decision

Table 8. Enjoyment and Satisfaction by Treatment

	T		TV		TVA	
	Enjoyment	Satisfaction	Enjoyment	Satisfaction	Enjoyment	Satisfaction
Extroverted	4.864	5.462	4.607	5.207	4.585	5.171
Introverted	4.492	4.712	4.282	5.188	4.322	4.942
Overall	4.678	5.087	4.445	5.198	4.454	5.056

aid were not significant, meaning that there were not significant differences among the T, TV, and TVA treatment conditions. Treatment means for these two constructs are shown in Table 8. Thus, it does not appear that negative affect toward the animation resulted in lower involvement with this treatment.

The earlier findings on vividness in decision making also provide an explanation for the detrimental effect of animation on involvement. Researchers noted that vivid stimuli that are unrelated to the product or alternative information may not increase involvement and may distract the decision maker from the task [40, 66]. Similarly, research on animation has shown that when animation is used as a nonprimary stimulus (nonprimary meaning that it is not directly related to the primary task objective), it can be distracting and reduce task performance [79]. In our study, the animation was used in the information acquisition and evaluation phases of the decision, but was not related to the actual apartment alternatives. The use of animation to display the floor plan of each apartment alternative would be an example of a primary stimulus.

Based upon the definition of vividness advanced by Steuer [64], there also appears to be a difference in the characteristics of vividness manifested in the three treatments. The visual and auditory channels provided in the T and TV treatments increase vividness breadth, whereas the addition of animation in the TVA treatment represents an increase in vividness depth by increasing the resolution of the visual channel. The use of animation in the decision aid thus represents an increase in the visual resolution of a nonprimary task effect and appears to have reduced the user's involvement with the decision aid.

Involvement and Satisfaction, Understanding, and Decision Time

H5a–H5c, the relationships between involvement and decision aid satisfaction, understanding, and decision time, respectively, were supported and have important implications for interface designers, as the positive relationship between involvement and decision-making outcomes was confirmed. Existing studies of user involvement with the interface (computer-mediated technology) have focused on technology acceptance constructs and have not investigated involvement in a decision-making context with multiple measures of decision-making outcomes. The current study provides designers with evidence that increased user involvement with a decision aid will improve both perceived (satisfaction, understanding) and objective (decision time) decision-making outcomes.

Involvement and Use of Decision Aid Features

H5d stated that involvement would positively affect the number of decision aid features used (a surrogate measure for effort) but was not supported as there was no significant relationship between involvement and the number of decision aid features used by the subjects. This lack of support may be attributed to the experimental procedures, as the subjects were instructed to put the apartments in order based upon their apartment preferences before selecting their preferred apartment. These instructions may have created an elevated level of feature use and minimized the variation among subjects. Decision time, another approach for measuring decision effort, was positively affected by involvement.

Involvement and Decision Quality

The lack of positive results for H5e is not unlike the results of prior decision-making studies. H5e stated that involvement would have a positive effect on decision quality (accuracy). Many studies have found that the use of incentives, a way to increase involvement, will increase decision-maker effort but will not increase decision accuracy [56, 71]. One explanation offered in the literature is that individuals will guard their effort and settle for less accuracy. Increased involvement may lead to an increase in effort but may not entice the decision maker to change to a more accurate decision-making strategy (such as using all the available information and performing weighted-additive calculations based upon preferences). Another explanation offered in the literature is that feedback on decision accuracy is not readily available to the decision maker [56]. In our study, and in most decision-making experiments, the decision makers are not provided with feedback on the accuracy of their potential selections, but they are easily able to assess their own effort. Given the number of nondominated alternatives (ten), the number of apartment attributes (eight), and the average number of features weighted by each subject (seven), the mental calculations required to determine the weighted value for each alternative based on individual preferences are not trivial. The level of decision accuracy obtained in the study (40.2 percent) is relatively high and, thus, does not appear to have influenced the results for H5e.

Limitations

THE LIMITATIONS OF THE STUDY RELATE to generalizability and should be considered in interpreting the theoretical and practical contributions of this research. The first limitation of this study is the choice of animation used for the TVA treatment. A nonhuman animation was purposely selected to avoid any confounds from gender bias. Subject responses might differ, however, based upon animation characteristics—

human and nonhuman. In addition, the same animation was used for both the extroverted and introverted treatments to avoid confounding the study with more or less appealing animations. By using the same animation, we limited our opportunities to accentuate the extroverted/introverted nature of the decision aid with the physical characteristics of the animation.

A second limitation relates to the use of only one dimension of personality traits. Other personality dimensions in the circumplex interpersonal model [78] or other models may have different affects on involvement in a decision-making context. Additional research with other personality dimensions is needed to make the findings of this study more generalizable. Finally, the use of student subjects is a limitation as student responses are not necessarily representative of the population of decision makers. We attempted to counter this limitation by using an apartment selection decision task that is realistic and relevant for both students and the general population of consumers.

Conclusion

THE THEORETICAL CONTRIBUTIONS OF THIS RESEARCH include the development of a theoretical model that explains the effect of involvement with a social, multimedia decision aid on decision-making outcomes. Antecedents of involvement with a social, multimedia decision aid were identified, and the relationship between involvement and multiple decision-making outcomes was tested. Computer playfulness, gender, personality similarity, and multimedia vividness were the antecedents identified and investigated. Existing research on involvement with computer-mediated technology has not utilized a decision-making context and investigated multiple antecedents and multiple decision-making outcomes in a controlled experimental setting.

Three antecedents, computer playfulness, gender, and personality similarity conveyed through social cues, were shown to significantly influence involvement with a decision aid. Women were more involved than men, and users with higher levels of computer playfulness were more involved. When the personality of the user was similar to the personality conveyed by the decision aid, the user was more involved with the decision aid. The personality of the decision aid was easily conveyed at all treatment levels of multimedia vividness (T, TV, TVA) and positively influenced involvement with the decision aid. In other words, it was possible to manifest decision aid personality in the leanest, multimedia vividness environment (text only).

Multimedia vividness, however, did not have the expected effect on involvement. Increasing the breadth of vividness, through the addition of voice, had no affect on involvement with the decision aid over a baseline text condition. And, the addition of animation, an increase in depth of vividness, reduced involvement with the decision aid. While additional research is needed to further understand the effect of multimedia vividness on involvement, the current study provides a foundation for this future work. Given that the current study used an analyzable task with unequivocal information, future studies should investigate whether multimedia vividness influences involvement in more complex decision-making tasks. In addition, both vividness depth and breadth should be further investigated when task complexity is varied.

The tested relationships between involvement and multiple decision-making outcomes contribute to the literature, as the involvement construct has received limited testing in a decision aid context with multimedia characteristics. Involvement was found to increase user satisfaction, understanding, and decision time with the decision aid. The relationships between involvement and both decision quality and use of decision aid features were not supported and may be due to the propensity of decision makers to modify their effort but not their accuracy, and to the experimental design (i.e., experimental instructions on using the decision aid). Future research should investigate whether these relationships are supported with different tasks.

Practical implications of the study include interface design considerations. The significant relationships found in the research model suggest that interface designers can manipulate user involvement with a decision aid by matching the personality of the user with the personality traits exhibited by a computing application and by providing more involving interfaces to users that report lower levels of computer playfulness. Gender differences also affect interface design considerations, as male users generally exhibit a lower level of involvement than do females. Technology characteristics can be manipulated to increase male involvement. Interface designers targeting their applications to specific groups of users (market segmentation by gender or general personality traits) can use the findings of this study to develop interfaces that are more attractive and engaging to their targeted groups. Interface designers are cautioned, however, as to their use of animation. The use of animation as a nonprimary stimulus, commonly found in many types of IS (e.g., the Microsoft Office paper clip animation), may distract the user, decreasing their involvement with the technology and negatively affecting decision-making outcomes. Additional research on the affects of changing multimedia vividness depth and breadth in primary and nonprimary stimulus environments may also prove insightful.

Acknowledgments: The authors thank the senior editor and reviewers for their comments and guidance, which substantially improved the quality of the manuscript. The authors also thank the participants of the 2003 Pre-ICIS Workshop on HCI Research in MIS, sponsored by the Special Interest Group on Human Computer Interaction (SIGHCI). Special thanks to T. Thomas Fennel for his work on the experimental interfaces.

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Appendix A. Treatment Scripts

THE TEXT SHOWN IN ITALICS IS PROVIDED for "descriptive" purposes and is not part of the script. The italicized text represents animation descriptions that specify the gestures made by the animation treatment during various parts of the script.

Extroverted Script

Introduction (Text Appears in Initial Splash Form)

Greet animation. Welcome to the Apartment Finder Tool. I am going to assist you in selecting an apartment. *Blink animation.* Local apartment data has been gathered and this tool will help you select an apartment based upon your apartment preferences. After you have reviewed the various alternatives, you will select the apartment that best meets your needs.

Tutorial

Explain animation. Before you use the tool I'm going to give you a brief tutorial. After the tutorial, you will use the tool to help you pick the best apartment.

Weight Form. *Move agent to top of screen. Show animation.* Before you begin, you need to specify the apartment features that are most important to you. To do this, allocate 100 points among the eight apartment features. *Gesturedown animation.* However, each feature does not need to receive points. *Movedown animation.* The total at the bottom will tell you how many points you have remaining. *Blink animation.* As an example, I have allocated points to some of the features as shown. Based on how I assigned points in this example, the Noise feature is most important, while the Internet Access feature is not important at all. *Gesture animation.* After the tutorial, you will assign points based on your own opinions. When you are finished allocating points, click the "Done" button.

Spreadsheet Form. *Moveup animation.* I am now going to show you how to use our apartment finder tool. Shown on this screen are 10 different apartment alternatives. Each apartment has different characteristics. *Alert animation.* The Apartment Finder Tool I am showing you provides many different functions for sorting and viewing the apartment choices. If you follow my instructions, this tool will help you select the apartment that is best for you.

- *Hide/Show Apartment Features: Move animation and gesture.* The "Hide" pulldown box allows you to hide an apartment feature. You need to hide features that are not important to you so you can better focus on features that are very important. For example, if the Noise feature is not important to you, hide this feature. To redisplay an apartment feature that you have previously hidden, use the "Show" pulldown box. *Redisplay Noise feature in spreadsheet.* Or, use the "Show All Features" button to redisplay ALL of the apartment features that you have hidden.
- *Rearrange Apartment Features: Move animation and gesture.* The "Rearrange Apartment Features" buttons allow you to change the order in which the apartment features are presented. For example, if size is an important feature to you, move the Size column left by clicking on the "Left" button, so that Size appears as the first column in the grid. If size is not important, move the Size column to the right side of the grid.
- *Hide/Show Apartment Choices: Move animation and gesture.* The "Hide" pulldown box allows you to hide an apartment alternative. Hide apartments that do not interest you so you can better focus on the apartments that best meet your needs. For example, if apartment J does not meet your needs, you need to hide this apartment. To redisplay an apartment alternative that you have previously hidden, use the "Show" pulldown box. *Redisplay apartment J in spreadsheet.* Or, use the "Show All Apartments" button to redisplay ALL of the apartment choices that you have hidden.
- *Rearrange Apartment Choices: Move animation and gesture.* The "Rearrange Apartment Choices" buttons allow you to change the order in which the apartment alternatives are presented. For example, if apartment D is your first choice, move apartment D up by clicking on the "Up" button so that it appears as the first row in the grid. If apartment D is not one of your favorites, move apartment D down, by clicking on the "Down" button.
- *Sorting: Move animation and gesture.* The sorting function allows you to sort the apartment alternatives. Use the "First Sort" pulldown box to select the feature that is most important to you and then sort the apartment choices in ascending or descending order by this feature. For example, if you would like to sort the apartment choices from the lowest to the highest rent, select the Rent feature from the pulldown box, click the "Ascending" option, and then click the "Sort" button. *Move animation and gesture.* The "Second" pulldown box allows you to specify what you believe is the second-most important apartment feature. You cannot select a Second Sort feature, until you have specified a First Sort feature.
- *Final Selection: Gesture.* When you have finished hiding, arranging, and sorting the apartment choices, you need to rank order the remaining apartments with the best one in the first row. Then select this apartment from the "Final Selection" pulldown box and click on the "Done" button. *Moveup animation to top of*

screen. If you have a question about any of the features that have just been described, just ask me by clicking on the "Question Mark" button next to that feature. *Congratulate animation.* You have finished the Tutorial! Now let's get to it! *End Tutorial—subject returns to the blank weight form and is now able to interact with the application.*

Experiment

Weight Form. *Announce animation.* You may now use the Apartment Finder Tool!

Spreadsheet Form. *Movedown and explain animation.* You now need to sort, move, and hide apartments and features to be sure that you select the best apartment. When you are done, order the remaining apartments with the best apartment in the first row. Then select the best apartment in the "Final Selection" pulldown box!

The scripts below will only be used if the user clicks on a "?" button.

- *Hide/Show Apartment Choices: Move and gesture animation.* The "Hide" pulldown box allows you to hide an apartment feature. You need to hide features that are not important to you so you can better focus on more important features. For example, if the Noise feature is not important to you, hide this feature. To redisplay an apartment feature that you have previously hidden, use the "Show" pulldown box. The "Show All Features" button, will redisplay all of the apartment features that you have hidden.
- *Rearrange Apartment Features: Move and gesture animation.* The "Rearrange Apartment Features" buttons allow you to change the order in which the apartment features are presented. For example, if size is an important feature to you, move the Size column left by clicking on the "Left" button, so that Size appears as the first column in the grid. If size is not important move the Size column to the right side of the grid.
- *Hide/Show Apartment Choices: Move and gesture animation.* The "Hide" pulldown box allows you to hide an apartment alternative. Hide apartments that do not interest you so you can better focus on the apartments that best meet your needs. For example, if apartment J does not meet your needs, hide this apartment. To redisplay an apartment alternative that you have previously hidden, use the "Show" pulldown box. The "Show All Apartments" button will redisplay all of the apartment choices that you have hidden.
- *Rearrange Apartment Choices: Move and gesture animation.* The "Rearrange Apartment Choices" buttons change the order in which the apartment alternatives are presented. For example, if apartment D is your first choice, move apartment D up by clicking on the "Up" button so that it appears as the first row in the grid. If apartment D is not one of your favorites, move apartment D down by clicking on the "Down" button.
- *Sorting: Move and gesture animation.* Use the "First Sort" pulldown box to select the feature that is most important to you and then sort the apartment choices

in ascending or descending order by this feature. For example, to sort the apartment choices from the lowest to the highest rent, select the Rent feature from the pulldown box, click the "Ascending" option, and then click the "Sort" button. The "Second" pulldown box allows you to specify what you believe is the second-most important apartment feature. You cannot select a Second Sort feature, until you have specified a First Sort feature.

- *Final Selection: Gesture animation.* When you have finished arranging and sorting the apartment choices and features, make your final apartment selection and click on the "Done" button.

Introverted Script

Introduction (Text Appears in Initial Splash Form)

Greet animation. Welcome to the Apartment Finder Tool. This tool may assist you in selecting an apartment. *Blink animation.* Local apartment data has been gathered, and this tool may help you select an apartment based upon your apartment preferences. After you have reviewed the various alternatives, you will be asked to select the most suitable apartment.

Tutorial

Explain animation. Before you use the tool, you will be given a brief tutorial. After the tutorial, you may use the tool to assist you in finding a suitable apartment.

Weight Form. *Show animation, as little movement as possible.* First, you will be asked to specify the apartment features that seem important to you. Allocate 100 points among the eight apartment features. *Lookupleft animation.* But remember, you do not need to assign points to all features. *Lookupleft animation.* The total at the bottom will display how many points you have remaining. *Blink animation.* As an example, points have been allocated to some of the features as shown. Based upon the points assigned in this example, the Noise feature might be most important while the Internet Access feature may not be important. *Lookupleft animation.* When you are finished allocating points, you may click the "Done" button.

Spreadsheet Form. *Same position, as little movement as possible.* There are 10 apartment alternatives. Each apartment has different characteristics. *Alert animation.* The Apartment Finder Tool provides many different functions for sorting and viewing the apartment choices. Using these different functions may help you find an apartment that is suitable.

- *Hide/Show Apartment Features: Lookleft animation—do not move agent.* The "Hide" pulldown box will allow you to hide an apartment feature. You may want to hide features that are not as important to you so you can focus on features that are more important. For example, if the Noise feature is not very important to you, you may want to hide this feature. *Lookleftblink animation.* To redisplay an apartment feature that you have previously hidden, you may use the "Show" pulldown box. *Redisplay Noise feature in spreadsheet.* Or, you may use the "Show All Features" button to redisplay all of the apartment features that you have previously hidden.

- *Rearrange Apartment Features: Lookleft animation.* The "Rearrange Apartment Features" buttons allow you to change the order in which the apartment features are presented. For example, if size is an important feature to you, you may want to move the Size column left by clicking on the "Left" button, so that Size appears as the first column in the grid. If "Size" is not important, you may want to move the Size column to the right side of the grid.
- *Hide/Show Apartment Choices: Lookleftblink animation.* The "Hide" pulldown box will allow you to hide an apartment alternative. You may want to hide apartments that do not appeal to you so you can better focus on the apartments that meet your needs. For example, if apartment J is not suitable, you may want to hide this apartment. To redisplay an apartment alternative that you have previously hidden, you may use the "Show" pulldown box. *Redisplay apartment J in spreadsheet.* Or, you may use the "Show All Apartments" button to redisplay all of the apartment choices that you have previously hidden.
- *Rearrange Apartment Choices: Lookleft animation.* The "Rearrange Apartment Choices" buttons may allow you to change the order in which the apartment alternatives are presented. For example, if apartment D is your first choice, you may want to move apartment D up, by clicking on the "Up" button, so that it appears as the first row in the grid. If apartment D does not seem suitable for you, you may want to move it down by clicking on the "Down" button.
- *Sorting: Lookleft animation.* The Sorting function will allow you to sort the apartment alternatives. The "First Sort" pulldown box will allow you to select the feature that seems most important to you, and will then sort the apartment choices in ascending or descending order by this feature. For example, if you would like to sort the apartment choices from the lowest to the highest rent, you may select the Rent feature from the pulldown box, click the "Ascending" option, and then click the "Sort" button. *Lookleftblink animation.* The "Second Sort" pulldown box will allow you to specify the apartment feature that seems most important to you after the First Sort feature. You may select a Second Sort feature after you have selected a First Sort feature.
- *Final Selection: Lookleft animation.* When you have finished hiding, arranging, and sorting the apartment choices and features, please rank order the remaining apartments with your favorite in the first row. Then select this apartment from the "Final Selection" pulldown box. After you have selected an apartment, you may click on the "Done" button. *Alert animation.* If you have a question about any of the functions that have just been described, you may click on the "Question Mark" button next to the feature. You have finished the Tutorial. *End Tutorial—subject returns to the blank weight form and is now able to interact with the application.*

Experiment

Weight Form. *Announce animation.* You may now use the Apartment Finder Tool.

Spreadsheet Form. You may now sort, move, or hide apartments. When you are finished, please order the remaining apartments with your favorite in the first row. Then select this apartment from the "Final Selection" pulldown box.

The scripts below will only be used if the user clicks on a "?" button.

- *Hide/Show Apartment Features: Lookleft animation.* The "Hide" pulldown box will allow you to hide an apartment feature. You may want to hide features that are not as important to you, so you can focus on features that are more important. For example, if the "Noise" feature is not very important to you, you may want to hide this feature. *Lookleft animation.* To redisplay an apartment feature that you have previously hidden, you may use the "Show" pulldown box. *Lookleft animation.* You may use the "Show All Features" button to redisplay all of the apartment features that you may have hidden.
- *Rearrange Apartment Features: Lookleft animation.* The "Rearrange Apartment Features" buttons allow you to change the order in which the apartment features are presented. For example, if size is an important feature to you, you may want to move the Size column left by clicking on the "Left" button, so that Size appears as the first column in the grid. If size is not important, you may want to move the Size column to the right side of the grid.
- *Hide/Show Apartment Choices: Lookleft animation.* The "Hide" pulldown box will allow you to hide an apartment alternative. You may want to hide apartments that do not appeal to you so you can better focus on the apartments that meet your needs. For example, if apartment J is not suitable, you may want to hide this apartment. *Lookleft animation.* To redisplay an apartment alternative that you have previously hidden, you may use the "Show" pulldown box. *Lookleft animation.* You may use the "Show All Apartments" button to redisplay all of the apartment choices that you may have previously hidden.
- *Rearrange Apartment Choices: Lookleft animation.* The "Rearrange Apartment Choices" buttons may allow you to change the order in which the apartment alternatives are presented. For example, if apartment D is your first choice, you may want to move apartment D up, by clicking on the "Up" button, so that it appears as the first row in the grid. If apartment D does not seem suitable for you, you may want to move it down by clicking on the "Down" button.
- *Sorting: Lookleft animation.* The sorting function will allow you to sort the apartment alternatives. The "First Sort" pulldown box will allow you to select the feature that seems most important to you, and will then sort the apartment choices in ascending or descending order by this feature. For example, if you would like to sort the apartment choices from the lowest to the highest rent, you may select the Rent feature from the pulldown box, click the Ascending option, and then click the "Sort" button. *Lookleftblink animation.* The "Second Sort" pulldown

box will allow you to specify the apartment feature that seems most important to you after the First Sort feature. You may select a Second Sort feature after you have selected a First Sort feature.

- *Final Selection: Lookdownleft animation.* When you have finished arranging and sorting the apartment choices and features, you may make your final apartment selection. After you have selected an apartment, you may click on the "Done" button.

Appendix B. Survey Scales

Presurvey Scales (Administered Seven Weeks Prior to the Postsurvey)

Subject Extroversion (Eight-Point Adjective Scale Anchored with Extremely Inaccurate and Extremely Accurate)

INSTRUCTIONS: FOR EACH WORD BELOW, please use the rating scale to describe how accurately the word describes you. Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you and roughly your same age. So that you can describe yourself in an honest manner, your responses will be kept in absolute confidence.

1. Outgoing.
2. Vivacious.
3. Enthusiastic.
4. Cheerful.
5. Perky.

Postsurvey Scales

Decision Aid Extroversion (Eight-Point Adjective Scale Anchored with Extremely Inaccurate and Extremely Accurate)

Instructions: For each word below, please use the rating scale to describe how accurately the word describes the Apartment Finder decision aid that you just used. Please read each word carefully, and then click on the response that is most accurate.

1. Outgoing.
2. Vivacious.
3. Enthusiastic.
4. Cheerful.
5. Perky.

Computer Playfulness (Seven-Point Adjective Scale Anchored with Strongly Disagree and Strongly Agree)

Instructions: The following questions ask you how you would characterize yourself when you use computers. For each adjective listed below, please click on the response that best matches a description of yourself when you interact with computers.

1. Spontaneous.
2. Flexible.
3. Creative.
4. Playful.

Involvement (Seven-Point Likert Scale Anchored with Strongly Disagree and Strongly Agree)

1. While using the Decision Aid, I am able to block out most other distractions.
2. While using the Decision Aid, I am absorbed in what I am doing.
3. With the Decision Aid, I am immersed in the task that I am performing.
4. With the Decision Aid, I get distracted by other attentions very easily.
5. With the Decision Aid, my attention does not get diverted very easily.

Satisfaction (Seven-Point Likert Scale Anchored with Strongly Disagree and Strongly Agree)

1. I am satisfied with the Decision Aid.
2. I am pleased with the Decision Aid.
3. I am content with the Decision Aid.

Understanding (Seven-Point Likert Scale Anchored with Strongly Disagree and Strongly Agree)

1. I understand how to use the features in the Decision Aid.
2. I have a good grasp of the functionality provided by the Decision Aid.
3. I can easily recall the functionality provided by the Decision Aid.
4. It is easy for me to remember how to use the Decision Aid.

Appendix C. Alternative Analysis of Personality Similarity

ALTHOUGH DIFFERENCE SCORES ARE COMMONLY USED to represent the notion of congruence between two related constructs, such as fit and similarity, there are known methodological problems with the use of such scores [17]. An alternative methodology, polynomial regression, has been recommended and tested in various contexts

[16, 17, 18]. We employed this alternative methodology in investigating how personality similarity between the subject and the decision aid affects involvement with the decision aid.

In our study, a five-item scale assessing extroversion was administered to the subjects to assess both their own personality and the personality of the decision aid. Before generating the polynomial terms, mean extroversion scores (from the five-item scale) for both the subject and the decision aid were calculated and standardized. The mean involvement scores (from the five-item involvement scale) were also calculated and standardized. Polynomial terms were then calculated up to the fourth order and included in a multiple, linear regression analysis using SPSS 11.0. The result was the regression equation shown below ($R^2 = 0.119$, adj. $R^2 = 0.069$).

$$z_i = 4.076 + 0.043s_i + 0.58d_i + 0.082s_id_i - 0.092s_i^2 + 0.201d_i^2 + 0.01s_i^3 - 0.067d_i^3$$
$$+ 0.002s_i^2d_i + 0.011s_id_i^2 + 0.006s_i^4 - 0.031d_i^4 + 0.017s_i^3d_i - 0.062s_id_i^3 + 0.017s_i^2d_i^2.$$

where s_i is standardized subject extroversion and d_i is standardized decision aid extroversion.

A response surface was rendered from the above equation in MathCAD (shown in Figure C1) and provides a more comprehensive description of how personality similarity affects involvement. The highest levels of involvement occur when subject and decision aid extroversion are high and similar. The lowest levels of involvement occur, however, when subject and decision aid extroversion are both low. Thus, similarity did not increase involvement when both subject and decision aid were very introverted. Involvement with the decision aid was generally high when the decision aid was perceived as extroverted, but there was a decrease in involvement when the subjects were very introverted (dissimilarity), as expected.

All polynomial terms were then included in the structural regression model as measures of personality similarity, in place of the difference scores used in Figure 5. We included all the terms initially instead of including only the significant terms from the regression analysis above, as SEM is a more comprehensive analysis technique. The polynomial terms that remained significant in the structural regression model were s, d, sd, d^2, d^3, and s^2d. Due to multicolinearity issues, however, d^2 and d^3 could not be retained in the model. The final structural regression model is shown in Figure C2, along with the fit statistics. The only change between the model shown in Figure 5 and the one shown in Figure C2 is the replacement of the difference scores with polynomial regression terms (s, d, sd, s^2d) for the personality similarity construct.

As shown in Figure C2, the fit statistics were slightly lower for the alternative structural regression model but were still within acceptable ranges. The standardized loadings for the polynomial terms were $s = 0.224$, $d = 0.915$, $sd = 0.233$, $s^2d = 0.640$, and were significant with p-values < 0.005. The standardized loading from personality similarity to involvement increased from 0.161 to 0.235, and the variance accounted for in involvement increased from 15.1 to 17.3. The other variances and standardized loadings in the model were largely unchanged with the exception of the loading from

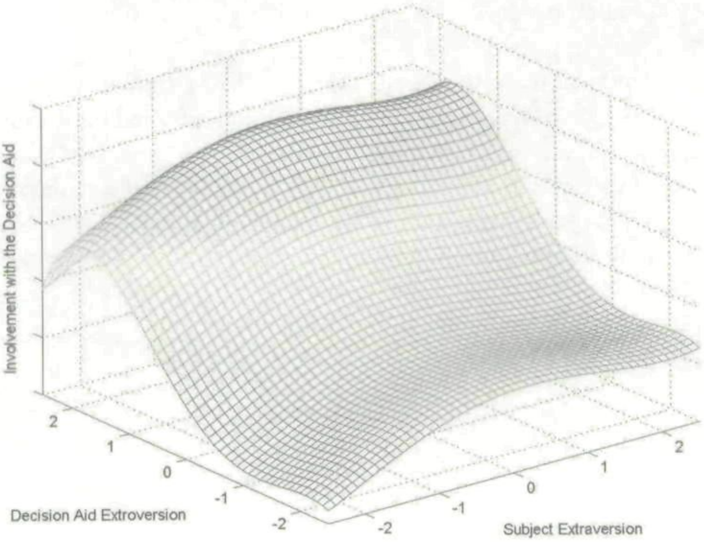

Figure C1. Response Surface of Subject and Decision Aid Extroversion Predicting Involvement

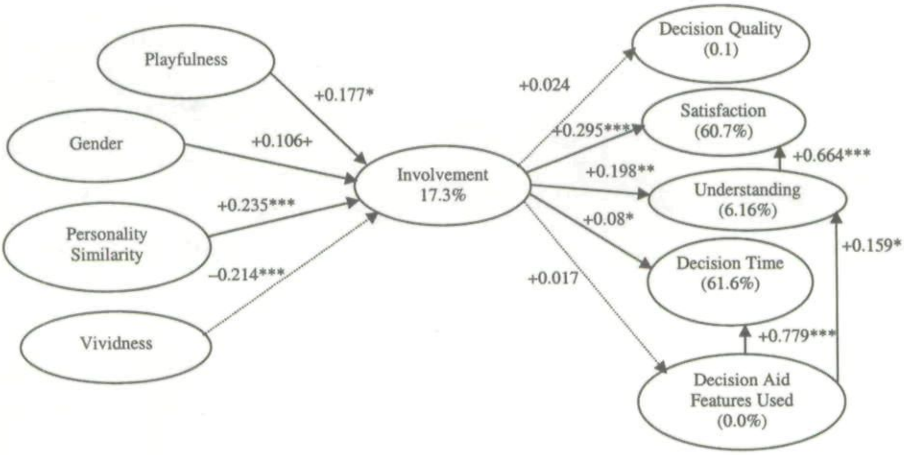

Figure C2. Structural Regression Model Results.
Fit statistics: CFI = 0.962; NFI = 0.900; GFI = 0.894; AGFI = 0.868; RMSEA = 0.45 (0.36–0.54); χ^2/df = 1.530; *** significant at 0.001; ** significant at 0.01; * significant at 0.05; + significant at 0.08; the solid line indicates the hypothesis is supported; the dotted line indicates the hypothesis is not supported.

gender to involvement, which decreased from 0.153 (*p*-value 0.013) to 0.106 (*p*-value of 0.08).

The use of polynomial terms to represent the personality similarity construct resulted in a stronger path loading between personality similarity and involvement, and an increase in the variance accounted for in involvement. The use of polynomial terms as observed variables in a structural regression model is not a commonly used technique and guidelines for this technique are not readily available [18]. As a result, this alternative approach is presented as a supplemental analysis to support the results presented in Figure 5.