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Research Note

The Influence of Trade-off Difficulty Caused by Preference Elicitation Methods on User Acceptance of Recommendation Agents Across Loss and Gain Conditions

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Prior studies on product recommendation agents (RAs) have been based on the effort-accuracy perspective in which the amount of effort required to make a decision and the accuracy of such decisions are two dominant antecedents of user acceptance of RAs. The current study extends the effort-accuracy perspective by considering trade-off difficulty, a type of negative emotion that arises when attainment of one's goals is blocked by the attainment of other goals; consequently, one must make trade-offs among the conflicting goals. Many product purchase choices for which RAs are used require users to make trade-offs among conflicting product attributes. A key feature of RAs, the preference elicitation method (PEM), often compels users to make explicit trade-offs. We examine whether an RA's PEM generates trade-off difficulty, which, in turn, affects users' evaluations (i.e., perceived amount of effort and perceived accuracy of recommendations) and the resultant acceptance of the RA. Trade-off difficulty influences users' evaluations of an RA via perceived control over execution of the RA PEM. In addition, the decision context in which users employ a PEM moderates the degree to which that PEM generates trade-off difficulty. Specifically, a PEM generates a greater degree of trade-off difficulty in a choice context that leads to a loss than in a choice context that leads to a gain. Consequently, users exert more effort to cope with trade-off difficulty in a loss condition. Because users voluntarily spend more effort, the negative influence of perceived effort on users' acceptance of an RA—which is supported in prior studies—decreases in a loss condition. A laboratory experiment was conducted using two between-subject factors: two RAs, one that employed a trade-off-compelling PEM and the other a trade-off-hiding PEM, and two decision contexts, one of which was a loss condition and the other a gain condition. The results supported all of the hypotheses.

Key words: product recommendation agent; effort-accuracy framework; decision context
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1. Introduction

Since their introduction in the early 1990s by the University of Minnesota's GroupLens Research Project,[1] product-brokering recommendation agents (RAs) have grown substantially more sophisticated and have become an integral part of many Web stores, including Dell.com and BestBuy.com (Leavitt 2006). RAs are Web-based software agents that elicit users' preferences for a product, use those preferences as criteria to identify suitable products, and recommend the identified product(s) to the user (Xiao and Benbasat 2007). According to Jupiter Research (February 6, 2006), by 2010, the Internet will influence nearly half of all retail sales—including sales transacted online as well as offline sales encouraged by online research—compared to just 27% in 2005.[2] Such rapid growth will be enhanced, in part, by recommendation technologies that transform Web surfers into buyers (Leavitt 2006).

The potential benefits and importance of RAs have served as the catalyst for a number of studies focusing on the role played by RAs in assisting the *cognitive*

[1] http://www.cs.umn.edu/research/GroupLens/index.html.

[2] http://www.webmediabrands.com/corporate/releases/06.02.06-newjup-research.html.

aspects of user decision making, specifically how RAs save users' effort and increase the accuracy of their decision making (Haubl and Trifts 2000). These studies have been based on the theoretical foundation of *the effort-accuracy framework*, which posits that individuals attempt to save the effort required to make a decision and to increase the accuracy of the decision; when these two goals conflict, they choose effort saving over increased accuracy to reduce their cognitive load (Payne et al. 1993).

The current study expands the effort-accuracy perspective by investigating the role of RAs in assisting users with managing trade-off difficulty. Trade-off difficulty refers to a type of particularly unpleasant emotion that occurs when the attainment of an important goal is threatened or blocked by the desire to attain one or more other goals, thus leading to the need to make trade-offs among the conflicting goals (Bettman et al. 1998). Favorable values of certain product attributes are correlated with unfavorable values of others. For example, an apartment's proximity to public transportation comes with a higher monthly rent, and the convenience of disposable plastic bags comes with environmentally harmful components. The conflicting attributes compel consumers to accept less of one for more of another, thereby causing trade-off difficulty (Luce et al. 2001). Trade-off difficulty has been recognized as the third determinant—in addition to effort and accuracy—of user decision making (Luce et al. 1997, Bettman et al. 1998); however, it has received only tangential attention in the RA literature. Investigation of trade-off difficulty in the RA literature is important and relevant because many of the products for which RAs are used have conflicting attributes (Haubl and Murray 2003). In addition, a key feature of RAs—namely, the preference elicitation method (PEM)—often compels users to make explicit trade-offs, because a PEM elicits a user's preferences via a dialogue in which the user is often asked to choose one attribute over another (e.g., "In your purchase, which factor—price versus advanced features—is more important?") (Aloysius et al. 2006). Trade-off difficulty caused by PEMs may impede users from accepting the RAs, despite the RAs' abilities to save users' effort and generate accurate recommendations (Aloysius et al. 2006). This issue has not been studied sufficiently, and the few existing studies have produced conflicting claims and results (Widing and Talarzyk 1993, Fasolo et al. 2005, Aloysius et al. 2006).

Given the equivocal results, the current study examines *whether* and *how* trade-off difficulty influences users' adoption of RAs. To this end, we introduce perceived control, which is known to be a robust predictor of people's behavior (Ajzen and Madden 1986) and adoption of Information Systems (Taylor and Todd 1995). Perceived control is defined as the degree to which a person feels that he or she can impact one's own activities or given conditions in correspondence with higher order goals (Frese 1987). Perceived control is determined by a user's assessment of the disparity between the current state of the system in use relative to the ideal state in her environment—the goal she wants to achieve by facilitating the system (Morris and Marshall 2004). By definition, any trade-off entails losses of product attributes and the goals associated with the attributes. Therefore, an RA PEM that compels explicit trade-offs draws a user's attention to the disparity, thereby negatively influencing her perceived control (Bagozzi 1992), which, in turn, affects her evaluations and the subsequent acceptance of RAs. No previous study has examined the role of perceived control on users' adoption of RAs for trade-off decisions.

The second goal of this study is to resolve the conflicting results in prior studies, which have hindered consistent and comprehensive understanding of the role played by trade-off difficulty. We argue that the equivocal results were caused, at least in part, by neglect of the decision context. Individuals' decision making is susceptible to many contextual factors (Payne et al. 1993), indicating that users' RA acceptance may also be vulnerable to a number of decision contexts (Eierman et al. 1995). We investigate the effect of trade-off difficulty in two distinct decision contexts: loss and gain conditions. According to the *theory of reference point effect*, the disutility of a loss is larger than the utility of an equivalent gain; thus, individuals make decisions in a way to avoid a loss rather than to pursue an equivalent gain (Tversky and Kahneman 1991). Because of their aversion to loss, decision makers react to consequences of trade-off choices more acutely in loss situations than in gain situations (Luce et al. 1997). In the RA use context, one may expect that the extent to which a PEM generates trade-off difficulty will be augmented in a loss compared to a gain condition. However, no prior study has considered the role of decision context in moderating the influence of a PEM on trade-off difficulty.

Investigating the moderating effects of decision context allows us to examine whether the antecedents of users' RA adoption vary across decision context. Decision makers value the goal that best addresses problems prominent in the given decision context. In loss situations, the overriding goal is to reduce the experience of trade-off difficulty, which offsets one's desire to save effort, which is the more important goal in gain situations as compared to accuracy (Bettman et al. 1998). Individuals in a loss condition are voluntarily engaged in deliberations to demonstrate to themselves and others that they work hard to make the best decision possible within given constraints, because, in so doing, they reduce trade-off difficulty (Luce 1998, Luce et al. 2001). Hence the amount of effort invested may no longer influence users' RA acceptance in a loss condition. We will put to the test the widely accepted notion that effort expenditure is the dominant influence on users' acceptance of RAs.

In summary, our primary goal is to extend the effort-accuracy perspective of understanding users' RA acceptance by including trade-off difficulty. To this end, we have three specific objectives: (1) to investigate how trade-off difficulty caused by PEMs affects users' evaluations and the subsequent acceptance of RAs via perceived control, (2) to examine how the degree to which PEMs generate trade-off difficulty changes across loss and gain conditions, and (3) to determine how the well-known importance of effort-saving changes across loss and gain conditions. To achieve the first objective, we designed two RAs, each of which employs a different PEM: one that compels (makes explicit) trade-offs among product attributes and one that hides (makes implicit) trade-offs. To achieve the second and third objectives, we created loss and gain conditions across which we compared users' RA acceptance. A laboratory experiment was conducted using a 2×2 full factorial design with two levels of RA PEMs (i.e., trade-off-compelling versus hiding PEMs) and two levels of decision contexts (i.e., loss versus gain).

The remainder of this paper is organized as follows. Section 2 outlines prior studies on RAs and the impact of decision context on users' decision making. Section 3 presents the hypotheses regarding the effects of trade-off difficulty on users' evaluations and the subsequent acceptance of RAs, along with the mediating effect of perceived control and the moderating effect of decision context. Section 4 describes the research methodology used for a laboratory experiment. Section 5 provides analyses of data and the results of hypothesis testing. Section 6 concludes with limitations, contributions, and suggestions for future research.

2. Literature Review

2.1. Previous Research on RAs

Previous research has identified constructs such as RA use, user characteristics, RA features (also called RA configurations and characteristics), and decision problems (such as decision tasks and context) as antecedents of users' decision making and/or their intentions to accept RAs (Eierman et al. 1995, Brown and Jones 1998, Xiao and Benbasat 2007). Among these relationships, the causal link between RA use and user decision-making behavior has received the most attention. Here, the primary research question is how RA use reduces users' effort in making decisions and increases the accuracy of those decisions. Empirical studies have shown that RA use reduces the number of products reviewed by consumers, indicating a decrease in effort (e.g., Haubl and Trifts 2000 and Haubl and Murray 2003). RA use also increases decision accuracy: RA users reported higher objective decision accuracy (Haubl and Trifts 2000, Swaminathan 2002, Diehl 2005) and higher confidence in their decisions (Haubl and Trifts 2000, Swaminathan 2002). User characteristics, including expertise with a product (Kamis and Davern 2005), user RA similarities (Gershoff et al. 2003), and user familiarity with RAs (Komiak et al. 2005, Komiak and Benbasat 2006), have been found to influence trust, perceived usefulness, ease of use, and satisfaction.

The effects of RA features on user decision making have been studied to a lesser extent (Eierman et al. 1995, Brown and Jones 1998, Xiao and Benbasat 2007). RA features include RA type and characteristics of input and output features (Xiao and Benbasat 2007). RA types refer to filtering methods such as content-filtering and collaborative-filtering RAs (Cosley et al. 2003) and to decision strategies such as compensatory versus noncompensatory strategies (Song et al. 2007, Wang and Benbasat 2009). Input features include PEMs (Aggarwal and Vaidyanathan 2003, Haubl and Murray 2003, Kramer 2007, Kamis et al. 2008), while output features include products recommended by the RAs (Wang and Benbasat 2005), product ratings (Cosley et al. 2003), and recommendation display methods (Diehl 2005).

PEMs may be designed variously, and each approach used influences user decision making in distinct ways (Xiao and Benbasat 2007). However, only a few design elements of PEMs have been examined thus far, and the nature and role of PEMs are still not fully understood (Aloysius et al. 2006). Most of the existing studies on PEMs have examined how they influence the construction of users' preferences (e.g., Haubl and Murray 2003, Aggarwal and Vaidyanathan 2003, Kramer 2007), but these studies have not focused on how PEMs assist users in dealing with decision trade-offs. Trade-offs are inevitable in any efficient market because many product attributes are negatively correlated (Haubl and Murray 2003), and because of these conflicts among the attributes, buyers must have less of one attribute to gain more from another (Bettman et al. 1998). When trading off a desired attribute, the buyer feels *trade-off difficulty*, defined herein as *the negative emotion, such as decision anxiety, that occurs when attainment of a goal is blocked by the desire to attain one or more other goals, and when one must make trade-offs among the conflicting goals* (based on Kottemann and Davis 1991 and Luce 1998). Whether or not a PEM helps users reduce the experience of trade-off difficulty influences their evaluations and the subsequent acceptance of the RAs (Kottemann and Davis 1991). To the best of our knowledge, however, only three empirical studies have examined the role of PEMs in assisting user trade-off decisions; refer to the online supplement for additional information.[3] These three studies have adhered to two opposing tenets and reported contrasting results. Aloysius et al. (2006) contended that users want to minimize the experience of decisional stress, so they prefer a decision aid that hides trade-offs. In contrast, Widing and Talarzyk (1993) and Fasolo et al. (2005) claimed that because users want to make explicit trade-offs to reach consistent and reliable choices, they prefer RAs with PEMs that make the trade-offs transparently. In short, the current RA literature has not yet reached consensus on the effects of trade-off-compelling PEMs.

Another important factor that affects decision making is the decision problem, which includes task and context effects (Payne et al. 1993, Eierman et al. 1995). A task is a job to be done, such as a decision to be made on what product to choose. The most frequently investigated task effects is the complexity of tasks manipulated by altering the number of alternatives and attributes in the choice set (e.g., Haubl and Trifts 2000, Van der Heijden and Sorensen 2002, Swaminathan 2002, Kamis et al. 2008). As task complexity increases, perceived usefulness of RAs increases, because the amount of effort the RA saves increases as the task becomes more complex.

Context is an external setting in which users make decisions (Eierman et al. 1995). The effects of context include the similarities of alternatives, the attractiveness of the alternative set, reference point effects, and so on (Payne et al. 1993). Consumer psychology literature has demonstrated the substantial impact of context effects on user decision making (Slovic 1995), but context effects have been largely neglected in the RA literature (Eierman et al. 1995, Brown and Jones 1998, Xiao and Benbasat 2007). Regarding the lack of research on context effects, Eierman et al. (1995) asserted that “[a] theory of DSSs would not be complete without considering the environment in which a DSS is developed, implemented, and used.” The next section describes how the decision context influences user evaluations and the acceptance of RAs in association with trade-off choices.

2.2. The Role of Decision Context in User Evaluations and the Acceptance of RAs

In contrast to the traditional view of individuals as rational decision makers, recent research has maintained the adaptive nature of human decision making (Bettman et al. 1998). Decision makers construct their preferences for products and decision approaches based on many contextual factors. Decision contexts affect the way trade-off difficulty influences user decision making in two ways.

First, the decision context influences the extent to which individuals feel trade-off difficulty (Luce et al. 1997, 1999). One of the context effects, *reference point effects*, influences how individuals perceive and manage trade-offs (Luce et al. 1999, Drolet and Luce 2004). Individuals tend to be “loss averse” and to make decisions to minimize losses rather than to maximize gains (Tversky and Kahneman 1991). The concept of loss aversion has been used in experiments to manipulate trade-off difficulty on the ground that decision makers perceive trade-offs more negatively and resist making the trade-offs in loss situations than in gain situations (Luce et al. 1999). Such reference point effect may explain the conflicting results reported in the three previous studies on trade-off-compelling PEMs. The decision contexts in the three prior studies have varied significantly: Aloysius et al. (2006) asked the participants to make a career choice, while Widing and Talarzyk (1993) asked them to select a software package and Fasolo et al. (2005) a digital camera (see the online supplement for the complete summary). A poor career choice in the Aloysius et al. (2006) study may have produced severe consequences because the attributes associated with job offers, such as quality of life and interest in work, are more difficult to regain once lost. Conversely, an error made in choosing the right software package or digital camera could be corrected easily at minimal or no cost. Thus, the decision context of Aloysius et al. (2006) was similar to the loss condition, whereas those of Widing and Talarzyk (1993) and Fasolo et al. (2005) were similar to the gain condition in that the former led to more severe consequences than the latter.

Second, decision context determines the priority of goals that individuals want to achieve; therefore, they choose a decision approach that appears to be most appropriate to achieve the prominent goal in a given context (Bettman et al. 1993, 1998). Two goals that address many of the most important motivational aspects in choosing decision aids are reducing cognitive effort to make a decision and increasing the accuracy of the decision. When these two goals conflict, individuals tend to choose effort saving over increased accuracy (Payne et al. 1993). This is because they try to save their cognitive load, and because feedback on effort is more readily available and observable than accuracy (Schwartz et al. 1986). Todd and Benbasat conducted a series of studies (1991, 1999) in which users chose a decision aid that reduced their effort over an aid that increased

[3] An electronic companion to this paper is available as part of the online version that can be found at http://isr.journal.informs.org/.

decision accuracy. However, such hierarchy of effort-accuracy changes across decision contexts. In loss situations, where individuals react to the consequences of trade-offs more acutely, they value effort saving less and instead make decisions more meticulously and deliberately (Luce et al. 1997, Bettman et al. 1998). Luce et al. (1997) explained the increase in effort as an attempt to reduce the trade-off difficulty augmented in loss situations. Decision makers want to demonstrate to themselves and to others that suboptimal trade-off choices were unavoidable despite their effort, and in so doing, they can alleviate the trade-off difficulty. However, the increased effort does not necessarily translate into more accurate decision outcomes (Luce et al. 2001). The change in user prioritization of goals across decision contexts suggests that effort expenditure may no longer be a significant factor in a loss context. To the best of our knowledge, no previous studies on RAs have examined this issue.

3. Hypotheses Development

3.1. Research Model

The review of previous studies demonstrates that research is needed to investigate the role of RA PEMs in assisting users with trade-off difficulty across decision contexts construed as a loss or gain. As shown in our research model (Figure 1), PEMs generate trade-off difficulty, which influences perceived control, which, in turn, affects the perceived accuracy of RAs' recommendations and users' perceived effort to make decisions using the RAs. Perceived accuracy and effort are antecedents of the intention to use the RAs. Decision context moderates two of these relationships: the association between PEMs and trade-off difficulty and the association between perceived effort and intention to use the RAs. The following sections explain why and how these variables are related.

3.2. Two RAs: RA-WEIGHTED and RA-CUTOFF

We implemented two types of RAs: (1) RA-WEIGHTED, which applies a weighted additive strategy that enables users to weigh the importance of attributes and obtain a ranked order of products based on each product's weighted average, and (2) RA-CUTOFF, which applies an elimination-by-aspect strategy that enables users to set a minimum value on each attribute that must be met for products to be presented by the RA as choices (Widing and Talarzyk 1993). We chose these two RAs because their PEMs computerize two decision strategies—the weighted additive strategy and the elimination-by-aspect strategy—that represent the opposite extremes in how they present trade-offs to users (Payne et al. 1993, Widing and Talarzyk 1993).

RA-WEIGHTED first presents a list of all the attributes and asks a user to choose an attribute she thinks is important. Then, the user is asked to judge the importance of the chosen attribute *relative* to the other attributes and to express this judgment of its relative importance by allocating to it some portion of 100 (total) importance weights (Figure 2). RA-WEIGHTED displays a clear message to the user that the attribute chosen is *negatively* correlated with one or more other attributes. It is important to note that the number of importance weights that remain (of the 100 total) after each allocation are shown at the top of the page. For instance, if the user allocated 40 to price, she is left with only 60 weights to assign to the remaining attributes. Thus the user is always aware of the fact that allocating more or less to one attribute will affect how many weights can be allocated to others. In other words, RA-WEIGHTED brings to the user's attention the fact that the user is making trade-offs. The user may skip attributes, which she thinks do not matter, and the attributes skipped are automatically assigned an importance weight of 0. When the user has allocated all 100 weights, she sees the resulting top five recommendations, along with their attribute levels. If the user is not satisfied with the results, she has the option of changing the previously allocated importance weights and restarts the process of allocating weights.

RA-CUTOFF also begins by asking a user to select an attribute that she thinks is important. After making

Figure 1 Research Model

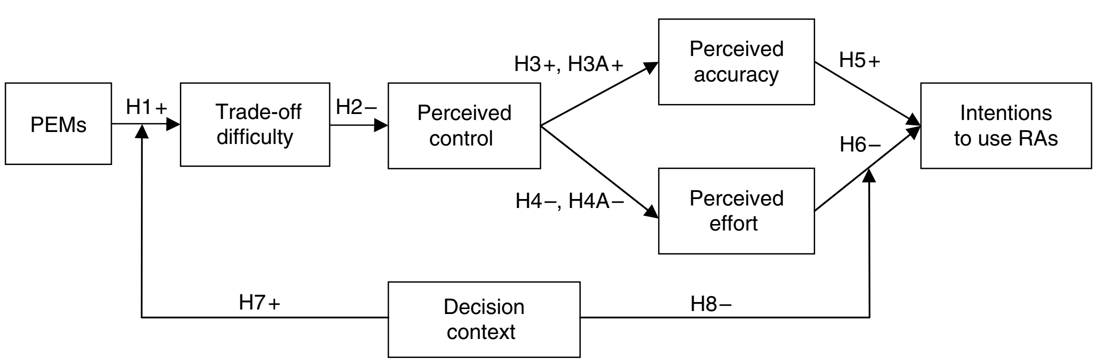
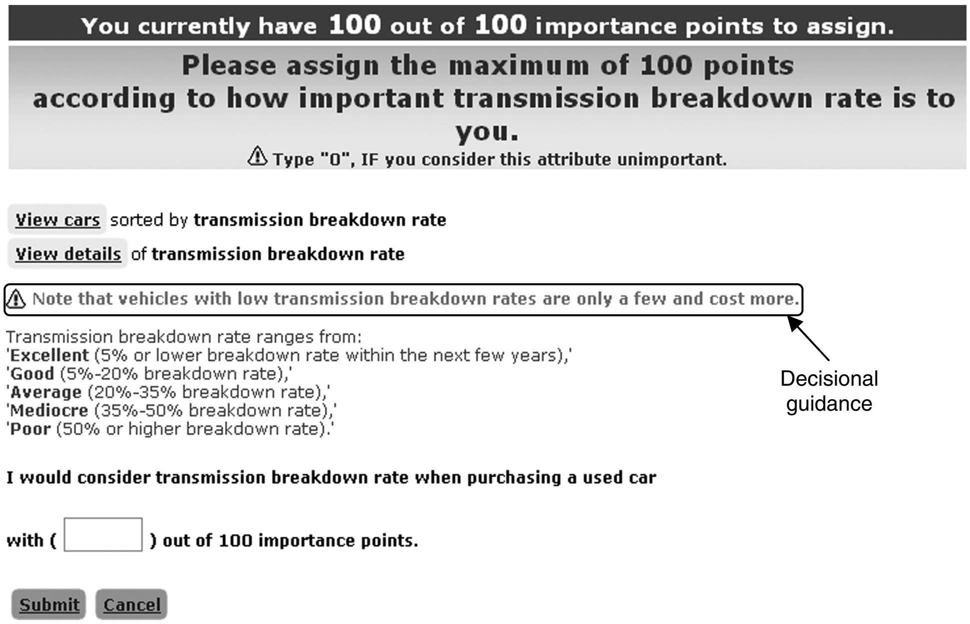


Figure 2 **RA-WEIGHTED**

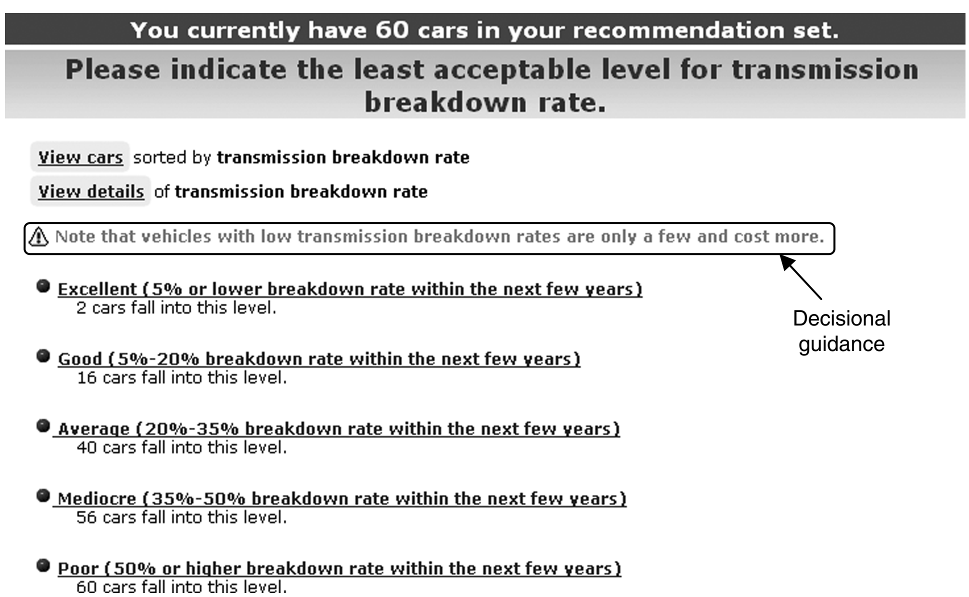


this choice, the user indicates the lowest level she is willing to accept out of the five levels of the attribute chosen (Figure 3). Like RA-WEIGHTED, RA-CUTOFF alerts the user to the negative associations the chosen attribute has with one or more other attributes. The number of products that fall into each level is listed, so that the user is aware of how many products are eliminated through her choice of the particular level. The number of products that remain after elimination is displayed at the top of the page, and the user continues eliminating alternatives until she reaches a manageable number of alternatives. Like RA-WEIGHTED, she may skip the attributes not considered important. The user examines the remaining products, and if unsatisfied with the recommendations, she may revise her preferences.

3.3. PEMS and Trade-off Difficulty

Based on Luce et al. (2001), we argue that RA-WEIGHTED PEM is trade-off compelling, while RA-CUTOFF PEM is trade-off hiding. The extent to which consumers feel trade-off difficulty is determined by: (1) whether they make trade-offs implicitly or explicitly and (2) whether they are provided with coping tactics to alleviate trade-off difficulty.

Figure 3 **RA-CUTOFF**



RA-WEIGHTED forces users to make explicit trade-offs by requiring them to allocate importance weights by directly comparing the importance of conflicting attributes because the total number of weight points to be allocated is a fixed number. Thus, RA-WEIGHTED makes users decide on the attribute to which they should assign fewer weights to assign more to others (Bettman et al. 1998). The relative importance-weighing PEM constantly reminds users of conflicts among the attributes and consequent trade-offs. In contrast, RA-CUTOFF requires users to choose one level of an attribute, presenting the decision as a choice *within* an attribute (e.g., choice of a price level from \$5,000, \$6,000, or \$7,000). By selecting one level of an attribute, the RA-CUTOFF users make essentially the same trade-offs as choosing a higher level of an attribute *suggests* choosing a lower level of another attribute that is negatively correlated (Payne et al. 1993). However, this trade-off is made *implicitly* when choosing a level within that attribute, rather than by comparing across the attributes directly and explicitly as required by RA-WEIGHTED (e.g., price versus safety). Implicit trade-offs allow users to *avoid* confronting the knowledge that they must make trade-offs (Hogarth 1987, Bettman et al. 1998), while the explicit trade-offs required by RA-WEIGHTED place those trade-offs in the core of users' decisions.

In addition, RA-WEIGHTED does not provide coping tactics as compared to RA-CUTOFF. One of the common coping tactics employed by decision makers is to cause the perceived trade-offs to appear outside of their responsibilities so they may easily justify their trade-off decisions. RA-WEIGHTED users make decisions based entirely on personal and subjective assignments of importance weights, which makes users feel accountable for potentially negative decision outcomes (Simonson 1989). In contrast, the elimination-based approach of RA-CUTOFF allows users to perceive a choice not as a personal choice but as an objective fact (Einhorn and Hogarth 1978, Hogarth 1987), because eliminations based on thresholds justify their trade-off decisions (Simonson 1989). A user may say, for instance, "I wanted to choose a higher level of safety features for my family vehicle, but I had only \$5,000. All the cars within my price range had poor safety features, so I had no other choice." Taken together, the evidence provided above leads to the conclusion that an RA-WEIGHTED PEM causes stronger trade-off difficulty than RA-CUTOFF PEM.

Hypothesis 1 (H1). *The PEM that highlights trade-offs will increase a user's trade-off difficulty.*

3.4. Perceived Control

We argue that trade-off difficulty influences users' perceived control over the RA. Perceived control over a system is determined by the extent to which one can use the system to achieve the intended goal (Morris and Marshall 2004). The "feedback-control loop" (proposed by Cybernetics and control theory) illustrates the process by which users build beliefs about the extent of their control over the execution of the system (Robertson and Powers 1990, Morris and Marshall 2004). An user sets an internal goal that represents the ideal state of her environment. Through interaction with the environment, the user receives feedback on the actual state of the environment and compares it with the ideal state. The user attempts to bring her current state into alignment with the ideal state. If the current state varies significantly from the ideal state, despite continuous efforts, the user deems the efforts to be futile and grows to believe that she has limited control over making changes in the environment (Robertson and Powers 1990). By the same token, when a user achieves the desired goal by manipulating a system and eliminates the discrepancy between the current system state and the goal, she feels having control over the execution of the system (Morris and Marshall 2004).

As previously discussed, trade-off difficulty arises when discrepancies arise between the goal (e.g., to have it all) and the current prospect of trade-offs (e.g., some attributes must be forsaken). If an RA PEM, such as RA-WEIGHTED, emphasizes such discrepancy and the user becomes clearly aware of it, she will make repeated attempts to align the two states. However, because the RA PEM manifests the discrepancy regardless of the users' attempt, she will realize more saliently that she is unable to reach the ideal state through the use of RA PEM. The realization will lower the user's perceived control over the RA.

The association between trade-off choices and perceived control is also evident in Averill's (1973) claim that perceived control is whether or not an individual feels that he or she has an adequate response available to a stressor. Trade-off is the most prominent stressor in many decision tasks (Luce et al. 2001). Consequently, an RA perceived to impede the minimization of trade-offs will decrease the user's perceived control (Frese 1987, Bagozzi et al. 2003).

Hypothesis 2 (H2). *Trade-off difficulty will decrease a user's perceived control.*

3.5. Perceived Accuracy of Recommendations and Perceived Amount of Effort Spent

Perceived control, in turn, positively influences the perceived accuracy of recommendations. The close association between one's perceived control and his or her subjective estimates of performance and success has been considered robust in the psychology literature (Försterling 1985, Schmitz and Skinner 1993).

This causal link is justified based on the laboratory experiments in psychology in which individuals who believe they can effectively control courses of action to achieve certain goals were found to perceive a high likelihood of obtaining those goals (Schmitz and Skinner 1993). That is, as a result of having high control, i.e., the ability to surmount the discrepancy between the current state and goal state, people believe that their actions will lead to progress toward obtaining the goal, and thus will have higher estimates of their performance (Schmitz and Skinner 1993, Skinner and Greene 2008). In this vein, users' perceived control over decision aids is postulated to affect their perceived performance of the aids. Users who believe that they were able to have specified their product preferences clearly and transparently to the aids would evaluate the subsequent recommendations more favorably (Kramer 2007).

The influence of perceived control on one's subjective estimates of performance of decision aids is maintained even in circumstances where perceived control does not enhance actual performance (Langer 1975). It is hard to figure out immediately the "objective" accuracy of one's decisions because feedback on decisions is not readily available or accessible in many cases (Payne et al. 1993). For instance, one can assess reliability of durable goods *only* after using them over an extended period of time. Likewise, decision support systems (DSS) users often overestimate the quality of outcomes produced by the DSS when, in fact, the DSS does not necessarily generate better quality outcomes (Kottemann et al. 1994, Kahai et al. 1998). Consistent with the literature, we expect that RA users who perceive high control over execution of the RA PEM will perceive the RA's recommendations to be more accurate, although the RA may or may not actually generate more accurate recommendations. This is because a consumer who thinks that she has been able to convey to the RA her true needs via the RA PEM without feeling constrained in doing so, i.e., by having full control, will expect that the RA will provide recommendations that are aligned with her attribute preferences. Specifically for trade-off choices, RA users who believe that they can control the RA PEM will find the subsequent recommendations to reflect their preferences accurately, although the RA may or may not help users reduce actual trade-off being made. Consequently, we hypothesize as follows.

Hypothesis 3 (H3). *Perceived control will increase a user's perceived accuracy of recommendations.*

Perceived control decreases the perceived amount of effort exerted to make a decision. Perceived control over a task is postulated to be negatively related to perceived difficulty of the task (Rodgers et al. 2008) and positively related to perceived ease of use (Venkatesh 2000). Venkatesh (2000) has defined perceived ease of use as "the extent to which a person believes that using a technology will be free of effort" (p. 344); therefore, perceived ease of use is a construct tied with the amount of effort exerted by users. The negative relationship between perceived control and perceived effort is justified as follows. When, because of the design of a system, the users believe that they do not have control, i.e., users cannot tell the RA what they need in a straightforward fashion or cannot convey to it their true needs, then users need to try to find alternative ways of doing so (Norman 2002). These additional attempts increase time and effort on the part of users (Norman 2002). Conversely, when it is perceived to provide enough control to complete a task successfully, the user feels that the system is transparent, predictable, and uncomplicated to use (Frese et al. 1987). Consistent with these prior studies, we posit that the higher perceived control an RA user has over execution of the RA, the less effortful she finds using the RA.

Hypothesis 4 (H4). *Perceived control will decrease a user's perceived effort.*

3.6. Mediating Effect of Perceived Control

In §§3.4 and 3.5, we discussed that trade-off difficulty lowers perceived control, which, in turn, increases perceived accuracy while decreasing perceived effort. In this section, we posit more explicitly that perceived control mediates the effect of trade-off difficulty on perceived accuracy and effort.

Perceived control is a *mediator* transmitting the impact of external challenges—such as making trade-offs among choices—to one's perceived performance and estimates of the difficulty of resolving the challenges (Carver and Scheier 1982, Schmitz and Skinner 1993). A user who believes that she has control over the RA (that is, believes that the RA is designed such that she is able to convey to it her true set of product preferences) will expect to have better performance in terms of decision accuracy and effort because of RA use. Consistent with the literature, we argued in §3.4 that a user's control over an RA is diminished by trade-off difficulty, which reflects the user's unpleasant realization that wanting more of a particular desirable attribute would mean having less of another desirable one. Note that this comes about because of the design of the PEM the user has to work with. We posit that this perception of trade-off difficulty is *not* the *direct* antecedent of perceived accuracy and perceived effort, but it is mediated. This is because the user will first try to manipulate the RA in different ways in an attempt to eliminate the discrepancy between the current system state and the goal, which is finding a product with all the desirable attributes the customer wishes to have. However, in attempting to do so repeatedly, the user would eventually come to the inevitable conclusion that the RA cannot be controlled by her in such a way to enable the full and faithful specification of her true preferences. Thus the consequence of this lack of perceived control is the main reason for the perceived low performance and increased effort (Carver and Scheier 1982, Schmitz and Skinner 1993).

Hypothesis 3A (H3A). *The negative effect of trade-off difficulty on perceived accuracy will be mediated by perceived control.*

Hypothesis 4A (H4A). *The positive effect of trade-off difficulty on perceived effort will be mediated by perceived control.*

3.7. Usage Intentions

Prior studies based on the effort-accuracy framework posit that perceived accuracy and effort influence users' intention to accept decision aids, as effort saving and accuracy increase are the two most important motivations of decision makers (Todd and Benbasat 1991, 1994, 1999). As such, users will be inclined to use a system that increases the accuracy of their decision and reduces the amount of effort required.

Hypothesis 5 (H5). *Perceived accuracy of recommendations will increase the intention to use the RAs.*

Hypothesis 6 (H6). *Perceived effort will reduce the intention to use the RAs.*

3.8. Moderating Effect of the Decision Context

The decision context in which users employ PEMs will moderate the extent to which PEMs affect trade-off difficulty. As argued in §2.2, the decision context changes the extent to which users experience trade-off difficulty. Compared to a gain situation, in a loss situation, trading off an attribute results in more severe consequences, and thus users will feel trade-off difficulty more intensely and trade-off-compelling PEMs will lead to higher trade-off difficulty.

Hypothesis 7 (H7). *The negative effect of a PEM on trade-off difficulty will be greater in a loss than in a gain situation.*

As noted in §2.2, decision context changes the way users prioritize their goals, and individuals select the decision aid that best supports the prominent goals under given circumstances (Payne et al. 1988, Bettman et al. 1998). In a gain situation, users value effort saving more than an increase in accuracy to reduce their cognitive load. In a loss situation, however, users' emphasis on effort saving is reduced because they want to demonstrate that they have exerted substantial effort to reduce the negative consequences associated with trade-offs (Luce et al. 2001). As a result, we hypothesize as follows.

Hypothesis 8 (H8). *The negative effect of perceived effort on usage intentions will be weaker in a loss condition than in a gain condition.*

4. Research Methodologies

The laboratory experiment that we conducted to test the hypotheses permitted control to be exercised over the variables to achieve a high degree of internal validity (Singleton and Straits 1999). A 2×2 factorial design with two between-subject factors was used. The first factor, RA types, had two levels: RA-WEIGHTED and RA-CUTOFF. The second factor, decision context, also had two levels: loss condition and gain condition.

4.1. Alternatives and Attributes

We chose *used cars* as the product type for several reasons. First, many attributes of used cars are directly related to the safety of passengers, an attribute individuals tend to avoid trading off (Tetlock et al. 2000). Second, most attributes of used cars are negatively correlated with price in the automobile market: As the quality of a feature increases, the price increases. Because of these qualities, used cars have been the subject of previous studies that investigate trade-off decisions (Luce et al. 1997, Luce 1998). Third, used cars are an appropriate choice for a study on Web-based RAs, as many websites employ RAs to sell or provide information about used cars; e.g., www.cars.com and www.autotrader.com.

Particularly, four-door sedans with automatic transmission were chosen to describe product alternatives with a common set of attributes. Nine attributes (except for price) related directly to passenger safety were selected: breakdown rate of (1) engine, (2) brakes, (3) transmission, (4) cooling system, (5) exhaust system, (6) fuel system, (7) crash test results, (8) safety features, and (9) price. With the exception of price, each attribute's levels were excellent, good, average, mediocre, and poor. Price also had five levels, ranging from Can$875 to Can$19,300. These attributes and levels were drawn from well-known consumer reviews, such as *Consumer Reports* and the *Kelley Blue Book*. All attributes were negatively correlated with price. Decisional guidance describing the attribute conflicts was provided to participants so that the attribute conflicts were noted (Figures 2 and 3).

4.2. Manipulation of Decision Context

Decision context consisted of a *loss* or *gain* condition. Participants in both treatment groups were told that they had a budget sufficient enough to buy a used car in average condition. Those in the loss group were asked to imagine that the car currently driven by their family was in better-than-average condition, whereas those in the gain group were asked to imagine that their current car was in worse-than-average condition. Thus, participants in the loss group decided how much of each attribute they had to give up, while those in the gain group decided how much of each attribute they could gain.

To ensure that participants anticipated losses realistically in the experiment, the reference points were accompanied with video clips that illustrated the potential consequences of a lower attribute level (Hung et al. 2007). Because participants anticipate losses more vividly when the loss condition was accompanied by visual cues that depicted the potential consequences of the loss (Luce et al. 1999), a prior study examining the influence of regret on DSS success used a video clip along with a short essay (Hung et al. 2007). In this study, participants in the loss group watched a video clip of a car crash, while participants in the gain group watched a video clip of safe driving tips for a summer vacation. To check if the manipulation was successful, we refined and administered two 7-point items from Drolet and Luce (2004) that assessed (1) the severity of the potential consequences of the upcoming decision and (2) the degree of threat associated with the decision task.

4.3. Operationalization of the Dependent Variables

Perceived control, perceived accuracy, perceived effort, and usage intentions were measured on 7-point semantic scales. Table 1 shows the scales used in the current study.

The process to measure trade-off difficulty involved content analysis, a research technique used to infer the *meaning* of messages unobtrusively by identifying specific characteristics within textual data (Stone et al. 1966). User-written comments offer richer evidence and more fine-grained information than numerical rating scales (Pavlou and Dimoka 2006). Participants' written answers to the following question were analyzed:

> How did you *feel* about the way the shopping advisor assisted with the conflicts among car features? Describe any feelings you experienced associated with advantages and disadvantages in the way the shopping advisors helped (or did not help) you deal with the conflicts.

A two-phased content analysis (i.e., segmentation and encoding) was conducted by two independent coders. Phase 1 involved segmentation of participants' responses to ensure a robust unit of analysis, which is critical in content analysis (Krippendorff 1980, Ericsson and Simon 1993, Miles and Huberman 1994, Vonk et al. 2006). The unit of analysis chosen for this study is a semantic chunk, that is, a thematic section of the content. A semantic chunk is commonly chosen to capture an idea or an expression because interpretation of subtle nuance in the content is necessary to identify an idea or an expression (Krippendorff 1980, Miles and Huberman 1994). As such, the participants' responses were segmented into semantic chunks, each of which pertains to only one idea or topic. Phase 2 involved identification of a semantic chunk referring to trade-off difficulty,

Table 1 Measures Used

Measure	Item	Source
Perceived control	(1) When specifying my preferences for used cars, I felt I was in control. (2) I think that I had a lot of control over the preference specification process. (3) The way I indicated my preferences for used cars made me feel I was in control.	Bechwati and Xia (2003)
Perceived accuracy	(1) Used cars that suit my preferences were recommended by the shopping advisor. (2) Used cars that best match my needs were provided by the shopping advisor. (3) Used cars recommended by the shopping advisor did NOT match my needs (reversed). (4) I would choose from the same set of alternatives provided by the shopping advisor in future purchase occasions.	Widing and Talarzyk (1993)
Perceived effort	(1) The task of using the shopping advisor to choose a used car took too much time. (2) Using the shopping advisor to choose a used car required too much effort. (3) The task of using the shopping advisor to select a used car was easy (reversed). (4) The task of using the shopping advisor to select a used car was too complex.	Bechwati and Xia (2003)
Usage intentions	(1) Assuming I have access to the shopping advisor, I intend to use it the next time I consider buying a used car. (2) Assuming I have access to the shopping advisor, I predict I would use it the next time I plan to purchase a used car. (3) Assuming I have access to the shopping advisor, I plan to use it the next time I consider buying a used car.	Pavlou (2003), Venkatesh and Davis (2000)

Note. We used the term "shopping advisor" instead of "recommendation agent" in the questionnaire because "shopping advisor" may sound more familiar to the participants.

i.e., an *emotional state caused by conflicts among product attributes and/or subsequent trade-offs*. A total of 63 such semantic chunks—agreed upon by the two coders—were identified. Agreement between the two coders was measured by Krippendorff's (1980) alpha, deemed the most rigorous measure of agreement among multiple coders (Pavlou and Dimoka 2006). It was 0.72, exceeding 0.70, the acceptable level suggested by Krippendorff (1980). Examples of the chosen semantic chunks include "*I feel very stressed. It's very hard to balance safety, probability of failure and money*," and "*I felt frustrated about having to give up reliability of parts to maintain a good price for her*." Trade-off difficulty was then measured by the sum of such semantic chunks provided by each participant, ranging from 0 to 4. More detailed description of the process used to measure trade-off difficulty is provided in the online supplements.

4.4. Participants and Experimental Procedures

One hundred students at a large North American university participated in the experiment, and 25 participants were assigned randomly to each of the four treatment groups. Participants' areas of study varied widely, including accounting, English literature, engineering, and others. Table 2 shows participants' demographics.

The participants' previous knowledge of the product category was controlled by recruiting only those who had (1) a driver's license, (2) no experience in purchasing a used car, and (3) moderate expertise with automobiles (only those who indicated 2–5 on a 7-point automobile expertise scale ranging from 1 [*not at all expert*] to 7 [*extremely expert*]). These conditions were implemented to ensure that we recruited participants with moderate knowledge of used cars. Only those without sufficient knowledge of the product would seek advice from RAs (Haubl and Trifts 2000, Swaminathan 2002). Also, novices regarding automobiles may be unable to recognize the negative consequences associated with automobile malfunctions and traffic accidents (Swaminathan 2002).

The experimental session proceeded as follows. The participants watched the video clips and read the decision task for the loss and gain conditions. The decision task involved a selection of a used car for one of their family members, because decision makers find it more difficult to trade off important attributes when the consequences of the trade-offs may affect the well-being of someone they care about (Tetlock et al. 2000). Next, they were asked to answer the questions for the manipulation check, after which they were trained on how to use the RAs. Then, they were asked to choose a used car without a time constraint. Once their decisions had been made, they were asked to complete a questionnaire containing all of the dependent variables. Participants were given monetary compensation ($20) for their participation. To motivate participants and to increase their involvement, we provided the top 25% performers with an additional incentive ($40). Upon completion of the experiment, participants were asked to explain why they chose the particular car. The selected top 25% of performers who justified their choices most appropriately received the additional incentive.

5. Results and Analyses

5.1. Overview

Manipulation checks indicated that participants in the loss condition believed that their upcoming decisions carried potentially more severe consequences (mean = 5.66) and that those decisions were potentially more threatening (mean = 4.86) compared to participants in the gain condition (4.98 and 4.12, respectively). The difference in the composite measure (aggregating the two items) between the two groups is statistically significant ($t = 2.87, p < 0.05$), indicating successful manipulation of decision context.

Smart partial least squares (PLS) with a bootstrapping technique was used to test the hypotheses and to assess the psychometric properties of the scales. We first analyzed the structural model for the entire

Table 2 Participants' Demographics in the Four Treatment Groups

Variable	RA-WEIGHTED	RA-CUTOFF	Total
Loss condition	20 females, 5 males 20.16 years old (SD = 1.620) 7.88 years of Web experience (SD = 1.760)	20 females, 5 males 20.84 years old (SD = 1.770) 8.48 years of Web experience (SD = 2.230)	40 females, 10 males 20.50 years old (SD = 1.717) 8.18 years of Web experience (SD = 2.017)
Gain condition	19 females, 6 males 22.04 years old (SD = 3.540) 9.08 years of Web experience (SD = 2.300)	18 females, 7 males 20.80 years old (SD = 1.800) 9.08 years of Web experience (SD = 1.840)	37 females, 13 males 21.42 years old (SD = 2.851) 9.08 years of Web experience (SD = 2.069)
Total	39 females, 11 males 21.10 years old (SD = 2.887) 8.48 years of Web experience (SD = 2.12)	38 females, 12 males 20.82 years old (SD = 1.769) 8.78 years of Web experience (SD = 2.053)	77 females, 23 males 20.96 years old (SD = 2.386) 8.63 years of Web experience (SD = 2.082)

Table 3 Means, SDs, Interconstruct Correlations, and AVE

Variable	Mean (SD)	Cronbach's alpha	Composite reliability	(1)	(2)	(3)	(4)	(5)
(1) Trade-off difficulty	0.610 (0.801)	1.000	1.000	—	—	—	—	—
(2) Effort	2.315 (0.846)	0.797	0.871	0.308**	**0.792**[a]	—	—	—
(3) Control	5.180 (0.994)	0.859	0.916	−0.354**	−0.463[b]**	**0.885**	—	—
(4) Accuracy	5.230 (0.946)	0.836	0.896	−0.412**	−0.430**	0.628**	**0.828**	—
(5) Usage intentions	5.463 (1.247)	0.950	0.969	0.009	−0.372**	0.453**	0.528**	**0.954**

[a]Diagonal cells indicate the AVE of the corresponding construct.
[b]Other cells indicate interconstruct correlations.
**Significant at the 0.01 level (two-tailed testing).

sample to test H1–H6. Next, to test the moderating effect of the decision context, H7 and H8, we split the sample into the loss and gain conditions and compared the corresponding path coefficients in these structural models (Keil et al. 2000). Because all the hypotheses are directional, we applied *one-tailed* testing.[4]

5.2. Measurement Validation

Internal consistency was assessed by examining Cronbach's alpha and composite reliability in Table 3. Both Cronbach's alpha and composite reliability for all constructs were above the suggested threshold of 0.7 (Barclay et al. 1995). Discriminant validity was assessed by Gefen and Straub (1997): (a) the square root of the average variance extracted (AVE) being larger than any correlation among any pair of latent constructs, and at least 0.50. Table 3 shows that this criterion was satisfied by the current data. (b) Items loading highly on their theoretically assigned factor and not highly on other factors. Table 4 shows that all items satisfy the second criterion. Lastly, we tested if there is a common method bias among the four dependent variables measured as perceptions—i.e., perceived control, perceived accuracy, perceived effort, and usuage intentions—using Harman's (1967) single-factor test. The results of an exploratory factor analysis show that no single factor explained a majority of the variance and that four factors with eigen-values measured as perceptions close to 1.00 or higher have emerged, thereby alleviating the concerns of common method bias.

5.3. Testing of Hypotheses Using the Entire Sample

Figure 4 shows the results of the structural model (path coefficients, t-statistics, and explained variance).

Table 4 Factor Loadings and Cross-Loadings

Measure	Trade-off difficulty (TD)	Perceived accuracy (ACCU)	Usage intentions (INT)	Perceived control (CTR)	Perceived effort (EFF)
TD	—	−0.44	0.00	−0.36	0.27
CTR1	−0.29	0.50	0.37	**0.85**	−0.30
CTR2	−0.33	0.62	0.43	**0.88**	−0.46
CTR3	−0.34	0.57	0.40	**0.93**	−0.46
ACCU1	−0.33	**0.85**	0.38	0.61	−0.35
ACCU2	−0.43	**0.89**	0.41	0.61	−0.42
ACCU3	−0.40	**0.83**	0.40	0.49	−0.47
ACCU4	−0.30	**0.72**	0.53	0.39	−0.26
EFF1	0.19	−0.34	−0.27	−0.37	**0.81**
EFF2	0.15	−0.35	−0.32	−0.31	**0.80**
EFF3	0.32	−0.40	−0.35	−0.44	**0.80**
EFF4	0.19	−0.27	−0.22	−0.36	**0.68**
INT1	−0.00	0.50	**0.96**	0.42	−0.37
INT2	0.21	0.51	**0.97**	0.45	−0.38
INT3	−0.01	0.47	**0.93**	0.43	−0.39

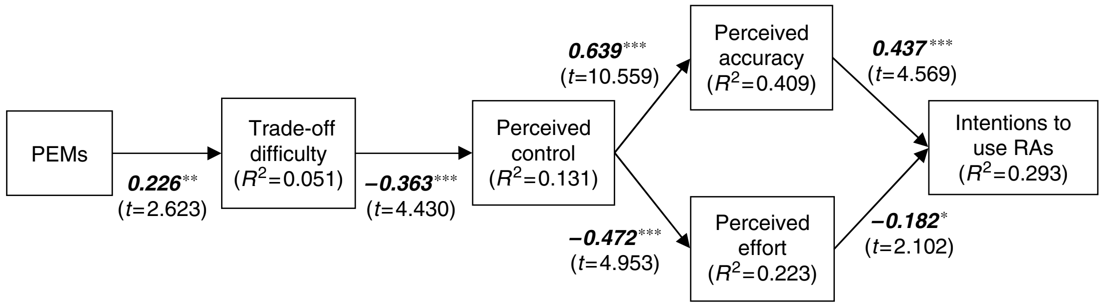
All path coefficients were significant, thus providing support for H1–H6.

To test H3A and H4A, we performed a mediation analysis following Baron and Kenny's (1986) four-phased testing and Sobel and Leinhart's (1982) tests to determine whether the indirect effect from trade-off difficulty through perceived control on perceived accuracy and effort are significant. Column 1 in Table 5 indicates that the three initial conditions for having a mediation effect are satisfied for both perceived accuracy and effort. Specifically, trade-off difficulty (independent variable [IV]) affects perceived control (mediator [M]); perceived control (M) affects perceived accuracy and effort (dependent variables [DVs]); and trade-off difficulty (IV) affects perceived accuracy and effort (DVs).

Column 2 shows that the fourth condition of having a mediation effect is satisfied for both perceived accuracy and effort. First, the path coefficient from trade-off difficulty (IV) on perceived accuracy (DV) is reduced but is still significant in column 2, where

[4] All the hypotheses were supported with two-tailed testing as well, except H8 (p-value for two-tailed testing = 0.066 at the significance level of 0.05).

Figure 4 PLS Results for the Combined Sample



Note. In Figures 4 through 6, *, **, and *** indicate significance at 0.05, 0.01, and 0.001, respectively (one-tailed testing).

the path from trade-off difficulty (IV) to perceived control (M) and the path from perceived control (M) to perceived accuracy (DV) are controlled. Sobel's test results indicate that the indirect effect of trade-off difficulty through perceived control on perceived accuracy is significant ($t = -3.774$, $p < 0.001$). These findings of the partial mediation support H3A that perceived control mediates the negative effect of trade-off difficulty on perceived accuracy. Second, the path coefficient from trade-off difficulty (IV) on perceived effort (DV) is reduced and not significant in column 2. Sobel's test results indicate that the indirect effect of trade-off difficulty through perceived control on perceived effort is significant ($t = 3.039$, $p < 0.01$) (Sobel and Leinhart 1982).[5] Therefore, H4A is supported (i.e., perceived control mediates the effect of trade-off difficulty on perceived effort).

5.4. Testing for the Moderating Effect of Decision Context

In the two structural models for the loss (Figure 5) and gain conditions (Figure 6), the path between PEMs and trade-off difficulty differed, confirming the moderating effect of decision context. The path coefficient from PEM to trade-off difficulty in the loss condition was significant ($t = 2.775$, $p < 0.01$), while the corresponding path in the gain situation was *not* significant ($t = 0.827$, $p > 0.05$). In addition, we followed the method specified by Keil et al. (2000) to compare statistically the path coefficient from PEM to trade-off difficulty for loss condition with the corresponding path coefficient for the gain condition. The result showed that the path coefficient from PEM to trade-off difficulty for the loss condition was significantly stronger than the corresponding path coefficient for the gain condition ($t = -20.347$, $p < 0.001$). These results support H7 that trade-off-compelling PEMs generate trade-off difficulty to a greater degree in a loss condition than in a gain condition.

The difference in the paths between perceived effort and usage intentions across loss and gain conditions was evident as well: the path from perceived effort to usage intentions in the loss condition was *not* significant ($t = 1.048$, $p > 0.05$), while it was significant in the gain condition ($t = 1.872$, $p < 0.05$). We also statistically compared the path coefficients from perceived effort to usage intentions for the loss condition with the corresponding path for the gain condition, following Keil et al. (2000). The result showed that the path for the gain condition was significantly stronger than that for the loss condition ($t = -5.694$, $p < 0.001$). These results support H8, which posits that the influence of perceived effort on usage intention is less in a loss condition than in a gain condition.

Figures 5 and 6 also suggest that the path coefficient between trade-off difficulty and perceived control was greater in the gain condition than in the loss condition. This finding indicates that trade-off difficulty affects perceived control to a greater degree in a gain

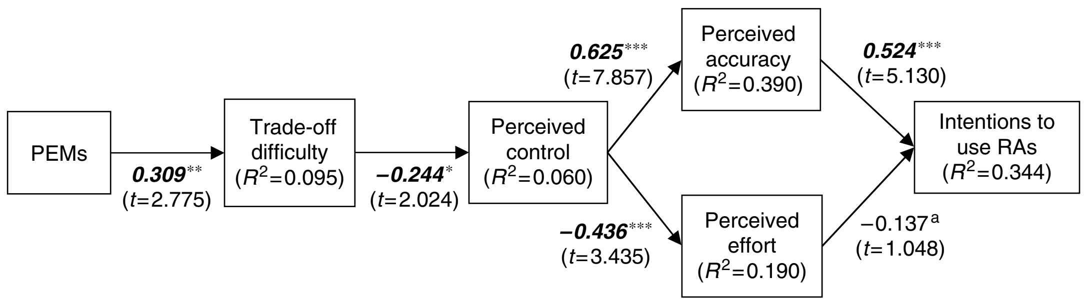
Table 5 Mediation Analysis

Path	1	2
Trade-off difficulty (IV) → Perceived control (M)	−0.363***	−0.363***
Perceived control (M) → Perceived accuracy (DV)	0.640***	0.549***
Perceived control (M) → Perceived effort (DV)	−0.473***	−0.429***
Trade-off difficulty (IV) → Perceived accuracy (DV)	−**0.446*****	−**0.246***
Trade-off difficulty (IV) → Perceived effort (DV)	**0.280****	**0.121**

Notes. (1) Column 1 represents path coefficients that are estimated *independently*, while column 2 represents path coefficients that are estimated *simultaneously* for all of the paths (Bulgurcu et al. 2010). (2) If the path from IV to DV in column 1 is significant while not in column 2, then perceived control *fully mediates* the impact of IV to DV. If the path from IV to DV in both columns 1 and 2 are significant, while column 1 is larger than column 2, then perceived control *partially mediates* the impact of IV to DV. (3) *, **, and *** indicate significance at 0.05, 0.01, and 0.001, respectively, for one-tailed testing (the results are the same for two-tailed testing).

[5] Mediation analyses were also performed for the loss and gain conditions. The results indicate that perceived control mediates the effect of trade-off difficulty on perceived accuracy and effort in the gain condition, but perceived control mediates the effect of trade-off difficulty only on perceived accuracy in the loss condition. These results coincide with our claims in §2.2 that individuals willingly spend more effort in a loss condition because working hard alleviates trade-off difficulty; consequently, trade-off difficulty exerts influence only on perceived accuracy, not on perceived effort. See the online supplement for detailed analyses and results.

Figure 5 PLS Results for the Loss Condition



[a]An 89% chance of detecting medium effect (0.30) for one-tailed testing at the 0.05 significance level. Source: Cohen 1992.

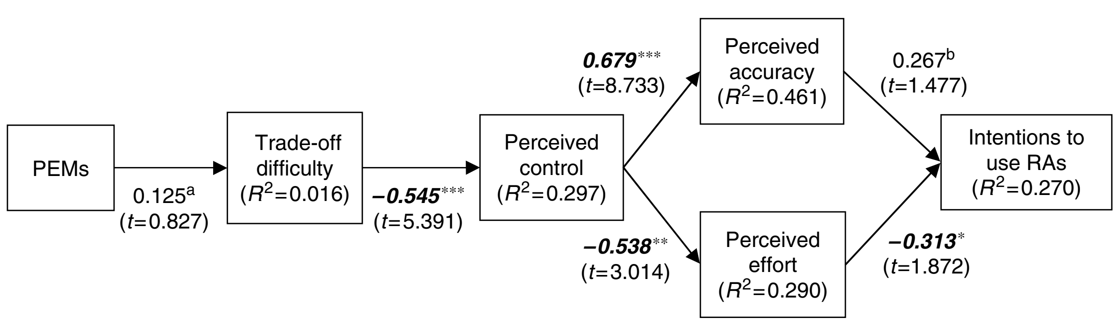
condition than in a loss condition. A possible theoretical explanation is based on the concept of *diminishing sensitivity*, which posits that the marginal impact of a loss is contingent upon the distance from the reference point (Thaler et al. 1997). A decision outcome has smaller marginal effects when it is more distant from the reference point. For example, an anticipated loss from \$1,400 to 1,380 has a smaller effect on decision making than a loss from \$30 to 10, when the reference point is \$0. Diminishing sensitivity in consumer behavior explains why repeated experience of losses invokes less disappointment (Erev et al. 2008). The initial experience of an undesirable outcome leaves the most negative impression on consumers; the more often consumers experience the undesirable outcome, the less sensitive they become in response to it (Erev et al. 2008). The first dollar lost hurts the most, and the first failed job application disappoints the most (Erev et al. 2008).

In our experiment, RA-WEIGHTED users in the loss condition experienced discrepancy between their intended goal (i.e., minimizing trade-off) and the inevitable trade-offs repeatedly: the loss task first introduced them to the prospect of the discrepancy and the RA-WEIGHTED PEM reinforced this prospect, yet they still had to use this PEM until they made the final choice. Each such repeated experience made them less sensitive to the discrepancy or loss. Because users become less sensitive to the discrepancy, trade-off difficulty affected perceived control less in the loss condition.

6. Discussion and Conclusions

As with many studies, this research has a number of limitations. First, investigating the influence of trade-off-compelling PEMs on a user's acceptance of RAs in a laboratory has its drawbacks. We conducted the experiments in a laboratory to control for other extraneous factors that may have affected user RA acceptance. However, this study was limited in imitating the intensity of trade-off decisions faced in a real purchase situation. Furthermore, the study did not include other potentially important factors for consumers' choice of used vehicles, such as family members' opinions and physical inspection of vehicles. Nonetheless, the control of such extraneous variables was necessary for investigating the effect of trade-off difficulty unaffected by other factors. Second, the variance explained in the construct of trade-off difficulty is approximately 5% in the combined sample and 2% in the gain condition (Figures 4 and 6). The low variance explained suggests a possibility that other factors than PEMs that generate trade-off difficulty may have existed and/or that our measure of trade-off difficulty did not capture trade-off difficulty completely.

Figure 6 PLS Results for the Gain Condition



[a]A 95% chance detecting medium effect (0.30) for one-tailed testing at the 0.05 significance level.
[b]A 57% chance of detecting medium effect (0.30) for one-tailed testing at the 0.05 significance level. The low chance of 57% suggests that power may be the reason for the nonsignificant result.

However, capturing emotions, particularly negative emotions, is limited inherently in any laboratory setting because of the social desirability bias. Participants tend to reply in a manner in which they are viewed favorably by the experimenter (Singleton and Straits 1999). Especially in the North American cultural context, where people refrain themselves from expressing emotions in an unfamiliar social setting, some participants may have refrained themselves from making negative comments. For instance, a participant who did not make any negative comment (thereby "0" point in our measure) might have felt trade-off difficulty but did not express it because of the cultural norm. We did not use a Likert scale measure, which could have led users to choose a point in the lower range of the scale (i.e., 1–3 on a 7-point Likert scale with 7 being the most negative) because of the pressure of social desirability. Our measure of trade-off difficulty, in contrast, successfully showed the differences between the two PEMs and explained the role of trade-off difficulty in reducing perceived control. However, given the low variance explained in the models, we acknowledge that our measure of trade-off difficulty can be improved. Finally, the current study did not measure the objective accuracy of decisions. The most common way to measure the objective accuracy of decisions is to include a nondominant product (a product alternative that has the highest level for every attribute) in the alternative set and observe the number of participants who select it as compared to those who choose other products in the set. However, a nondominant product cannot be included in the alternative set for a study that investigates trade-off choices as a nondominated product, by definition, has attribute conflicts to a lesser degree than the other products in the set.

Despite these limitations, this study makes important contributions to the advancement of theory. First, previous studies have focused primarily on how PEMs elicit user preferences with minimal user effort, while generating the most accurate recommendations. This study demonstrates that the manner in which PEMs assist users in managing trade-offs significantly affects users' RA acceptance. Specifically, trade-off difficulty generated by an RA PEM influences perceived accuracy and effort through perceived control. The inclusion of perceived control as the mediator provides richer explanations about the mechanism through which trade-off difficulty influences perceived accuracy and effort than the alternative hypothesis, which asserts a direct link between such relationships (as shown by Aloysius et al. 2006). Thus, it enhances our understanding of how trade-off difficulty translates into users' evaluations and the subsequent acceptance of RAs.

Second, this is the first study to investigate the role of PEMs in assisting users with trade-off difficulty across different decision contexts (i.e., loss and gain conditions). By demonstrating the moderating effect of decision context, we were able to show that inconsistent results in prior research stemmed from—at least, in part—neglecting the decision context. Decision context has largely been omitted in the literature on decision aids, thereby leading to inconsistent results (Eierman et al. 1995). The current study demonstrated that users evaluated the same PEMs differently under different circumstances. These findings indicate that researchers should either incorporate or control for the effect of decision context to obtain consistent results in investigations into PEMs. Finally, this study showed that perceived effort—the factor found to be the determinant of users' RA acceptance—no longer has a significant influence in the loss condition.

This study also provides several implications for practice. First, the finding that perceived control positively affects perceived accuracy and effort, and thus usage intentions, suggests that RA developers may want to find a way to increase perceived control. One suggestion is to provide users with decisional guidance from experts who support their trade-offs (Wang and Benbasat 2007). Supported by experts' guidance, users may feel trade-off difficulty to a lesser degree. Second, this study suggests that RA developers provide users with different RA options by allowing users to choose an RA that satisfies their goals for particular decisions. For some consumers, the goal of enjoying their shopping experience is more important than making the most accurate decision (Armstrong and Kotler 2004). Thus, practitioners may want to provide RA-CUTOFF for these consumers because it is perceived to be more controllable, and therefore more enjoyable.

Future researchers may further examine the diminishing sensitivity found in this research. In the loss condition, approximately 10% of variance in trade-off difficulty and 6% of variance in perceived control is explained, whereas, in the gain condition, roughly 2% of variance in trade-off difficulty and 30% of variance in perceived control is explained (Figures 5 and 6). The little variance (i.e., 2%) explained in trade-off difficulty in the gain condition is in accordance with our claims that little trade-off difficulty will emerge in the gain condition. However, the difference in the variance explained in perceived control across the gain (30%) and the loss conditions (6%) leaves us room for further examination. We explained such results by referring to the concept of diminishing sensitivity in §5.4, in that a small variance in trade-off difficulty can lead to a large variance in perceived control when a person experiences trade-off difficulty for the first time. Future researchers may examine this issue further.

Future studies also should examine how another type of decision context, defined by consumers' buying stages, moderates the effect of trade-off-compelling PEMs. Consumer-buying processes begin with the recognition of a need and continue through information search, evaluation of alternatives, purchase decision, and postpurchase evaluation (Engel et al. 1968). Given that a user's primary goal depends on where she is situated within the buying process, the user's evaluations of and intentions to accept the RAs that employ trade-off-compelling PEMs may also vary. In particular, in the information search stage, the user's goal is simply to search for information rather than make a commitment to a choice; as such, the negative effect of a trade-off-compelling PEM may decrease. However, in the purchase decision stage, where the user needs to commit to the final choice, the negative effect of a trade-off-compelling PEM may increase. The changes in users' evaluations of PEMs according to their buying stage will be a relevant topic for future research.

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://isr.journal.informs.org/.

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