DESIGNING RECOMMENDATION AGENT

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A DISSERTATION SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF INFORMATION SYSTEMS

NATIONAL UNIVERSITY OF SINGAPORE

2008

ACKNOWLEDGEMENT

I am sincerely indebted to many people, who deserve accolades for their guidance, support, and encouragement throughout the dissertation process.

A special note of gratitude is given to my dissertation advisor, A. P. Teo Hock Hai, who has provided more attention, mentorship, and (most of all) patience than any one student deserves. I am honored and inspired to follow his footsteps.

Dr. Goh Khim Yong has been a mentor, a friend and an associate to me. I have benefited from our ensuring relationship as an academic and as a person, and I look forward to our future collaboration.

Dr. Jack Jiang and Dr. Tan Gek Woo have served as my thesis committee. They gave interesting and useful suggestions for carrying out this series of work. I am grateful to them. In addition, I am indebted to the rest of the faculty members in the Department of Information Systems, National University of Singapore for providing me good advice and guidance to upgrade the quality of my research work.

Senior Information Systems scholars like Professor Izak Benbasat and Professor Dov Te'eni have contributed to the success of this study. Their valuable advice and suggestions have enriched my research and expanded my conception of scholarly contribution. I have certainly gained much insight from the discussions with them. I look forward to more opportunities for joint research with them.

Close friends and peers like David Phang Chee Wei, Juliana Sutanto, Li Yan, Oh Lih Bin, Tan Wee Kek, Tong Yu, Wang XinWei, Xu Heng, and Yang Xue have experienced the PhD roller coaster ride with me. Their companionship smoothed the ride considerably and I will always remember our shared experiences fondly.

Last, but not least, I thank my parents for giving the constant support, encouragement and inspiration to keep me going on in spite of all the difficulties and time constraints involved. Throughout the process, I could not have asked for a more supportive family. Any success that I achieve will be theirs as well.

SUMMARY

Recommendation Agent (RA) is an online decision-aiding tool that assists a consumer to screen, evaluate, and choose suitable purchase options in the electronic marketplace. This dissertation focuses on the means by which RA could support the decision making stages involving information search, alternative evaluation and choice selection. Information search refers to a consumer's search for information, which can occur internally and externally. A consumer engages in internal search when one recalls about products/services from memory, which is determined by the consumer's existing knowledge about the products and his ability to retrieve relevant product information. External search occurs when a consumer gathers information through accessing online information. With the gathered information, a consumer proceeds to the alternative evaluation stage, where a set of alternatives is extracted and evaluated. Often a consumer would delineate the criteria to for retrieval and evaluation. Based on the evaluation of the alternatives, a consumer makes an explicit choice selection. Applying a wide variety of theories drawing from Psychology, Information Systems, Marketing, Economics, and Computer Science, we propose and validate distinct RA mechanisms that could affect consumer decision-making behavior and performance.

The dissertation encompasses of three essays. Essay One focuses on proposing and examining product learning and preference elicitation supports. A product learning support uses different communicating modes, i.e., text and video modes, to educate consumers on the meanings and importance of product attributes. A preference elicitation support, on the other hand, focuses on assisting consumers in articulating their preferences. The tools investigated are need-based and attribute-based. Building on the Cognitive-Experiential Self-Theory (CEST), we posit that: 1) where the provisions of the product learning and preference-elicitation supports facilitate the consistent

practice of one dominating form of processing system (i.e., either the “experiential” or “analytical”) a consumer will experience greater decision confidence and exhibit a lower propensity for purchase-avoidance; and 2) where the provisions of the two supports lead to switching between the two processing systems, a consumer will experience poorer decision performance. A laboratory experiment was subsequently conducted to test our hypotheses. The results provide empirical evidence for our supposition.

Essay Two focuses on examining RA features that aid consumer decision-making during the stages of alternative evaluation (screening support) and choice selection (evaluation support). This study explores how consumers utilize online decision aids with screening and evaluation support functionalities under varying product attribute-load conditions. Drawing upon resource-matching theory, we conducted a 3x2 factorial experiment to test the interaction between decision aid features (i.e., low versus high-screening support, and aids with weight assignment and computation decision tools) and attribute-load (i.e., large versus small number of product attributes) on decision performance. Unlike theories of cognitive fit and task-technology fit, the resource-matching theory provides clear predictions of under-fit, ideal-fit and over-fit conditions in the decision-aiding context. The findings reveal that: 1) where the decision aids render cognitive resources that match those demanded for the task environment, consumers will process more information and decision performance will be enhanced; 2) where the decision aids render cognitive resources that exceed those demanded for the task environment, consumers will engage in less task-related elaboration of decision-making issues to the detriment of decision performance; and 3) where the decision aids render cognitive resources that fall short of those demanded for the task environment, consumers will either employ simplistic heuristic decision strategies to the detriment of decision performance, or invest additional effort in information processing to attain a better decision performance, if they perceive the additional investments in effort to be manageable.

Essay Three concludes the dissertation by proposing an overarching framework governing the design of RA artifacts. Specifically, this article seeks to propose a set of RA design artifacts to address decision difficulties entailed during consumer procurement expedition with the outlook of alleviating purchase-avoidance propensity. We first establish that decision difficulty could lead to purchase-avoidance behavior, a tendency to postpone committing to a purchase or to seek a less painful way out that involves no action or no change (i.e., abandon the inclination of committing to a purchase). Six factors related to decision-difficulty are identified. We contend that if a purchase is difficult to perform because of RA support not being available, adequate or appropriate, a consumer then has a high tendency to abandon the purchase. We next propose and theorize a research framework demarcating seven RA design artifacts, i.e., preference learning, preference discovering, preference framing, option framing, decision strategy-based screening, decision guidance, and RA personalization, in alleviating decision-difficulty.

The essential objective of this dissertation is to incorporate and extend the current state of our knowledge on literature in consumer behavior and decision making to provide empirical and theoretical justification to the deployment of RA in online context.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

A. RESEARCH OVERVIEW

A.1 INTRODUCTION

Shopping for gifts during the holiday season can be an enjoyable or a terrifying task. In order to enhance the shopping experience, more people in recent years, have been turning to the online Recommendation Agent (RA) to help them find the best gifts (Häubl and Murray 2003; Grenci and Todd 2002). You may picture an RA as a dedicated shopping assistant, obedient and wise, who can help you to find the ideal slimming belt for your mother-in-law and the perfect body massager for your father-in-law. Of course, RA is not just an automated tool that searches for and consolidates available products for consumers. It also seeks to assist consumers in eliciting preferences, searching for product options and choosing among the retrieved alternatives by providing explicit or implicit recommendations (Xiao and Benbasat 2007).

Using an RA raises the question: What are the pertinent features of RA that will best serve consumers? In other words, if you are a consumer, how would you expect RA to assist you in the decision-making of a purchase? Over the past five years, both commercial implementations and research prototypes have begun to explore the versatility of RA. As in many commercial RAs, such as mySimon and Dealtime, consumers using these RAs navigate through the products using hyperlinks that delineate the search criteria, such as a price range of between $100 and $250. An example of a newly-emergent application is the Yahoo's SmartSort that filters products based on the elicited importance of an attribute (e.g., presence of airbag can be ranked as a more important attribute compared with leather seat for car). Another application by Amazon accords consumers with recommendations indicating the number of people who purchase similar or complementary products.

Researchers have explored many additional applications, including delving into automating various decision strategies (Aksoy, Bloom, Luri, and Cooil 2006; Tan 2003), comparing the use of collaborative-based and content-based filtering of products (Ariely, Lynch and Aparicio 2004), and evaluating the persuasiveness of RA in many factors, such as personalization, trust establishment and justification for recommendations (Tam and Ho 2005; Komiak and Benbasat 2004).

While technological advances have brought issues of RA within the scope of Information Systems (IS) and Human-Computer Interaction (HCI), we are far from being the pioneers in this field. Particularly, the idea of providing RA was first conceived by Negroponte (1970) and later examined by Kay (1984), preceding the birth of the Worldwide Web. Furthermore, over the past 20 years, behavioral scientists have conducted countless studies on how to improve individual decision-making by making the task easier to execute (see Payne, Bettman and Johnson 1993). The relevance of such works to the design of RA is evident: RA embodies some psychological and behavioral understanding of what makes decision-making easier. Drawing from these fields of research can provide both a firmer foundation as well as practical design artifacts for RA. In our review, we observe that no study has offered a conclusive architectural view of RA by drawing from multiple disciplines. The studies closest to achieving this goal are that of Xiao and Benbasat (2007), which focuses on addressing the issues of trust and acceptance of RA, and that of Adomavicius and Tuzhilin (2005), which centers on comparing two extant RA models (i.e., collaborative-based and content-based) and proposing a hybrid preference model. Even with the presence of these studies, little has been known about how RA can be designed to assist consumers in making more informed and higher-quality decisions throughout the whole decision-making process.

The purpose, and hence a distinguishing feature of this dissertation is to introduce a unified design framework for the RA with which designers are encouraged to provide system features to support a range of decision-making stages ranging from information search, through alternative evaluation and choice selection. We adopt the view that RA should provide informed guidance and recommendation to consumers in 1) learning about a product, 2) constructing preferences, and 3) evaluating alternatives and choosing a purchase alternative.

In order to achieve our objectives, we first review previous theoretical and empirical studies of RAs in online shopping environments that were published since 2000 when RA becomes visible. A search of literature in IS, Marketing, Psychology, Economics and Computer Science was undertaken to identify 1) the relevant RA and related HCI studies, and 2) the theoretical justifications for the existing RA implementations and our visualized RA design. Academic databases for published journal articles, such as EbscoHost, were searched by using relevant keywords. The tables of contents of leading journals in various referenced disciplines were also scanned for relevant and related theories and studies.

We next present two empirical studies and one theoretical article on RA. Essay One builds on the theoretical underpinning of Cognitive-Experiential Self-Theory to examine two features of RA: product learning and preference elicitation supports. Product learning support uses different communicating modes, i.e., text and video, to educate consumers on the meanings and importance of product attributes. Preference elicitation support, on the other hand, focuses on assisting consumers in articulating their preferences. The tools investigated are need-based and attribute-based. Drawing on the Cognitive-Experiential Self-Theory (CEST), we posit that: 1) where the provisions of the product learning and preference-elicitation supports facilitate the consistent practice of one dominating form of processing system (i.e., either the “experiential” or “analytical”) a consumer will experience greater decision confidence and exhibit a lower propensity for purchase-avoidance; and 2) where the provisions of the two supports lead to switching between the two processing systems, a consumer will experience poorer decision performance.

Essay Two focuses on examining two RA features: screening support and evaluation support. The study references the Resource-Matching Theory to examine the interaction between decision aid features (i.e., low versus high-screening support, and aids with weight assignment and computation decision tools) and attribute-load (i.e., large versus small number of product attributes) on decision performance. The findings from a laboratory experiment reveal that: 1) where the decision aids render cognitive resources that match those demanded for the task environment, consumers will process more information and decision performance will be enhanced; 2) where the decision aids render cognitive resources that exceed those demanded for the task environment, consumers will engage in less task-related elaboration of decision-making issues to the detriment of decision performance; and 3) where the decision aids render cognitive resources that fall short of those demanded for the task environment, consumers will either employ simplistic heuristic decision strategies to the detriment of decision performance, or invest additional effort in information processing to attain a better decision performance, if they perceive the additional investments in effort to be manageable.

Essay Three concludes the dissertation by proposing a set of RA design artifacts to address decision difficulties entailed during consumer procurement expedition with the outlook of reducing purchase-avoidance propensity. Specifically, we propose and theorize a research framework demarcating seven RA design features, i.e., preference learning, preference discovering, preference framing, option framing, decision strategy-based screening, decision guidance, and RA personalization, in alleviating decision-difficulty.

A.2 RA RESEARCH

The idea of having an RA in the electronic marketplace was first conceived to help consumers in addressing the information overload problem (Smith 2002). Specifically, RA builds on the preference information elicited by users to filter product options and propose suggestions to the users (Haübl and Murray 2003; Grenci and Todd 2002). In other words, rather than flooding the consumers with an overwhelming plethora of product offers and information, an RA assists consumers by using information about the consumers' preferences to identify a small subset of alternatives that are more likely to interest them (Smith 2002; Ansari, Essegaier and Kohli 2000).

One of the earliest academic demonstrations of the worth of RA in alleviating information overloading problem is the work by Haübl and Trifts (2000). The authors examine two aiding features of RA: one that assists in screening alternatives, and another one that rearranges alternatives to make evaluation easier. Their study shows that the provision of aid that supports screening and/or rearrangement of alternatives significantly improves the quality of the decision made. This view is supported by Montgomery and his colleagues (2004) who conjecture that by reducing the cognitive effort associated with evaluating the alternatives, decision aids could substantially increase consumers' propensity to increase the search for more information and commit purchases. Other studies have also reported similar findings (see Xiao and Benbasat 2007; Smith 2002).

Beyond articulating the benefits of having an RA with cognitive-effort minimization, a vast body of literature has also been devoted to understanding the extent to which RA influences consumer decision-making behavior. Extant studies suggest that RA could induce consumers to 1) evaluate unfamiliar products together with the familiar (Cooke, Sujan, Sujan, and Weitz 2002), 2) render an attribute more prominent by explicitly including it in the recommendation (Haübl and Murray 2003),

3) decrease price sensitivity by lowering the search cost for quality information (Diehl, Kornish and Lynch 2003), 4) help consumers to learn more about the product domain and better match their preferences by controlling the information flow (Ariely 2000), and 5) assist consumers to discover new products or generate demand for unfamiliar products through providing personalized offers (Tam and Ho 2005).

Other studies focus on identifying the conditions in which RA performs best. For instance, RA is: 1) observed to possess a greater impact on consumer behavior under conditions of high product risk (Swaminathan 2003), 2) evaluated more favorably for search goods than experience goods (Aggarwal and Vadyanathan 2005), 3) assessed less positively when the unsolicited recommendation or advice contradicts consumer's initial impressions (Fitzsimons and Lehmann 2004), 4) better received by consumers when the recommendations are more transparent (Sinha and Swearingen 2002), and 5) perceived to be more useful if the RA provided takes into consideration the consumer's characteristics, such as frequency of purchase and perceived risk (Sproule and Archer 2000). The thesis underlying these studies is that RA could offload consumers' effort in evaluating every single alternative by providing guidance and restricting the evaluation to the few recommended alternatives that are highly correlated with consumers' overall elicited preferences (Tan 2003). To this end, RA could induce consumers to make decisions in accordance with the intention of the agent, which is to encourage consumers to procure (Haübl and Murray 2003; Diehl et al. 2003). However, when such intent is perceived to contradict with the consumers' initial impressions of RA usage, a behavioral backlash of ignoring the agent's recommendations may result (Fitzsimons and Lehmann 2004).

This leads to the next question: How can we design an RA that is well received by consumers? To arrive at the answer, we need to first understand that the ability of RA to recommend suitable alternatives depends on how well information on consumers' preferences is obtained. This approach accords with the view that the cost of relying on a badly-designed RA that makes poor recommendations, such as those that do not match the consumer's preferences, can well negate the value of using it (Haübl and Murray 2006).

Table 1 tabulates some of the key studies related to RA.

Table 1. Review of Extant RA literature

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Adomavicius and Tuzhilin (2005)	Review of the implementations of collaborative-based and content-based RA.	Conceptual	Not applicable	Multi-criteria	A hybrid model of an RA that combines collaborative-based and content-based techniques is proposed. Suggestions on the extension of RA to incorporate other factors including the consideration of contextual information and the provision of more flexible and less intrusive types of recommendations.
Aggarwal and Vaidyanathan (2005)	How will search and experience goods affect consumers' perceived effectiveness of two RA routines, i.e., rule-based filtering and collaborative filtering?	Laboratory Experiment	• Perceived Quality of Recommendations, • Satisfaction with the RA, • Intent to Follow-Up on Recommendations	Applied Psychology	RA was evaluated more favorably for search goods than experience goods. Further, rule-based recommendations were preferred for search goods. However, for experience goods, recommendations based on rule-based processes and collaborative-filtering processes were perceived to be comparable.
Aksoy et al. (2006)	What is the impact of the similarity in the attribute weights and decision strategies of an agent and consumer, on the decision performance and perception of the agent?	Experiment	• Decision strategy • Attribute weight • Perceived benefits • Perceived costs • Conformity to recommendations • Quality of decision made	Concept of similarity	Consumers made better decisions using a similar agent but were believed to make better choices without using an agent than when using a doubly dissimilar agent.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Ansari et al. (2000)	Recommendations are based on content and/or collaborative filtering methods. The merits of these methods are examined and preference models used in marketing are examined if they are good alternatives.	Statistical Model, Computer Simulation	• Person's Expressed Preferences • Preferences of other Consumers • Expert Evaluations • Item Characteristics • Individual Characteristics	Preferences Models used in Marketing, Regression, Hierarchical Bayesian Approach, Markov chain Monte Carlo methods.	Described a Bayesian preference model that allows statistical integration of five types of information useful for making recommendations: a person's expressed preferences, preferences of other consumers, expert evaluations, item characteristics and individual characteristics.
Ariely (2000)	Marketers have to select the type of information system they want to utilize in order to deliver to their consumers the most appropriate information on which they can base their decisions. An interesting and distinguishing dimension of such information systems is the level of control the consumer has over the information system.	Laboratory Experiment	• Level of Information Control • Cognitive Load imposed by the Information System • Amount Experienced with the Interface • Decision Quality • Memory • Knowledge • Confidence	Information Control	Controlling the information flow can help consumers better match their preferences, have better memory and knowledge about the domains they are examining, and be more confident in their judgments. However, controlling the information flow creates demands on processing resources and therefore, under some circumstances can have detrimental effects on consumers' ability to utilize information.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Ariely et al. (2004)	Intelligent recommendation systems can be based on 2 basic artifacts: collaborative filters and content-based agent. Examine the learning function that results from these 2 general types of learning-smart agents.	Computer Simulation	• Algorithms for Intelligent Agents (Random, Collaborative filtering by K-mean clustering, Collaborative filtering by nearest neighbor, Content-based logistic-regression intelligent agents) • Success Measurement (Probability of Purchasing, Comparing the performance of the agent to an omniscient who always recommended the product of the highest utility for target consumers.	Recommendation Agent, Clustering, Nearest-Neighbor Algorithm, Regression	Comparing collaborative filters, K-mean agents learning as well as nearest-neighbor algorithm for consumers who are close to the centroids of their clusters, but less well for consumers farther from cluster centroids. Compared to collaborative filters, individual agents (a) learn more slowly initially, but are better off in the long run if the environment is stable; (b) recover faster after a permanent change in the consumer's utility function; and (c) are less adversely affected by random error in the purchase thresholds that make purchase a noisy indicator of underlying utility functions. Do not necessarily imply that collaborative agents are inferior. Best approach for smart agents is to base their recommendations on a mixture of these two approaches: When there is little or no knowledge, there should be a reply on the collaborative component, but as information about a consumer accumulates, the recommendations of individual agents should prevail.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Cooke et. al. (2002)	How do consumers respond to recommendations of unfamiliar products made by electronic agents? How might recommendation context (assimilation and contrast) affect the evaluation of unfamiliar recommendations? How might the provision of item-specific information affect the evaluation of unfamiliar recommendations? How might recommendation context and item-specific information affect the evaluation of electronic agents?	Laboratory Experiment	• Recommendation Context • Item-Specific Information • Purchase Likelihood • Agent Rating • Reservation Price	Consumer Behavior	Additional recommendations of familiar products serve as a context in which unfamiliar recommendations are evaluated. When the presentation of the recommendations makes unfamiliar and familiar products appear similar, evaluative assimilation results. When additional information about unfamiliar products is given, consumers discriminate them from the familiar products, which produce evaluative contrast. Information that leads to higher evaluations when context is absent can lead to contrast and lower evaluations in the presence of attractive contextual recommendations.
Dastani et al. (2005)	How should a generic recommendation agent be designed to support preference elicitation?	Conceptual/algorithm-based	Not applicable	Formal analysis, Inductive Logic Programming	Generic agent architecture is proposed. In the view of the authors, an agent should induce preferences of the involved participants (either human or automated agent) by observing their behavior. Through the observation, the agent could fine-tune the preference model according to the interacting environment.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Diehl et al. (2003)	In markets in which price and quality are uncorrelated, will the use of screening agents increase or decrease prices paid compared to searching from an unordered list of options? Will increasing the size of the store's underlying assortment increase or decrease prices paid when options have been screened on quality? In markets where higher priced goods have higher quality, will the use of screening increase or decrease prices paid and quality selected?	Laboratory Experiment	• Type of Search Agent • Assortment Size • Order of Search • Order of Recipient • Sequence of Search • Relative Importance of Price in the Reward Function	Consumer Behavior	Contrary to previous findings lower search costs for quality information decreased price sensitivity; decreasing search costs for quality information by the screening and sorting mechanisms has the opposite effect on differentiation and price sensitivity.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Fitzsimons and Lehmann (2004)	Consumer response when recommendations are made by experts and intelligence agents contradict initial impressions of choice options.	Laboratory Experiment	• Source of Recommendation (Expert, Non-Expert) • Recommendation Valence (Supportive, Nonsupportive) • Attractiveness of Recommended Option (Dominant, Dominated) • Expectation of Ability to Choose • Individual Reactance • No. of Target Attractive Options Chosen • Choice Percentage of Target Attractive Options • Decision Satisfaction • Difficulty in Making Decisions • Confidence Correct Decisions Made	Recommendations, Intelligent Agents, Decision Support System, Theory of Reactance	Unsolicited advice that contradicts initial impressions leads to the activation of a reactant state on the part of the decision-maker. This reactance, in turn, leads to a behavioral backlash, which results not only in consumers ignoring the agents' recommendations but in intentionally contradicting them.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Gershoff et al. (2003)	Past opinion agreement between the consumer and an agent is an important cue in customers' acceptance of current agent advice. Different types of past agreements can have different effects on the acceptance of current agent advice.	Laboratory Experiment	• Overall Opinion Agreement • Extreme Opinion Agreement • Preference Structures for Extreme Objects • Likelihood of Accepting the Agent's Advice • Acceptance of Agent Advice	Determinant of Diagnosticity, Relative Diagnosticity between Positive and Negative Areas of the Preference Structure.	Individuals weigh different types of prior agreements differently, depending on aspects of the decision-making context. In addition to the overall level of agreement, people also consider agreement on extreme opinions when assessing the usefulness of agent advice. Positive extreme agreement was more influential than negative extreme agreement when the agent provided positively balanced advice, but the converse was not true in the case of negatively balanced advice.
Haübl and Murray (2003)	The inclusion of an attribute in a recommendation agent renders this attribute more prominent in customers' purchase decisions, everything else being equal. This preference construction effect may persist beyond the initial shopping experience and into subsequent choice settings in which no recommendation agent is available.	Laboratory Experiment	• Inclusion of Attribute • Inter-attribute Correlation • Perceived Rationale for Attribute Inclusion in the Agent • Amount of Information Search	Information Presentation Format, Feature-Based Priming, Potential Information Value of Attribute Inclusion	Preferences of human decision-makers can in fact be influenced in a systematic and predictable manner by merely altering the composition of the set of product attributes that are included in an electronic recommendation agent. This preference-construction effect is likely to persist for some time and affect subsequent purchase decisions in different settings – either in an electronic shopping environment or possibly in bricks-and-mortar stores.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Haübl and Murray (2006)	Recommendation agents are "double agents" in the sense that they act on behalf of both the buyer and the seller, and have the potential to both aid and influence buyers in their decision-making.	Conceptual	• Product Choices • Search Effort • Prices • Influence of Recommendation Agent • Trust	Electronic Recommendation Agent, Decision Support System, Consumer Decision - making, Human-computer Interaction	The consumer-centric double agent perspective provides a framework for the design of product recommendation agents that focus on delivering value to consumers by accelerating their decision processes, while at the same time improving the quality of the product choices they make. This perspective takes into account the competitive advantage gained by a vendor that delivers the benefits of agent-assisted shopping and improves its own position in the marketplace through its electronic agent's influence on consumer preferences.
Haübl and Trifts (2000)	How does the use of interactive decision aids such as an Recommendation Agent and Comparison Matrix affect consumers' search for product information, the size and quality of their consideration sets and the quality of their purchase decisions in an online shopping environment?	Laboratory Experiment	• Interactive Decision Aids – Recommendation Agent and Comparison Matrix • Amount of search for product information • Consideration Set Size • Consideration Set Quality • Decision Quality	Marketing, Judgment and Decision-making, Psychology, Decision Support System	Interactive decision aids designed to assist consumers in the initial screening of available alternatives and to facilitate in-depth comparisons among selected alternatives in an online shopping environment may have strong favorable effects on both the quality and the efficiency of purchase decisions – shoppers can make much better decisions while expending substantially less effort.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Herlocker et al. (2004)	How to evaluate collaborative filtering recommender systems and their algorithms.	Review, Conceptual, Computer Simulation	• User Tasks for Recommender System • Types of Analysis • Types of Data Set • Accuracy Metrics	Collaborative Filtering Recommendation Agent, Accuracy Metrics	Reviewed the evaluation strategies used by previous researchers. Empirical results from the analysis of various accuracy metrics on one content domain shows that all the tested metrics collapsed roughly into three equivalence classes. Metrics within each equivalency class were strongly correlated, while metrics from different equivalency classes were uncorrelated.
Ho and Tam (2005)	How does exposure to personalized offers affect subsequent product consideration and choice outcome? Examine the effect of three major elements of web personalization strategy on users' information processing through different decision-making stages: personalized content quality, features overlapping among alternatives and personalized message framing.	Laboratory Experiment	• Personalization Timing • Personalized Content Quality • Feature Overlapping • Personalized Message Framing • Composition of Consideration Set • Final Choice	Human-Computer Interaction, User Behavior, Decision-making, Web Personalization, Consideration Set Theory	When users are forming their consideration sets, the agent can play a role in helping users discover new products or generate demand for unfamiliar products. Once a decision has been made, however, the personalization agent's persuasive effects diminish. The role of personalization agents changes at different stages of a user's' decision-making process.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Komiak and Benbasat (2004)	Persuasiveness of an recommendation agent (RA) – Identifying the most persuasive recommendation agent type and explaining why it is so.	Conceptual	• RA Types • Appropriateness • Consistency • Effectiveness • RA's Persuasiveness	Recommendation Agent, Decision Support System, Reardon's Persuasion Theory – ACE (Appropriateness, Consistency, Effectiveness) Theory	Builds a research model grounded in Reardon's Persuasion Theory to examine which type of recommendation agent is most persuasive and why. The persuasiveness of an RA may vary with customer expertise and product complexity; however, it is not clear how and why these differences will happen.
Middleton et al. (2004)	How to profile consumers when building the collaborative-based algorithm.	Conceptual	• Not applicable	Artificial Intelligence	The authors adopted the ontological approach toward profiling users within an RA. Two experimental systems were built to create user profiles from unobtrusively monitored behavior and relevance feedback. Experiments were subsequently conducted. They showed that the ontological inference can improve user profiling.
Miller, Joseph, Konstan and Riedl (2004)	How to build an RA that does not only run on large server computers (but in small devices such as handheld tools as well) and harness the peer-to-peer network to offer personal assistance to individual consumers.	Conceptual/System design	Not applicable	Computer science	A collaborative-based RA, PocketLens, is proposed. Simulation results suggest that PocketLens can offer recommendations that are as good as the best published algorithms to-date, even when residing in connected workstations and occasionally, portable devices.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Moon (2003)	When consumers use computers to help make purchase decisions, how do they attribute responsibility for the positive or negative outcomes of those decisions?	Laboratory Experiment	• Decision Outcome • Intimate Self Disclosure with Computer	Self-Serving Bias, Theory of Social Response	Attribution of responsibility reflects a self-serving bias: Consumers tend to blame computers for negative outcomes and tend to take personal credit for the positive. However, when consumers have a history of intimate self-disclosure with a computer, this pattern of attribution is significantly mitigated: Consumers are more willing to credit the computer for positive outcomes, and are more willing to accept responsibility for negative outcomes.
Sinha et al. (2002)	The role of transparency (user understanding of why a particular recommendation was made) in a Recommender System.	Survey	• Music Recommender System • Liking • Confidence • Transparency	Recommendation Agent, Human-Computer Interaction	In general, users like and feel more confident in recommendations perceived as transparent. Users are not just looking for blind recommendations from a system, but are also looking for a justification of the system's choice.
Smith (2002)	Will RA benefit consumers at the expense of retailers? How will consumers respond to the presence of RA services and to the information presented by RA? How should retailers adjust the elements of their marketing mix in response to RA? How should the RA design and price its services to achieve profitability?	Review, Conceptual	• RA Taxonomy • Impact of RA • Consumer Behavior • Retailer Behavior	Consumer Behavior	An RA places pressure on retailer margins in some circumstances. However retailers retain numerous opportunities to differentiate their products, leverage brand names, set strategic prices, and reduce the effectiveness of consumer search at an RA.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Sproule and Archer (2000)	How theories and findings from DSS and marketing research can be used to develop and design software agents that buyers will find useful and usable in e-commerce.	Conceptual	• Frequency of Purchase • Perceived Risk • Search Behavior • Search Support • Choice Behavior • Choice Support	Marketing Models and Decision Support System	Frequency of purchase and perceived risks provide a framework that can help match agent functions to buyer's need. The Purchasing Situation Model can identify important differences in the type of information required, the extent and duration of search behavior, and the choice processes likely to be used.
Swaminathan (2003)	Use of recommendation agents can lead to increase in consumer welfare. The role of category risk, product complexity, and customer category knowledge, in moderating the impact of recommendation agents on consumer welfare.	Laboratory Experiment	• Product Complexity • Product Category Risk • Category Knowledge • Amount of Search • Decision Quality • Recommendation Agent	Information Overload, Information Search	Recommendation agents have a greater impact on decision quality under conditions of the high risk category. In addition, recommendation agents have a greater impact on reducing the amount of search when the number of attributes used to describe a product is smaller.
Tam and Ho (2005)	What are the effects of different personalization strategies applied at different stages in the process of persuasion? What are the variables related to the user's personal disposition and technology features that may have an impact on each stage of the process?	Field Experiment	• Preference Matching • Need for Cognition • Use of Sorting Cue • Set Size • Attention • Elaboration • Accept Personalized Offer	Recommendation Agent, Human-Computer Interaction, Elaboration Likelihood Model of Persuasion, Information-Processing Model	Web personalization influences users in two major ways: (1) It affects elaboration and decision-making through the central route of persuasion by offering products that match the preferences of customers. (2) A personalization agent can manipulate the presence or absence of a sorting cue and the number of recommended offers to invoke heuristic rules for users. This is the peripheral route of persuasion. Personal disposition, as measured by Need for Cognition (NFC), played a pivotal role in influencing a user's level of elaboration and choice outcome. Users who have little motivation to exert cognitive effort to evaluate the merits of alternatives tend to rely on recommendations suggested by the personalization agent.

Authors and Year	Research Question/Focus	Research Methodology	Constructs used	Underlying Theoretical Framework	Main Findings/Contributions
Xiao and Benbasat (2007)	How do RA use, RA characteristics and other factors influence consumers' shopping decision-making processes and outcomes? How do RA use, RA characteristics and other factors influence users' evaluations of RAs?	Conceptual	• Outcomes of RA Use (Consumer Decision Making and Users' Evaluation of RA) • Product • User • User-RA Interaction • RA Characteristics • Provider Credibility • RA Use • Intention for Future Use • Future Use of RA	Decision Support System, Consumer Decision Making, User's Subjective Evaluation of RAs, Theories of Human Information Processing, Theory of Interpersonal Similarity, Theories of Trust Formation, Technology Acceptance Model, and Theories of Satisfaction.	Presented a set of theory-based propositions concerning the outcomes of RA use and RA adoption intentions in e-commerce settings. Went beyond generalized models such as TAM to identify the RA specific features, such as RA input, process and output design characteristics, that influence users' beliefs and evaluations, including usefulness and ease-of-use concerning RA.
Xiao et al. (2003)	Lack of customer service and marketing analysis tools in most e-commerce web sites.	Prototype, Laboratory Experiment	• Order-Based Similarity Measure • Weight Modification • Adaptation	Recommendation Agent, Case-Based Reasoning, Collaborative Filtering, Clustering Analysis	Constructed an intelligent agent based on Case-Based Reasoning and collaborative filtering. This agent is included in a product recommendation system called PCFinder. The validity test of PCFinder indicates that most people are satisfied with the Order-Based Similarity Measure, and they also believe that both weight modification and adaptation can improve its performance. Furthermore, applying either short-term or long-term constraints resulted in more satisfactory recommendations (than not applying them).

B. ESSAY ONE
ASSESSING PRODUCT LEARNING AND PREFERENCE ELICITATION DECISION SUPPORTS: A COGNITIVE-EXPERIENTIAL SELF PERSPECTIVE

B.1 INTRODUCTION

Understanding how consumers utilize decision aids to make purchase decisions has been a topic of enduring interest in Information Systems (IS) literature, particularly in the arena of Decision Support Systems (DSS). With a growing commercial interest arising from firms[1] offering a wide variety of decision aids, such as Recommendation Agents (RAs), on the Internet to support consumer decision-making (Ansari, Essegaier, and Kohli 2000), DSS research becomes more pertinent. The bulk of the research effort in this field has been directed towards understanding the provision of screening and evaluating supports in its entirety[2] (Xiao and Benbasat 2007; Montgomery, Hosanagar, Krishnan, and Clay 2004; Olson and Widing 2002; Haübl and Trifts 2000). Essay Two will examine the decision supports for screening and evaluation of alternatives in detail. Implicit in these studies, and relatively untested, are the assumptions that most consumers: 1) have adequate knowledge about the product of interest and 2) are able to elicit preferences sufficiently well to engage in alternative screening and evaluation.

The paucity of empirical studies devoted to examining decision supports for product learning and preference elicitation can be understood from two aspects. First, the majority of the DSS literature focuses on helping individuals to process and filter the vast amount of available information to

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[1] The U.S. Census Bureau's Quarterly Retail E-Commerce Sales reported that e-commerce sales for the fourth quarter of 2005 were $22.9 billion, 23% higher than the fourth quarter, 2004 sales of $18.4 billion.

[2] Consumers typically initiate the decision-making process by establishing a list of minimally acceptable product attribute level(s) that an alternative must possess in order to be considered further as a possible choice, known as screening (Olson and Widing 2002; Edwards and Fasolo 2001). The screened alternatives are then assessed carefully

make an informed decision (Eom 2003; Edwards and Fasolo 2001). While it is plausible that consumers could learn about a product by engaging in extensive screening and evaluation of the alternatives (i.e., by trial-and-error), consumer decision-making literature has clearly documented that consumers often engage in important stages of the decision-making process such as learning about a new product or service (Hoeffler 2003) and eliciting preferences based on gained knowledge (Kardes, Cronley and Kim 2006) before screening and evaluating alternatives (Schwartz 2004). Decisional supports to be provided, and hence their effectiveness, could differ depending on the objectives and purposes of the usage (Häubl and Murray 2006; Edward and Fasolo 2001). Towards this end, the capacity of an RA to recommend suitable alternatives depends on how well information on consumers' preferences is obtained (Xiao and Benbasat 2007), which in turn depends on the extent to which a consumer is familiar with the product. Consequently, an inability to better support consumer decision-making process could yield a devastating impediment to Internet Commerce. For instance, consumer decision-making literature has suggested that when a consumer faces difficulties during decision-making (e.g., a lack of product knowledge to elicit preference clearly), he has an inclination to exhibit the purchase-avoidance behavior despite having the need to consume the product/service (Anderson 2003). Purchase-avoidance behavior refers to a tendency to postpone committing to a purchase or to seek a less painful way out that involves no action or no change (i.e., abandoning the inclination of committing to a purchase). An online manifestation of purchase-avoidance behavior is the

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to make a choice, and this process is known as evaluation (Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer, and Wood 1997).

shopping cart abandonment rate, which hovers at a disturbingly high level of around 70 percent even for today[3] (Mummalaneni 2005).

Second, we attribute the paucity of empirical studies researching on decision supports for product learning and preference elicitation to the well-documented complexity of assessing the impact of IT artifacts. Specifically, as highlighted by Kumar and Benbasat (2006), developing and mimicking websites equipped with RAs, for instance, could be difficult due to: 1) the complexity in building online decision aids that are of adequate realism, and 2) the constraints in generating sufficient product data. For instance, in our study, the challenges in replicating online product reviews, inoculating preference elicitation mechanisms, and collecting information on product alternatives could all impede research initiatives. Our study takes a similar approach to Kumar and Benbasat (2006) by studying the commercial implementations and extracting the product content of commercial websites to manipulate the supports offered for the product learning and the preference elicitation. With respect to our product learning support, we referenced websites such as mySimon.com and Shopper.com, which leverage on review websites, such as CNET.com and About.com, to assist consumers to acquire relevant product knowledge. For the preference elicitation support, we observe that websites such as CNET ExactChoice, Surprise.com, Dealtime, and mySimon, offer two different forms of preference elicitation supports, namely need-based and attribute-based systems (Grenci and Todd 2002). Attribute-based preference elicitation refers to the indication of consumer preferences through defining product attribute criteria while need-based

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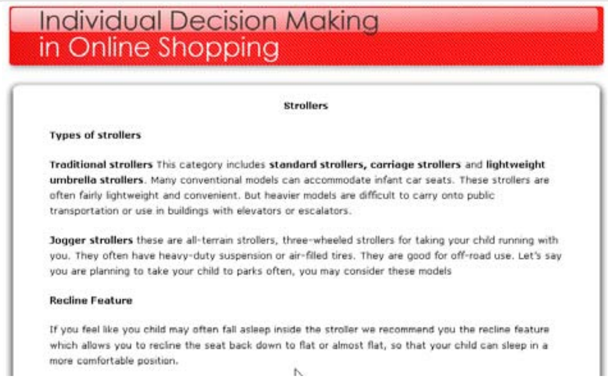
[3] Cherkassky, I. "Improving the E-Tail Shopping Experience," E-Commerce, 2006 [url: http://www.vovici.com/pdf/200603-targetmarketing.pdf; last accessed: March 20, 2008]

preference elicitation denotes a set of rules to interpret or translate consumer-specified preferences (i.e., needs) into alternative product attribute criteria.

Figure 2: Sample Screenshots of the Experiment

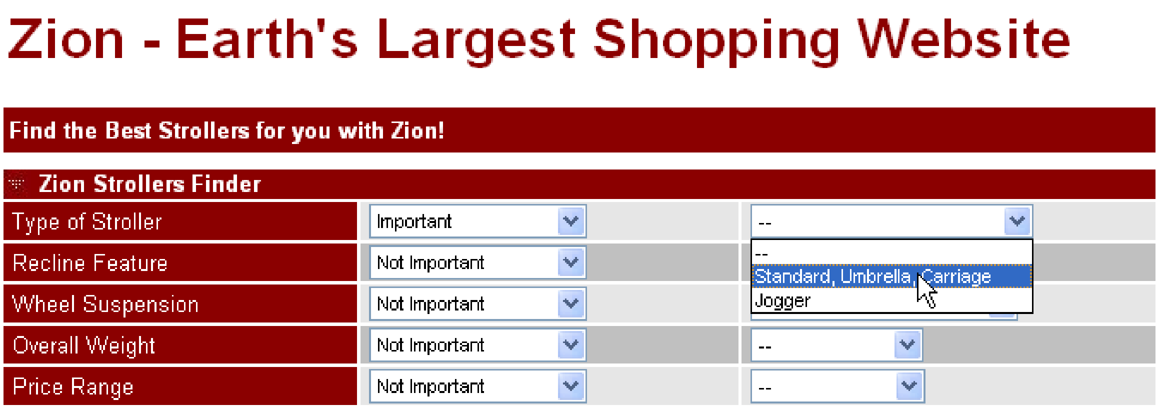
Product Learning Support

Video-based

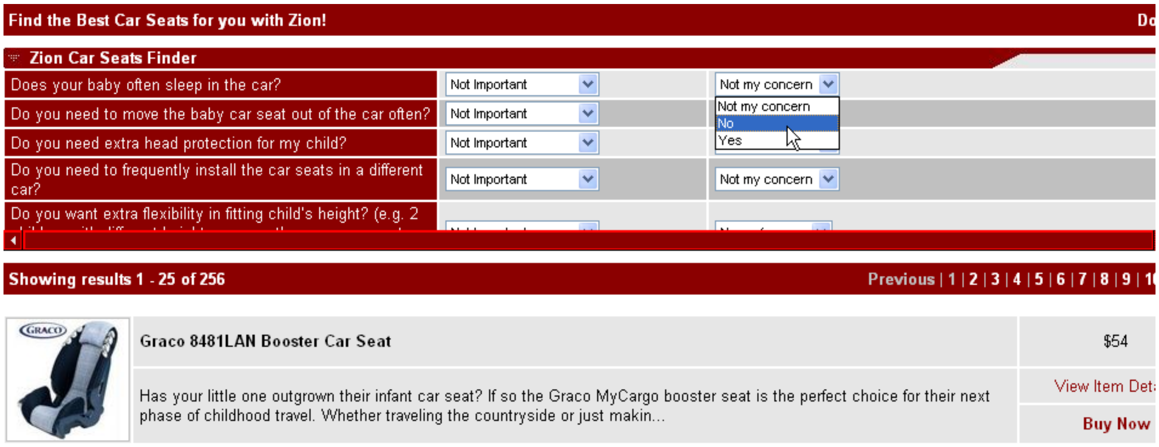


Text-based

Preference Elicitation Support



Attribute-based



Need-based

In response to the lack of understanding of decision supports for product learning and preference elicitation, this study focuses on assessing two decisional supports offered by an RA, namely product learning and preference elicitation supports. We examine the effectiveness of the product learning support and preference elicitation support in terms of their influence on decision performance. The central proposition to be examined in this study is that a Web store's provision of the product learning support, as it is implemented in the forms of product reviews in the text and video modes; and of the preference elicitation support, as it is implemented by the attribute-based and need-based product preference elicitation mechanisms, will influence a consumer's perception of the decision-making process and outcomes. We assess this proposition by drawing on the Cognitive-Experiential Self-Theory (CEST) to posit that: 1) where the provisions of product learning and preference-elicitation supports facilitate the consistent practice of one dominating form of processing system (i.e., either the "experiential" or "analytical"), a consumer will experience greater decision confidence and exhibit a lower propensity for purchase-avoidance; and 2) where the provisions of the two supports lead to switching between the two processing systems, a consumer will experience a poorer decision performance. By focusing on the interaction effects of the *product learning support* and the *preference elicitation support* on decision performance, we seek to provide a more nuanced theoretical understanding of the impact of decision aids in an online consumer decision-making environment.

B.2 THE RA AND DECISION-MAKING

Before we examine the product learning and preference elicitation supports of RA, it is imperative that we first gain a good understanding of RA in general. The idea of having an RA in the electronic marketplace was first conceived to help consumers in addressing the information overload problem (Kumar and Benbasat 2006; Smith 2002; Alba et al. 1997). Specifically, an RA builds on the preference information elicited by users to filter product alternatives and propose suggestions to the users (Haübl and Murray 2003; Grenci and Todd 2002). For instance, Haübl and Trifts (2000) studied two aiding features of RAs: one that assists in screening alternatives and another that rearranges alternatives to make evaluation easier. They demonstrated that the provision of aid that supports screening and/or rearrangement of alternatives significantly improves the quality of the decision made. This view is supported by Montgomery and his colleagues (2004) who hypothesized that by reducing the cognitive effort associated with evaluating the alternatives, decision aids could substantially increase consumers' propensity to increase the search for more information and commit to purchases. Other studies have also reported similar findings (see Xiao and Benbasat 2007; Smith 2002).

Beyond articulating the benefits of having an RA to address information overloading problems, an increasing amount of literature has been devoted to extending the application of RAs to better support the consumer's decision-making process. For instance, extant studies have suggested that RAs could induce consumers to: 1) evaluate unfamiliar products together with the familiar, (Cooke, Sujan, Sujan, and Weitz 2002); 2) render an attribute more prominent by explicitly including it in the recommendation (Haübl and Murray 2003); 3) decrease price sensitivity by lowering the search cost for quality information (Diehl, Kornish and Lynch 2003); 4) help consumers to learn more about the product domain and better match their preferences by controlling the information flow (Ariely 2000); and 5) assist consumers to discover new products or generate demand for unfamiliar products through providing personalized offers (Tam and Ho 2005).

These studies collectively suggest the plausibility of equipping RAs to assist a consumer in: 1) acquiring knowledge about new products (i.e., product learning); and 2) articulating preferences (i.e., preference elicitation).

B.2.1 PRODUCT LEARNING

Studies related to product learning in an online context share the common objective of providing consumers with virtual product experiences that enable potential consumers to learn about a product (Li, Daugherty, and Biocca 2003). Such experiences could be built through the use of stimuli to induce desired product affordances, which in turn lead to better learning outcomes. Affordance is defined as a natural and intuitive set of rules that guide the manner in which consumers interact with products during pre-purchase inspection. Building on this definition, product affordance refers to the real and perceived cues that are available to direct consumers in interacting with a product during inspection (Norman 1998).

Applying this affordance concept to online shopping, a new form of affordance termed as virtual affordance is proposed (Li et al. 2003). Virtual affordance refers to the use of an online medium or stimuli to induce consumers to learn and gain knowledge about a product without having direct and/or physical contact with the product. To gain virtual affordance on the Internet, consumers can either access online consumer reports, which are mainly in descriptive text formats, or watch related online product review videos. A significant amount of extant literature on product learning focuses on comparing the effectiveness and impact of product learning across different modes, such as the text and video modes (e.g., Hoeffler and Ariely 1999; Bradley and Meeds 2004).

Traditional online product information is usually delivered in the form of text and image modes. However, with the increasing availability of broadband and more advanced streaming technologies, consumers now enjoy a much richer virtual experience, involving multi-sensory interactions, incorporating videos with high-density resolution visuals, stereo sound, and 3-D imagery. This study focuses on comparing the traditional form of product learning (i.e., through the text mode) and the more recent presentations (i.e., through the video mode).

In comparing the text and video modes, it is often posited that the video presentation mode can result in superior learning outcomes compared to equivalent text forms (Sweller 1994). The modality effects induced by video may lead to effective expansion of working memory which consequently results in better recall as well as better processing of intrinsic and extraneous information in product learning material (Chandler and Sweller 1991). The boom in online video consumer guides in the product review industry seems to affirm this inference. Increasing multimedia capability brought about by broadband has empowered the migration of Internet users' online learning experience from a text based and two-dimensional visual experience to a multimedia and three-dimensional interactive experience. For instance, CNET, one of the world's largest online review providers, now offers thousands of multimedia reviews produced by CNET editors on the latest technology and products and attracts more than 3 million unique visitors per month[4]. The immense success of CNET provides a compelling reason to investigate the future

[4] CNET's Expansion May Signal a Turnaround in Tech Journalism, http://www.ojr.org/ojr/glaser/1080709262.php (last visited: 24 March, 2007)

trend of online shopping if a proper alignment can be found between product learning and the RA websites.

While there is a wealth of studies indicating that video which offers vivid information is likely to attract greater attention and is thus more persuasive than pallid information, i.e., one that is text-based (e.g., Daft and Lengel 1986), it may not always yield positive outcomes. For instance, when a medium is too rich for a task (e.g. choice of product), consumers with an excessively rich presentation mode such as a video could be distracted by non-essential cues and information, leading to poorer learning performance (McGill and Anand 1989). Furthermore, it has been suggested that when people are able to process vivid and non-vivid information in detail, similar levels of attention can be devoted to message processing thus eliminating the vividness effect (Kisielius and Sternthal 1984).

Essentially, the comparison between the effects of providing product learning through text and video formats is inconclusive. Indeed, the discursive (symbolic or linguistic) information processing perspective (Foxall, Goldsmith, and Brown 1998), suggests that product learning should be designed to match the users' procurement goals through the support of cognitive elaboration (i.e., reading, interpreting and storing the product information in memory for future use), which could in turn yield favorable product learning outcomes. However, from the perspective of imagery information processing (Green and Brock 2002), an RA that evokes mental images (i.e., though video) could yield a more favorable product learning performance. While both forms of processing can be supported and can occur concurrently, the dominance of one over the other could vary depending on how it is used.

B.2.2 PREFERENCE ELICITATION

Preference elicitation support in extant RAs can be classified into two categories: attribute-based and need-based. The design of an attribute-based RA tends to align the product search criteria with names of common key features for the product category (e.g., optical and digital zooms for digital cameras). Consumer preference is assessed by analyzing the input value for each criterion. On the other hand, a need-based RA usually designs the product search criteria in accordance with the customer's common needs. The search criteria are usually presented in a question-and-answer format. The consumer's preferences are indicated by selecting the most suitable answers to the questions which are embedded in the description of a specific need.

Compared to an attribute-based RA, a need-based RA is able to link customers' personal needs to product attribute configurations, thus facilitating the customers' articulation of their information needs and making the need-based RA's rationale easy to understand (Komiak and Benbasat 2004). The extra facilitation and increased transparency will make the need-based RA more favorable to the consumer than the attribute-based RA. In addition, the need-based RA is more preferable to the attribute-based RA should a consumer lack knowledge of a particular product category, especially if one does not even understand the key features. Using the attribute-based RA in the latter case could turn out to be a very challenging task and hence the recommendation is unlikely to be accurate.

Existing literature on the preference for need-based RAs is advocated by various streams of research. Some focus on the nature of products, for example, Grenci and Todd (2002) suggested that compared to the attribute-based RAs, need-based RAs would be the preferred method especially for recommending a complex good or service. On the other hand, others focus on both the consumer's nature and prior knowledge (Grenci and Todd 2002; Felix, Niederberger, Steiger, and Stolze 2001). For instance, consumers may recognize the need to purchase a product; but they may not be able to determine the specific product features required. A need-based RA, which frames product features based on the needs instead of the values of attributes, is recommended as an effective solution in this situation (Grenci and Todd 2002). In addition, even if customers understand their need for certain attributes, they might not understand the process required to configure the correct solution or to make the best product choice (Grenci and Todd 2002). An example cited by Häubl and Murray (2003) is the configuration of inter-related attributes such the weight and durability of a backpacking tent. This argument accords with the findings of Stolze and Nart (2004). The authors observed that novice customers regard need-based RAs as more helpful than attribute-based RAs. Felix et al. (2001) also acknowledged that, for buyers with little product knowledge, it can be particularly problematic to use an attribute-based RA, if they desire to receive recommendations based only on their personal needs and expected uses of the product.

However, the findings of some empirical studies have produced inconsistent results and raise doubts concerning the common findings. In an experiment conducted by Felix et al. (2001), the authors observed that novice consumers who use need-based RAs are not significantly more satisfied than those who use attribute-based RAs. It appears that consumers may still prefer to manually check technical features in an attribute-based RA, even after receiving need-based or other types of recommendations (Spiekermann and Parachiv 2002).

B.3 THE COGNITIVE-EXPERIENTIAL SELF-THEORY

The Cognitive-Experiential Self-Theory (CEST) builds on the theorem that the human information processing system is dual in nature to hypothesize the relationship between the human processing system and behavior (Briňol, Petty and Wheeler 2006). The CEST posits that a consumer learns and constructs an implicit model of the world based on two distinct modes of information processing systems, namely the *experiential* and the *analytical* (Epstein 1991, 2003). The experiential processing system is based on the visual recognition of patterns or associations that are often formed with rudimentary and rapid processing. An individual who utilizes the experiential processing system often constructs product knowledge based on images, feelings and sensations. The analytical processing system, in contrast, is consciously directed and intense, often characterized by more deliberative and refined processing of information. An individual who activates the analytical processing system tends to gain an understanding of a product through symbols, words and figures. The CEST postulates that a consumer could utilize both processing systems (i.e., the experiential system enables a consumer to learn and think quickly and conceptually, while the rational processing system focuses on the details) concurrently under certain conditions. However, the impact on behavior could differ along a continuum and is influenced by the relative contribution of these two systems (Epstein 1991, 2003).

The CEST was first proposed and tested empirically by Epstein and his colleagues (Kirkpatrick and Epstein 1992; Epstein 1994; Morling and Epstein 1997; Pacini, Muir and Epstein 1998). They demonstrated that the distinction between the experiential and rational processing systems is useful for understanding a variety of human behaviors. For instance, these studies have applied the CEST to demonstrate and explain the existence of the two processing systems (Epstein, Lipson, Holstein and Huh 1992); to predict and identify the conditions in which individuals will prefer either self-enhancing or self-verifying feedback (Morling and Epstein 1997); and to compare the consequences, such as the probability of judgment errors (Epstein and Pacini 1999) and the choices made (Kirkpatrick and Epstein 1992), when adopting different processing systems.

In recent years, the CEST has been widely adopted by other researchers and applied in many psychology-related fields of study. For instance, it has been observed that: 1) when an experientially motivated individual is primed to think about his own death, he is more likely to be in agreement with having proper measures against terrorism when compared to a rationally motivated individual (Simon, Greenberg, Harmon-Jones, Solomon, Pyszczynski, Arndt and Abend 1997); 2) experientially motivated jurors have a tendency to award significantly lower damages to the plaintiff when the defendant is attractive as opposed to rationally motivated jurors (Lieberman 2002); and 3) when a consumer has limited processing resources, he would exhibit more affective reactions (i.e., experiential) compared to another consumer who has substantial processing resources, and would thus exhibit a rational reaction (Shiv and Fedorikhin 1999).

Despite the importance of the CEST in contributing to a better understanding of human behavior, no Information Systems (IS) study has yet applied this theory to evaluate the effects of decision aids on decision-making performance. There could be two plausible explanations for this. First, prior IS studies have traditionally referenced related human information processing theories (Eom 2003). They include: 1) the Cognitive Fit Theory developed by Vessey and Galletta (1991) which postulates that an individual's performance is the degree to which the problem representation matches the representation of the task; 2) the Information Processing Theory proposed by Miller (1956) which dictates that humans process information through various stages of information encoding, retention and retrieval by engaging short-term and long-term memories; and 3) the Social Cognitive Theory posited by Bandura (1986), which dictates that an individual's behavior is the result of the interaction between personal factors and his environment. Studies applying these theories generally conclude that: 1) decision supports could be designed to take advantage of the competencies of individuals while using decision supports to compensate for their weaknesses; and that 2) decision supports could be provided to induce desirable decision performance (Xiao and Benbasat, 2007; Montgomery et al. 2004; Whitecotton, Sanders and Norris 1998; Hoch and Schkade 1996).

A shortcoming of these studies is that they primarily anchor on general human psychology theories to evaluate decision supports; but seldom do these empirical studies (e.g., Hoch and Schkade 1996) delineate clearly the forms and types of processing systems within the human mind. The CEST complements the existing theories by explicitly building on the dual human information processing system paradigm (Gawronski and Vodenhausen 2006; Sloman 1996) to propose the presence of and to distinguish between two processing systems, which could be triggered depending on the type and form of information presented (Kirkpatrick and Epstein 1992; Epstein 1994). In relation to our study, we postulate that the provision of a product learning support could potentially trigger experiential or rational processing systems depending on whether video-based or text-based information is offered. Furthermore, the degree to which the preference elicitation mechanism triggers a similar processing system like in the provision of a product learning support could well determine a consumer decision-making performance. Essentially, the CEST offers us a concise theoretical underpinning and prediction on the influence of different decision supports on consumer decision making behavior and performance.

B.4 RESEARCH MODEL AND HYPOTHESES

In Figure 1, we seek to assess the impact of different product learning supports and preference elicitation supports on the propensity for purchase-avoidance and perceived decision confidence. The theory which guides our research consists of three propositions:

1. Where the provision of a product learning support induces the activation of the experiential processing system, consumers will experience a lower degree of learning difficulty;

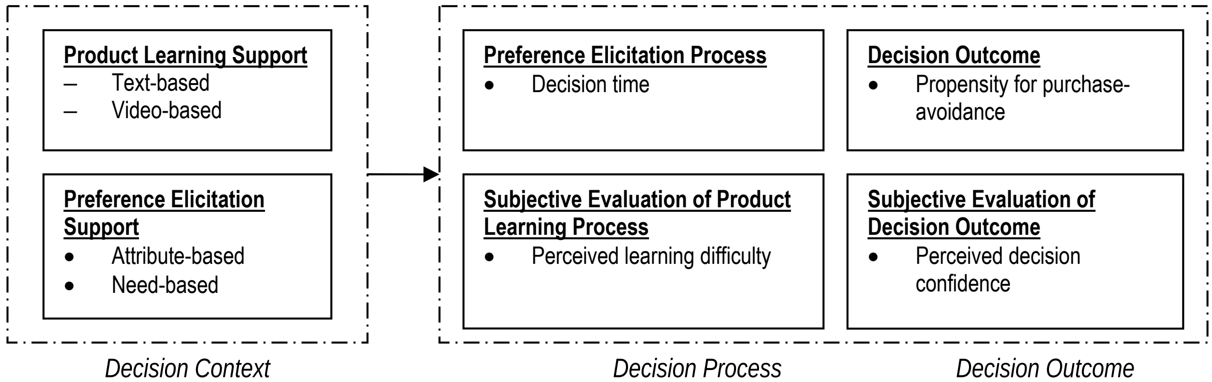
2. Where the provisions of the product learning support and the preference-elicitation support facilitate the consistent practice of one dominating form of processing system ,

(i.e., either the "experiential" or "analytical" system), a consumer will experience greater decision confidence and exhibit a lower propensity for purchase-avoidance; and

3. Where the provisions of the two supports lead to switching between the two processing systems, a consumer will experience a poorer decision performance.

In line with the taxonomy proposed by Lilien, Rangaswamy, Bruggen, and Starke (2004), we assess the decision performance of consumers who use decision aids based on two criteria — the decision process and the decision outcome — for which both objective and subjective evaluations are included. The decision process, which involves the use of both the product learning and preference elicitation supports to arrive at a decision, is characterized by product learning difficulty and decision time. Product learning difficulty is assessed by using the affective measure suggested as one of the three measures for product learning effectiveness (Mehta 2000). Preference elicitation supports help consumers to screen and evaluate product information and select their choices. Decision time is an important determinant for the performance of preference elicitation support since it is an objective indicator of the amount of effort exerted to process information before a decision is made (Payne, Bettmand and Johnson 1993). It should be noted that we evaluate the effects of a product learning support on perceived learning difficulty (perceptual); as well as the effects of a preference elicitation support on decision time (objective). Both measures reflect the level of cognitive difficulty of the decision-making process.

Figure 1: Research Framework



The joint influence of both the product learning and the preference elicitation supports is evaluated on two outcome measures: the propensity for purchase-avoidance and perceived decision confidence. According to extant literature, purchase-avoidance refers to the tendency of consumers to postpone commitment to a purchase or seek a less painful way out, which involves no action or no change, when faced with difficult decisions (Anderson 2003). However, our review of RAs indicates that most of the existing RA studies suffer from the assumption that consumers will ultimately commit a purchase from the given choice set. In many situations, however, consumers often have the option of seeking new alternatives (i.e., delay making a choice) and/or deciding whether to choose at all (Dhar and Nowlis 1999). Specifically, distress over the need to make an explicit selection could also result in a consumer halting a purchase. Such discontinuation of procurement directly threatens the existence of RAs. One of the contributions of this study is to complement prior studies by looking at the propensity for purchase-avoidance as an assessed consequence of the joint influence of the two RA aids.

B.4.1 EFFECTS OF PRODUCT LEARNING SUPPORT

We postulate that a video-based product learning support will generate greater effectiveness in product knowledge acquisition compared to a text-based product learning support, and consumers will hence report a lower degree of learning difficulty. This is because, according to the CEST, video-based information, which is sensory-based, could trigger an experiential processing system that generates primitive, schematic and conceptual processing (Kirkpatrick and Epstein 1992). Comparatively, text-based information requires an analytical processing system, which is associated with more refined, detailed and deliberative processing (Shiv and Fedorikhin 1999). Comparing the two information processing systems, a consumer who activates an experiential processing system, which is often related to lower-order processes, could experience a lower level of difficulty in absorbing the information since a primitive, affective-based understanding of the information is simply needed. In contrast, a rational processing system, which is associated with higher-order processes, could cause a consumer to experience a higher level of difficulty in comprehending the information as a more detailed understanding is required.

This view is in accordance with the Media Richness Theory that suggests that information (e.g. product learning supports) rich in multiple perceptual systems are better perceived than those which are perceived favorably in single or fewer perceptual systems (Daft and Lengel 1986). Consumers who experience a rich media product learning support (e.g. video) are more likely to be able to form an effective acquirement of product knowledge faster than those who experience a lean media product learning support (e.g. text). Similarly, the cognitive load theory suggests that a different modality will expand or reduce the working memory processing capacity, thereby enhancing or reducing the consumer's performance in product knowledge acquisition (Sweller, 1994). Specifically, a video-based product learning support combines both visual and auditory channels (i.e. dual-mode), and thus can allow a consumer to process the information more quickly (Mousavi, Low, and Sweller 1995).

Essentially, the modality effects induced by a video-based system may lead to the activation of the experiential processing system, and also an effective expansion of working memory, thus resulting in the quicker comprehension of the information as well as the better processing of intrinsic and extraneous information in product learning materials (Chandler and Sweller 1991). Consequently, participants who use a video product learning support are likely to report a lower level of learning difficulty due to an enhanced ability to handle information.

H1: Consumers with video-based product learning supports will perceive a lower level of learning difficulty compared to those with text-based product learning supports.

B.4.2 EFFECTS OF PREFERENCE ELICITATION SUPPORT

The difference between attribute-based RAs and need-based RAs lies in the way in which the preference elicitation questions are asked. Consumers using attribute-based RAs, articulate preferences by inputting the product attribute criteria. However, consumers using need-based RAs will articulate preferences by selecting the answers to the questions which are embedded in a description of a specific need. Compared to attribute-based RAs, need-based RAs can link customers' personal needs to product attribute configurations, thus facilitating the articulation of their information needs and enhancing the ease in understanding the rationale of need-based RAs. In this sense, using need-based RAs facilitates the preference elicitation process, thereby leading to a shorter decision-making time, compared to the use of attribute-based RAs.

However, it should be noted that preference elicitation is not a single-step decision-making process but rather, it is an iterative process of articulating preferences and evaluating alternatives presented. Particularly, product alternatives are often presented in an attribute-based format in most RA websites (e.g., digital cameras of optical zoom of 2x, 3x, 4x, 6x, 7x and above). Consumers using a need-based preference elicitation support are presented with the search criteria in a need-based question and answer format (Spiekermann and Paraschiv 2002) but the results are still presented in an attribute-based format. These consumers could require additional cognitive effort to switch between the two modes of processing. Nevertheless, consumers employing an attribute-based elicitation aid, are presented with the same information format (i.e., attribute-based) when articulating preferences and evaluating the results. According to the Cognitive Fit Theory, when there is a match between the task (i.e., to articulate preference in this case) and the presentation of information (i.e., to evaluate the result set), a cognitive fit will occur, which produces a consistent mental representation for problem-solving, and subsequently leads to faster and more accurate performance in decision-making (Hubona, Everett, Marsh, and Wauchope 1998; Vessey and Galleta 1991).

The comparative effects of the two preference elicitation supports on decision time can also be predicted through the CEST. Specifically, the need-based preference elicitation support builds on the proposition that preferences are often formed based on the needs instead of values of attributes and such formation often entails imagining the usage of the product (Grenci and Todd 2002). More elaborately, the use of the need-based preference elicitation support could primarily activate the *experiential* processing system to visualize the product and utilize the *analytical* processing system to complement the experiential processing system in articulating the details of how the product is to be used. The concurrent activation of both forms of processing systems is observed in many of the prior empirical studies (Briňol et al. 2006; Berger 2007) and highlighted explicitly by Epstein (1994, 2003). When two systems operate in parallel, with the experiential processing system dominating the analytical processing system, we posit that decision performance could be affected. Evidently, it is observed that imagination is a cognitive process that requires more cognitive effort from the consumer (Dahl and Hoeffler 2004) and is more timeconsuming than accessing memory directly for attribute values. As a result, a consumer is likely to spend more time on the need-based preference elicitation support.

H2: Consumers with an attribute-based preference elicitation support will take less time to make decisions compared to those with a need-based preference elicitation support.

B.4.3 JOINT EFFECTS OF THE PRODUCT LEARNING SUPPORT AND THE PREFERENCE ELICITATION SUPPORT

We postulate that a consumer could experience a greater degree of decision confidence and exhibit a lower propensity for purchase-avoidance when the provisions of the product learning support and the preference-elicitation support facilitate the consistent practice of one dominating form of processing system (i.e., the dominance of either the "experiential" or "analytical"). To fully understand this proposition, we examine the joint influences of product learning supports and preference elicitation supports in detail.

A consumer could trigger the usage of the experiential processing system with the presence of a video-based product learning support (H1), and the dominating practice of the experiential processing system with the use of the need-based preference elicitation support (H2). One common characteristic result of the use of the two types of decision supports is the heavy reliance on the usage of the experiential processing system, with the analytical processing system playing a secondary role. While it is plausible that both processing systems (i.e., both the experiential and analytical processing systems) could be activated concurrently (Strack and Deutsch 2004), it is understood from empirical evidence that a consumer's behavior and performance could be improved with the consistent adoption of a dominating processing system among the two. Specifically, when extensive context switching among the two processing systems occurs, a consumer could experience a greater demand for cognition to handle the activation and deactivation of the two processing systems within a short span of decision-making time. We will elaborate this point with further theoretical support.

When a consumer is presented with the video-based product learning support and the attribute-based preference elicitation support, he may not find the vividness of the product learning video to be useful. In the study by McGill and Anand (1989), for instance, the authors highlight that a consumer is likely to show more liking for vivid information than non-vivid information only when there is a need to visualize or imagine the use of the product. However, when the consumer is instructed not to imagine product usage, indifference to product preference is reported. Lim and Benbasat (2000) also found that multimedia representation led to a lower level of ambiguity of information only for the tasks in which the predefined response and/or knowledge needed is not clear (Daft and Macintosh 1981).

A similar scenario is likely in the use of the attribute-based preference elicitation support. Since the differences in attribute values directly indicate the different levels of functionalities and usages, consumers do not need to visualize the product usage in order to use attribute-based elicitation. If product learning is able to effectively educate consumers about the meaning of attribute values, then the attribute values can be self-explanatory and the comparison of product usage can be directly translated to comparison of attribute values in the attribute-based system. Hence, consumers may not feel that a video is superior compared to plain text when they use attribute-based elicitation. A supporting argument can be found in the study of Chewning and Harrell (1990) in which the authors argue that if a presentation mode is too rich for a choice task, it may not necessarily lead to effective communication due to the distraction of non-essential cues.

However, when a video-based product learning support is presented to a consumer with a need-based preference elicitation support, the presence of vivid information could facilitate the use of the elicitation aid since both require the consumer to imagine and visualize the usage of the product. Video as a rich medium should be able to facilitate the visualizing of the need when a consumer is using a need-based preference elicitation support. Thus, we postulate that the presence of both the video-based product learning support and the need-based preference elicitation support could help consumers to achieve the desired decision-making performance (Vessey and Galletta 1991). Likewise, the presence of both the text-based product learning support and the attribute-based preference elicitation support could induce a consumer to utilize lesser degree of cognitive effort to make procurement decisions. When consumers are able to make procurement decisions more easily, it is often observed that a lower propensity for purchase-avoidance and higher decision confidence could be yielded (Anderson 2003).

H3a(i): Compared with the use of the attribute-based preference elicitation support, the use of the need-based preference elicitation support will lead to a lower propensity for purchase-avoidance in the presence of video-based product learning support.

H3a(ii): Compared with the use of the attribute-based preference elicitation support, the use of the need-based preference elicitation support will lead to a higher propensity for purchase-avoidance in the presence of text-based product learning support.

H3b(i): Compared with the use of the attribute-based preference elicitation support, the use of the need-based preference elicitation support will lead to a higher decision confidence in the presence of video-based product learning support.

H3b(ii): Compared with the use of the attribute-based preference elicitation support, the use of the need-based preference elicitation support will lead to a lower decision confidence in the presence of text-based product learning support.

B.5 EXPERIMENTAL DESIGN

We employed a 2x2 full factorial experimental design to investigate the main and interaction effects of product learning supports and preference elicitation supports on consumer decision outcomes in the context of a multi-alternative, multi-attribute purchasing decision-making context (see Table 1 for the operationalization of the dependent variables). The experimental manipulations consisted of two types of product learning supports (text-based and video-based) and two types of preference elicitation supports (attribute-based and need-based).

Table 1. Operationalization of Dependent Variables

Dependent variable	*Operational measure*
Propensity for purchase-avoidance	Decision to procure (coded as 0) or not to procure (coded as 1).
Decision time	Time taken to make a decision.
Perceived decision confidence (Cronbach's Alpha = 0.90) *(Sources: Fitzsimons 2000)*	1. I believe I have made the best choices at this website. 2. I would make the same choices if I had to do it again. 3. I believe I have selected the best models for both products.
Perceived decision difficulty (Cronbach's Alpha = 0.95) *(Sources: Bottomley et al. 2000; Steenkamp and Van Trijp 1997)*	1. It is very difficult for me to derive the decision. 2. It is very hard for me to derive the decision. 3. It is not easy for me to derive the decision. 4. The decision making is thorny.

B.5.1 EXPERIMENTAL PROCEDURES

Our experiment drew the participation of 68 Information Systems (IS) undergraduate students in an open university. Among them, 26 (38.2%) were females and 42 (61.8%) were males. They were recruited by electronic mail and advertisements. Their average age was 22.07 (δ = 1.739) years. As part of their degree requirements and coursework, all participants had had web-surfing and computing experience. They were randomly assigned to each of the four treatments to minimize the effects of individual differences on the results. This resulted in 17 participants per treatment group. The participants were told explicitly that their task was to decide whether to procure and should one decide to procure, to select any of the alternatives they would like to have in five product categories. In order to ensure experimental realism, the participants were told that they would be paid a fixed participation fee. They were given monetary incentives consisting of $10.00 for an hour's work.

Each experimental session was conducted in the following sequence. Upon arrival, the participants were assigned to one terminal and logged in by using a unique account (according to the treatment group to which they belonged). Subsequently, the participants were asked to fill in demographic information, in particular, name, gender, age, etc. After submitting their demographic information, the participants listened to pre-recorded instructions and viewed illustrations that introduced them to the various system features as well as learned how to view the product learning support and use the online shopping website.

Participants were given the scenario of purchasing products for themselves or their best friends. They were presented with five product categories and were asked to decide whether to procure, and should a 'buy decision' be made, to select the best product from each product category. This setup was consistent with most experimental studies on information seeking and decision-making behavior (Haübl and Trifts 2000) and was necessary to induce mundane realism[5]. The five product categories were: baby strollers, baby car seats, Global Position System (GPS) units, digital camcorders, and multimedia projectors. To meet the basic purpose of product learning, the

[5] Mundane realism refers to the degree to which the experiment resembles real-life application of the decision aids (Neuman 2006).

products were not supposed to be familiar to the participants. Our choice of the product categories was supported by the results of a pre-test conducted on 20 students who were told to rank the level of familiarity of over 40 products listed in the RA websites. To further ensure that the five product categories were less familiar to the participants, they were asked to rate their level of product knowledge on a 7-point Likert scale. The results confirmed our supposition that the participants were not familiar with the products (mean = 2.87 out of highest 7, $\delta = 1.30$). Real product data was used in this experiment. All product information was gathered from mySimon.com using a self-developed web crawler in the month of January 2007.

Two types of product learning supports were used in this experiment: text-based and video-based. The text-based product learning support introduced each product category according to the key features of the products in that product category. To ensure that only the vividness aspect of the information was altered in the video, two measures were taken. First, all the five videos were self-produced to minimize the differences in the contents of the products. Second, all the videos were created using semantically identical text-based product learning scripts (Lim and Benbasat 2000). Each video lasted about 3 to 5 minutes. Participants were able to fully control the video with functions provided by the embedded player, i.e., pause, rewind, forward, and restart.

Then, the participants were presented with input parameters to enter the weights (seven levels: from "Least important" to "Most important") for different attributes (for the attribute-based support) or needs (for the need-based support). Each input parameter had 3 to 7 options, which were the values of the product-attribute for the attribute-based preference elicitation support or the indications of the needs for the need-based preference elicitation support. The participants were not required to complete all the parameters. The screening algorithm was based on the weighted-additive (WADD) decision strategy, i.e., strategy that computes a weighted score for each alternative based on the input attribute importance by which the alternatives among the highest scores are selected (Payne et al. 1993). The system then used the inputs to calculate a score according to the specified weight of each selected attribute, and compared that score against the scores computed for each product in the database. All products with scores equal to or higher than the elicited score were presented to the participant. The order of the alternatives was deliberately randomized. The rationale was to encourage the participants to be more involved in the experiment by scanning through the list and selecting the best product according to their indicated preferences. During this process participants would need to reconsider the preferences and articulate them in more detail in order to shorten the list. Though the phrasing of each search criterion was different, every need-based elicitation question was mapped to only one corresponding product attribute and vice versa. When he was satisfied, the participant made a choice of whether to make a purchase or not.

B.6 RESULTS

Individual characteristics such as age, gender, experience and the skills of participants that could potentially affect decision-making and its outcomes were controlled by randomization. Further control checks indicated no significant difference for participants in all four treatments in terms of gender, age, and online buying experience. F-tests indicated no significant difference for participants in all four treatments in terms of age ($F = 1.053$, $p > .10$) and online buying experience ($F = 1.527$, $p > .10$). There was also no significant difference in the gender ratio of participants across the treatments as indicated by a Kruskal-Wallis test ($\chi = 3.451$, $p > .10$). Control over participant characteristics through randomization appeared successful.

Manipulation checks were also conducted to ensure that our manipulation of the product learning support and the preference elicitation support were successful. Product learning support manipulation was verified by asking the participants to rate on a 7-point Likert scale how well they could understand what the product was all about from the way in which the information was provided. A non-parametric Mann Whitney U test comparing the mean ratings obtained for providing text-based (mean=4.320, δ=1.273) and video-based (mean=4.970, δ=1.141) product learning supports yielded a significant result ($Z = -2.102$, $p < 0.05$). A preference elicitation support manipulation check was also conducted by asking the participants to rate on a 7-point Likert scale how well individual participants were able to define the criteria when compared to an open-ended method of defining the search criteria (e.g., which were the attributes that were important to them). A non-parametric Mann Whitney U test comparing the mean ratings obtained for providing attribute-based (mean=5.45, δ=0.99) and need-based (mean=5.00, δ=1.09) preference elicitation supports yielded a significant result ($Z = -2.044$, $p < 0.05$).

B.6.1 HYPOTHESIS TESTING

Table 2 depicts the descriptive statistics. All statistical tests were conducted at a five-percent level of significance. To control for the possible influence of the decisional sequence (i.e., the order in which product categories are displayed), product type, risk propensity, level of involvement, and product knowledge on dependent variables, as well as the Multivariate Analysis of Covariance (MANCOVA), logistic regressions, and Analysis of Covariance (ANCOVA) were all used to assess the effects of manipulated variables, (i.e., product learning support and preference elicitation support,) on decision process measures (i.e., perceived learning difficulty and decision time) and on the propensity for purchase-avoidance and perceived decision confidence.

Table 2. Means (Standard Deviations) of Dependent Variables

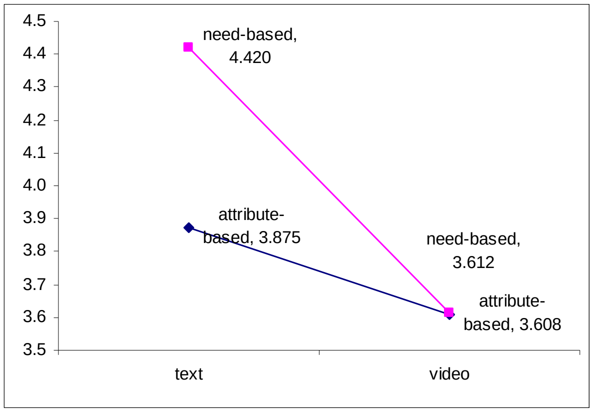
Manipulation		Decision Performance				
Product learning support	*Preference elicitation support*	*Process measures*		*Outcome measures*		
		Perceived learning difficulty	*Decision time (seconds)*	*Propensity for purchase-avoidance*		*Perceived decision Confidence*
				Choice made	*Choice not made*	
Text	**Attribute**	**3.875 (1.500)**	**246.890 (184.785)**	**80**	**5**	**5.251 (0.977)**
	Need	**4.420 (1.184)**	**301.560 (180.409)**	**77**	**8**	**4.722 (0.943)**
	Total	**4.147 (1.375)**	**274.230 (184.121)**	**157**	**13**	**4.986 (0.993)**
Video	**Attribute**	**3.608 (1.442)**	**210.620 (130.582)**	**68**	**17**	**4.949 (1.337)**
	Need	**3.612 (1.447)**	**269.460 (157.485)**	**81**	**4**	**5.318 (0.783)**
	Total	**3.610 (1.440)**	**240.040 (147.218)**	**149**	**21**	**5.133 (1.108)**
-	**Attribute**	**3.741 (1.473)**	**228.760 (160.555)**	**148**	**22**	**5.100 (1.177)**
	Need	**4.016 (1.379)**	**285.510 (169.599)**	**158**	**12**	**5.0196 (.914)**

Before conducting the MANCOVA test, we needed to perform three tests on the data. First, we examined the normality of the three dependent variables, namely perceived learning difficulty, decision time and perceived decision confidence. The propensity for purchase-avoidance was not inspected due to its binary nature. Normality tests included the skewness and kurtosis tests. Our tests suggest that perceived learning difficulty (Skewness Z = -.034; Kurtosis Z = -.734), decision time (Skewness Z = 1.424; Kurtosis Z = 2.749), and perceived decision confidence (Skewness Z = -.759; Kurtosis Z = 1.859) have skewness and kurtosis values near the normal range of -3 to 3, which are deemed acceptable (Hair, Anderson, Tatham and Black 1998). Second, we used Bartlett's test for sphericity, which examines the correlations among the three dependent variables (i.e., perceived learning difficulty, decision time and perceived decision confidence) and determines whether significant intercorrelation exists. The results indicated the existence of significant intercorrelations (χ^2 = 5379.339, $p < .01$). Third, we tested whether the data conformed to the assumption of the homogeneity of the variance-covariance matrices among the groups. Bartlett-Box's M test, which focuses on assessing the overall equivalence of the variance-covariance matrices, was adopted. A significant Box's M value of 73.411 ($p < .01$) suggested that it was appropriate to conduct the MANCOVA test.

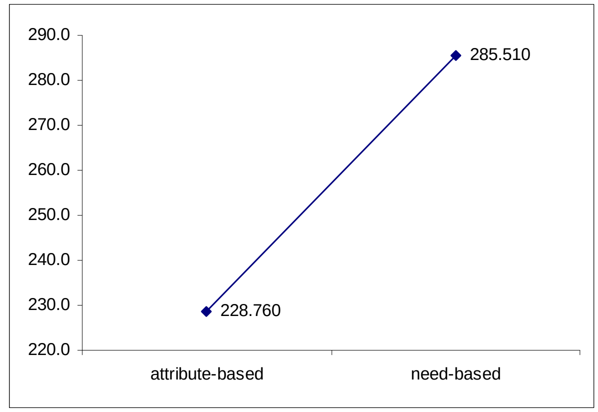
MANCOVA testing involving all independent variables and three dependent variables were then applied to assess hypotheses H1, H2 and H3b. The results revealed significant main effects for the product learning support (Wikes' Λ = 0.970, F = 3.332, p < 0.05) and the preference elicitation support (Wikes' Λ = 0.971, F = 3.249, p < 0.05), and significant interaction effect for the product learning * preference elicitation supports (Wikes' Λ = 0.945, F = 6.362, p < 0. 01). It was also observed that control variables, such as risk propensity, level of involvement and product knowledge, were found to significantly influence the dependent variables.

Further univariate tests using ANOVA were conducted separately for each of the three dependent variables by controlling for product type, risk propensity, level of involvement, and product knowledge. The effects of the manipulated variables on the propensity for purchase-avoidance were examined separately using logistic regression. Table 3 summarizes the test results and Figure 2 depicts the graphical analysis of the decision support impacts. An examination of the psychometric properties of the perceived learning difficulty and perceived decision confidence scales used in the survey yielded Cronbach's Alpha values of 0.95 and 0.90 respectively, which are well above the recommended threshold value of 0.7 (see Table 1). We observed significant main effects of the product learning support on perceived learning difficulty and the propensity for purchase-avoidance and of the preference elicitation support on decision time, as well as the significant interaction effects on perceived learning difficulty, the propensity for purchase-avoidance and perceived decision confidence. Each of the significant interaction effects was further examined using the method of simple effects analysis (Keppel 1991). Table 4 presents the results of the simple effects analysis.

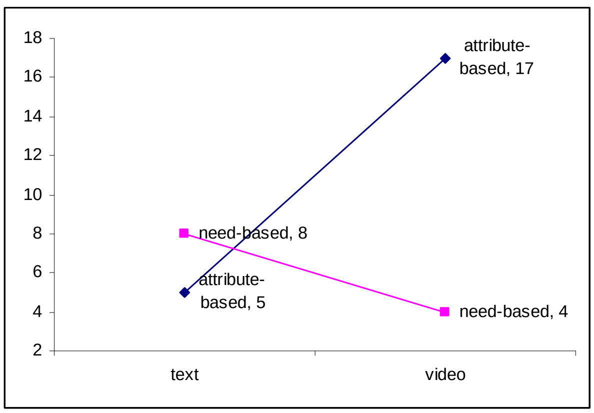
Figure 2. Graphical Analysis Of The Impacts Of Decision Supports



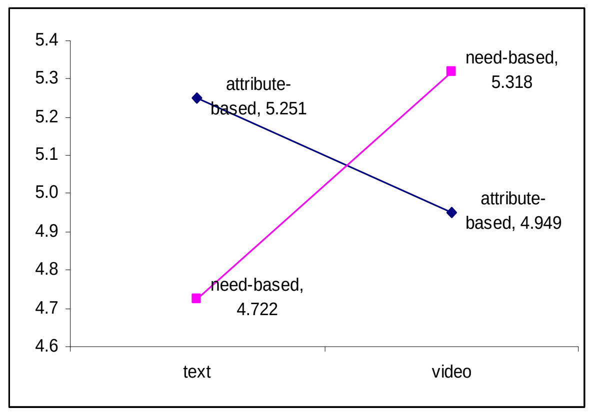
Perceived learning difficulty



Decision time



Propensity for purchase-avoidance
(no. of participants who did not choose any alternative)



Perceived decision confidence

Table 3. Univariate (ANCOVA) and Logistic Regression Tests

Source of variation	*Decision Performance*			
	Decision difficulty		*Overall outcome*	
	Perceived learning difficulty	*Decision time (seconds)*	*Propensity for purchase-avoidance*	*Perceived decision confidence*
Manipulation variables				
Product learning support	**F = 9.607*****	**F = 1.541**	**b = 1.746*****	**F = 1.050**
Preference elicitation support	**F = 1.744**	**F = 9.343*****	**b = .547**	**F = .009**
*Product learning support * Preference elicitation support*	**F = 8.196****	**F = .001**	**b = -2.675*****	**F = 18.036*****
Controlled variables				
Product viewing sequence	F = .074	F = 5.950**	**b = .272***	F = .969
Product type (car seat)	F = 1.100	F = .206	**b = .361**	F = .123
Product type (camcorder)	F = .031	F = 3.837*	**b = -1.201**	F = .119
Product type (projector)	F = .961	F = .313	**b = .367**	F = .708
Product type (GPS)	F = .815	F = 1.149	**b = -.784**	F = 1.564
Risk aversion propensity	F = .986	F = 10.816***	**b = .335**	F = 2.514
Perceived level of involvement	F = 4.492**	F = 5.477**	**b = .224**	F = .336
Perceived product knowledge	F = 9.683***	F = .765	**b = -.635**	F = 8.174***

**** - significant at 99% level; ** - significant at 95% level; * - significant at 90% level*

Table 4. Simple Effect Analyses of Product Learning Support * Preference Elicitation Support

Dependent variable	Data Split by product learning support			
	Text-based		Video-based	
	Hypothesis	Result	Hypothesis	Result
Attribute-based (AB) vs. Need-based (NB)				
H3a: Propensity for purchase-avoidance	**NB > AB**	**t = -.863, p > .10** Not Supported	**NB < AB**	**t = 3.097, p < .01** Supported
H3b: Decision Confidence	**NB < AB**	**t = 3.595, p < .01** Supported	**NB > AB**	**t = -2.194, p < .05** Supported

H1 posits that users with the video-based product learning support will perceive lower levels of learning difficulty compared to those with text-based product learning support. As predicted, we observed a significant main effect of product learning support and an interaction effect on perceived learning difficulty. Comparing the means of perceived learning difficulty, we observed that text-based product learning support users reported greater perceived learning difficulty than those with the video-based product learning support (i.e., main effect: $mean_{text} = 4.147$, $mean_{video} = 3.610$; $t = 3.518$, $p < .01$). Hence, H1 is supported. The significant interaction effect is further analyzed using the simple effects analysis. Two observations were made. First, in the presence of the need-based preference elicitation support, users with text-based product learning support experienced significantly higher perceived levels of learning difficulty compared to those with video-based product learning support (i.e., $mean_{tneed,text} = 4.420$, $mean_{need,video} = 3.612$; $t = 3.983$, $p < .01$). Second, in the presence of the text-based product learning support, participants with the need-based preference elicitation support reported significantly higher levels of perceived learning difficulty than those with attribute-based preference elicitation support (i.e., $mean_{need,text} = 4.420$, $mean_{attribute,text} = 3.875$; $t = -2.630$, $p < .01$).

H2 hypothesizes that users with attribute-based preference elicitation support will take less time to make decisions compared to those with need-based preference elicitation support. As predicted, the results suggest that attribute-based preference elicitation support users expend less decision time (in seconds) compared to others (i.e., main effect: $mean_{attribute} = 228.760$, $mean_{need} = 285.510$; $F=9.343$, $p < .01$). Hence, H2 is supported.

H3a denotes that compared to attribute-based preference elicitation support users, need-based preference elicitation support users will exhibit a lower propensity for purchase-avoidance in the presence of video-based product learning support but not in the presence of text-based product learning support. The results show that participants with need-based preference elicitation support did significantly exhibit a lower propensity for purchase-avoidance compared to those with attribute-based preference elicitation support in the presence of video-based preference elicitation support ($t = 3.097$, $p < .01$); but they did not perform significantly better than attribute-based preference elicitation support participants in the presence of text-based preference elicitation support ($t = -.863$, $p > .10$), although the effect was in the right direction. Hence H3a(i) is supported but not H3a(ii). However, as predicted in H3b, participants with need-based preference elicitation support expressed a significantly greater perceived decision confidence than others with attribute-based preference elicitation support when using video-based product learning support ($t = -2.194$, $p < .05$) but perceived lower decision confidence than attribute-based preference elicitation support users when using text-based product learning support ($t = 3.595$, $p < .01$). Hence, H3b(i) and H3b(ii) are supported.

B.7 DISCUSSION

The purpose of this study was to examine the influence of a Web store's provision of product learning support on a consumer's perception of the decision-making process and its outcome, by means of providing text-based and video-based product reviews, and preference elicitation support, as executed in the forms of attribute-based and need-based product preference elicitation mechanisms. Based on prior work on the Cognitive-Experiential Self-Theory (CEST) by Epstein and his colleagues (Kirkpatrick and Epstein 1992; Epstein 1994; Morling and Epstein 1997; Pacini et al. 1998), the primary proposition was that under conditions where the consumer is induced to adopt a dominating processing system (i.e., whether the experiential or analytical), he is more likely to choose a product and thus expresses a higher decision confidence. This shall be discussed at a later stage, after we have examined two additional propositions that were made: one relating to the mode of product learning support and the other relating to the provision of preference elicitation support.

With respect to the investigation on the product learning support, our results suggest that participants with text-based product learning support reported a higher level of perceived difficulty in learning about a product than participants with video-based product learning support did. To investigate further, we asked the participants to articulate the number of attributes (for the text-based condition) or features (for the video-based condition) of the products encountered. The findings suggest that participants with text-based product learning support reported fewer attribute recalls (mean = 2.60, δ = 1.81) than participants with video-based product learning support (mean = 3.31, δ = 1.85). These results could suggest that the introduction video in the product learning support could facilitate the construction of a mental schema of a product. By learning about a product through a video, a consumer is able to retrieve more information about the product when prompted to recall about the product. This coincides with the observation on the deployment of experiential processing system postulated by the CEST (Epstein 1994).

Based on the initially-built impression of the various product attributes, a consumer proceeds to the second stage: cross-attribute processing and linking. At this stage, a consumer will combine constituent product attributes to form a conjunction of features known as the master map of locations. Such a map allows a consumer to “activate” a particular node within the map. Explicitly, when a consumer learns about a product through a video, he/she could be easily “triggered” to extract stored product feature information and associated preferences. Essentially, the extent to which a consumer initially forms an impression of the various product attributes and features and subsequently links up all these features into a cognitive map for retrieval , (i.e., activates the experiential processing system), determines the outcome of learning about (i.e., stored in memory) and visualizing (i.e., retrieved from memory) a product.

With respect to the study of the preference elicitation support, we asked how the use of attribute-based and need-based preference elicitation supports would affect the decision-making time. Prior research on comparing need-based and attribute-based preference elicitation supports suggests the use of a need-based preference elicitation tool is likely to lead to better decision performance (Stolze and Nart 2004; Grenci and Todd, 2002). Our findings indicated that participants with the attribute-based preference elicitation support expended less time on decision-making compared to those with the need-based preference elicitation support when appropriate product learning support was offered (i.e., text-based support). One plausible reason is that participants might need to expend additional cognitive effort to switch between need-based elicitation of preference and attribute-based comparison of the alternatives retrieved (Spiekermann and Paraschiv 2002). From the theoretical perspective of the CEST, we find support for the argument that the use of the need-based preference elicitation support could primarily activate both the experiential and analytical processing systems. When two systems operated in parallel with the experiential processing system dominating the analytical processing system, our participants experienced longer decision-making times.

Our last and most important research question is how the different combinations of product learning supports and preference elicitation supports affect decision outcome (i.e., the propensity for purchase-avoidance and decision confidence). The results from the experiment suggest that the joint presence of both the video-based product learning support and the need-based preference elicitation support leads to a lower propensity for purchase-avoidance compared to the presence of a video-based product learning support and attribute-based preference elicitation tool. Likewise, the presence of the text-based product learning support and the attribute-based preference elicitation support leads to a higher perceived decision confidence compared to the situation where an RA is equipped with the text-based product learning support and the need-based preference elicitation support.

Before we discuss the study's implications, readers should be cautioned about the limitations of this research. First, our experimental task has focused on the decision choice for less familiar products. While we believe the participants were less familiar with both products, and extra effort was devoted to describing and explaining product attributes prior to the experiment, some student participants might have had trouble comprehending the given task. To the extent that the nature of the products could affect the willingness and involvement level of decision-makers in task execution (Swaminathan 2003), further experiments could be conducted to examine the impact of other more familiar products (e.g., digital cameras) on decision performance.

Second, in a real online shopping environment, consumers may first proceed to explore the products available rather than start with utilizing the product learning support. In this sense, the use of the preference elicitation support precedes the use of the product learning support. It is plausible that the change in the sequence of aids used could affect the results (Vessey and Galletta 1991). Future research could seek to explore this outcome.

Third, this study has examined RAs in the context of goal-driven settings. An examination of other task environments, decision contexts, and individual characteristics would also be valuable. For instance, factors such as consumer characteristics (e.g., window shoppers versus goal-driven buyers), amount of risk (e.g., decision accountability) and incentives (e.g., decisions on high risk products with high returns such as shares versus low risk products with low returns such as government bonds) associated with the purchase, decision confidence, and trust in the integrity of the aid, could all alter the results (Payne et al. 1993). Future studies could seek to examine the effects of these contextual factors on the design of an RA.

In spite of the limitations that serve as suggestions for future research, this study offers several contributions. First, this study draws from the CEST (Epstein 1991, 1994, 2003) to examine RA tools and distinguish differences among them. This study thus contributes to the existing decision support literature (Todd and Benbasat, 1999) by embedding the supports for product learning and preference elicitation within RAs, and examining how these tools help consumers to make procurement decisions. Specifically, our results suggest that where the provisions of the product learning support and the preference-elicitation support facilitate the consistent practice of one dominating form of processing system, a consumer will experience higher decision confidence and exhibit a lower propensity for purchase-avoidance; otherwise, decision outcome is adversely affected. This finding also adds to the CEST by indicating that the concurrent activation of two processing systems (though plausible and often occurring) could have an adverse impact on the consumer decision-making process.

Second, this study differs from and complements prior RA studies. Previous research has investigated decision supports that help individuals to process and filter the vast amount of available information to make an informed decision (Komiak and Benbasat 2006; Eom 2003;

Edwards and Fasolo 2001). For instance, studies such as Häubl and Trifts (2000) focused on one aspect of an RA that reduces the cognitive load of evaluating the product information. Our study ventures one step forward by asking how RAs can be designed to aid consumers in learning about a product and eliciting preferences. In our view, this research could offer tangible recommendations on what decision support tools should be offered toward the design of RA websites, and decision-aided websites in general.

Third, through referencing the commercial implementations from leading RA-equipped websites to develop the IT artifacts and empirically assess them (Kumar and Benbasat 2006), we have provides empirical support to a conjecture: with the increasing popularity of online user-generated product review videos (e.g., ExpoTV and YouTube) and new product introduction videos generated by experts (e.g., CNET), existing RA implementations, which are attribute-based, could be fine-tuned to cater to consumers who form initial knowledge of a product through videos. We have further added that the provision of need-based preference elicitation support in addition to video-based product learning support could alleviate a consumer's propensity for choice avoidance. Our study hence can offer some insights into how different forms of preference elicitation supports could be offered by RAs depending on the type of product learning supports (i.e., text-based or video-based) available.

B.8 CONCLUSION

As computer and Internet penetration intensifies inexorably around the world (especially in China, India and emerging economies), electronic commerce has the potential to grow exponentially. For instance, it is projected that sales from China's electronic-commerce alone may reach USD2.5

billion by 2010, which is more that triple that of 2006[6]. With introduction of more advanced in Internet technologies such as Web 3.0, decision aids have perhaps the greatest potential to facilitate and realize this growth in electronic commerce. However, without a careful understanding of how these decision aids are utilized during the decision-making process, it is plausible that the growth may be stunted or remain lackluster at best. This study took a modest step toward developing a theoretically sound understanding of how decision aids, implemented as product learning and preference elicitation supports, affect consumer decision-making and performance, and in doing so, we hope to help online merchants and consumers gain maximum value from electronic commerce, and thereby contribute to its growth.

6 Source: http://seattletimes.nwsource.com/html/businesstechnology/2003735845_amazon06.html [last visited: June 29, 2007]

C. ESSAY TWO
ASSESSING SCREENING AND EVALUATION DECISION SUPPORT SYSTEMS: A RESOURCE-MATCHING APPROACH

C.1 INTRODUCTION

In essay One, we discuss on equipping RA with product learning and preference elicitation supports. Such supports could assist consumers to be cognizant with the products of interest as well as the ability to articulate the preferences. Despite such decisional supports, little is studied on how to better aid consumers in scanning and evaluating the product alternatives returned. It is to be noted that RA is a unique online decision aid in which it assists consumers from acquiring necessary knowledge about the desired products to evaluating the products. Most of the online decision aids are mainly restricted to screening and evaluation supports, which we will study in detailed in Essay Two here.

Firms keen on exploiting the growing markets associated with electronic commerce[7], have begun to provide a variety of online decision aids to facilitate consumer decision-making (Redmond 2002). These online decision aids vary in sophistication and features, with some providing only basic screening support and others more complex screening and evaluation support (Xiao and Benbasat 2007; Haübl and Trifts 2000). While these aids have been gaining acceptance among consumers[8], there are still a number of behavioral concerns associated with how they are utilized (Montgomery, Hosanagar, Krishnan and Clay 2004). For instance, it is not entirely clear in what fashion

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[7] The U.S. Census Bureau's Quarterly Retail E-Commerce Sales reported that e-commerce sales for the fourth quarter of 2005 were $22.9 billion, 23% higher than the fourth quarter, 2004 sales of $18.4 billion.

[8] In a survey (source: Web Search Guide Newsletter, Comparison Shopping on the Web, by Harris, Gwen, November 29, 2003, Last visit: June 28, 2007) conducted by Nielsen/NetRatings, almost one third of all online consumers used decision aids, such as comparison shopping agents, to shop in the 2003 holiday season. In another survey (source: CMP TechWeb, Online Marketing Heats Up Holiday e-Retailing, October 4, 2006, Last visit: June 28, 2007) conducted

consumers will use these aids under varying information load environments, and how such use will affect performance.

Two fundamental issues associated with the existing decision aids literature contribute to this lack of understanding. First, extant decision-aiding literature has produced mixed and conflicting findings. Some have found that these aids extend decision-makers' cognitive capacities to analyze the problems in greater depth and scope, hence resulting in better decision outcomes (e.g., Song, Jones and Gudigantala 2007; Hostler, Yoon and Guimaraes 2004), while others have noted that these aids induce effort minimization and cognitive laziness, resulting in the blind acceptance of satisfactory outcomes (e.g., Glover, Prawitt and Spilker 1997; Skitka, Mosier and Burdick 1999). One plausible reason for the mixed findings could be attributed to the differences in the design of these artifacts. Many studies do not clearly delineate the specific design functionality that influences decision performance, making it difficult to attribute decision performance to the specific features of the decision aids. Second, there is a paucity of research comparing the use of decision aids under varying information environments. In addition, most previous research efforts on decision aids generally have not considered the match between the cognitive resources that are demanded for the task and the support provided by the decision aids.

In response to these two concerns, we examine the effectiveness of three online decision support features in terms of their influence on decision performance under varying information load environments. We do this by investigating how different degrees of screening and evaluation support features will affect perceived and objective decision performance under high and low information load conditions. Specifically, we provide consumers with one of three decision support

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by BizRate, 97.4% of 80 online retailers interviewed indicated that they would invest in decision-aiding technology, tools - a single-attribute screening tool, a multiple-attribute screening tool or a multiple-attribute screening cum weight computation evaluation tool - to identify and select a best product alternative under either a low product attribute-load or a high product attribute-load condition. We investigate this problem by drawing on the *resource-matching theory* (Anand and Sternthal 1989) to posit that decision performance is enhanced when the supply of cognitive resources available for information processing matches, rather than either exceeds or falls short of, those that are required to perform the decision task in a way that enables consumers to achieve their goals.

In this study we focus on *attributes* rather than alternatives when characterizing information load. This is because most prior IS research that has examined the impact of decision aids on decision performance, manipulated information load by a change in the number of *alternatives* available to choose from (e.g., Todd and Benbasat 1999, 2000), and not by a change in the number of *attributes* used to describe the alternatives. Our focus on attributes serves to complement the existing studies on information load (Todd and Benbasat 1999, 2000) as well as aligning our study to the online shopping context where consumers often delineate their preferences in terms of product attributes, such as what threshold values to specify or what weights to assign to each attribute, when using online decision aids (Haübl and Trifts 2000). For instance, in a comprehensive review of the existing studies on Recommendation Agents (RA), an online decision aid, Xiao and Benbasat (2007, table 5, pp. 146) identified three general forms of RA implementations based on product attributes (e.g., compensatory versus non-compensatory). Furthermore, the number of alternatives in an online environment tends to be very large, which makes it more challenging for consumers to immediately engage in alternative-based evaluation

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such as comparison shopping agents, to attract more online sales during the 2006 holiday season.

(Swaminathan 2003) without first conducting some attribute-based eliminations and repeat such attribute-based eliminations until the resulting number of alternatives after screening is deemed to be small and manageable.

Essentially, by focusing on the *interaction effects of the specific decision support and the product attribute-load* on decision performance, we seek to provide a more nuanced theoretical understanding of the impact of decision aids in an online consumer decision-making environment.

C.2 RESOURCE-MATCHING PERSPECTIVE ON DECISION-AIDING

Resource-matching theory explains the effects of utilizing cognitive resources to process information for a given task. It states that judgments are affected by the balance between the cognitive resources available to process the information and those required for the task (Anand and Sternthal 1989). Processing should be most efficient and effective when the level of supplied cognitive resources matches the mental resources required for a task, i.e., when RA = RD (Mantel and Kellaris 2003). Conversely, it is predicted that decision performance will decline when the cognitive resources available either exceed or fall below the mental resources required, i.e., when RA ≠ RD (Anand and Stemthal 1989). This theory has been applied and tested in the context of promotional stimuli, where an explicit inclusion and reordering of visual cues (e.g., narration and pictures) were found to enhance the persuasiveness of an advertisement through bridging the cognitive distance between the resources demanded and resources available (Brennan and Bahn 2006; Martin, Sherrard and Wentzel 2005; Meyers-Levy and Malaviya 1999).

However, despite the increasing use of the resource-matching theory in the advertising context, no Information Systems (IS) study has yet applied this theory to evaluate the effects of decision aids on decision-making performance. Prior IS studies have referenced two closely related theories that share the same notion of "fit" as the resource-matching theory does (Eom 2003). They are: 1) the *cognitive fit theory*, which posits that decision performance improves when the problem representation and the decision aid(s) promote a consistent mental representation for decision-making (Vessey 1991); and 2) *task-technology fit*, which posits that decision performance is enhanced when the functionality of a decision aid matches the task as well as the ability of the decision-maker (Goodhue and Thompson 1995). Both these theories have been applied to study a wide variety of technologies such as virtual team communication (Maruping and Agarwal 2004) and mobile computing (Junglas and Watson 2003), and to measure the performance impacts of consumers' search for product information (e.g., Hong, Thong and Tam 2004). While these theories have merit, they primarily focus on postulating the outcome of an ideal-fit (i.e., RA = RD) condition but do not provide predictions concerning the two no-fit conditions, namely, the cases of under-fit and over-fit (Junglas and Watson 2003). The resource-matching theory compensates for this limitation in the cognitive fit theory and the task-technology fit paradigm by offering more detailed and systematic predictions about the under-fit (i.e., RA < RD) and over-fit (i.e., RA > RD) conditions in addition to the ideal-fit situation. Furthermore, the resource-matching theory is applicable to the online decision-aiding context because Decision Support Systems (DSS), if provided appropriately, could be used to match the working memory and computational capacities of humans (i.e., resources available) to the needs of the decision environment (i.e., resources required) by increasing or decreasing the information processing capacity of a consumer (Eom 2003; Sharda, Barr and McDonnell 1988; Todd and Benbasat 1999). We will next review some of the key DSS studies through the theoretical lens of resource-matching.

There is no dearth of empirical evidence demonstrating that the right combination of decision tools and decision-making outperforms unaided humans (Lilien, Rangaswamy, Bruggen and Starke 2004). For instance, Haübl and Trifts (2000) examined two aids: one that assists in screening alternatives and one that rearranges alternatives to make the evaluation of alternatives easier. Their study found that the provision of an aid that supports screening and/or rearrangement of alternatives significantly improves the quality of the decisions made. A more recent study by Montgomery and his colleagues (2004) showed that by reducing the cognitive effort associated with evaluating the alternatives, decision aids induce consumers to search for more information and commit to purchases. Using the resource-matching theoretical lens, we proffer that the provision of appropriate decision aid that supplements the cognitive resources of the consumers to match those required to accomplish the decision choice task (i.e., RA = RD), would lead to a better decision outcome.

Conversely, according to the resource-matching theory the provision of a decision aid that is overly sophisticated and affords excessive cognitive resources for a given task (i.e., RA > RD) could result in two possible outcomes: 1) the decision maker employs the surplus resources to engage in idiosyncratic and less task-related elaboration of the decision-making issues, leading to poorer decision performance (Anand and Sternthal 1989; Keller and Block 1997), or 2) the abundance of cognitive resources may result in decision makers being more inclined to exhibit cognitive laziness by blindly following the decision aid's recommendations (Chenoweth, Dowling and Louis 2004). For instance, in a study that compared the decision outcomes between the provision of non-automated aid and automated aid, users with the automated aid underperformed in terms of the number of decision errors compared with those with a non-automated one (Skitka et al. 1999). Similarly, contrary to expectations, interactive (user-inputted attribute importance weights) decision aids were found to lead to lower decision quality than passive (using equal attribute importance weights by default) decision aids (Olson and Widing 2002).

In the same vein, when cognitive resources are insufficient to meet the cognitive demands of the task due to the under-provision of decision support (i.e., RA < RD), the problem of information overload ensues (Peracchio and Meyers-Levy 1997). Insufficient cognitive resources may result in: 1) limited information processing, which could result in consumers abandoning the procurement (Anderson 2003), or alternatively, 2) individuals may cope with such situations by adopting simplified decision strategies, such as heuristic processing that reduce the information considered when making decisions (Payne, Bettman and Johnson 1993).

The question that emerges from this analysis is what types of decision aiding features would enhance performance through the matching of the cognitive resources required and those that are available? Based on a series of studies conducted by Payne and his colleagues (1993) who have applied the concept of cognitive effort to understand human decision-making behavior, they suggested that decision performance could vary according to the types of decision strategies that consumers are induced to adopt. The choice of decision strategies (i.e., their cognitive response) depends on the nature of the decision aid and the information load that exist in the decision environment. Toward this end, a decision aid could result in consumers achieving better decision performance if it facilitates the use of appropriate decision strategies to meet the cognitive demands of the task (Edwards and Fasolo 2001). For instance, normative decision strategies (e.g., compensatory decision strategies or more complex non-compensatory strategies) that traditionally demand substantial cognitive resources to be executed could be facilitated by decision aids that offload the cognitively demanding and menial processes from the consumers. Conversely, when the specific aids provided do not induce the adoption of appropriate decision strategies, a significantly poorer performance when compared to their absence might occur (Todd and Benbasat 1999, 2000). The conflicting findings about how decision aids affect decision performance in the last few decades lend support to this conjecture (Eom 2003; Skitka et al. 1999). Given the crucial role of decision strategies in determining the quality of decision-making, it is important to examine the decision aids in terms of the strategies they facilitate.

C.3 DECISION STRATEGIES AND DECISION AIDS

When using decision aids, consumers typically initiate the decision-making process by establishing a list of minimally acceptable product attribute level(s) that an alternative must possess in order to be considered further as a possible choice (Olson and Widing 2002; Edwards and Fasolo 2001; Todd and Benbasat 1999, 2000). This process of delineating such attribute levels and filtering alternatives that fail to meet the criteria is known as screening. The screened alternatives are then assessed carefully to make a choice, and this process is known as evaluation (Edwards and Fasolo 2001; Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer, and Wood 1997).

When a consumer engages in screening, he is likely to expend conscious cognitive effort to eliminate undesirable alternatives using non-compensatory strategies (Bettman, Luce and Payne 1988), which implies that the screening is based on the cutoff point of the most important attribute(s) and information related to the other attributes would be ignored. Non-compensatory strategies are broadly classified into two types: single-attribute screening, i.e., strictly involving only one attribute, or multiple-attribute screening, i.e., involving one or more attributes (Payne et al. 1993). A consumer who adopts a single-attribute non-compensatory strategy, such as Lexicographic (LEX), chooses *the* most important attribute and executes the cutoff. As a consequence, alternatives with attribute-values that are best for the most important attribute are presented. A consumer would then evaluate whether or not the reduced set of alternatives allows him/her to make a choice. If another screening attempt is needed, the consumer then determines which of the remaining attributes is the most important. The second step is repeated until no further screening is needed.

A consumer who adopts multiple-attribute non-compensatory strategies, in comparison, would utilize one or more attributes simultaneously for screening. Two such decision strategies are the elimination-by-aspect (*EBA*) and the majority of confirming dimensions (*MCD*) strategies. EBA removes alternatives if at least one attribute value fails to meet the minimum acceptable level, and MCD chooses those alternatives that are acceptable on the largest number of attributes. It is important to note that EBA could also function as a single-attribute based, non-compensatory decision strategy, depending on its usage. For instance, a consumer could start by delineating only one attribute at the first screening attempt (e.g., warranty of at least two years for a mini audio system), which is equivalent to adopting single-attribute screening. However, if subsequent screening attempts are delineated based on the previous screening criteria (e.g., warranty of at least two years and at least the inclusion of an analog tuner for the mini audio system), then one is deemed to use multiple-attribute screening. Similar to a single-attribute non-compensatory strategy, alternatives that do not meet the specified threshold values of all the attributes will be discarded. After this attempt is completed, the consumer then assesses whether additional simplification is desirable, and another set of cutoffs can be selected to eliminate more alternatives in subsequent attempts, and so on (Payne et al. 1993). The use of MCD, in contrast, would often involve more than one attribute per screening attempt. Regardless of whether one would use EBA or MCD, a consumer could select many attributes simultaneously without knowing the combined impact of the cutoffs on the number of alternatives that will survive (Bettman et. al.1998).

Based on the above discussion of the types of non-compensatory strategies, different decision strategies are characterized based on either single-attribute or multiple-attribute screening capabilities, namely: 1) screen alternatives with a restricted single-attribute for each screening attempt, and 2) screen alternatives with one or more attributes for each screening attempt. We label these as **L**ow **S**creening **S**upport (**LSS**) and **H**igh **S**creening **S**upport (**HSS**), respectively.

Consumers who engage in alternative evaluations often employ more cognitively-demanding compensatory strategies in order to increase the accuracy of their final choice (Bettman et al. 1998; Payne et al. 1993). Using compensatory strategies, consumers first define the importance of each attribute and then compute a weighted score for each alternative based on the inputted attribute importance. The alternative with the highest score is selected. The benefit of the compensatory strategy is that it facilitates, for the consumer, the selection of an alternative that is good from an overall perspective. Two strategies that best represent compensatory-based processing are the equal weighting (*EQW*) and weight additive (*WADD*) strategies. EQW assigns equal weight to all attributes and chooses the alternative with the highest score, while WADD derives a weighted score for each alternative based on the user-inputted weights of importance and then selects the alternative with the highest score.

The literature suggests that, in general, utilizing a decision aid that supports evaluation would first entail reducing (i.e., screening) the large number of alternatives using a non-compensatory decision strategy and then switch to a more elaborated, compensatory strategy to evaluate the remaining alternatives (Van, Paluchowski, and Beach 1992; Malhotra 1982). Consequently, we conceptualize a third form of decision aid, labeled *W*eight *Evaluation Support (WES)*, that has the capability to use information about the consumers' utility function to *screen* a large number of alternatives and to *evaluate* remaining alternatives based on the attribute importance weights (Haübl and Murray 2003).

While we have used decision strategies to theoretically motivate the selection of the types of decision aids to be studied in this research, it is important to note that the decision strategy chosen by the decision-makers is based on the joint consideration of the information load in the decision environment (i.e., the cognitive resources demanded) and the cognitive support afforded by the decision aids (i.e., the cognitive resources available). For instance, in a high information load environment, a decision-maker equipped with a *WES* may be inclined to adopt a compensatory decision strategy, which would otherwise not be adopted if he were not to have a *WES,* because a compensatory decision strategy is cognitively inhibiting (Todd and Benbasat 1999). If a decision-maker is not provided with any decision aid or with a simplistic one like *LSS* in such an environment, he might very well simply adopt the satisfactory and less demanding lexicographic strategy. Table 1 highlights the decision strategies that could be induced from the availability of each decision aid.

Table 1: Characteristics of Decision Aids and Induced Decision Strategies

	Low Screening Support (LSS)	High Screening Support (HSS)	Weight Evaluation Support (WES)
Non-compensatory based Decision Strategies Supported (screening support)			
Single attribute-based screening (i.e., delineation of ONLY 1 attribute criterion per screening attempt)			
Lexicographic (LEX) *Chooses alternatives that are best on most important attributes*	√	√	√
Multiple attribute-based screening (i.e., delineation of 1 or more attribute(s) criteria per screening attempt)			
Elimination-by-Aspect (EBA) *Removes alternatives with at least one attribute value that fails to meet the minimum acceptable level*		√	√
Majority Confirming Dimensions (MCD) *Chooses alternatives that are acceptable on the largest number of attributes*		√	√
Compensatory-based Decision Strategies Supported (evaluation support)			
Equal-Weighting (EQW) *Assigns equal weight to all attributes and chooses alternative with highest score*			√

Weight-Additive (WADD) *Derives a weighted score for each alternative based on the inputted attribute importance and selects the alternative with the highest score*	√

C.4 HYPOTHESIS DEVELOPMENT: IMPACT OF DECISION AIDS

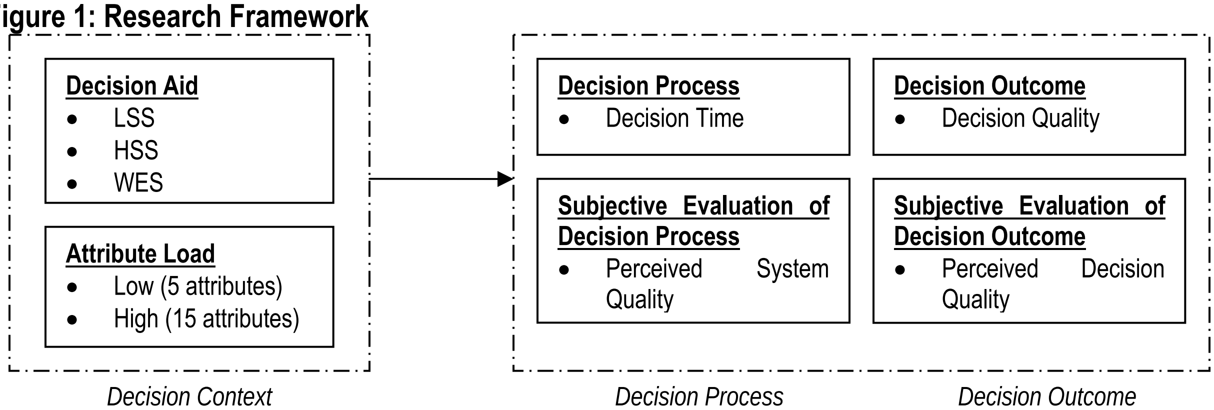
As depicted in Figure 1, we seek to assess the impact of different levels of decision support, characterized by screening and evaluation support, on decision performance within the context of product attribute-load. The theory which guides this research has three propositions:

1. where a decision aid renders cognitive resources to match those demanded for the task environment (RA = RD), a consumer will process more information which will lead to enhanced decision performance;

2. where a decision aid renders cognitive resources that exceed what is needed (RA > RD), a consumer could engage in less task-related elaboration leading to detrimental decision performance, such as poorer decision quality; and

3. where a decision aid renders cognitive resources that fall short of those needed (RA < RD), a consumer could either engage in i) simplistic heuristic decision strategy leading to detrimental decision performance, or ii) invest additional effort within manageable levels, to process more information to yield better decision performance.

Figure 1: Research Framework



In line with the taxonomy proposed by Lilien et al. (2004), we assess the decision performance of consumers who use decision aids based on two criteria - the decision process and the decision outcome - for which both objective and subjective evaluations are included. The decision process, which involves the screening and the evaluation of product information to arrive at a choice, is characterized by the *decision time* and the *perceived system quality* (Sharda et al. 1998). The *decision time* is an objective indicator of the amount of effort exerted to process information before a decision is made (Roberts and Lattin 1997). The *perceived system* quality, a subjective indicator, reflects the degree to which the consumer perceives during the decision-making process that the decision aid to be capable of assisting him/her in reaching a decision (DeLone and McLean 1992).

The decision outcome is manifested by two variables: observed *decision quality* and *perceived decision quality*. The common approach to assessing decision quality objectively is to determine whether the alternative chosen is a non-dominated option (Haübl and Trifts 2000; Olson and Widing 2002). An alternative dominates another if it has at least one product attribute that is superior while none of its other attributes are inferior (Payne et al. 1993). A non-dominated alternative is hence, one that is not dominated by any other alternative. This binary approach of defining decision quality, however, does not take into consideration the distance between the chosen alternative and the non-dominated alternative (Bettman et al. 1998). Our study addresses this concern by assigning a utility value (π_j) to each alternative (see the Research Methodology section for more details). The perceived decision quality is a subjective indication of how a decision-maker perceives his decision to be accurate, correct, precise and reliable (Mennecke and Valacich 1998).

Before proceeding to the formulation of hypotheses, we stress that as decision support increases from LSS to HSS to WES, user control afforded by these aids also increases, making it easier for the consumer to remove inferior alternatives and make comparisons (see Table 1). However, because LSS and HSS differ in the number of attributes supported for each screening attempt (i.e., single only versus single/multiple attribute-based screenings) while HSS and WES differ in the provision of assigning importance weights to attributes (i.e., no weight assignments versus user-inputted weight assignments), we decided to develop and test our hypotheses by comparing the differences that arise when utilizing LSS vis-à-vis HSS (screening support) and those that arise from utilizing HSS vis-à-vis WES (evaluation support) under varying product attribute-load environments in a dyadic fashion in order to provide a comparison based on the absence or presence of one decision support feature at a time.

C.4.1 SCREENING SUPPORT: LSS VERSUS HSS

A consumer who utilizes LSS would adopt the single-attribute non-compensatory strategy (i.e., LEX), which chooses the most important attribute as a basis to perform the cutoff or elimination of alternatives. The consumer will evaluate the remaining alternatives and decide whether or not to make a choice. If the consumer is not satisfied with the set of alternatives and deems that another screening attempt is needed, he then determines which of the remaining attributes could be the most important. Note that LSS would re-screen the original choice set during the new $n+1^{th}$ attempt rather than those alternatives left from the n^{th} screening attempt. In this way, consumers using LSS are likely to repeat the screening process several times to identify the most critical attribute for screening alternatives (Payne et al. 1993). In contrast, *HSS* allows consumers to define any number of attributes to simultaneously serve as the cutoff criteria in each screening attempt. Depending on the number of attributes selected for screening, the decision strategies employed could vary. For instance, if consumers screen alternatives using only one attribute at a time, HSS functions exactly like LSS, thus inducing LEX processing. If multiple attributes were chosen instead of those used for screening, the EBA strategy would be induced. When consumers screen alternatives using all attributes at once, they are said to be employing MCD.

We posit that in a **high product attribute-load condition**, consumers with HSS would achieve better decision performance than those using LSS in terms of decision time, perceived system quality, decision quality, and perceived decision quality. Consumers using LSS, which restricts each screening attempt to one attribute criterion, lack the ability to screen off a large number of inferior (i.e., lower quality) alternatives. They need to expend a great deal of cognitive resources and effort to process the large number of product attributes and screen the resultant large number of alternatives. Clearly, LSS is inadequate to support their decision-making tasks as the cognitive resources and mental efforts demanded by consumers in a high product load condition are very high (i.e., RA < RD). Consequently, this causes consumers a high degree of cognitive difficulty to accomplish the decision-making task.

Even if the consumers employing LSS were to exert more effort in screening and scanning, the limited single-attribute screening facility of LSS would lead to a large resultant set of alternatives that has a smaller share of non-dominated alternatives (or a good set of alternatives of higher utility value). Faced with these larger resultant sets of alternatives that have a large number of attributes, consumers again have to exert greater cognitive effort to visually inspect and compare these alternatives to arrive at a choice, which should translate into longer decision time. This would indicate a scarcity of available cognitive resources relative to required cognitive resources (Peracchio and Meyers-Levy 1997). Hence, owing to the limitations of human information processing capabilities and the low support provided by LSS, the likelihood of the consumers making an inferior choice is very high.

Thus, when the cognitive resources available fall short of the cognitive resources demanded (i.e., RA < RD), decision performance should deteriorate. In line with the resource-matching theory, consumers involved in cognitive resource-demanding tasks (i.e., RA < RD) are also likely to have less confidence in the decision outcomes (Anand and Sternthal 1989). Moreover, in addition to experiencing a shortfall in cognitive resources support, large resultant sets of alternatives, and longer processing and evaluation times, consumers with LSS would also feel that they have less control over the decision process, which will negatively influence their perceived system quality.

In contrast, because HSS permits the specification of multiple criteria for each screening attempt, HSS affords consumers greater flexibility, ease, and control to remove a large number of less attractive alternatives from the overall choice set. This advantage is particularly significant in dealing with product alternatives that have a large number of attributes. With better support provided by HSS for the high product attribute-load task, consumers would enjoy comparatively higher cognitive resources than those with LSS. By specifying multiple attribute criteria at each screening, consumers with HSS should be able to eliminate inferior alternatives to arrive at both a high quality consideration set and a better decision more quickly than those using LSS (Haübl and Trift 2000). While HSS may not fully overcome the high cognitive load associated with evaluating the alternatives, it still reduces the gap between the available and required cognitive resources. Since HSS provides better decision support to overcome the cognitive overload and facilitates greater control over the decision process, consumers using HSS should experience better decision performance in terms of decision time and decision quality, and perceive higher system quality and decision quality than those using LSS in the high product attribute-load condition.

However, in a **low product attribute-load condition**, we expect consumers using LSS to attain better decision performance than those using HSS in terms of *decision quality* and *perceived* *decision quality only*. Consumers using LSS may be able to identify alternatives of higher utility value when inspecting the returned alternatives due to a lower demand for cognitive resources associated with the lower product attribute-load (i.e., having fewer numbers of attributes to consider). Payne et al. (1993) observed that consumers who adopt LEX (induced by LSS) could still identify higher quality alternatives compared to those who adopt other non-compensatory strategies (e.g., EBA and MCD), if they perceive the cognitive efforts to be manageable and are willing to exert effort. In our context, a goal-oriented task to select a non-dominated product was used and the cognitive effort demanded in the low product attribute-load condition is much less than that demanded in the high attribute-load environment, and should fall within the consumers' level of available cognitive resources. Hence, we argue that consumers would be inclined to expend more time and effort to identify better alternatives.

When there is a better match between cognitive available resources and cognitive resources that are demanded, consumers experience a higher level of motivation and self-regulation and will spend more time and effort on the decision-making task, thus leading to a higher level of decision accuracy and perceived decision quality (Peracchio and Meyers-Levy 1997). However, because more time and effort will be spent on the decision-making task, consumers are unlikely to perceive LSS as a high system quality product compared to HSS.

In fact, compared to LSS, the use of HSS in a low product attribute-load condition may lead to a poorer decision performance for two reasons. First, consistent with the resource-matching theory, consumers are likely to be distracted from the real task at hand (i.e., evaluating the alternatives) and engage in more idiosyncratic and task-distanced activities (e.g., excessive manipulation of the HSS screening features) when they have more cognitive resources (that are afforded by HSS) than needed in a low product attribute-load environment. More specifically, owing to the ease of screening afforded by HSS, consumers could become engaged in trying out different combinations of multiple attribute criteria and expending less cognitive effort on evaluating the resultant sets of alternatives. That is, as argued earlier, the abundance in cognitive resources (i.e., RA > RD) may result in consumers being more inclined to exhibit cognitive laziness when performing decision-making tasks (Chenoweth et al. 2004). Such an allocation of cognitive resources could lead to poor decision quality. This conjecture is in accordance with the stream of empirical evidence from prior studies indicating that the provision of more decision-aiding features does not necessarily benefit the quality of the decision (e.g., Silver 1991; Schwartz 2004). Second, HSS may also imbue consumers with overconfidence in the aid, leading to less evaluation time spent, and unwarranted effort minimization and reliance on the HSS to make decisions (Skitka et. al. 1999). Because of the sophistication of HSS and its ability to reduce consumers' time and cognitive effort, the system quality of HSS will be perceived as high. Hence, we posit:

H1a(i): Using HSS will lead to lower ***decision time*** *compared to using LSS in high product attribute-load condition.*

H1a(ii): Using HSS will lead to lower ***decision time*** *compared to using LSS in low product attribute-load condition.*

H1b(i): Using HSS will lead to higher ***perceived system quality*** *compared to using LSS in high product attribute-load condition.*

H1b(ii): Using HSS will lead to higher ***perceived system quality*** *compared to using LSS in low product attribute-load condition.*

H1c(i): Using HSS will lead to higher ***decision quality*** *compared to using LSS in high product attribute-load condition.*

H1c(ii): Using HSS will lead to lower ***decision quality*** *compared to using LSS in low product attribute-load condition.*

H1d(i): Using HSS will lead to higher ***perceived decision quality*** *compared to using LSS in high product attribute-load condition.*

H1d(ii): Using HSS will lead to lower ***perceived decision quality*** *compared to using LSS in low product attribute-load condition.*

C.4.2 EVALUATION SUPPORT: HSS VERSUS WES

WES differs from HSS by providing the capability to perform additional *compensatory* computations of the attractiveness of the alternatives that are extracted based on the screening capability of the HSS (Lilien et al., 2004). Hence, WES (relative to HSS) assigns an overall attractiveness score to each alternative (that has passed the initial screening) in a ranked order that allows consumers to quickly identify those alternatives that best meet their expectations. Compared to HSS, we thus posit that WES renders a *higher* supply of cognitive resources to better match the *demanding* cognitive needs of a **high product attribute-load** *condition* but *not in a* **low product attribute-load** *condition* where the cognitive demands are much lower.

Specifically, in the **high product attribute-load** condition, WES, which facilitates efficient discrimination among alternatives with respect to their subjective utilities, requires less cognitive effort (i.e., screening attempts) from consumers to eliminate inferior alternatives and identify superior ones (Haübl and Trifts 2000). Moreover, insofar as consumers could offload the effort of the scanning and consideration of the tradeoffs among all available alternatives, they would experience less choice uncertainty (Hauser and Wernerfelt 1990), use less time to derive a choice and yet achieve a higher quality decision with greater confidence (Song et al. 2007; Payne et al. 1993) compared to consumers using HSS. Even though HSS facilitates multiple-attribute based screening, consumers using HSS would nevertheless encounter significant cognitive load in evaluating the resultant sets of alternatives, a task that WES facilitates through compensatory-based evaluations. Essentially, the use of WES renders a higher supply of cognitive resources to the consumers to match what is required in the high attribute-load environment (Mantel and Kellaris 2003). Consumers using WES should thus attain better decision performance in terms of decision time and accuracy, and perceive a higher level of system quality and decision quality than those using HSS.

In a **low product attribute-load** condition, following the reasoning used when comparing LSS and HSS, because of the sophistication of WES due to its compensatory evaluation capability, and hence its ability to reduce consumers' time and cognitive effort, the system quality of WES will be perceived as higher than that of HSS. However, we do not expect significant differences between HSS and WES in terms of decision performance. Our reasoning for this prediction is as follows. Recall that when formulating hypothesis H1, we had provided the reasons as to why in a low product attribute-load condition, HSS represents a case where RA > RD. Clearly, in the same condition, this is also true for WES. Therefore, in a low attribute-load condition, both HSS and WES provide an abundance of cognitive resources (i.e., RA > RD) hence the deterioration in performance expected due to this criterion (i.e., proposition #2 stated in the beginning of the "hypotheses" development section), applies to both of these decision aids. Furthermore, another reason for not expecting performance differences is that with only five attributes to evaluate across the resultant consideration sets in the low product attribute-load condition, consumers with HSS could compensate for the lack of compensatory evaluation function in WES by engaging in a mental assessment of the alternatives, which may not be as cognitively taxing as in the case of a high (15) product attribute-load condition (Eom 2003). Hence, we hypothesize:

> *H2a(i): Using WES will lead to lower **decision time** compared to using HSS in high product attribute-load condition.*

H2a(ii): Using WES will lead to lower **decision time** *compared to using HSS in low product attribute-load condition.*

H2b(i): Using WES will lead to higher **perceived system quality** *compared to using HSS in high product attribute-load condition.*

H2b(ii): Using WES will lead to higher **perceived system quality** *compared to using HSS in low product attribute-load condition.*

H2c(i): Using WES will lead to higher **decision quality** *compared to using HSS in a high product attribute-load condition.*

H2c(ii): Using WES will lead to no significant difference in **decision quality** *compared to using HSS in a low product attribute-load condition.*

H2d(i): Using WES will lead to higher **perceived decision quality** *compared to using HSS in a high product attribute-load condition.*

H2d(ii): Using WES will lead to no significant difference in **perceived decision quality** *compared to using HSS in a product attribute-load condition.*

C.5 RESEARCH METHODOLOGY

A 3 (LSS, HSS and WES) x 2 (low and high attribute-load) factorial experimental design was employed to investigate the main and interaction effects of decision aids and product attribute-load on consumer decision performance in a multi-alternative, multi-attribute, purchasing decision-making context. The decision aid was operationalized using LSS, HSS and WES. Product attribute-load was operationalized using five (low) and 15 (high) product attributes. The rationale behind the delineation of the number of product attributes is that providing 10 or more product attributes tends to decrease human ability in processing drastically (Malhotra 1982). Table 2 describes the operationalization of the dependent variables.

It is important to note that decision quality is operationalized by assigning a utility value (π_j) to each alternative. The utility value, π_j , of each alternative for a given product brand is calculated as $\pi_j = 1 - \sum_{k=1}^{K} X_k$, where $X_k = [l_k / L_k] * MAX_k$, signifying the difference in ranked value for an attribute ***k*** of alternative ***j*** against that of the non-dominated alternative. L_k refers to number of ranked levels for attribute ***k*** (e.g., 3 levels for warranty: 1-year, 2-year, 3-year). l_k represents the ranked level of the attribute ***k*** with zero value for highest rank and so on (relative to the non-dominated alternative). For instance, an alternative ***j*** with a 2-year warranty will have l_k =1 when compared to a non-dominated alternative with 3-year warranty. $MAX_k = 1/K$, which represents the maximum amount each attribute can contribute towards the utility of an alternative with ***k*** attributes. It is imperative to note that, any attribute value on the non-dominated alternative is at least as good as in any other alternative corresponding attribute values thus gets a score of 0. In other words, the non-dominated alternative has a utility value of 1.0 (i.e., $\sum_{k=1}^{K} X_k = 0$) and the others will have utility values below 1.0 since $\sum_{k=1}^{K} X_k > 0$.

To illustrate, we refer to Table 3, which depicts two sets of five alternatives for two fictitious brands, namely Sierra and JohnSteel, in the low product attribute-load condition of 5 attributes ($MAX_k = 1/5$), with attributes of price (differing in $5 scalar between two attribute levels), warranty (1, 2 and 3 years), CD type (repeat; repeat, shuffle; repeat, shuffle and programmable), system (basic; mini hi-fi; mini-theater) and tuner (no; analog; digital). In the experiment to be reported later, there were 6 brands of 20 alternatives each, with one non-dominated alternative in each brand category ($\pi = 1.0$). To compute the utility value for the Sierra AV-2003 model, for example, we need to compare the product attribute values of the AV-203 model against those of the non-dominated alternative AV-402 model. The Sierra AV-402 model has the following attribute values: price ($554.03), warranty (2 years), CD type (repeat), system (mini-theater) and tuner (digital). Comparatively, the Sierra AV-203 model has the following attribute attributes: price ($559.19), warranty (2 years), CD type (repeat), system (mini-theater) and tuner (no). The Sierra AV-203 model is inferior to the Sierra AV-402 model in terms of price by 1 level (X_1 = [1 / 3] * (1/5) = 0.07) and tuner by 2 levels (X_5 = [2 / 3] * (1/5) = 0.13), yielding a utility value (πj) of 0.80 (1.0 – 0.07 – 0.13).

Table 2: Operationalization of Dependent Variables

Dependent variable	Operational measure
Decision time	Time taken to make a decision.
Decision quality	Decision quality has a scale from 0 to 1.Six brands per product category are available. Within each brand, there are 20 alternatives and **only** one alternative is non-dominated while the other 19 are dominated. For each of the dominated alternatives, distance from the non-dominated alternative is computed with the non-dominated alternative having a quality of 1.0. Across brands, none of the non-dominated alternatives is dominated.
Perceived decision quality (Cronbach's Alpha = .855)	1. I believe I have made the best choices at this website. 2. I would make the same choices if I had to do it again. 3. I believe I have selected the best models for both products.
Perceived system quality (Cronbach's Alpha = .832)	1. The function provided by the tool is what I would need to make decisions. 2. The tool has helped me in making good decisions. 3. The tool is one of the best ways to accomplish the tasks assigned.

Table 3. Illustration of Decision Quality Computation

Brand	Model	Price($)		Warranty		CD type		System		Tuner		πj
		Value	*X_1*	*Value*	*X_2*	*Type*	*X_3*	*Type*	*X_4*	*Type*	*X_5*	
Sierra	**AV-402 ***	**554.03**	**-**	**2 years**	**-**	**Repeat**	**-**	**Mini-theater**	**-**	**Digital**	**-**	**1.00**
Sierra	AV-405	559.04	0.07	2 years	0.00	Repeat	0.00	Mini-theater	0.00	Digital	0.00	0.93
Sierra	AV-605	559.03	0.07	2 years	0.00	Repeat	0.00	Mini hi-fi	0.07	Digital	0.00	0.87
Sierra	AV-203	559.19	0.07	2 years	0.00	Repeat	0.00	Mini-theater	0.00	No	0.13	0.80
Sierra	AV-404	564.02	0.13	1 years	0.07	Repeat	0.00	Mini-theater	0.00	No	0.13	0.67
………												
JohnSteel	**J-310R ***	**607.48**	**-**	**3 years**	**-**	**Repeat, shuffle, programmable**	**-**	**Basic**	**-**	**Digital**	**-**	**1.00**
JohnSteel	J-506V	607.49	0.00	2 years	0.07	Repeat, shuffle, programmable	0.00	Basic	0.00	Digital	0.00	0.93
JohnSteel	J-203Q	612.00	0.07	3 years	0.00	Repeat, shuffle	0.07	Basic	0.00	Digital	0.00	0.87
JohnSteel	J-503W	607.80	0.00	2 years	0.07	Repeat, shuffle	0.07	Basic	0.00	Analog	0.07	0.80
JohnSteel	J-410V	617.00	0.13	2 years	0.07	Repeat	0.13	Basic	0.00	Digital	0.00	0.67

D – Difference in the attribute value of the alternative relative to the same attribute in the non-dominated alternative with each ↓ symbolizing a level difference; * - Non-dominated alternative.

C.5.1 EXPERIMENTAL PROCEDURES

One-hundred and fifty-six undergraduate Information Systems students enrolled in an advanced Management of Information Systems (MIS) course, participated in the experiment. This sample size provides an acceptable level of a statistical power (0.8) with an effect size of 0.5 at a two-tailed 5 percent significance level (Sawyer and Ball 1981). Participants were recruited through electronic mail and advertisements. Their average age was 22.0 years, and 80 of them were females (51.3%). As part of their degree requirements and coursework, all participants had web-surfing and computing experience. They were randomly assigned to one of the six treatments to minimize the effects of individual differences on the outcomes. As a result, there were 26 participants per treatment group. The participants were told explicitly that their task was to select any of the best alternatives in two product categories. In order to ensure experimental realism, the participants were told that they would be paid a fixed participation incentive and a variable performance-based incentive. The computation of the variable incentive was based on the decision quality, i.e., utility value of the alternative identified, and the level of difficulty in completing the two decision tasks. On an average, each participant was paid US$10 for an hour's work.

Participants were first given the scenario of moving to a new home, and primed to shop at a website for two household products: a washing machine and a mini audio system. This setup is consistent with most experimental studies on information seeking and decision-making behavior (Haübl and Trifts 2000) and is necessary to induce mundane realism[9]. The two product categories were chosen because they represent household items familiar to the participants who may have

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[9] Mundane realism refers to the degree to which the experiment resembles real-life application of the decision aids (Neuman 2006).

had experience in relocation (e.g. moving from home to hostels), or whose families own or might have purchased a new home, etc. We made sure that our participants were familiar with the two products by thoroughly briefing them about the attributes of each product, and, furthermore, to minimize ambiguity in interpreting product attributes, descriptions and value levels of the attributes were provided in a help file for their easy reference. The participants were asked to rate their levels of knowledge and familiarity with the two products.

In each product category, there were six fictitious brand names, with each brand having 20 alternatives, culminating in a total of 120 alternatives. All participants, irrespective of the experimental treatment, faced the same 120 alternatives. As proposed by Haübl and Trifts (2000), the alternatives in each category were created by manipulating the combinations of attribute levels[10]. Each alternative was described using *five product* attributes in the case of the low product attribute-load and an additional *10 product* attributes in the case of the high product attribute-load treatment. For each product category, six non-dominated alternatives—one for each of the six brands—were created. Each non-dominated alternative in its respective brand category dominated the remaining 19 alternatives, and parity among the non-dominated alternatives across brands was upheld (Haübl and Trifts 2000). No alternative emerged as the best in terms of all its attribute values. This design ensures that participants would evaluate each alternative carefully to identify the higher quality alternatives.

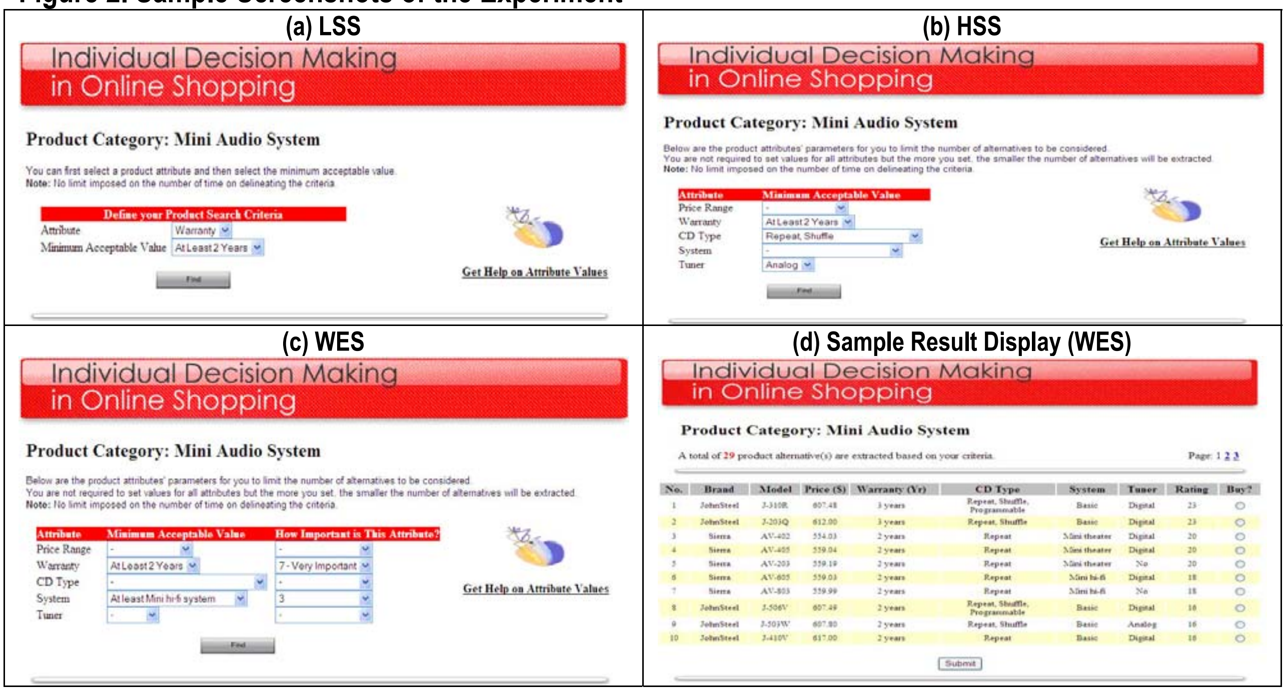
The participants were given a tutorial on the use of system features to conduct product comparisons in order to make a choice. The participants first had a trial session, where they

[10] The list of 120 alternatives for each product category can be furnished on request.

attempted to select the best possible choice out of several alternatives of a fictitious product. They were asked to provide their demographic information and rate their online buying experience, computer literacy level, web-surfing proficiency, and product category knowledge level. This was done for the purpose of conducting a control check.

The participants were then presented with two different product categories, and the sequence of the product purchase (i.e., washing machine or mini audio system) was randomly determined by the computer system. As in Haübl and Trifts (2000), the participants were told to choose the best alternative for each product category. Depending on the treatment condition, a participant was presented with the LSS, HSS or WES decision support aid. Figure 2 depicts screenshots of the three decision-aiding experimental implementations in the low product attribute-load condition. The participants in the LSS condition (see Figure 2a) started by selecting *one* attribute for screening and then deciding on the associated cutoff attribute value, (e.g., at least 2 years of warranty). The LSS would then present the alternatives that meet the defined attribute-cutoff criterion. In contrast, participants with HSS were able to define more than one attribute value criterion per screening attempt. For instance, Figure 2b depicts the screening criteria of at least: 1) 2 years of warranty, 2) repeat and shuffle functions for CD, and 3) the analog tuner. For the WES condition, participants could not only define the attribute criteria but also delineate the relative importance of the attributes (i.e., attribute with a 7-point weight indicated as most important). For instance, as depicted in Figure 2c, participants with WES could define screening criteria of: 1) at least 2 years of warranty and 2) at least a mini hi-fi system; and evaluate the alternatives based on the delineated importance for the warranty attribute (7-point weight attribute being the highest) and the hi-fi system (the highest being a 3-point weight). Figure 2d presents the screenshots of the results returned from a set of search criteria. It was observed that in the WES condition, the rating column displayed depicts the degree of attractiveness of the alternative as it was computed based on the attribute importance delineated in Figure 2c. The participants would then need to evaluate the list of the alternatives presented and determine whether a purchase should be made.

Figure 2. Sample Screenshots of the Experiment



At the end of each purchase, participants were asked to indicate their level of perceived decision quality. After completing both the purchase tasks, the system prompted the participants to provide feedback on task meaningfulness and perceived system quality. The whole experiment was completed within three days, and the model names of the non-dominated alternatives were changed prior to the commencement of each session. A “double-blind” research assistant (who was not aware of the research objectives) was recruited to serve as the administrator of the experiment.

C.6 RESULTS

C.6.1 CONTROLS AND MANIPULATION CHECKS

Individual characteristics, such as age, gender, experience and the skills of participants, which could potentially affect decision-making approaches and outcomes, were controlled by means of randomization. Further control checks indicated no significant differences among participants in all six treatments in terms of gender, age, online buying experience, surfing experience, and computer skills. Control over participant characteristics through randomization appeared successful. Manipulation checks were also conducted to ensure that our manipulation of decision aids and product attribute-load were successful. Decision aid manipulation was checked by asking the participants to rate on a 7-point Likert scale how easy it was for them to reduce the number of alternatives using the system. A one-way analysis of variance comparing the mean ratings obtained for the LSS, HSS and WES conditions (i.e., 4.68, 5.08 and 5.45, respectively) yielded a highly significant result ($F = 4.73$, $p < .01$). All pair-wise differences in the means were also highly significant, which suggest that our manipulation of decision aids was successful. The product attribute-load manipulation check was also conducted by asking the participants to rate on a 7-point Likert scale their ability to consider as many product attributes as possible before making a purchase decision. Comparing the means ratings obtained for the low and high product attribute-load conditions (i.e., 5.33 and 4.75 respectively) yielded a highly significant result ($t = -.2458$, $p < .05$). Perceptions on task meaningfulness were also significantly different from the neutral value of 4 (mean = 5.36, $t = 21.509$, $p < .01$), which suggests that experimental realism is not a problem. Table 4 provides the descriptive statistics of the dependent variables.

Table 4: Means (Standard Deviations) of Dependent Variables

Product Attribute-load	Decision aid	Process measures		Outcome measures	
		Decision time (in minutes)	Perceived system quality	Decision quality	Perceived decision quality
Low	LSS	9.027 (4.796)	4.039 (.958)	.858 (.231)	5.212 (1.054)
	HSS	7.992 (5.318)	4.808 (1.297)	.676 (.364)	4.404 (.955)
	WES	5.931 (3.137)	6.308 (.679)	.707 (.368)	4.519 (.727)
High	LSS	10.563 (5.490)	3.269 (1.185)	.609 (.333)	4.308 (.981)
	HSS	7.949 (4.838)	5.077 (1.093)	.669 (.341)	4.827 (1.024)
	WES	6.381 (2.784)	6.115 (1.306)	.814 (.270)	5.289 (1.016)

C.6.2 HYPOTHESIS TESTING

All statistical tests were conducted at the 5% level of significance. Before conducting the MANCOVA test, we need to perform three tests on the data. First, we examined the normality of the three dependent variables, namely decision time, decision quality and perceived decision quality. Normality tests include the skewness and kurtosis tests. Our tests suggest that decision quality (Skewness Z = -.724; Kurtosis Z =-.973) and perceived decision confidence (Skewness Z = .088; Kurtosis Z = .334) have skewness and kurtosis values near the normal range of -3 to 3, which are deemed acceptable (Hair, Anderson, Tatham and Black 1998). However, decision time (Skewness Z = 1.507; Kurtosis Z = 3.603) yields the Kurtosis Z value to be beyond the normal range of -3 to 3. Square-root transformation was performed on decision time. After the transformation, decision time satisfy the normality test (Skewness Z = .625; Kurtosis Z = .448). Second, we used the Bartlett's test for sphericity, which examines the correlations among the three dependent variables (i.e., perceived learning difficulty, decision time and perceived decision confidence) and determines whether significant intercorrelation exists. The results indicated the existence of significant intercorrelations ($\chi 2$ = 314.657, p < .01). Third, we tested whether the data conforms to assumption of the homogeneity of the variance-covariance matrices among the groups. The Bartlett-Box's M test, which focuses on assessing the overall equivalence of the variance-covariance matrices, was adopted The M test reveals significant (Box' M = 55.702, $p < .01$), which is deemed to be acceptable for MANCOVA to be conducted.

In light of this finding, and to control for experiment-wide error rate and the possible influence of product knowledge on dependent variables, the Multivariate Analysis of Covariance (MANCOVA) was first applied on the three dependent variables, namely decision time, decision quality and perceived decision quality. The perceived system quality was omitted from the MANCOVA test because the measure was captured at the end of the experiment as opposed to the other three measures that were captured after each purchase task. The results reveal the main effects for decision aid (Pillai's Trace = .138, $F = 7.508$, $p < 0.01$, power = 1.00) and the interaction effects for decision aid * information load (Pillai's Trace = .167, $F = 9.179$, $p < 0.01$, power = 1.00), with product knowledge (Pillai's Trace = .012, $F = 1.230$, $p > .1$, power = .329) and decision sequence (Pillai's Trace = .019, $F = 1.928$, $p > .1$, power = .496) as insignificant covariates. As no significant effects were detected for product knowledge and decision sequence, they were omitted from subsequent statistical tests involving the dependent variables.

Further univariate tests using ANOVA were run separately for each of the dependent variables. Table 5 summarizes the univariate test results. We observe significant main effects for decision aids on decision time and perceived system quality, and significant interaction effects on decision quality and perceived decision quality (Table 5). Each of the significant interaction effects was further examined using the method of simple effects analysis (Keppel 1991). In line with the formulation of hypotheses comparing differences in the usage of LSS vis-à-vis HSS (screening support; H_1), with those of HSS vis-à-vis WES (evaluation support; H_2) under varying attribute-load environments, subsequent data analyses were conducted by splitting the dataset into four categories (i.e., LSS versus HSS in low and high product attribute-load conditions and HSS versus WES in low and high product attribute-load conditions).

Table 5: Univariate Tests (ANOVA)

	Process measures		Outcome measures	
Source of variation	Decision time	Perceived system quality	Decision quality	Perceived decision quality
Decision aid	$F = 18.204, p < .01$	$F = 69.272, p < .01$	$F = 2.017, p > .10$	$F = 2.320, p = .10$
Attribute-load	$F = 2.390, p > .10$	$F = 1.692, p > .10$	$F = 1.864, p > .10$	$F = .773, p > .10$
Decision aid * Attribute-load	$F = .602, p > .10$	$F = 2.867, p < .10$	$F = 8.236, p < .01$	$F = 21.745, p < .01$

C.6.2.1 Evaluating Screening support: LSS versus HSS

Process measures: H1a posits that HSS participants would spend less time on decision-making than LSS participants in both high and low product attribute-load environments. As predicted, our results show a main effect of decision aid on the amount of time spent ($F = 18.204$, $p < .01$). Comparing the means of decision time, we observe that HSS users spent significantly less time to make decisions than those with LSS (i.e., main effect: $mean_{HSS} = 7.970$, $mean_{LSS} = 9.795$; $t = 2.569$, $p < .05$). LSS's drawback of not being able to assist consumers in reducing the number of alternatives for evaluation by specifying multiple attribute values at each screening resulted in longer decision making time, a problem that was exacerbated with an increase in product attribute-load. Hence, H1a(i) and H1a(ii) are supported. Similarly, H1b suggests that users of HSS would perceive higher system quality than users of LSS in both high and low product attribute-load environments. The lower amount of effort and time spent by HSS users in comparison to LSS users led them to perceive significantly higher perceived system quality across both high and low information loads (i.e., main effect: $mean_{HSS} = 4.942$, $mean_{LSS} = 3.654$; $t = 5.636$, $p < .01$). Hence, H1b(i) and H1b(ii) are supported.

Outcome measures: H1c and H1d posit that compared to LSS participants, HSS participants would attain and perceive lower decision quality in the low product attribute-load condition but higher decision quality in the high product attribute-load condition. The results show that HSS participants fared significantly worse than LSS participants in terms of decision quality in the low product attribute-load condition ($t = 4.307$, $p < .01$) but they did not perform significantly better than LSS participants when product attribute-load was high ($t = 1.294$, $p > .10$), although the effects were in the right direction. Hence, H1c(ii) is supported but H1c(i) is not supported. As predicted in H1d, HSS participants perceived lower decision quality than LSS participants in the low product attribute-load condition, but perceived higher decision quality than LSS participants in the high product attribute-load situation, despite their not attaining significantly higher decision quality than their LSS counterparts. Table 6 lists the results of the simple effect analyses.

Table 6: Simple Effect Analyses of Decision Aid * Information Load for LSS versus HSS

Dependent variable	Data Split by Information Load			
	Low		High	
	Hypothesis	Result	Hypothesis	Result
LSS versus HSS				
H1c: Decision quality	(ii) HSS < LSS	t = 4.307, p < .01 **Supported**	(i) HSS > LSS	t = 1.294, p > .10 **Not Supported**
H1d: Perceived decision quality	(ii) HSS < LSS	t = 4.095, p < .01 **Supported**	(i) HSS > LSS	t = 2.641, p = .01 **Supported**

C.6.2.2 Assessing Evaluation Support: HSS versus WES

Process measures: H2a posits that compared to HSS participants, WES participants would spend less time on decision-making in both high and low product attribute-load conditions. The results provide empirical support to this hypothesis by showing that WES participants consistently took less time to complete the decision-making tasks than HSS participants in both product attribute-load conditions (i.e., main effect: $mean_{WES} = 6.156$, $mean_{HSS} = 7.970$; $t = 3.157$, $p < .01$). Hence, H2a(i) and H2a(ii) are supported. Similarly, H2b posits that compared to HSS participants, WES participants would perceive higher system quality in both high and low product attribute-load conditions. Because WES participants expended less time and effort in making decisions than HSS participants, WES users reported higher perceived system quality in both product attribute-load conditions (i.e., main effect: $mean_{WES} = 6.212$, $mean_{HSS} = 4.942$; $t = 5.789$, $p < .01$). Hence, H2b(i) and H2b(ii) are also supported.

Outcome measures: H2c and H2d suggest that compared to HSS participants, WES participants would achieve and perceive higher decision quality in the high product attribute-load environment but not in the low product attribute-load environment. The results (see Table 7) show that WES participants did better than HSS participants in the high product attribute-load environment ($t = 2.388$, $p < .05$) but did not significantly out-perform HSS participants in the low product attribute-load environment ($t = .431$, $p > .10$). Likewise, WES participants also perceived higher decision quality than HSS participants in the high product attribute-load environment ($t = 2.307$, $p < .05$) but not in the low product attribute-load condition ($t = -.693$, $p > .10$). According to Sawyer and Ball (1981, p. 278), "any credible decision to 'accept the null hypothesis' of no effect must be accompanied by a highly powered research design that reveals only a very small effect size". Since the observed effect sizes in our highly powered research design are only 0.085 and 0.136 for decision quality and perceived decision quality, respectively -- which are very small -- we are confident that the decision quality and the perceived decision quality of WES participants did not differ significantly from those of HSS participants in the low product attribute-load condition. Hence, H2c(i), H2c(ii), H2d(i) and H2d(ii) are supported.

Table 7: Simple Effect Analyses of Decision Aid * Information Load for HSS versus WES

Dependent variable	Data Split by Information Load			
	Low		High	
	Hypothesis	Result	Hypothesis	Result
HSS versus WES				
H2c: Decision quality	WES = HSS	t = .431, p > .10 **Supported**	WES > HSS	t = 2.388, p < .05 **Supported**
H2d: Perceived decision quality	WES = HSS	t = -.693, p > .10 **Supported**	WES > HSS	t = 2.307, p < .05 **Supported**

C.7 DISCUSSION

The aim of this study is to improve our understanding of how consumers would utilize online decision aids of varying sophistication and features, and how their use affects decision performance under different information environments. Our basic proposition, which draws upon the resource-matching theory (Mantel and Kellaris 2003; Peracchio and Meyers-Levy 1997; Anand and Sternthal 1989), is that, *all other things being equal, if a decision aid facilitates the match between the cognitive resources available and those required for the decision task, decision performance should improve*. *However, when a decision aid renders cognitive resources that exceeded or fall short of those demanded, decision performance should deteriorate.*

Our findings provide strong empirical support for the resource-matching theory. To gain further insights into what drives the performance of the decision aids, we have also examined the number of screening submissions made by LSS, HSS and WES participants in our log file. WES, which encompasses the multi-attribute screening feature and the weight computation and evaluation feature, yields the best performance in terms of decision time (6.381 minutes) and decision quality (.814) in the **high product attribute-load** environment. WES participants engaged in 14.52 screening submissions, but used the least time in making the best decision compared to LSS and HSS participants, probably because of the rank-ordered nature of the resultant sets of alternatives. Clearly, WES has rendered a high supply of cognitive resources to the participants to enable them to meet the demanding cognitive needs associated with the screening and the evaluation of alternatives in a high product attribute-load context. In contrast, in the high product attribute- load environment, LSS with only a single-attribute screening feature yields the worst performance in terms of decision time (10.563 minutes) and decision quality (.609). Our results show that LSS participants made only 4.48 screening submissions compared to 16.75 and 14.52 screening submissions made by HSS and WES participants, respectively. Since the decision times taken by LSS participants were very lengthy, their low number of screening submissions would imply that that they were relying on heuristic and visual processing (i.e. trying to identify the key attributes and make a choice through visual inspection) instead of abandoning the task of information processing when they encountered situations where the cognitive resources available to them fell short of those that were demanded, i.e., when RA < RD (Payne et al. 1993). The heuristic decision strategy supported obviously did not help the LSS participants to achieve a better decision quality.

LSS, the most simplified tool, yields the best decision quality in the **low product attribute-load** environment, albeit with the worst decision time. In our setup in which the participants were asked to identify the non-dominated product, LSS participants were somehow motivated to supplement the cognitive resources supplied by LSS with their own efforts to arrive at a better decision, as evident by their lengthy decision time (9.027 minutes), high number of screening submissions (8.63), and hence a long evaluation time per submission (9.027 ÷ 8.63 = 1.046 minutes). Comparatively, HSS participants used a shorter time (7.992 minutes) but engaged in a higher number of screening attempts (14.17) than LSS participants. However, HSS participants fared worse than LSS participants in decision quality (.676), probably because HSS participants "played around" with the HSS tool more frequently and engaged in less information processing and evaluation per submission (7.992 ÷ 14.17 = 0.564 minutes). Despite being provided with the most sophisticated tool, WES participants used only a very short time (5.931 minutes) and submitted only 5.88 screening attempts to achieve a decision quality of only .707. As the resultant sets of alternatives for WES are rank-ordered, the long evaluation time per submission (5.932 ÷ 5.88 = 1.008 minutes) taken by WES participants in the low product attribute-load environment suggests that they were focusing on idiosyncratic and less task-related elaboration of the decision-making issue. These behavioral consequences of using HSS and WES in the low product attribute-load condition coincide with the theoretical explanations offered by the resource-matching theory for the situation when the cognitive resources available to the consumers exceed those required by the task environment (Anand and Sternthal 1989; Chenoweth et al. 2004).

There are a few interesting observations that arise from these findings. First, based on decision quality, it appears that HSS is a dominated decision tool in both information environments; it is neither suitable in the high product attribute-load environment nor appropriate in the low product attribute-load situation. Second, perceived system quality does not necessarily correlate with perceived decision quality, contrary to some prior studies, which imply that effort induced by poor decision support would result in negative effects toward the decision-making outcome (Lilien et al. 2004). In our study, among the three categories of participants, LSS participants had the highest perceived decision quality despite having the lowest perceived system quality in the low product attribute-load environment, which suggests that they valued the additional efforts they invested in the decision-making task to supplement the lack of decision support they obtained from LSS. The positive relationship between perceived system quality and perceived decision quality, however, holds in the high product attribute-load environment. In light of these observations, it is therefore important for IS researchers to be circumspect about the relationships between perceived system quality and user perceptions. Third, while the sophistication of the decision aids has a straightforward association with process performance (i.e., decision time and perceived system quality), its impact on decision outcomes is contingent on the information environment in which it is being deployed as well as how it is being used by the decision makers. This is in line with the general thesis of DSS that decision aids are agents of change (based on the features they contain) that influence the decision-making process (Todd and Benbasat 1999; Silver 1991) by reducing or inducing appropriate cognitive resources associated with screening and evaluating the alternatives (Montgomery et al. 2004).

C.7.1 LIMITATIONS

Our research findings come with some caveats. Most importantly, the context in which this research was conducted may limit the external validity of our study. First, this study has examined the effects of decision aids in the context of a goal-driven setting (i.e., to identify a non-dominated product). Given that the behavioral consequences of using decision aids in other settings might be different, we feel that an examination of other task environments, decision contexts, and individual characteristics would be valuable. For example, factors such as consumer characteristics (e.g., window shoppers versus goal-driven buyers; prior product knowledge and experience), framing effects, biases (e.g., choice shifts and hindsight bias), task and problem definition, amount of risk (e.g., decision accountability) and incentives (e.g., decisions on high-risk but high-return products such as shares versus low risk and low returns products such as government bonds) associated with the purchase, consumer confidence, and trust in the integrity of the aid, these could all alter the results (Payne et al. 1993).

Our choice of mini-audio systems and washing machines as products may also limit the external validity of our findings. While we believe the participants were familiar with both products, and extra effort was devoted to explain the product attributes prior to the experiment, some student participants might still have trouble relating to the products and comprehending the issues involved in choosing these products. To the extent that the nature of the products could affect the willingness and involvement level of decision makers in the task execution (Swaminathan 2003), further experiments should be conducted to include other products (e.g., digital cameras) to insure the robustness and validity of these findings.

The way in which we conceived the highest decision quality (i.e., a participant should choose a non-dominated alternative among all others) may pose a problem to WES participants. While WES participants using WES were informed to select the best alternative that is superior in at least one attribute while not being inferior in any other attributes to others (Payne et al. 1993), it is plausible that some of these participants might still have evaluated the alternatives based on their individual preferences for certain attributes, which might potentially have skewed the overall values generated. Since the subjective utility of different alternatives may differ across individuals, further research should examine decision quality with the use of HSS and WES based on stated individuals' attribute preferences.

We have tested our hypotheses using 120 alternatives per product. In situations involving more than 120 alternatives, it is plausible that consumers using LSS may experience greater cognitive difficulty in processing the product information and hence obtain poorer decision quality even in the low product attribute-load environment. Although it is not common to find more than 200 alternatives per product in one merchant's product database, it might be prudent for future research to replicate our study using a larger product database.

C.7.2 THEORETICAL AND PRACTICAL IMPLICATIONS

This study contributes to several schools of literature. First, this study constitutes one of the first attempts to employ and extend resource-matching theory into the IS discipline with the aim of understanding the effects of online decision aids on individual decision performance. By marrying the streams of resource-matching and decision support literature, we have demonstrated that the resource-matching theory could complement the traditionally-adopted theories of cognitive-fit and task-technology fit (Vessey 1991; Goodhue and Thompson 1995) by providing clear predictions of the under-fit (i.e., RA < RD) and over-fit (i.e., RA > RD) conditions in addition to the ideal-fit (i.e., RA = RD) condition. Additionally, this study also offers a nuanced understanding of the effects of decision aids on decision-making performance and helps to reconcile the two conflicting views of DSS in the extant literature. Specifically, we show that the effectiveness of online decision aids in helping consumers choose the best product is contingent on whether these aids facilitate the matching of the cognitive resources available to the cognitive resources required in the task environment. Where the decision aids render cognitive resources to match those demanded in the task environment, consumer will process more information, and consequently, decision performance will be enhanced; where the decision aids render cognitive resources that exceed those needed, consumers will engage in less task-related elaboration of decision-making issues to the detriment of decision performance (Silver 1991); and where the decision aids render cognitive resources that fall short of those needed, consumers will either employ a simplistic heuristic decision strategy to the detriment of decision performance or invest additional efforts in information processing to attain a better decision performance if they perceive the additional investments to be manageable. As such, DSS can lead to either greater information processing or effort minimization, depending on whether there is a match or mismatch in cognitive resources available to the consumers and those demanded in the task environment.

Second, our study also adds to existing DSS literature (see Xiao and Benbasat 2007) by providing a more granular testing and evaluation of the decision aids features in multiple information environments. Our literature review is consistent with the observations of some scholars who have noted that many prior DSS studies seldom clearly delineate the specific design functionality (Eom 2003; Silver 1991; Todd and Benbasat 1999), making it difficult to attribute decision performance to specific features of the decision aids (Hevner, March, Park and Ram 2004). Others have evaluated the effectiveness of decision aids in a simplistic fashion such as comparing the performance of consumers in a "with or without DSS" environment (e.g., Haübl and Trifts 2000). In this study, we went beyond the "availability/absence of DSS" design; we derived the decision aids (i.e., LSS, HSS, and WES) to be tested in multiple information environments (i.e., low and high product attribute-load conditions) from the decision-making stages (van Zee et al. 1992) and decision strategies literature (e.g., Edwards and Fasolo 2001; Payne et al. 1993); described how they are likely to be used, and discussed the cognitive and psychological mechanisms under-girding their impacts on consumer decision process and performance (see sections 2, 3 and 4). To our best knowledge, studies assessing screening and evaluation capabilities in high and low product attribute-load environments are still sorely lacking. For instance, a recent study by Song et al. (2007) only evaluated the effects of decision aids characterized by non-compensatory strategies, compensatory strategies, and a hybrid of decision strategies, on subjective evaluation measures, such as decision satisfaction, without explicit consideration of information load. Most prior DSS studies that did consider information load examined the impact of decision aids on decision performance in an environment where information load was manipulated by a change in the number of *alternatives* provided (e.g., Haübl and Trifts 2000; Todd and Benbasat 2000, 1999) rather than by a change in the number of attributes to be considered, which is of more relevance and importance in an online electronic commerce context.

Third, our study complements the consumer behavioral decision-making research studies that are concerned with the management and impact of information load as characterized by product attribute-load. While there are some consumer behavioral decision-making research studies that have investigated information load by varying the number of product attributes, few have examined this aspect of consumer decision-making in a decision support technologies-enabled decision environment. Furthermore, even the few consumer research studies that focused on varying the number of product attributes have reported equivocal results. Some (e.g., Malhotra 1982; Keller and Staelin 1987) have found deterioration in decision performance with an increase in the number of attributes while others (e.g., Russo 1977) have discerned an enhancement in decision performance enabled by the "informativeness" of a bigger group of attributes (see Bettman et al. 1998 for a detailed review). Our study demonstrates that if an appropriate decision aid is used to "manage" a high product attribute-load, it can enhance the consumer decision-making performance substantially.

Our study also provides some practical implications for online merchants and product information brokers (e.g., comparison-shopping websites). The Internet is replete with examples of online merchants and product information brokers providing decision aids to consumers without considering the type of product they are searching for. For a simple product with few descriptive attributes, providing an overly sophisticated decision aid such as WES may result in the consumers not choosing the highest quality product whose profit margin is likely to be the biggest[11]. Conversely, for a complex product with several attributes, offering a simplistic tool such as LSS or HSS may result in consumers choosing a low quality product with a low profit margin at best, or

[11] Product quality has been found to be positively correlated with profit margin (see Philips, Chang and Buzzell 1983).

abandoning the cognitively debilitating search, evaluation and purchase process at worst. Additionally, as in our case, we feel that online merchants and product information brokers can benefit from logging the usage and effects of the decision aids they provide to develop a better understanding of consumer behavior and choice.

C.8 CONCLUSION

As the dust from the dot-com bust settles and as computer and Internet penetration intensifies inexorably around the world (especially in China, India and emerging economies), electronic commerce has the potential to grow exponentially. For instance, it is projected that sales from China's electronic-commerce alone may reach $2.5 billion in 2010, which is more that triple that in 2006[12]. Among other technological developments such as Web 3.0, decision aids have perhaps the greatest potential to facilitate and realize this growth in electronic commerce. However, without a careful understanding of how these decision aids influence consumer decision-making and performance, it is plausible that the growth may be stunted or remain lackluster at best. This study took a modest step toward developing a theoretically sound understanding of how decision aids affect consumer decision-making and performance, and in doing so, we hope to help online merchants and consumers gain maximum value from electronic commerce, and thereby contribute to its growth.

[12] Source: http://seattletimes.nwsource.com/html/businesstechnology/2003735845_amazon06.html [last visited: June 29, 2007]

D. ESSAY THREE
DECISION DIFFICULTY AND RECOMMENDATION AGENT: AN ARCHITECTURAL DESIGN FRAMEWORK

D.1 INTRODUCTION

The consumer decision-making process can be complicated and is important to both consumers and merchants (Payne, Bettman and Johnson 1993). Consequently, the study of how to assist a consumer in completing the individual as well as a series of decision-making stages has been a focal area of research for the past two decades (Butler and Highhouse 2000; Bettman, Luce and Payne 1998). Among many research initiatives, a pertinent and enduring concern that spans across three of the five stages[13] (i.e., product information search, alternative evaluation and choice selection), is how to assist a consumer to address the problem of decision-difficulty (Anderson 2003; Dhar 1997).

Decision-difficulty refers to the complexities encountered by a consumer during the purchase expedition that starts from the moment he realizes a desire or need for a particular product (Anderson 2003; Dhar 1997). Decision-difficulty could be experienced during the stages of information search, alternative evaluation and choice selection. For instance, prior studies have highlighted that a consumer could encounter difficulty: 1) when learning about a new product or service (Hoeffler 2003); 2) when eliciting preferences (Kardes, Cronley and Kim 2006) and evaluating the enormous number of product alternatives (Bettman et al.1998); and 3) when making an explicit decision to select one alternative and forgo all others (Schwartz 2004). It is to be noted

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[13] The other two stages are need recognition and post-purchase evaluation (Blackwell, Miniard, and Engel 2001).

that the other two stages of the decision-making process, i.e., the need recognition and the post-purchase evaluation stages, are beyond the scope of our focused issue on decision-difficulty as need recognition is ex-ante while post-purchase evaluation is ex-post to a consumer's purchase expedition; and hence, consumers in these two stages are less prone to suffer from decision-difficulty (Anderson 2003; Bettman et al. 1998).

When a consumer faces difficulties during decision-making, he has an inclination to exhibit purchase-avoidance behavior[14], a tendency to *postpone* committing to a purchase or to seek a less painful way out that involves *no action* or *no change* (i.e., abandoning the inclination of committing to a purchase), despite having the need to consume the product/service (Anderson 2003). Such an inclination creates a devastating obstruction to Internet commerce; for example, an online manifestation of purchase-avoidance behavior is the shopping cart abandonment rate, which hovers at a disturbingly high level of around 70 percent even today[15] (Mummalaneni 2005).

A widely proposed technological solution to addressing decision-difficulty is to put in place an appropriate decision aid, such as the Recommendation Agent (RA), to support stages of the decision-making process (Edwards and Fasolo 2001; Haübl and Trifts 2000; Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer, and Wood 1997). The RA is an online decision-aiding tool that assists a

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[14] It is to be noted that in addition to decision difficulty, there are others reasons proffered for purchase avoidance behavior, including doubt on the authenticity of the procuring website (i.e., trust), unreliable or insufficient payment options, lack of transparency in shipping charges, and difficulties in screening and evaluating the sheer number and complexity of product offers (Kim and Benbasat 2006; Mummalaneni 2005). However, given our primary focus is on addressing decision difficulty with the prospect of lower decision avoidance propensity it is beyond the scope and not in accordance with the objective of the article to explore all factors leading to purchase avoidance behavior.

[15] Cherkassky, I. "Improving the E-Tail Shopping Experience, E-Commerce, 2006 [url: http://www.redorbit.com/news/technology/443549/improve_the_etail_shopping_experience/index.html; last accessed: September 05, 2007]

consumer to search for, evaluate, and choose suitable purchase options in the electronic marketplace (Xiao and Benbasat 2007). While several researchers and website developers have provided variations of RAs (e.g., Häubl and Murray 2003; Grenci and Todd 2002), most of these solutions are somewhat disparate and piecemeal in nature, addressing only fractional stages of the consumer decision-making process. For instance, some studies focus on the alternatives evaluation stage, such as automating and embedding various decision strategies in RAs to minimize cognitive effort (Aksoy, Bloom, Luri, and Cooil 2006; Tan 2003) or the use of collaborative-based and content-based filtering to recommend product options (Adomavicius and Tuzhilin 2005; Ariely, Lynch and Aparicio 2004), while others address general issues such as the trustworthiness of these RAs when making a choice (Wang and Benbasat 2007; Xiao and Benbasat 2007).

Hence, the purpose of this article is to introduce a unified design framework for an RA with which designers are encouraged to provide a host of system features to provide informed guidance for online consumers in accomplishing purchase expedition. The focus on the decision-making stages of information search, alternative evaluation, and choice selection is also in accordance with the literature in consumer decision-making (Payne et al. 1993) and decision support systems (Eom 2003), which collectively suggest that decision aids are best and most aptly deployed in these decision-making stages.

The article proceeds as follows. We first draw on the literature in consumer psychology and decision-making to identify the underlying causes of decision-difficulty and then establish the theoretical linkages between decision-difficulty in each of the three stages of decision-making and consumer purchase-avoidance behavior. We next define the recommendation agent (RA) as an online Information Technology (IT) artifact that assists an online consumer in: 1) learning about the products, 2) eliciting preferences and evaluating the product offered, and 3) making an explicit choice based on product recommendation. With a good theoretical understanding of decision-difficulty and a nuanced appreciation of the current knowledge of RA, we propose a unified design framework for an RA that seeks to assist consumers in alleviating decision-difficulty, thereby leading to lower purchase-avoidance behavior. Specifically, a set of propositions relating to seven proposed RA design artifacts (i.e., preference learning, preference discovering, preference framing, option framing, decision strategy-based screening, decision guidance, and RA personalization) is set forth in this paper. Based on these propositions, we lay down a clear research agenda for examining the relationships between RA design features and decision-difficulty. This study, in particular, contributes to theory building surrounding the effectiveness of RA and in general, enriches the literature on decision support systems with theoretical underpinnings from consumer psychology and decision-making.

D.2 DECISION DIFFICULTY AND PURCHASE-AVOIDANCE

Purchase-avoidance builds on the principle that in every decision that we make, there is always an implicit option of not committing to a purchase (Anderson 2003; Dhar 1997). For instance, you may spend your weekend afternoons surfing the Internet to look at new electronic gadgets or to compare expenses like phone services, car loans and insurance quotes across merchants. When you spot a product or service of interest, the first decision you have to make is to either act on the opportunity or decide not to procure (at least for the moment). The latter refers to inaction inertia – a tendency not to make a purchase decision despite more attractive alternatives appearing (Butler and Highhouse 2000) - or choice deferral – a tendency not to choose for the time being (Tversky and Shafir 1992).

An intuitive theoretical justification for purchase-avoidance behavior is that the tendency to avoid making explicit purchase commitments can be perceived to be a natural human behavior for two reasons. First, making choices is considered an “abnormal” course of action because when a human being does nothing or takes “no action”, psychologists and biologists would interpret that such a person is resting or conserving energy for future needs (Dhar 1997). However, making explicit choices or purchases would require exertion of energy (costs) to deviate from the “no action” state. Indeed, theoretical justifications, such as the Expected Utility Theory (Rabin 2000), could be easily used to explain a consumer’s decision to (or not to) deviate from the “no action” state: none of the alternatives in the choice set are sufficiently attractive for a consumer to select them.

Second, a consumer may decide not to choose when the decision to be made is viewed as difficult. In other words, when a consumer has to make a judgment of the worthiness of a purchase, he or she must have a certain degree of certainty in making a judgment based on personal knowledge about the product, on fondness for the product, and the actual monetary value of the option’s benefits. However, it is contested that preference elicitation and decision-making often entail substantial ambiguities and uncertainties, i.e., cognitive difficulty (Bettman et al. 1998). Specifically, a consumer who encounters difficulty is likely to exhibit ambiguity aversion in which he or she prefers known probability distributions such as “no action”, over uncertain probability distributions, such as an option’s benefits (Fox and Tversky 1995; Curley, Yates and Abrams 1986). For instance, in an experiment conducted on 120 executives, Sawers (2005) observed that participants facing more difficult decisions reported a higher level of anxiety and had a greater desire to postpone making the decision than participants facing less difficult decisions. However, when the participants were provided with a decision aid that assisted them to reduce the level of difficulty, they reported a lower desire to postpone making the decision than participants without the decision aid.

Furthermore, according to the Dissonance Theory, a consumer experiences emotional discomfort (e.g., unpleasant psychological tension) when he or she has to forgo valued benefits to resolve the negative emotions experienced during decision-making (Festinger 1957). Simple disagreements between choice attributes (i.e., emotional difficulty), in terms of which alternative yields the highest utility value, could elicit negative emotional feelings as they require a consumer to give up attempts to maximize some valued goals such as price, for other goals, such as safety (Tversky and Shafir 1992). Such negative effects could increase the propensity of purchase-avoidance as, very often, a consumer chooses to adhere to the inactive inertia not because none of these options is more preferred, but as a way to resolve a difficult decision (Dhar and Simonson 2003).

With the knowledge of purchase-avoidance and an awareness that decision-difficulty could lead to purchase-avoidance behavior, the question to ask next is: What are the sources of decision difficulties that result in purchase-avoidance?

D.2.1 PURCHASE-AVOIDANCE

Purchase-avoidance builds on the principle that in every decision that we make, there is always an implicit option of not committing to a purchase (Anderson 2003; Dhar 1997). For instance, you may spend your weekend afternoons surfing the Internet to look at new electronic gadgets or to compare expenses like phone services, car loans and insurance quotes across merchants. When you spot a product or service of interest, the first decision you have to make is to either act on the opportunity or decide not to procure (at least for the moment). The latter refers to inaction inertia – a tendency not to make a purchase decision despite more attractive alternatives appearing (Butler and Highhouse 2000) - or choice deferral – a tendency not to choose for the time being (Tversky and Shafir 1992).

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Second, a consumer may decide not to choose when the decision to be made is viewed as difficult. To explain, when a consumer has to make judgment of the worthiness of a purchase, he or she must have a certain degree of certainty in making a judgment based on personal knowledge about the product, on fondness for the product, and the actual monetary value of the option’s benefits. However, it is contested that preference elicitation and decision-making often entail substantial ambiguities and uncertainties, i.e., cognitive difficulty (Bettman et al. 1998). Specifically, a consumer who encounters difficulty is likely to exhibit ambiguity aversion in which he or she prefers known probability distributions such as “no action”, over uncertain probability distributions, such as an option’s benefits (Fox and Tversky 1995; Curley, Yates and Abrams 1986). For instance, in an experiment conducted with 120 executives, Sawers (2005) observed that participants facing more difficult decisions reported a higher level of anxiety and had a greater desire to postpone making the decision than participants facing less difficult decisions. However, when the participants were provided with a decision aid that assisted them to reduce the level of difficulty, they reported a lower desire to postpone making the decision than participants without the decision aid.

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With the knowledge of purchase-avoidance and that decision difficulty could lead to purchase-avoidance behavior, the question to ask next is: What are the sources of decision difficulties that result in purchase-avoidance?

D.2.2 DECISION DIFFICULTY

Decision-difficulty is defined as the degree to which a decision-maker experiences complexity during three stages of decision-making process, consisting of information search, alternative evaluation and choice selection (Anderson 2003; Luce, Bettman and Payne 2001; Dhar 1997). Our review of extant literature suggests that various sources of decision-difficulty emerge during different stages of the decision-making process. Table 1 summarizes the six causes of decision difficulties, namely *knowledge uncertainty*, *preference uncertainty*, *choice conflict*, *need for justification*, *information structure load*, and *decision style* (Anderson 2003; Bettman et al. 1998).

Generally,, decisions become more difficult: 1) as the product becomes more unfamiliar to the consumer, i.e., knowledge uncertainty emerges during the information search stage; 2) as the degree of conflict (i.e., mismatch) between the initial-thought preference and options available, (i.e., preference uncertainty), increases and as the need to trade-off attribute values among the alternatives, (i.e., choice conflict), increases during the alternative evaluation stage; 3) as the need to provide compelling reasons to choose an alternative over the rest, (i.e., need for justification), increases during the choice selection stage; and 4) as the amount of information, (i.e., information structure load), increases and as the decision styles vary across individual consumers across the stages. It is imperative to highlight that the six sources of decision difficulties are not mutually exclusive but, rather, interrelated, such as birds to bats. Hence, it is plausible that a consumer could encounter similar sources of decision-difficulty in more than one decision-making stage, such as choice conflict, information structure load and decision style.

Table 1. Sources of Decision Difficulty and Consumer Decision-making

	Consumer decision-making process stages		
Decision difficulties	*Information Search*	*Alternative Evaluation*	*Choice selection*
1. Knowledge uncertainty	√		
2. Preference uncertainty		√	
3. Choice conflict		√	√
4. Need for justification			√
5. Information structure load	√	√	√
6. Mismatch in decision style	√	√	√

D.2.2.1 Information search

Information search refers to a consumer's search for information, which can occur internally and externally. A consumer engages in internal search when recalling information about products/services from memory and this is determined by the consumer's existing knowledge about the products and his ability to retrieve relevant product information. External search occurs when a consumer gathers information through personal interaction, such as word-of-mouth communication, and accessing online information, such as an Internet search (Moorthy, Ratchford and Talukdar 1997).

Knowledge uncertainty denotes a state of mind of being unsure whether the decision-maker has personally acquired adequate knowledge of the product to elicit a preference based on product knowledge in order to identify and evaluate the choice set. In other words, knowledge uncertainty refers to “uncertainty regarding what is known about the alternatives (products)” (Urbany, Dickson and Wilkie 1989, pp. 208). While the acquisition of more information could alleviate knowledge uncertainty to a certain extent, it may not be able to address decision problems faced during the alternative evaluation stage. For instance, decision problems characterized by options within a product category could have: 1) highly complex attribute values such as aesthetics, or 2) alternatives that are from multiple product categories such as cinema and musical shows. Under these two decision conditions, comparison and evaluation of the alternatives and attributes in a standardized manner would not be appropriate (Johnson 1984). For instance, when confronted with alternatives of non-comparable attributes (e.g., television resolution and camera screen resolution), consumers are no longer able to adopt the strategies (e.g., additive difference and elimination by aspects) that compare alternatives directly with attributes.

Furthermore, the inclusion of multiple product categories would further add to the knowledge demand for consumers. In this light, consumers would have to research the ways in which the individual products are evaluated and search for substituting strategies of comparison. Making decisions under such cognitively-demanding conditions could arouse doubts (and negative emotions) about the relevance of the information and the accuracy of choices made. If the overall costs and uncertainty are high, there is very little motivation for consumers to select any option (Anderson 2003).

D.2.2.2 Alternative evaluation

With the gathered product information, a consumer proceeds to the alternative evaluation, during which a consumer would delineate the criteria for retrieval and evaluation. Alternative evaluation is characterized by: 1) the elicitation of preference and 2) the evaluation of the options. In relation to decision-difficulty, they correspond to preference uncertainty in elicitation and the degree to which a consumer faces conflicting options.

Preference uncertainty: Prior research on preference construction indicates that preference is constructed while interacting with the information environment (Punj and Stewart 1983); hence, preference thus elicited is unstable and can be easily changed by small changes in the decision-making context (Bettman et al. 1998). When these changes lead to a mismatch between the initial preference constructed and the options presented (i.e., during the alternative evaluation stage), consumers are forced to readjust their preferences; and when consumers do this, they may no longer be able to provide stable assessments and hence suffer from preference uncertainty, i.e., a mental state of being unsure of the options that best meet the goals or criteria of a consumer (Hoeffler 2003). For instance, a choice involving making trade-offs on key attribute dimensions can cause high levels of preference uncertainty and arouse negative emotions (Shafir, Simonson, and Tversky 1993). The evaluation of product features forces a consumer to consider his preferences with respect to the options available more carefully, in an attempt to reduce anticipated regret. When the consumer identifies more conflicts between goals and options during the evaluation, uncertainty increases (Dhar 1997). The decision-maker may give up or postpone choice if he fails to find a dominant structure for a hopeful option. Evidently, preference uncertainty, caused by choice sets with options showing small differences in attractiveness, often leads to decisional conflict that precedes purchase-avoidance (Anderson 2003)

Choice conflict: Discussion on the decision-difficulty factors leading to purchase-avoidance has thus far mainly focused on the approach-avoidance conflict that involves alternatives of both attractive and unattractive features (Chatterjee and Heath 1996). Two additional forms of choice-conflict, which make evaluation and selection of the alternatives difficult, are the approach-approach conflict (decisions based on attractive alternatives) and avoidance-avoidance conflict (decisions based on unattractive alternatives). For instance, an approach-approach conflict could have one deciding whether to go for a movie or go out to play; while an avoidance-avoidance conflict would have one deciding whether to endure a painful toothache or to visit a dentist for a tooth extraction. Research on choice conflict in general indicates that approach-approach conflicts are often resolved with little cognitive and emotional difficulty, whereas the contrary is true of avoidance-avoidance conflicts and approach-avoidance conflicts (Schneider 1992). Dhar and Nowlis (1999) observed that purchase-avoidance is less likely in approach-approach conflicts than in avoidance-avoidance conflicts. This observation supports their conjecture on the importance of the overall attractiveness of all the available alternatives in influencing consumers' preferences.

D.2.2.3 Choice selection

Based on the evaluation of the available alternatives, a consumer makes an explicit choice selection. A critical factor influencing a decision to be made is the presence of sufficient reasons motivating a consumer to procure, which is commonly termed as justification. **Justification**, or the need to provide reasons, can have important effects on a consumer's decisions. When a consumer needs an explanation for his decision, he is particularly susceptible to effects on choice and judgment that operate through the manipulation of the salient reasons for preference (Anderson

2003). Building on this accountability conception, researchers have posited that the need to provide reasons forces a consumer to weigh the ease of justification more heavily and this leads to a search for good reasons to use as justification when making a decision (Simonson 1992). For instance, Simonson and Nowlis (2000) observed that when subjects were told to provide justifications for their decisions, the focus of their decision process shifted from the choice of good options to the choice of good reasons. However, an underlying assumption of that study and many related ones is that a consumer is always able to find reasons for supporting his decisions. As it happens, the context in which options are situated could make identification of reasons and justifications difficult (Tversky and Shafir 1992). Particularly, the number of potential reasons for making a particular choice, the ratio of reasons for selecting one option over another, the saliency of reasons, and the subtlety of differences among those reasons, could all increase decision-difficulty that precedes choice deferral and inaction inertia (Anderson 2003).

D.2.2.4 Across stages of decision-making

We have so far identified four sources of decision-difficulty through different stages of the decision-making process. Two sources of decision-difficulty that span across the three stages are information structure load and decision style. The former characterizes the difficulty entailed by the decision environment and the latter denotes the differences across individual consumers.

Information structure load: Information overloading has been an enduring concern for consumers and a problem for system designers (Payne et al. 1993). Specifically, it is observed that providing too much information to consumers could lead to dysfunctional consequences on decision performance (Jacoby 1984). In other words, a consumer’s information processing performance, in terms of the cognitive ability to process increasing amounts of information, deteriorates on reaching the optimal information processing level (Schroder, Driver and Streufert 1967). Traditional research on information load defines load as the number of alternatives and the number of attributes describing the alternatives. A simple illustration would be when during the information search stage, a consumer could encounter lesser difficulty in learning about an USB flash drive, which has less than 10 attributes (e.g., capacity) as opposed to a HDTV product, which has over 25 attributes (e.g., contrast ratio, resolution, rear and front connector types). In recent years, researchers have added another dimension to the definition of information load. According to Lurie (2004), the amount of information load could be better reflected by the information structure – number of alternatives, number of attributes describing each alternative, the number of different attribute levels associated with each attribute and the attribute levels distributed across the alternatives. With respect to the attribute level distribution, Lurie (2004) notes that one could suffer from information overload when attribute levels are evenly distributed across the presented alternatives. For instance, during the alternative evaluation stage, a consumer could experience difficulty when a RA that presents 50% of alternatives with three-year warranties and 50% of the remaining alternatives with one-year warranties compared to another RA that presents 90% of alternatives with three-year warranties and 10% of alternatives with one-year warranties. This is because the consumer with the former RA would have to gain more product information to determine whether one should focus on warranty as the determining factor of the purchase. This information structural view is analogous to the contrast effect that dictates the relative attractiveness of each option within the set of alternatives presented (Mandel and Johnson 2002). To the extent that more competing options are present, the difficulty of processing and evaluating the options should increase.

Decision style: Research on decision style, which is defined as "the selection among alternative courses of action" (Henderson and Nutt 1980 pp. 371), has informed us that consumers could respond differently even for the same given task. The underlying premise of the decision style research is that consumers could process information and arrive at a decision in different manners depending on individual personal characteristics (Benbasat and Taylor 1978). It is observed that different decision-making styles could be deduced depending on the type and approach towards information search, the number and type of preferences elicited, and the use of reasoning (e.g., analytic or heuristic approaches) in evaluating and choosing among alternatives (Lynsonski, Durvasula and Zotos 1996; Eisenhardt and Zbaracki 1992). For instance, decision-makers in general could: 1) be analytic, i.e. systematic in analyzing a problem and deriving a set of alternative courses of actions, or heuristic, i.e. rely on common sense and intuition when solving a problem (Huysman 1970); 2) adopt perceptive versus receptive styles during information gathering and intuitive versus systematic styles during information evaluation (McKenney and Keen 1974); and 3) exhibit directive, analytical, conceptual and behavioral (Rowe and Mason 1987). In relation to consumer decision-making, Sproles and Kendall (1986) posit that consumer decision styles could differ along eight dimensions: 1) perfectionism or high quality consciousness, 2) brand or price-equal-quality consciousness, 3) novelty or fashion consciousness, 4) recreational and hedonistic shopping consciousness, 5) price or value-for-money consciousness, 6) impulsiveness, 7) confusion due to excessive choices, and 8) habitual or brand-loyal orientation. Notwithstanding the various classifications and categorizations of decision styles, the general premise deduced from this field of research is that a consumer could have a preferred mental model that governs the decision-making process so as to arrive at a decision (Sproles and Kendall 1986). Leading from this, a consumer could experience decision-difficulty when there is a mismatch between the preferred decision style and the decision-making environment (Shiloh, Koren and Zakay 2001; Vessey 1991) and that the consumer fails to adjust to the environment (Payne et al. 1993), which could in turn lead to choice deferral and inaction inertia (Anderson 2003).

With the knowledge of the six decision difficulties, the next natural question to ask is: what is the existing knowledge gained regarding RA implementation in addressing the decision difficulties faced by consumers?

D.3 RESEARCH ON RECOMMENDATION AGENT

The RA presents a consumer decision-making problem that has been traditionally studied by computer scientists (Adomavicious and Tuzhilin 2005). The interest of these scientists lies in the technical challenges of constructing intelligent agents that are equipped with the ability to learn and represent knowledge as well as to communicate with other agents (Montgomery, Hosanagar, Krishnan and Clay 2004). The consumer-centric aspect of designing an RA, such as in the arena of addressing decision-difficulty, has often been neglected. Studies more closely related to our interest, particularly in Information Systems (IS) and adjacent disciplines such as consumer psychology and decision-making, build on the notion that a consumer suffers from cognitive limitation (Eom 2003) and that the RA uses the preference information elicited by the consumer to filter product options and propose suggestions (Xiao and Benbasat 2007; Haübl and Murray 2003; Grenci and Todd 2002; Haübl and Trifts 2000). In other words, rather than flooding consumers with an overwhelming plethora of product offers and information (i.e. information overloading), an RA could be designed to use information about the consumers' preferences to identify a small subset of alternatives that are more likely to interest them (Smith 2002; Ansari, Essegaier and Kohli 2000).

There are two general forms of RAs in terms of filtering and recommending product options: collaborative-based or content-based. In the collaborative-based approach, the construction of a consumer's preference model is based on the indicated preferences provided by that consumer, and the preferences indicated by other consumers, represented as a set of rated items (Ariely et al. 2004). The collaborative-based RA first utilizes the indicated preferences of the consumers to profile the consumers and offer the alternatives according to a set of predefined profiles (Middleton, Shadbolt and de Roure 2004). The RA then recommends alternatives that likeminded consumers have rated highly, and that the target consumer has not rated. The alternative referred to here can be a product type or a specific product brand (Dastani, Jacobs, Jonker and Treur 2005; Herlocker, Konstan, Terveen and Riedl 2004). The underlying intuition of having a collaborative-based RA is that an item is perceived to be of interest to a consumer if other consumers of similar inclinations are keen on that item too. A group of consumers who rate items similarly are deemed as sharing like-minded preferences or interests. The quality of the recommendations by such an RA improves as the number of consumers and the number of rated items increases (Herlocker, Konstan, Terveen and Riedl 2004). Conversely, if new items are not rated by other consumers previously, it may not be able to recommend them to a consumer.

In comparison, a content-based RA builds on the preference model constructed by asking the consumers about the properties and attribute values of the items, such as a notebook with at least 1GB RAM memory (Balabanović and Shoham 1997). More importantly, a content-based RA offers recommendations solely based on a profile built up by analyzing a consumer's elicited preferences and criteria for an item and/or the content of the items which that consumer has rated in the past. Regardless of whether the RA implementations are collaborative-based or content-based, the applied techniques in designing the agent mainly draw from work on machine-learning to learn a consumer's preferences (Terveen and McDonald 2005) and on information retrieval to recommend items that consumers may be interested in (Salton 1989). This study focuses on content-based RAs.

One of the earliest academic investigations of the content-based RA in addressing the information overloading problem is the work by Haübl and Trifts (2000), which they refer to as the RA. The authors examine two aiding features of the RA[16]: one that assists in screening alternatives, and another one that rearranges alternatives to make evaluation easier. The adopted theoretical underpinning is the decision-making principle that dictates that when using decision aids, such as RAs, consumers typically initiate the decision-making process by establishing a list of minimally acceptable product attribute level(s) that an alternative must possess in order to be considered further as a possible choice, known as screening (Olson and Widing 2002; Edwards and Fasolo 2001). The screened alternatives are then assessed carefully to make a choice, and this process is known as evaluation (Edwards and Fasolo 2001; Alba et al. 1997). The study shows that the provision of aid that supports screening and/or evaluation of alternatives significantly improves the quality of the decision made (Haübl and Trifts 2000). This view is supported by Montgomery and his colleagues (2004) who conjecture that by reducing the cognitive effort associated with evaluating the alternatives, decision aids could substantially increase consumers' propensity to increase the search for more information and commit to purchases. Other studies have also reported similar findings (see Xiao and Benbasat 2007; Smith 2002).

This collection of extant studies mainly examines the impact of RAs, or decision aids in general, by manipulating information load by a change in the number of alternatives available to choose from (e.g., Todd and Benbasat 2000, 1994), and not by a change in the number of attributes used to describe the alternatives. Such manipulation may not be aligned to the online shopping context where consumers often delineate their preferences in terms of product attributes, such as what threshold values to specify or what weights to assign to each attribute, when using RAs. For

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[16] Due to the numerous RA implementations, many researchers use different terms such as recommender systems, recommendation systems, comparison-shopping agent, shopping agent, pricebot and shopbot. In the case of Haübl and Trifts (2000), the authors labeled RA as an online decision aid. In accordance with Xiao and Benbasat (2007), their study assumes these terms to be synonyms of RA.

instance, in a comprehensive review of the existing studies on RAs, Xiao and Benbasat (2007, table 5, pp. 146) identified three general forms of RA implementations based on product attributes (e.g., compensatory versus non-compensatory). Furthermore, the number of alternatives in an online environment tends to be very large, which makes it more challenging for consumers to immediately engage in alternative-based evaluation (Swaminathan 2003) without first conducting some attribute-based eliminations and repeating such attribute-based eliminations until the resulting number of alternatives after screening is deemed to be small and manageable. Towards this end, the ease of eliciting preferences could be affected by the number of attribute levels associated with each attribute, as we reviewed earlier. Hence, there remains a lack of sufficient knowledge of RAs in addressing the information structure load (e.g., the attribute aspect) of decision-difficulty.

In addition to RA research to address the information overloading problem, an increasing amount of literature from the decision-making discipline suggests that an RA could possess not only the capacities to screen and present a list of items but also to guide consumers in choice-making. For instance, it is suggested that an RA could "guide" consumers to: 1) evaluate unfamiliar products together with the familiar (Cooke, Sujan, Sujan, and Weitz 2002); 2) render an attribute more prominent by explicitly including it in the recommendation (Haübl and Murray 2003); 3) decrease price sensitivity through lowering the search costs for quality information (Diehl, Kornish and Lynch 2003); 4) engage in more systematic decision-making processes and better match their preferences by controlling the information flow (Ariely 2000); and 5) discover new products or generate demand for unfamiliar products through providing personalized offers (Tam and Ho 2005).

At the same time, researchers have also defined the boundary within which an RA could be deployed. For instance, an RA is: 1) observed to possess a greater impact on consumer behavior under conditions of high product risk (Swaminathan 2003); 2) evaluated more favorably for search goods than experience goods (Aggarwal and Vadyanathan 2005); 3) assessed less positively when the unsolicited recommendation or advice contradicts consumer's initial impressions (Fitzsimons and Lehmann 2004); 4) better received by consumers when the recommendations are more transparent (Sinha and Swearingen 2002); and 5) perceived to be more useful if the RA provided takes into consideration the consumer's characteristics, such as frequency of purchase and perceived risk (Sproule and Archer 2000).

Essentially, relating these studies to decision-difficulty, we could conjecture that an RA could alleviate preference uncertainty and choice conflict to a certain extent by providing guidance and restricting the evaluation to the few recommended alternatives that are highly correlated with consumers' overall elicited preferences (Tan 2003). Towards this end, it is plausible that an RA could induce consumers to make decisions in accordance with the intention of the agent should appropriate features be built into the RA (Diehl et al. 2003; Haübl and Murray 2003). However, when such intent is perceived to contradict with the consumers' initial impressions of RA usage, a behavioral backlash of ignoring the agent's recommendations may result (Haübl and Murray 2006; Fitzsimons and Lehmann 2004). Leading from this, the question to ask is how an RA could be designed to minimize the behavioral backlash? A solution to this could be to design an RA that is able to better support the consumer decision-making process by alleviating all the six identified sources of decision-difficulty (Anderson 2003; Edwards and Fasolo 2001).

D.4 PROPOSED RA DESIGN

Table 2 depicts our proposed unified RA design framework that encapsulates seven system features - product learning, preference discovering, preference framing, option framing, decision-strategy-based screening, decision guidance, and personalization – to address the identified roots of decision-difficulty. Specifically, we anchor on the consumer decision-making process model to envision an RA to assist consumers in accomplishing three stages of decision-making process - information search, alternative evaluation, and choice selection (Blackwell et al. 2001; Doyle and Thomason 1999; Payne et al. 1993). Specifically, we posit that an RA could be designed to allow a consumer to: 1) gain adequate knowledge and information about the product, i.e., the information search stage; 2) use the acquired product knowledge to elicit preferences and to screen and evaluate alternatives, i.e., the alternative evaluation stage; 3) make explicit decisions on whether to and which alternative to acquire, i.e., the choice selection stage; and 4) address the information overloading problem and enable the consumer to gain greater confidence when interacting with an RA that personalizes information and services to his decision style (Xiao and Benbasat 2007; Montgomery et al. 2004; Murthi and Sarkar 2003).

It is essential to note that some of these features, (e.g., decision strategy-based screening), are implicit in previous work; and we are simply presenting them and examining their consequences. Other features, (e.g., preference discovering and framing), are derived from our experience with RAs and our intuitions about the prolific research directions to pursue. They are also motivated by our perusal of the relevant purchase-avoidance and decision-difficulty literature. It is hoped that these seven features embrace the issues we deem most important, capture our intuitions about how RA design should progress and serve to articulate interesting research directions that are worthy of attention. Our most ambitious objective is to create the research agenda in the field of RA design. We aim to stimulate discussion and identify opportunities for researchers who are keen to explore this field. The following discussions of each of the seven traits of RA provide the context for our research agenda.

Table 2. RA Features and Sources of Decision Difficulty

Information search						
Alternative evaluation						
Choice selection						
System features	*Knowledge uncertainty*	*Preference uncertainty*	*Choice conflict*	*Need for justification*	*Information structure load*	*Decision style*
1. Product learning	√				√	
2. Preference discovery		√			√	
3. Preference framing		√				
4. Decision strategy based screening		√				√
5. Option framing			√			
6. Decision guidance				√		
7. Personalization						√

D.4.1 INFORMATION SEARCH

Information search is often driven by a consumer's lack of sufficient product knowledge and characterized by the process of learning about a product. Research on **product learning** can be generally separated into direct and indirect experiences. A direct experience is derived from the actual product contact, such as putting on a new dress at the boutique; whereas indirect experience can be generated through advertising, reading magazines, surfing the Internet, and word-of-mouth dissemination. For the reason that this article focuses on RA design, our discussion shall revolve around the issue of product learning and visualization through indirect experience.

Studies related to product learning and visualization share a common objective of providing consumers with a virtual product experience that enables potential consumers to learn about a product (Li, Daugherty and Biocca 2003). Such an experience can be built through the use of stimuli to induce desired product affordances, which in turn lead to product visualization. Product affordance refers to the real and perceived cues that are available to direct consumers in interacting with a product during inspection (Norman 1998). According to Norman (1998), when we are presented with a product, we often attempt to formulate preliminary judgment of a product and how this product can be utilized or evaluated. For instance, a consumer inspecting an unfamiliar PDA, may automatically press on the silver button to power up the PDA without anyone indicating to him the purpose of the button. Such affordance is born of a natural and intuitively derived set of rules and actions that guides consumers, though such judgments may not be accurate all the time. Germane to the issue of product affordance and learning are the questions of how the set of rules is cognitively derived by consumers when facing a new product and what cues and/or information should be provided to induce product learning.

Two theoretical perceptions of human learning could shed light on the preceding questions. The first comprises the category-learning theories that collectively posit that when an unfamiliar product is encountered, a consumer has a high tendency to associate that unfamiliar stimulus with the most similar product category encountered previously (Ashby and Maddox 2005). Such association allows a consumer to quickly formulate an initial set of rules and interpretations of the newly-encountered product. To achieve this association, a consumer first determines which region the product is in (e.g., home electronics or entertainment electronics), and then forms associations of that product within that region, according to the Decision Bound Theory (Ashby 1992). Should more than one similar product category within that region be retrieved from memory, the new product is mapped to the category that has the highest sum of attribute similarities, according to the Exemplar Theory (Nosofsky 1986).

Applying the category-learning theories to our context, we conjecture that for an RA to support new product learning and visualization, it ought to be equipped with the capacity to first assist a consumer to associate the product with a category that is most familiar among average consumers. Such association could be formed through analogy (Gregan-Paxton, Hibbard, Brunel and Azar

2002). For instance, suppose one is interested in acquiring new software that allows one not only to download images and videos from the Internet but also to view and read the downloaded content. One way one can learn about the software is to relate that software to a physical video recorder. Using the knowledge one has acquired about the video recorder, one can relate the software to the video recorder which allows one, as a consumer, to both store and retrieve the media content. Extending this understanding, one could also be aware that the amount of content that both recording devices could store depends on the available capacity. For instance, you are interested in acquiring a new convergent device such as a PDA phone. One way to learn about this new category of device is to relate it to common and familiar usage scenarios of more traditional devices such as the ordinary PDA and the mobile phone. To illustrate further, you could visualize yourself recording an appointment on an ordinary PDA and making a phone call on a mobile phone. Using such knowledge, you can relate to the new PDA phone as if you were performing the two familiar tasks on a single device. Knowledge gained through analogy could further your understanding of the new product category (Gregan-Paxton et al. 2002). Hence, we posit that the difficulty of learning about an unfamiliar product can be alleviated if consumers are offered a comparison of the new product to something more familiar. Analogy allows the consumers to transfer some basic knowledge from one domain to the one that is targeted, thereby leading to the construction of the mental representation for the product and for the initial information to be incorporated into that representation (Gregan-Paxton and John 1997).

> *Proposition 1.1.1: Allowing consumers to relate a new product to existing familiar products will reduce decision-difficulty due to knowledge uncertainty, thereby leading to a decrease in the propensity for purchase-avoidance.*

Proposition 1.1.2: Seeking to relate a new product to the existing stored memory of a familiar product (category) through analogy can lead to reduced decision-difficulty in learning about a product.

It must be noted that Proposition 1.1.2 does not imply that the RA must always provide analogical product learning for all consumers. In fact, providing such product learning to consumers who are already knowledgeable about the new product may be counterproductive as it adds on unnecessary cognitive load to process the analogy. Furthermore, if the analogy contradicts the consumer's prior understanding of the new product, it may also result in undue emotional difficulty. Either way, decision-difficulty is likely to increase. Exactly how the RA should determine whether analogical product learning should be provided is the subject of RA personalization; and thus at this point we shall defer the discussion. At present, the more interesting question to ask is: How should the RA provide analogical product learning?

Returning to our previous example on the PDA phone, we suggest that the RA could pose a series of usage questions pertaining to ordinary PDAs and mobile phones in order to stimulate the association with the PDA phone. For instance, an RA could ask the consumers whether they prefer to use a built-in keypad, touch screen or stylus for inputting the telephone numbers on a mobile phone; or activating the address book functionality on an ordinary PDA so as to elicit consumers' preferences for the type of input mechanism supported by the PDA phone. Such a mechanism falls into the realm of the need-based RA which we will discuss in greater detail in the preference-framing section. At this juncture, it suffices to state our suggestion of a personalized RA that offers a hybrid of feature-based and basic need-based preference elicitation to guide consumers in initial product learning. We will discuss this suggestion in much greater detail when we propose RA personalization design in Section 4.4.

The second theoretical reference originates from the Feature Integration Theory (Quinlan 2003), which dictates that the perception of an object (i.e., a product) is shaped by two mental processing stages. Processing at the initial stage is pre-attentive, where individual product attributes are coded independently and in parallel, based on the information provided (i.e., content) and the way in which such information is provided (i.e., text, image or voice). The output of this stage is the array of product features and attributes (Treisman and Gelade 1980). This theory, however, does not indicate specifically how the location of any given attribute is specified within the memory of this array.

Based on the initially-built impression of the various product attributes, a consumer proceeds to the second stage: cross-attribute processing and linking. At this stage, a consumer will combine constituent product attributes to form a conjunction of features known as a master map of locations. Such a map allows a consumer to “activate” particular nodes within the map. Expressly, through either the application of focused attention or by presenting a particular object that is related to the product of interest (Treisman and Schmidt 1982), a consumer could be led by external aids to “trigger” stored product feature information and associated preferences. Essentially, the extent to which a consumer initially forms an impression of the various product attributes and features and subsequently links all these features into a cognitive map for retrieval, determines the outcome of product learning (i.e., how it is stored in the memory) and visualizing (i.e., how it is retrieved from memory). The question to ask next is: What features could an RA offer?

To answer this question, we need to first understand the cognitive load inherited from learning. According to the Cognitive Load Theory (Leahy and Sweller 2005), there are three primary forms of cognitive loads that could affect learning performance. The first type, intrinsic cognitive load, refers to the inherent difficulty of processing the information. It is often dictated by the number of learning elements (i.e., simplest form of information) and the interactivity among the elements that needs to be simultaneously processed. It may be cognitively more difficult as the number of product attributes and the level of attribute increases. For instance, the digital camera has the optical zoom and digital zoom as one of many product attributes while the optical zoom comprises 2x, 3x, 4x, 5x, 6x, 7x or even higher levels of attributes. Intrinsic cognitive load is immutable. As opposed to intrinsic cognitive load, extraneous cognitive load and germane cognitive load can be altered by an RA designer.

Extraneous cognitive load is usually undesirable for it is produced by external cues that do not serve to enhance learning performance. Such a load is often induced through an instructional format or a procedure of learning (Chandler and Sweller 1991). For instance, presenting a consumer with a list of product feature definitions as opposed to offering a consumer a typical example of a product may alter extraneous cognitive load. The germane cognitive load refers to the cognitive effort necessary to process and construct a mental schema of the product. This is similar to cross-attribute processing and linking in the Feature Integration Theory (Quinlan 2003). It is suggested that when a consumer imagines a product, he processes and constructs the relevant schemas in working memory, which facilitates subsequent retrieval for preference elicitation.

Leading on from the Cognitive Load Theory (Leahy and Sweller 2005), which states that intrinsic cognitive load is not alterable, we could propose that a RA designer could assist a consumer in yielding better learning performance through limiting the extraneous cognitive load while promoting a certain degree of the germane cognitive load. Specifically, the presence of external aid in an RA may help a consumer not only to reduce the difficulty of completing the whole learning process, but as well to trigger the elicitation of preferences associated with the product. Two primary modes of RA feature supports could be explored. The first is in line with the discursive (symbolic or linguistic) information processing paradigm (Foxall, Goldsmith, and Brown 1998) which dictates that an RA could be designed to match the users' procurement goals through the support of cognitive elaboration (i.e., reading, interpreting and storing the product information in memory for future use) to yield favorable product learning outcomes.

However, from the perspective of imagery information processing, an RA that evokes mental images (i.e., through a video) could yield more favorable product-learning performance. This is seen for example, in the transportation-imagery model by Green and Brock (2002). Specifically, according to the principle of imagery information processing (MacInnis and Price 1987), knowledge about a product is stored or represented as images. Imagery is a form of representing information in which it denotes the process by which sensory information is encoded and represented in working memory. For instance, when we think of a PDA, we often picture the shape, size, color and appearance of a PDA (i.e., in pictorial form) rather than in descriptive words (e.g., the processing speed, the dimensions in centimeters). This imagery view shares a similarity with the perspective of motor resonance which dictates that consumers are able to acquire better understanding of a product when they are able to mentally simulate its usage through observing others' actions such as from a video, and predicting their own actions, in other words, from personal usage (Zwaan and Taylor 2006; Cooper, Tindall-Ford, Chandler and Sweller 2001).

While both forms of information processing can be supported by an RA and occur concurrently, it is unclear from the two perspectives whether an RA that promotes cognitive elaboration or one that supports imagination would lead to better performance (Schlosser and Shavitt 2002). To explore further, we referenced the study by Leahy and Sweller (2005). Through a series of experiments, the authors observed that when participants first encountered a complex and unfamiliar set of information, those who were requested to study the information outperformed those who were told to imagine. In other words, support for discursive information processing outperformed support for imagery information processing. However, when participants were able to gain preliminary understanding of the information, those told to imagine outperformed those who were told to continue to study. In other words, support for imagery information processing outperformed support for discursive information processing.

Relating the findings of the Leahy and Sweller (2005) study to our context, we posit that a personalized RA that entails a hybrid model of learning support could be offered. When a consumer has little prior knowledge of a product, he should be encouraged to first read and understand a product through discursive information processing, and when such preliminary understanding is yielded, the consumer could then be encouraged to engage in imagery information processing. This view shares similarity with the findings of Tindall-Ford and her colleagues (1997), where they observed that the use of dual-mode presentation (e.g., through auditory text and visual diagrams) can lead to a better learning outcome compared to the single-modality format (e.g., through visual text and visual diagrams). It is further noted that when such supports are facilitated, a consumer may overcome the limited working memory to process complex product information (Leahy and Sweller 2005). Essentially, when a consumer is able to better learn about and visualize a product, knowledge uncertainty is lowered, resulting in a lower propensity for purchase-avoidance.

> *Proposition 1.2: Different information processing supports could offer different phases of learning. Consumers could develop initial appreciation of a product through discursive information processing and subsequently construct a complete understanding of a product through imagery information processing. This approach of offering personalized learning support should lead to reduced difficulty in learning about a product or to reduced knowledge uncertainty.*

D.4.2 ALTERNATIVE EVALUATION

Based on the acquired product information, a consumer would delineate the criteria (or preferences) for retrieval and evaluation of product alternatives. The notion of preference elicitation has received a fair measure of attention in consumer behavior literature (e.g., Aggarwal and Vaidyanathan 2005; Ariely et al. 2004; Haübl and Murray 2003, 2006; Ariely 2000). The theoretical underpinning of preference elicitation research is the Behavioral Decision Theory (Einhorn and Hogarth 1981), which posits that a consumer's preferences are often ill-defined initially, and are constructed through his interaction with the information environment, rather than retrieved from a pre-existing list of preferences and values from his memory (Haübl and Murray 2003; Bettman et al. 1998). In this section, we propose three RA features: preference discovery, preference framing and decision strategy based screening.

D.4.2.1 Preference discovery

In the information search stage, we focus our discussion on proposing RA design to assist a consumer to learn about a problem. Notwithstanding the attempt to foster product learning through virtual experience, it is observed that inconsistency in preference elicitation and choice-making may still persist even when the effects of learning, satiation or change in taste are controlled (Tversky 2004). In other words, the mere presence of an environment that promotes learning may not be sufficient in addressing the issue of preference uncertainty. To address this concern, a significant cohort of standard preference models advocates the revision of the models and developing elicitation methods that incorporate appropriate controls that address the anomalies observed. In our view, knowledge gained from this field of research could enhance the design of an RA in many ways. Here, we propose several theoretical directions in which an RA designer could venture in future.

The first approach as posited in the Construal Level Theory (Trope and Liberman 2003) is to have a good level of the abstractness of consumers' mental representations within the targeted temporal, spatial or sensory distance from the purchase task. According to the Construal Level Theory (Trope and Liberman 2003), mental space is a facet of psychological distance along temporal, spatial or sensory dimensions. Psychological distance affects the way consumers interpret and represent information, for example, psychologically-distant products are represented more by their general, essential and prototypical features, i.e., high level construals, while psychologically-near products are represented in terms of their specific, incidental, and unique features, i.e., low-level construals (Henderson, Fujita, Trope and Liberman 2006).

High-level construals are often characterized by abstract product schemas that convey the general and essential features of the product (Trope and Liberman 2000). However, low-level construals are often denoted by the contextual and incidental details of the product. To illustrate, the action of using an MP3 player can be mentally represented as being entertained (a high-level construal) or as pressing buttons (a low-level construal). It is posited that when products are perceived to be psychologically closer to the consumer (i.e., internalized), preference uncertainty is reduced, while preference stability and preference-behavior consistency increase due to clearer and more precise formulated product schemas (Kardes, Cronlet, and Kim 2006).

In order for the products to be perceived as being psychologically closer to the consumer (i.e., in terms of relatedness), the RA could offer simulated product search and evaluation exercises, which ease the difficulty of constructing preferences (Urban, Qualls, Weinberg, Dohlmann and Chicos 1997). Hoeffler (2003), for instance, proposes the concept of letting the consumers mentally simulate using the products in some existing usage scenarios. The author observes that encouraging consumers to ***mentally simulate*** how the product fits into existing usage scenarios helps consumers to better identify and articulate their preferences, leading to lower preference uncertainty and higher preference stability. The rationale is that mental simulation brings the product closer to the actual usage of the product on the part of consumers. It is the usage that determines the value of a product rather than the product attributes themselves. Particularly, consumers often form preferences for a product that are not based on every single product attribute but on a subset of the whole collection of attributes that interests them. A paper by Jiang and Benbasat (2004) illustrates this point. The authors posit the provision of both visual and functional control to be important for electronic products. Visual control enables consumers to manipulate the product images (e.g., view the product from different angles) and functional control affords consumers to explore the different features of the products, thus enabling consumers to learn more about a product. They observed that the provision of both controls increases the perceived diagnosticity – the extent to which a consumer judges the shopping experience to be helpful when evaluating and learning about a product. It is believed that the increase in diagnosticity of the product could facilitate better understanding of the product (Li et al. 2003).

Mental simulation could be achieved through prompting consumers to supply information about how they would use the product (Grenci and Todd 2000). Such mental simulation could alleviate the influence of complex information structure in addition to preference uncertainty and knowledge uncertainty. This is because by mentally simulating product usage, one is able to focus on the necessary and desired product attributes, thereby reducing the amount of attribute information to be considered. Essentially, the provision of an RA feature that guides the consumers in simulating the use of the product could potentially reduce preference uncertainty and the complex product information structure inherited from a product.

Proposition 2.1: Allowing consumers to simulate the use of a product will lower decision-difficulty due to preference uncertainty, and channel the focus of preference discovery towards usage, thereby alleviating information overload for consumers due to a complex product information structure. Hence, the result is a decrease in the propensity for purchase-avoidance.

The underlying assumption that the provision of an RA feature encourages mental simulation is based on the understanding that consumers have abstract knowledge (high-level construal) of a product's usage. Thus, through mental simulation, the RA could direct consumers to articulate more concise and consistent preferences, which define the search criteria. However, it is plausible that such abstract levels of preference knowledge may not be congruent with what is provided commercially. For instance, you may envision a need for a PDA of a relatively large memory capacity that allows you to store a large number of movies. However, such a requirement may not be satisfactorily met by those currently available in the market. Moreover, the demand for a larger memory capacity may lead to a higher price tag which the consumer may not find affordable. When such situations are encountered, it is imperative that consumers be cautioned with respect to the appropriate search criteria definition.

A way to address this concern is to provide instantaneous feedback and suggestions to consumers during preference elicitation. Specifically, if there is an external aid that engages the consumers in an iterative process of refinement of preferences, and which offers feedback on the consequences of the actions (i.e., preferences are elicited), such interaction with the external tool may induce appropriate behavior (i.e., reduce decision-difficulty in our context). The inclusion of such an information aiding feature is particularly beneficial in a situation where the product is new to a consumer, and articulating realistic preferences and criteria for evaluating the alternatives would be a cognitively-demanding task. Indeed, when facing a new product, one must first have the baseline knowledge or experience in the same or a related product domain to understand what the product is and what can be offered by the market. To this end, an information aid could be applied in several ways. Before examining two such instances, we first state a general proposition on the key concept highlighted above:

> *Proposition 2.2.1: Consumers could be offered a repertoire of feedback-related supports to govern the elicitation and refinement of preferences leading to reduced decision-difficulty, thereby resulting in a lower propensity for purchase-avoidance.*

The first approach is to make it easier to input the preference parameters without considerable mental deliberation. Iyengar and Lepper (2000), for instance, observed that the provision of a default option could serve as a quick way of addressing decision-difficulty. Extending this argument, we could posit that the provision of default preferences could reduce the difficulty of delineating preferences and reducing preference uncertainty, thereby leading to a lower propensity for purchase-avoidance. By providing a default option, a consumer could use this option as a standard or benchmark with which to evaluate other options of different attribute values. In summary, the inclusion of default preferences could decrease the level of difficulty in eliciting preferences, leading to a lower propensity for purchase-avoidance. Pursuing this argument, we propose that:

> *Proposition 2.2.2: An RA could provide a default option for each product attribute to alleviate decision-difficulty due to preference uncertainty, thereby leading to a lower propensity for purchase-avoidance.*

The second approach is to provide information cues to reflect the possible returned set of alternatives based on different preference criteria. The rationale is simple: a consumer often faces the predicament of over-specifying the criteria, leading to the presentation of very few alternatives;

or under-specifying the criteria and resulting in the extraction of overwhelming alternatives (Schwartz 2004). The former option fails to satisfy the natural quest for choice assortments while the latter may result in choice-overloading. By offering an instant estimation of the number of products to be returned from the search based on different input criteria, a consumer could adjust his search criteria way before the results are presented; thereby leading to the lower formation of negative emotions resulting from either over- or under-specifying the preferences (Aaker and Lee 2001). This proposition rests on the principle of flow experience which dictates that every piece of information a consumer processes is evaluated to determine if it threatens his procurement goal (i.e., need for assortment or need for minimizing of evaluation effort). When information supports a consumer procurement objective, a consumer is more likely to experience positive emotions during the whole procurement process (Ciskszenthmihalyi 1990). Furthermore, the provision of an instant information cue could allow a consumer to adjust his preferences to what can be offered, thereby leading to lower difficulty of preference elicitation and a lower propensity for purchase-avoidance.

> *Proposition 2.2.3: An RA could provide instant information cues, such as the estimation of the number of alternatives associated with different search criteria prior to the submission of search criteria, to alleviate decision-difficulty due to information structure; thereby leading to a lower propensity for purchase-avoidance.*

D.4.2.2 Preference Framing

We have thus far proposed two features that an RA could offer – a default option and result set information cues. However, these two features may not be adequate to address two fundamental issues of how preferences are elicited in a conventional shopping environment: 1) the tendency to articulate preferences based on needs rather than product attributes; and 2) the inclination to elicit trade-offs between product attributes.

The initial formation of purchase intent is motivated by needs. Indeed, it is often the case that consumers may recognize the need to procure a product but they are unable to determine the specific product features required (Bettman et al. 1998). For instance, one may visualize a need for a laptop so that one can work while one travels. Yet, one may not be capable of delineating what is desired (e.g., the minimum acceptable weight, the battery life, the processor speed, the memory size, hard disk size). In this regard, the traditional approach of attribute-based preference elicitation may not be feasible. An attribute-based preference elicitation method denotes the declaration of the set of preferences for a product (e.g., weight of less than 2.0kg for a laptop and a duo-core processor). It is believed that even if consumers understand their need for certain attributes, they might not understand the process required to configure the correct solution or to make the best product choice (Grenci and Todd 2002). For instance, consumers may not be able to define the criteria involving inter-related attributes such as the weight and durability of a backpacking tent (Haübl and Murray 2003).

To address this concern, researchers have advocated the use of a need-based RA, which presents product features based on the needs instead of product attribute values (Grenci and Todd 2002). In a need-based RA, the agent will either use a set of rules to interpret customer-specific information or intentions and formulate a recommended product configuration, or translate customer-specified preferences into alternative product configurations (Grenci and Todd, 2002). Need-based RAs can link customers' personal needs to product attribute configuration, thus facilitating customers' expression of their information needs and making the rationale of the need-based RAs easy to understand. In this regard, need-based RAs could alleviate the difficulty of eliciting preferences, or preference uncertainty.

In delineating the applicability of need-based RAs, some researchers observe that a need-based RA is preferred over an attribute-based RA when consumers are novices at using the product (Stolze and Nart 2004). Explicably, Felix and his colleagues (2001) have demonstrated that, for consumers with little product knowledge, it could be particularly problematic to use an attribute-based RA if they seek to receive recommendations only based on their personal needs and expected use of the product. Conversely, for expert consumers, the use of an attribute-based RA could lead them to better elicit preferences since they would have the knowledge capacity to mentally convert the needs into well-defined preference criteria (Grenci and Todd 2002). While such cognitive mapping of needs to attributes requires additional effort, the ease of evaluating the product alternatives presented could compensate for the further effort. (Spiekermann and Parachiv 2002). Indeed, it is imperative to note that the alternatives presented only contain product attributes and their associated values. The consistency in both the attribute-based preference elicitation and attribute-based comparisons of the returned alternative methods in an RA could better assist the expert consumers in making a procurement decision.

> *Proposition 3.1: The choice of the preference elicitation method could depend on the extent of a consumer's acquisition of product knowledge. Consumers who are new to a product could prefer the need-based elicitation approach; however, as their knowledge and experience of a product increases, they could prefer the attribute-based elicitation method. Matching consumers with the appropriate preference elicitation method could reduce the difficulty of articulating preferences (i.e., preference uncertainty), leading to a lower propensity for purchase-avoidance.*

Another concern with respect to the traditional preference elicitation method is that it focuses more on capturing singular attribute preferences (Doyle and Thomason 1999), for example, "I prefer a perfume with a refreshing scent." than generic tradeoff preferences such as "I prefer a perfume with a refreshing fragrance than one with a fruity scent." To the extent that elicitation of tradeoff preferences is another common form of expressing preferences, an essential requirement of an RA is to facilitate a consumer in facing and delineating trade-offs.

When confronted with a tradeoff decision that has to be made, a consumer may adopt one of the two coping strategies: (1) problem-focused coping involving direct actions intended to improve the situation of eliciting preferences; and (2) emotion-focused coping involving indirect actions intended to minimize experienced negative emotion through changes in the amount or content of thought about the preference elicitation situation (Anderson 2003; Folkman and Lazarus 1980). The former coping strategy, comparatively, is more desirable as the latter coping strategy often leads to purchase-avoidance or poorer decision-performance resulting from the use of the non-compensatory decision strategy (Folkman and Lazarus 1980). In a non-compensatory strategy, a good value on one attribute cannot make up for a poor value on another (Bettman et al. 1998).

Whether a consumer chooses the problem-focused coping strategy often depends on the degree of conflict (i.e., negative correlation) between attribute values which a consumer has to resolve (Payne et al. 1993). A significant degree of negative correlation between attribute values is generally associated with decision-difficulty and indecision (Hogarth 1987). Some researchers observe that decision-makers use more trade-off confronting processing strategies when decision-conflict increases; presumably because such a strategy tends to lead to higher decision-accuracy compared to trade-off avoidance (i.e., non-compensatory) strategies (Payne et al. 1993).

However, other researchers argue that merely requesting or even encouraging the consumer to recognize the need to delineate trade-offs may not lead to the adoption of a problem-focus coping strategy. One promising technique proposed by Luce and her colleagues (2001), is to alter the presentation of decision attributes such that a consumer is either more comfortable with the delineation of preferences or is at least less motivated to choose a trade-off avoiding a coping or compensatory decision strategy. Particularly, conflict between highly important core values is both cognitively and emotionally costly, and publicly making trade-offs between attributes with links to such values is considered to be both distressing and embarrassing (Tetlock 1991).

To address this problem, an RA could reframe the trade-off problem by allowing a consumer to trade-off core attribute values against less valued attributes (Janiszewski, Silk and Cooke 2003). The agent could subsequently compute the relative weight of the core attributes. Viscusi, Magat and Huber (1987), for instance, suggest the use of risk comparisons in order to generate a willingness to pay for risk reduction. Particularly, they advocate that respondents are more emotionally comfortable when comparing one risk (e.g., from a car accident) to another (e.g., from food poisoning) rather than trying to set a price (utility level) directly for either risk. Such a method could reduce preference uncertainty by facilitating the adoption of a problem-focused (i.e., compensatory) coping strategy in preference elicitation, thereby leading to a lower purchase-avoidance propensity.

> *Proposition 3.2: The framing of trade-offs of important core attribute values against less valued attributes could result in consumers being more willing to confront trade-off preferential problems, resulting in lower decision-difficulty arising from preference uncertainty. A lower propensity for purchase-avoidance is the result.*

D.4.2.3 Decision-strategy-based screening

Once a consumer gains sufficient knowledge of a product and is aware of his own preferences, he will need to devise the decision strategy towards screening and extracting the product information. A decision strategy is a sequence of mental and effector (actions on the environment) operations used to transform an initial state of knowledge into a final-goal state of knowledge where the decision-maker views the particular problem as solved (Payne et al. 1993). It is imperative to note that screening is a continuation of the previous preference framing referred to previously and it is conceptualized as part of RA support for preference elicitation.

Decision strategies can be separated into two main categories: compensatory and non-compensatory. Consumers employing non-compensatory strategies typically do not consider tradeoffs between attributes, i.e., a positive value of one attribute cannot compensate for a negative value of another attribute. Furthermore, alternatives are usually eliminated once negative information about them is obtained. Decision strategies such as elimination-by-aspect, lexicographic and satisfying heuristics are some of the most frequently discussed non-compensatory strategies. Conversely, consumers employing compensatory strategies typically assign a relative importance to each product attribute and then compute an overall value for each alternative based on the impact of the relative weights of each product attribute. The alternative with the best value is often selected. These strategies are of an analytical nature and require significant amounts of mental and cognitive effort in order to yield an accurate result. Whilst using non-compensatory strategies requires less effort, compared to choosing one of many alternatives, existing research indicates that compensatory strategies should lead to a better, more accurate, and higher quality choice. Where a decision involves the examination of a large amount of data, compensatory strategies carry too high a cognitive cost, and non-compensatory strategies have emerged as the choice (Bettman et al. 1998; Payne et al. 1993). Commonly studied compensatory strategies include the weight-additive rule, the equal-weight heuristic, and the additive difference rules.

As none of the above-mentioned strategies have been able to yield high accuracy (i.e., the best choice made) with little effort, consumers often have had to make explicit tradeoffs between result accuracy (by adopting compensatory strategies), and effort requirement (by adopting non-compensatory strategies) as in Johnson and Payne (1985). To elaborate, the basic premise of the effort-accuracy framework is that people tend to prefer choices with high levels of accuracy that also require less effort. However, strategies yielding higher decision accuracy (i.e., choosing the best product option in our context) often require more effort. Therefore, a person's strategy selection is the result of a compromise between the desire to make the most correct decision and the desire to minimize effort, which is commonly termed as effort-accuracy trade-off (Posavac, Herzenstein, and Sanbonmatsu 2003; Swait and Adamowicz 2001). It is assumed that the choice of the decision strategy is based on a careful evaluation and computation of utility derived from the attributes of alternatives available, rather than from the decision strategies available (Payne et al. 1993; Malhotra 1982).

Examining the effects of adopting decision-strategies on decision performance, Payne and his colleagues (1993), in particular, suggested that decisional support (facilitated by technology such as an RA) could be provided to facilitate a decision-maker's adoption of the "divide-and-conquer" approach when dealing with complex decision tasks involving large quantities of product information. This view has gathered much empirical support (Edwards and Fasolo 2001). For instance, researchers observe and propose that consumers could harness the availability of online decision aids (e.g., RAs) to screen and evaluate product offers from many online merchants (Edwards and Fasolo 2001; Haübl and Trifts 2000). Looking beyond the consumer shopping context, we do observe companies making use of decision aids to manage, screen, and select from among the large quantity of options for other decision tasks, e.g., job applicants[17] and technology to embrace (Klein and Beck 1987).

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[17] http://www.wsjclassroomedition.com/archive/03feb/CARE.htm (last visited: May 5, 2006)

Relating to our context, an RA could be designed to facilitate the adoption of decision strategies in two ways. First, an RA could induce consumers to employ more cognitively-demanding compensatory strategies in order to examine individual alternatives more closely. Using compensatory strategies, a consumer defines the importance of each attribute. An RA then computes a weighted score for each alternative based on the importance of the indicated attribute. The alternative with the highest score is recommended. The benefit of the compensatory strategy is that it facilitates the consumer's selection of an overall excellent alternative. Two strategies that best represent compensatory-based processing are: 1) equal weighting, which involves assigning equal weights to all attributes and choosing the alternative with the highest score; and 2) weight additive, in which a weighted score for each alternative based on the indicated attribute's importance is given and the alternative with the highest score is selected.

Second, an RA could support a consumer in eliminating options that are less likely to be considered for procurement. RA decision support begins with a consumer establishing a (list of) minimum product attribute(s) of acceptable level(s) that an alternative must possess to be considered further for as a choice (Chen, Iyer and Padmanabhan 2002; Olson and Widing 2002; Todd and Benbasat 2000, 1994). The process of delineation of minimum attribute-acceptable levels and the filtering of alternatives that have failed the criteria is known as screening. The screened alternatives are then assessed carefully to make a choice, and this process is known as evaluation (Edwards and Fasolo 2001; Alba et al. 1997).

Comparing the compensatory and non-compensatory approaches, we posit that the extent of the criteria to be input into the RA before further screening or weight computation could be performed, would affect the choice of the RA features. Particularly, since RA features that adopt non-compensatory strategies would eliminate options that have failed the threshold, users could feel more at ease with delineating fewer attribute criteria per submission. Comparatively, since RA features with compensatory strategies would be able to compute more accurate scores of the options with more criteria and weights entered, it could exert pressure on the users to delineate more attempts per submission. In this regard, when consumers have only a set of vague preferences, the use of an RA that supports a non-compensatory decision strategy could be a better choice. Conversely, when a specific criterion is defined, the use of an RA supporting compensatory-based decision strategy could be a better fit.

> *Proposition 4.1: Consumers developing more abstract dictation of preferences would tend to prefer an RA-supporting, non-compensatory decision strategy. However, if a specific criterion is primed and defined, consumers would prefer an RA-supporting compensatory decision strategy. Matching consumers with the appropriate decision strategy afforded by an RA could lower the decision-difficulty due to decision style preference, leading to a lower propensity for purchase-avoidance.*

When a consumer engages in screening, he is likely to expend conscious cognitive effort to eliminate undesirable alternatives using non-compensatory strategies (Bettman et al. 1998). By definition, the use of non-compensatory strategies implies that the definition of the cutoff point should focus on the most important attribute(s) and the information about the other attributes would hence be ignored. Non-compensatory strategies identified by researchers could be broadly classified into two types which could be supported by an RA, i.e., single-attribute or multiple-attribute screening (Payne et al. 1993).

A consumer who adopts the single-attribute non-compensatory strategy would choose the most important attribute. He or she then evaluates whether the reduced number of alternatives allows the decision-maker to make a choice. If another screening attempt is needed, the consumer then determines which of the remaining attributes is the most important. The second step is repeated based on the resultant set of alternatives from previous screenings until no further screening is needed. In choice-making, two approaches are used: 1) lexicographic, i.e., choosing the alternative that is best on the most important attribute, and 2) elimination-by-aspect, i.e., removing alternatives with at least one attribute value that fails to meet the minimum acceptable level (Bettman et al. 1998).

With a non-compensatory strategy that utilizes multiple attributes, such as that based on a majority of confirming dimensions (*MCD)*, a consumer chooses the alternatives that are acceptable on the largest number of attributes. Hence a consumer would select more than one attribute simultaneously without knowing the combined impact of the cutoffs on the number of surviving alternatives. Similar to the single-attribute non-compensatory strategy, alternatives that do not meet the specified threshold values of all the attributes will be discarded. After this attempt is completed, the consumer then assesses whether additional simplification is desirable, and another set of cutoffs can be selected to eliminate more alternatives in subsequent attempts, and so on (Payne et al. 1993).

In terms of cognitive processing demand, multi-attribute screening affords consumers greater flexibility in controlling and choosing the amount of information than single-attribute screening does. Intuitively, by allowing consumers to increase the number of attributes in the screening criteria, multi-attribute screening requires less effort and fewer cognitive resources from consumers to arrive at a more accurate decision than does single-attribute screening. However, it is plausible that defining multiple screening criteria per attempt may be cognitively and emotionally difficult. Comparatively, single-attribute-based screening is more structured and the cognitive effort demanded for delineating screening criteria could be more structured and progressive in nature. In this regard, the level of cognitive dissonance experienced by consumers using the single-attribute screening feature is lower (Todd and Benbasat 1994), thereby reducing the propensity for purchase-avoidance due to cognitive-difficulty.

> *Proposition 4.2: Providing single-attribute screening features could result in consumers engaging in slow but progressive refinement of the elimination criteria, leading to lower decision-difficulty in eliciting preferences (i.e., lower preference uncertainty), thereby leading to a lower propensity for purchase-avoidance, compared to providing multi-attribute screening features.*

D.4.3 CHOICE SELECTION

RA support for the choice selection decisional stage focuses on assisting a consumer in assessing the set of alternatives generated by the matching support. We earlier proposed the application of option framing and decision guidance that could serve to lower two forms of decision-difficulty, namely choice conflict and need for justification, which could in turn influence the propensity for purchase-avoidance.

D.4.3.1 Option framing

One of the values of an RA is that it allows for revision of preferences after receiving a preliminary set of alternatives. Besides iteratively using the preference elicitation tools such as preference discovering and preference framing, and relying on decision-strategy-based screening, consumers could add (remove) alternatives to (from) the consideration set (the choice set). Choice set denotes the general set of alternatives that a consumer is faced with while consideration set refers to the specific set of alternatives that a consumer has viewed just before making a decision. The mechanism of adding and removing alternatives is similar to that of the shopping cart in online websites except that, in this context, the list of options is not an aggregated purchase list but rather consists of options that are further extracted for subsequent evaluation of purchases.

Prior research on the addition of alternatives to a consideration set or subtraction of alternatives from an original choice set has been limited. Among the few, a significant proportion of such research has focused on the formation of product bundling, such as a car audio system and reverse sensors) as in Chakravarti, Krish, Paul and Srivastava (2002). While these studies focus on the creation of product bundling and features, and there is little conflict among the options as a consumer could procure the whole set of options as a whole; in our view, product bundling can be equally applicable to our context, i.e., there is a high degree of conflict among the options as a consumer can only choose one rather than all options ultimately. This is because the theoretical justifications are independent of the specific decision-making context and if our conjecture is correct, it could suggest that option framing may be a potentially powerful feature of an RA.

Within this field of research, scholars articulate that the number of alternatives remaining in the set tends to be larger for consumers using exclusion (i.e., removing alternatives from the choice set) than for those using an inclusion (i.e., extracting alternatives from choice sets to form consideration sets) strategy. For example, Levin and his colleagues (2001) observed that when participants were given the description of a number of job applications, fewer applications were screened when participants were asked to exclude applicants from further consideration than when participants were asked to include applications for further consideration.

The consistent observations from prior studies could be explained by loss aversion. Participants who were under the exclusion treatment were more likely to be more sensitive to the utility losses incurred by deleting an option than consumers in the inclusion condition that was characterized by gains in utility when adding an option. Hence, it is believed that consumers engaged in inclusion would perceive the task of creating a consideration set to be less difficult than those who engaged in exclusion of alternatives. This is because exclusion induces a higher level of conflict in the consumer's mind than does inclusion. When a consumer faces a choice that entails a desired option, exclusion may create a conflict between utility loss (fewer choices) and effort gain (less cognition effort needed to make a choice later on). In contrast, inclusion creates a conflict between utility gain (more choices) and effort loss (more effort needed to make a choice later on). Differential loss aversion suggests that a consumer is more sensitive to utility losses (Botti and Iyengar 2004). Therefore, a consumer may perceive it to be more difficult and, hence, has a higher propensity for purchase-avoidance under an exclusion condition versus an inclusion condition, as they face utility loss decisions in the former condition.

> *Proposition 5.1: Providing an alternative-based inclusion-screening feature in the consideration set will lead to reduced decision-difficulty in evaluating the choice sets arising from choice conflict, thereby leading to a lower propensity for purchase-avoidance, compared to providing an alternative-based exclusion-screening feature.*

Despite the provision of the alternative-based inclusion-screening or exclusion-screening feature, it is observed that the addition (or removal) of an alternative to the choice set could still make a consumer's choice difficult to justify due to the degree of conflict generated by the choice set (Tversky and Shafir 1992). Specifically, the availability of competing alternatives of comparable attractiveness could induce cognitive and emotional difficulties because it fails to present an instantaneous reason to include or exclude an alternative for further evaluation. What our research implies is that when consumers face multiple alternatives of comparable quality, they will suffer from decision-difficulty and therefore the likelihood of purchase among the alternatives is reduced.

Prior research examining the influence of attributes on consumer decision-making indicates that the way alternatives are represented (e.g., via attributes) and the comparison process is conducted (e.g., inclusion versus exclusion) influences the choices made (Houston, Sherman and Baker

1991). For instance, consumers tend to find it easier to compare alternatives with attributes that are related to common aspects (i.e., alignable differences) compared to situations where alternatives of attributes are unique to individual options i.e., non-alignable differences (Dhar and Sherman 1996; Mantel and Kardes 1999; Slaughter and Highhouse 2002). On their part, Zhang and Fitzsimons (1999) advocated that aligned differences could induce a perception of a greater amount of information processed. However, non-alignable differences among attributes could induce consumers to fail to perceive a thorough evaluation of alternatives, leading to reduced chances of learning the value of the alternatives presented. This could suggest that an RA needs to be designed to facilitate comparison of alternatives based on attributes that are aligned. Such facilitation could serve to mitigate decision-difficulty arising from a complex information structure.

> *Proposition 5.2: Presenting attributes of alignable differences will allow a consumer to experience reduced decision-difficulty in evaluating the choice set (i.e., choice conflict), thereby resulting in a lower propensity for purchase-avoidance, compared to providing attributes of non-alignable differences.*

D.4.3.2 Decision guidance

The Regret Theory (Loomes and Sugden 1987) predicts that a decision-maker is more likely to choose the default choice, i.e., opt for purchase-avoidance, when he expects not to learn the outcome of the decision than when he expects he will. More generally, the tendency to be risk averse will vary, depending on whether or not feedback is expected on foregone options (Bell 1983). In Bell's terms (1983), the amount a decision-maker is willing to forego in order to avoid feedback (i.e., actual outcome after decision is made) on foregone alternatives is referred to as "regret premium". However, when the decision outcome can be altered (i.e., made reversible), a consumer is less likely to experience emotional difficulty when making a choice (Tsiros and Mittal 2000). In this sense, "bringing forward" the feedback could not only condition the decision-maker into reducing the anticipated regret due to a high level of uncertainty but also align the goals with what the environment can offer (Anderson 2003). For this reason, an RA could alleviate decision-difficulty by providing appropriate decisional guidance in the form of feedback, during the decision-making process.

Decision guidance refers to the means by which an RA "enlightens or sways its users as they structure and execute their decision-making process that is, as they choose among and use the system's functional capabilities" (Silver 1991, pp. 157). A variety of structural designs for decisional guidance is available (see for example Montazemi, Wang, Nainar, and Bart 1996; Silver 1991). The focus of our study is to build on the concept of decisional guidance (Silver 1991), distinguished by suggestive guidance (what to do, what input values to use) and informative guidance (provision of pertinent information without suggesting the course of action). Additionally, it proposes the provision of feedback to reduce preference uncertainty and assist the formation of reasons for decisions. The feedback proposed here is somewhat different from the system feedbacks proposed in DSS literature (Silver 1991). In our study, the outcome feedback includes the simulation of what would be the experienced regret if a consumer chooses to forego an alternative. In relation to the concept of decisional guidance, this form of feedback corresponds to informative guidance.

To illustrate, consider a situation where a consumer is facing two options: (1) a cheap and slow processing laptop, and (2) an expensive and fast processing laptop. The two alternatives with conflicting attributes require the decision-maker to make explicit trade-offs. It may subsequently be difficult for a consumer to decide which laptop to purchase. However, if the RA could further include information such as expert rating that rates the second option more favorably and justification (i.e., reason) that explicitly states that the first option has a higher defective rate, then the added information heightens the contrast between the two options and provides sufficient reasons for selecting one over the other. In this sense, the RA reduces the anticipated regret of choosing the second option, and thereby, leads to a lower propensity to avoid making an explicit choice.

> *Proposition 6.1: The inclusion of feedback will reduce decision-difficulty in choice selection due to choice conflict and the need for justification, thereby leading to a reduced propensity for purchase-avoidance.*

The provision of justification or explanation can be considered from two theoretical perspectives (Silver 1991; Payne et al. 1993). The system either provides knowledge and explanations necessary for the user to carry out his or her task; or alternatively, the system carries out some action and then explains the need and reason for the action the system itself has chosen for the user. The latter role of explanation is applicable in the context of an RA in which it solicits consumers' preferences and executes the particular decision strategy to generate a set of recommendations matching the consumers' preferences. The RA then explains the reasons for making the recommendations. Dhaliwal and Benbasat (1996) proposed that explanations were provided so that users could learn from the system. Wang and Benbasat (2007) further add that explanations enhance consumers' initial trusting beliefs and acceptance. Explanations play a teaching role in an RA by assisting the consumers to learn about how available products match their preferences, and thereby allowing consumers to make educated purchase decisions.

There are generally three dimensions to the generation of an explanation: 1) generating an explanation's basic content, 2) responsiveness, and 3) human-computer interface (Chandrasekaran, Tanner and Josephson 1989). The first dimension is concerned with generating an information structure containing elements that make up an explanation and is considered to be the most important dimension. In addition, explanation content can be put together in a way known as introspection (Chandrasekaran et al. 1989). The term introspection refers to: 1) the examination of a record of its own problem-solving activity and picking up appropriate traces containing information for user query; or 2) retrieval of knowledge-based portions used in making the decision. Basing the explanation content on introspection of the system's own problem-solving behavior, several researchers have proposed different taxonomies of explanation types (Chandrasekaran et al. 1989; Ye and Johnson, 1995; Gregor and Benbasat 1999). The various taxonomies are listed in Table 3. Moreover, Gregor and Benbasat (1999) have also provided two additional classifications of explanations: (1) Presentation format – text-based and multimedia; (2) Provision mechanism – user-invoked, automatic and intelligent.

Here, we will focus our discussion on Justification (JUST) and Strategic (STRG) explanations, based on the Gregor and Benbasat (1999) classifications, which are the latest and most comprehensive[18]. JUST refers to the provision of short descriptive explanations to justify recommendations, while STRG denotes the presentation of a single piece of aggregated information to represent a high level strategy. We reasoned that these two explanation types are most relevant with respect to the design of an RA from the consumers' perspective of choice selection. Specifically, the explanations offered serve to assist the consumers in evaluating the alternatives presented. JUST is one of the more popular explanation types used by commercial RA

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[18] One could wonder why the other two forms of explanations (i.e., Type I and Type IV) are not explored. We believe that providing mere definitional information to explain the various attributes of the product (i.e., Type IV) may be insufficient, while articulating the series of steps taken by the RA to generate its recommendation (i.e., Type I) may be unnecessarily complex and extraneous to the evaluation of the alternatives. Hence, trace and terminological explanations are unlikely to provide much assistance to consumers in evaluating the RA's recommendations.

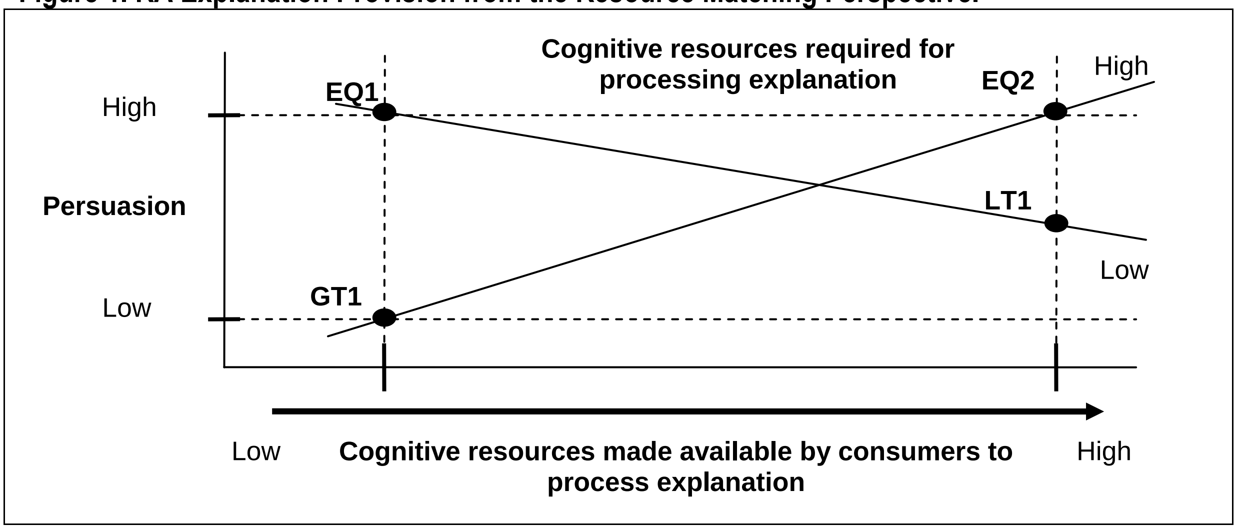
implementations such as Yahoo! and SmartSort, while explanations such as numeric-ranking or star-rating STRGs are present in almost every online shopping website. We suggest that processing a single piece of aggregated information for STRG, be it a numerical ranking or starred rating, requires a much lower level of cognitive effort than JUST because such a simple piece of factual information can be more readily elaborated on and understood by consumers. JUST requires the reading of a paragraph of textual information followed by an in-depth elaboration in order to relate to the actual values of product attributes. The immediate line of reasoning may be unclear to the consumers and thus could add a cognitive burden to them, leading to a higher level of decision-difficulty.

Table 3. Taxonomies of Explanation Types

Authors	Taxonomy
Chandrasekaran et al. (1989)	**Type 1** – Explaining why certain decisions were or were not made (portions of data in a particular case relate to knowledge for making specific decisions or choices). **Type 2** – Explaining knowledge-based elements (for example, justifying a system's compiled knowledge by linking it to the indepth knowledge from which it was derived. **Type 3** – Explaining the problem-solver's control behavior and problem-solving strategy.
Ye and Johnson (1995)	**Trace or Line of Reasoning** – Refers to a record of the inferential steps taken by an expert system to reach a conclusion. **Justification** – Explicit description of the causal argument or rationale behind each inferential step taken by the expert system. **Strategy** – High-level goal structure that determines how the expert system uses its domain knowledge to accomplish a task.
Gregor and Benbasat (1999)	**Type I** – Trace or line of reasoning. **Type II** – Justification or support **Type III** – Control or strategic. **Type IV** – Terminological, supplies definitional or terminological information.

The next logical question to ask would be: Under what conditions should a STRG or JUST explanation be provided, respectively? The Resource-Matching Theory (Anand and Sternthal 1989), which explains and predicts the utilization of cognitive resources in an information-processing task, provides a plausible theoretical explanation for this crucial question. The theory posits that when there is congruence between the cognitive resources required and those made available, information elaboration and processing are enhanced, thus leading to an increase in persuasion. This proposition has found support in many empirical studies (Keller and Block 1997; Peracchio and Meyers-Levy 1997; Meyers-Levy and Peracchio 1995; Anand and Sternthal 1990). The intuition of the Resource-Matching Theory and the findings from extant literature with respect to RA explanation provision is best summarized in Figure 1.

Figure 1. RA Explanation Provision from the Resource Matching Perspective.



If a consumer makes available low cognitive resources for an online shopping task, then the RA could only effectively reduce decision-difficulty if the explanation provided to guide the consumer is processed adequately, i.e., it is one that requires only low cognitive resources; and this is when we suggest STRG to be a suitable candidate. This condition is represented by point EQ1 in Figure 1. One could then deduce that if the consumer makes available high cognitive resources, he would definitely be able to process STRG and thus the level of decision-difficulty and the propensity for purchase-avoidance should also be reduced. However, this is less likely to be the case as the consumer is likely to redirect the surplus cognitive resources to activate personal or idiosyncratic associations which are likely to limit persuasion (Anand and Sternthal 1989). For instance, the consumer might use the excess resources to relate the list of alternatives presented in the result set with his prior knowledge of the product category and thus override the recommendations of the RA; or alternatively, to relate the current recommendations of the RA with past opinion agreement, resulting in non-acceptance of the current recommendations (Gershoff, Mukherjee and Mukhopadhyay 2003). These two scenarios are likely to complicate the decision-making process since the consumer ends up having to consider information beyond those provided by the RA. Thus, if the consumer makes available high cognitive resources, the RA should "*fit*" the consumer's ability by providing an explanation that requires a high quantity of resources for processing, (which is what JUST does), so as to reduce both decision-difficulty and the propensity for purchase-avoidance.

Consistent with the resource-matching perspective (Anand and Sternthal 1989), enhanced persuasion will increase the appropriateness, consistency and effectiveness of the RA explanation (Komiak and Benbasat 2004), thus resulting in higher acceptance of the explanation by consumers (Jiang, Klein and Vedder 2000). It then follows that the consumer is also more likely to accept the recommendation of the RA and make a purchase decision (Gregor and Benbasat 1999). We thus propose the following:

> *Proposition 6.2.1: Providing explanations that "fit" the cognitive ability of the consumer will lead to greater effectiveness in evaluating the choice set due to reduced decision-difficulty and higher persuasion, thereby leading to a reduced propensity for purchase-avoidance.*
>
> *Proposition 6.2.2: Providing STRGs (JUST) with low (high) cognitive ability to consumers will lead to a lower (higher) propensity for purchase-avoidance.*

D.4.4 SYNTHESIZED SUPPORT

With the knowledge acquired on the six RA traits, the next step is to delineate a set of RA traits that could cater to varying consumer needs. We, hence, propose RA **personalization**, which synthesizes the supports for information search, alternative evaluation and choice selection.

Within the field of RA-assisted online shopping, current commercial implementations of decision aids are too rigid to provide this personalization. For instance, most of the existing RA implementations, such as mySimon, offer a single interface and common set of functionalities to all consumers. Furthermore, there is limited guidance on how consumers could and should go about selecting an appropriate type of RA for their individual decision styles. This form of non-customizable RA could plausibly contribute to decision-difficulty from two perspectives. From the cognitive perspective, a rigid RA is unable to adequately assist consumers in processing a large quantity of product information (i.e., decision-difficulty due to information structure overloading). Consequently, consumers are forced to exert additional cognitive effort to manually perform certain unsupported processes such as product learning; or to bridge the inherent incompatibility of the decision aid provided, such as an incompatible preference elicitation mechanism. From the emotional perspective, a rigid RA does not understand the unique decision styles of different individuals, and thus the functionalities provided may not meet the expectations of the consumers. This could trigger counter-intuitiveness in the interaction between the consumer and the rigid RA, thus inducing negative affect, such as distress (Fitzsimons and Lehmann 2004). A plausible resulting scenario could be that the consumer develops suspicions on the ability of the RA to provide recommendations, thus increasing decision-difficulty. Ultimately, a rigid RA is likely to reduce the satisfaction of consumers (Fitzsimons and Lehmann 2004).

Extant literature has generally agreed that the RA is capable of reducing the cognitive effort that arises from making purchase decisions (Haübl and Trifts 2000), thereby helping consumers to overcome their cognitive resource constraints (Simon 1955). However, the implicit assumption underlying both the theoretical perspective of the RA and the practitioner's viewpoint is that most users are equal in most aspects, for example, in cognitive ability. Unfortunately, this hidden assumption has not been adequately addressed. We reason that this assumption is not pragmatic and in fact contains an inherent deficiency. Hence, one of the key objectives of our paper is to propose how the RA can be made more flexible to achieve personalization for most individual consumers.

While a flexible decision aid has numerous advantages, we ought to exercise caution when designing the extent to which consumers may benefit from a personalized RA, since veering to the other extreme also results in disadvantages. Most notably, the personalization tools may become overly-complex for consumer use, resulting in non-usage of the RA altogether (Manber, Patel and Robison 2000). To avoid this situation, we argue that only essential aspects of the RA, i.e. those that could effectively lower the other five types of decision-difficulty, should be considered for personalization.

The ability to personalize the RA injects a level of enhanced flexibility for a consumer. By affording consumers with both greater flexibility and a greater degree of control in their interaction with the RA (Brusilovsky and Tasso 2004), their personal needs can be better met, thus resulting in a positive effect on trust and personal satisfaction (West, Ariely, Bellman, Bradlow, Huber, Johnson, Kahn, Little and Schkade 1999) as well as in reduced perceived financial and socio-psychology risks, for example (Spiekermann and Paraschiv 2002). Towards this end, prior personalization researchers indicate that when users have personalized access to information (i.e., when generated content matches their tastes and preferences), then they are able to engage in more intense retrieval of associated materials in memory by stimulating stronger and more memorable encoding (Miller and Kulhavy 1991). In this regard, personalization may not only build stronger associations related to the task, but in the process, it may also ease the intrinsic cognitive load imposed by the task (Lopez and Sullivan 1992). This view is in accordance with the Cognitive Load Theory (Leahy and Sweller 2005).

Prior RA research has suggested that future research in this domain should focus on providing new capabilities that assist users to process the recommendations provided by an RA (Riedl and Dourish 2005). Such capabilities will involve new algorithms, and more importantly, new interfaces for exposing the capabilities enabled by these new algorithms (Riedl and Dourish 2005). For instance, researchers have examined current state-of-the-art recommendation technologies such as social navigation (Svensson, Höök and Cöster 2005) and social matching (Terveen and McDonald 2005) to understand their design and feasibility. Our current proposition on RA personalization differs slightly but yet complements this line of thought. First, we have already addressed the searching, browsing and understanding of RA recommendations by proposing features such as preference discovery, preference framing, decision strategy based screening and decision guidance. An important but missing piece in the jigsaw puzzle is refining the interaction process between a consumer and the RA so that the capabilities enabled by these new features can be effectively consumed, resulting in reduced decision-difficulty. Second, we do not propose any new algorithms but rather we build on and advocate the correct usage of existing RA technologies. Thus, we connote that the correct RA technologies should be provided for the correct users. Third, consistent with the advocation of Riedl and Dourish (2005) that research in RA interfaces will provide higher economic marginal returns, we suggest that a revamp of the current RA interfaces through the introduction of personalization is in order. In summary, an RA with a correct set of features that matches the needs and abilities of each user can overall enhance the online shopping experience. However, we caution that any customization of the RA interfaces must be done systematically and support the RA's fundamental objective of reducing decision-difficulty rather than to add any unnecessary cognitive load.

Theoretical support for RA personalization can be found in the work of Zmud (1979) on how individual differences affect the success of Management Information Systems (MIS). In the same paper, Zmud suggests a cognitive-influences path involving individual differences, cognitive behavior, MIS design characteristics, and MIS success. Individual differences such as decision style, personality and demographic/situational variables are conjectured to affect the behavior of decision-makers. Since decision aids are provided to overcome limitations inherent in human cognition (Haübl and Trifts 2000) and to ensure that available information is sensed and used; their design is dependent upon the cognitive behavior of the decision-maker. More precisely, it has been suggested that decision aids designed to direct the decision-maker's behavior and to provide support for decision strategies are likely to improve decision performance. Consistent with this argument, an MIS designed with quantitative models, graphical reports, color-coded graphics and multi-line graphs has been found to improve decision performance; while format improvements have led to increased MIS usage (Eom 2003).

The implications of the cognitive path influences of Zmud (1979) can be analyzed from the three aspects of individual differences, namely, level of product knowledge, experience in preference dictation and cognitive ability, which are most relevant to consumers engaging in RA-assisted online shopping tasks. We posit that these three differences have a non-trivial impact on the cognitive behavior of consumers. For instance, in our previous discussion on Proposition 1.1.2 we argued that allowing consumers with low product knowledge to relate a new product with an existing familiar product through the provision of analogical product-learning can reduce decision-difficulty. This implies that consumers with low product knowledge are likely to have higher information requirements through exposure to additional information on familiar products. On the contrary, consumers with high product knowledge do not need this requirement. In accordance with the cognitive path influences (Zmud 1979), different RA features must be provided to these two groups of consumers in order to ensure the successful application of an RA. Specifically, consumers with low product knowledge need to be given an analogical product learning aid, while those with high product knowledge do not. To achieve such RA design characteristics, the RA must be personalized, based on the three aspects of individual differences (e.g., decision style).

Agarwal and Prasad (1999) have also proposed and found empirical support for a theoretical model that posits the relationship between individual differences and technology acceptance to be mediated by perceived usefulness and perceived ease-of-use. The individual-differences variables selected represent traits that could potentially interfere (positively or negatively) with their acceptance of the new technology: We build on this observation by arguing that insofar as consumers differ in their level of product knowledge, and their experience in preference dictation and cognitive ability to process information, an RA that is designed to match the cognitive characteristics of a consumer in reducing decision-difficulty could induce higher perceived usefulness and perceived ease-of-use. This line of reasoning is consistent with the prediction on the MIS success of the cognitive path influences (Zmud 1979). We thus propose that RA personalization is an important design trait in reducing the overall decision-difficulty of consumers:

> ***Proposition 8.1:*** *RA personalization allows the correct design traits to be provided for individual consumers. Since each design trait is designed to reduce a particular aspect of decision-difficulty; RA personalization can reduce the overall decision-difficulty encountered by different individuals, thereby leading to a lower propensity for purchase-avoidance.*

We shall now examine three detailed propositions on how RA personalization could be plausibly operationalized. To personalize an RA based on the level of product knowledge, an RA needs to delineate the knowledge level for each new product category that a consumer enquires about. For a new product category, the RA could pose a series of questions to derive a mean score used for determining the product knowledge level. Two approaches may be feasible. First, a product-specific approach could pose a series of usage or feature questions pertaining to a particular product category. Returning to our earlier analogy of the PDA phone, an example of a usage question could be: “Do you know how to make a phone call to a contact whose phone number is stored in the PDA address book?” An example of a feature question could be: “Do you know that a PDA phone does have a scheduler function?” Second, a generic approach could incorporate an instrument scale for measuring a participant’s product class knowledge, such as that developed by Smith and Park (1992), in which an “I feel very knowledgeable about this product” ranking denotes good product knowledge. The RA needs to remember this mean score for future use should the consumer enquire about the same product category. However, the RA should also permit a consumer to change the score by amending his responses to the personalization questions. Based on the product knowledge mean score, the RA can then decide whether analogical product learning support should be offered (see Proposition 1.1.2) and/or whether the need-based or attribute-based preference dictation method should be feasible (see Proposition 3.1).

> *Proposition 8.1.1: Personalization of an RA through a consumer’s product knowledge level enables the RA to provide the appropriate product learning and preference framing features to reduce the associated decision-difficulty (i.e., knowledge uncertainty and preference uncertainty), thereby leading to a lower propensity for purchase-avoidance.*

Personalization of an RA based on cognitive ability can be accomplished by using a questionnaire-type instrument scale such as the one developed by Cacioppo, Petty and Kao (1984), which measures a person's tendency to engage in and enjoy challenging information processing, i.e., one requiring cognition. Based on the consumer's response, the RA can determine whether strategic or justification explanation should be provided in the RA's recommendations. The consumer is allowed to change his responses to the questionnaire. Alternatively, the RA could move a step further by observing the consumer's usage of the RA and his purchasing behavior, over a period of time. For instance, if the time spent evaluating justification explanation is excessively long, this may indicate that the consumer may be unable to process the information provided. Furthermore, if the consumer disregards the RA recommendations by choosing an alternative that deviates remotely from the consumer's expressed preferences, then this may also indicate that the decision-guidance provided is not being utilized effectively. Either way, the RA can learn to recognize such patterns and offer to provide the other explanation type to the consumers. It seems plausible for personalization to enable a smart learning RA rather than the current *run-of-the-mill* types.

> *Proposition 8.1.2: Personalization of an RA through a consumer's cognitive ability enables the RA to provide the suitable decision-guidance features to reduce the associated decision-difficulty (i.e., need for justification), thereby leading to a lower propensity for purchase-avoidance.*

Personalizing the RA based on the consumer's degree of preference dictation could prove problematic because it might overlap his level of product knowledge, since a consumer with higher product knowledge can be expected to have a clearer expectation of the desired criteria and articulate his preference for a wider range of attributes. Additionally, it could also confound one's cognitive ability to analyze the criteria of multiple attributes concurrently, versus analyzing single attributes sequentially. Thus, it is entirely plausible for the RA to infer the preference dictation from the first two customizations. For instance, the RA could assume abstract (specific) preference dictation should the consumer possess low (high) product category knowledge and low (high) cognitive ability. A direct approach would be for the RA to ask the consumer if he prefers or is able to evaluate a single attribute sequentially or multiple attributes concurrently. In any case, the RA could render an appropriate preference elicitation from two options: a compensatory or non-compensatory interface (Payne et al. 1993). As is possible with cognitive ability, the RA can attempt to learn the consumer's usage and learning behavior and counter-offer with the other interface, if necessary.

> *Proposition 8.1.3: Personalization of an RA through a consumer's degree-of-preference elicitation enables the RA to provide the proper decision-strategy-based screening features to reduce the associated decision-difficulty (i.e., preference uncertainty and information structure load), thereby leading to a lower propensity for purchase-avoidance.*

We will next examine the plausibility of hybridization, a form of personalization, of the product learning and preference-framing design traits. We have suggested previously during our discussion of Proposition 1.1.2 that a plausible way of implementing analogical product learning is by asking the consumer a series of usage questions pertaining to the specific product category. This is very similar to how a need-based RA's functions (Grenci and Todd 2002). In other words, regardless of the base type of the RA, the elements of a need-based RA can be used **jointly**. Furthermore, we also posited in Proposition 3.1 that consumers with little or no knowledge of a product category should be provided with a need-based RA while those who are already familiar with the product category should be provided with a feature-based RA. Hence, another way of achieving RA personalization is to incorporate both need-based and feature-based methods, but offer only one to each individual consumer depending on his level of expertise for a product.

Proposition 8.2.1: RA personalization achieved through the hybrid use of need-based and feature-based methods, either jointly or alternatively, depending on a consumer's level of product knowledge could yield lower decision-difficulty due to preference uncertainty, thereby leading to a lower propensity for purchase-avoidance.

We next examine hybridization of alternative screening mechanisms. In our previous discussion on Proposition 4.1, we argued that consumers with abstract preference-dictation should be provided with a non-compensatory decision strategy while those with specific preference-dictation should be provided with a compensatory decision strategy (Payne et al. 1993). Since this is independent of the preference elicitation mechanism, elements of compensatory RA and non-compensatory RA can be used **alternatively**.

Proposition 8.2.2: RA personalization achieved through the hybrid use of compensatory and non-compensatory methods alternatively allows the best of each method to be provided for consumers, thus reducing decision-difficulty due to preference uncertainty and information structure load, and thereby leading to a lower propensity for purchase-avoidance.

Finally, we reason that the best features of each RA method can only be effective in reducing decision-difficulty if they are correctly provided to consumers based on their individual differences, e.g., decision styles. On the one hand, providing a "full featured" RA that allows the consumers to mix and match those features that they want without appropriate guidance is likely to cause unnecessary confusion and complications in the use of the RA, and may require additional cognitive effort to figure out a set of RA features that the consumers perceives to be appropriate for themselves, but which may in reality be sub-optimal. On the other hand, we suggest that RA personalization on an appropriate level of product knowledge, experience in preference-dictation and cognitive ability, can all provide the correct guidance discussed in our propositions for RA personalization.

> *Proposition 8.2.3: RA personalization enables effective and efficient hybridization to provide a set of RA features that can best reduce decision-difficulty due to decision styles, thereby leading to a lower propensity for purchase-avoidance.*

D.5 DISCUSSION AND IMPLICATIONS

We have at this stage built on consumer psychology and decision-making literature, particularly, in the areas of decision-difficulty and purchase-avoidance, as well as on existing DSS studies, to present a framework governing RA design, leading us to propose a set of theory-based propositions. The propositions provide answers to an important yet often overlooked question of how an RA could be designed to offer informed guidance and recommendations to consumers in constructing preferences and choosing an alternative rather than avoiding making a purchase commitment (e.g., shopping cart abandonment). This question should be of interest to academic researchers, RA and general consumer-based decision-aiding designers, as well as current and future RA providers. Before we proceed to delineate the boundary of the RA framework which serves as providing suggestions for further exploration, and to discuss the implications of this study for research and practice, it is imperative that we first review the existing RA implementations with our set of design propositions in mind.

D.5.1 EXISTING RA IMPLEMENTATIONS

In an exciting and promising recent development, some limited but recognizable aspects of the hitherto proposed RA features are available commercially (see Table 4). Exploring them is a good way to further theorize the proposed seven traits of an RA, which are oriented towards improving the next generation of commercial RAs.

Most of the commercial RAs have chosen to focus on decision strategy based screening and option framing which could be of fundamental functionality. In decision strategy based screening, most RAs have opted for a non-compensatory decision-strategy, resembling an elimination-by-aspect approach using a single-attribute screening mechanism. An exception is PriceGrabber.com which also offers the majority of confirming dimensions using multi-attribute screening. Another notable example that is a departure from mainstream RAs is Yahoo! SmartSort, which offers a lexicographic variant, and also a non-compensatory decision strategy, using multi-attribute screening. The trend towards non-compensatory strategy is consistent with the prediction of Proposition 4.1, provided the main target participants of the shopping websites are casual shoppers with abstract preferences dictation, while the use of single-attribute screening supports Proposition 4.2. In the case of option framing, we note that the majority of commercial RAs incorporate inclusion-screening in the form of side-by-side comparisons or what has been more formally termed comparison matrices (Haübl and Trifts 2000) in addition to presenting attributes of alignable differences, albeit mixed with attributes of non-alignable differences. Hence, this development also provides support for Propositions 5.1 and 5.2, respectively.

While features of product learning, preference discovery, preference framing and decision guidance have been partially implemented, we reason that the current state-of-the-art commercial RAs have not fully exploited the potential benefits of these four design traits. Out of the 15 websites reviewed, only CNET Shopper.com provides both discursive and imagery information processing. An additional seven websites provide only text-based product buying guides. However, both Shopping.com and Yahoo! SmartSort merely provide links to external guides. Analogical product learning support is clearly absent.

In terms of preference discovery, we observe that two-thirds of the surveyed websites implement instant information cues by displaying the number of items that will be returned to the user if a particular filter link is clicked on. Further, only NetMarket and PCFinder (Xiao, Aïmeur and Fernandez 2003) attempt to provide default options to guide users, although it should be noted that NetMarket only provides very few default options, limited in terms of price range and manufacturer. Product stimulation is not available on any of the surveyed RAs. For preference framing, all the RAs either implement need-based or attribute-based preference elicitation methods. However, none of them implements the framing of more important attributes against less valued attributes. Finally, 10 out of the 15 RAs provide strategic explanations in various formats, such as star ratings. Of the 10 RAs that provide strategic explanation, only Yahoo! SmartSort provides additional justification-explanation. Unfortunately, Yahoo! SmartSort merely shows both types of explanations without attempting to "*fit*" each of them to the user with the correct cognitive ability. Given that these four design traits are still not widely implemented commercially, it is necessary to test Proposition Sets 1, 2, 3 and 6 empirically to determine their practical implications.

The remaining design trait, RA personalization, is yet to be implemented in existing commercial RAs. The only exception we observe that resembles RA personalization is Price Grabber, which provides a basic and advanced filtering mechanism for users to choose from. The default basic option is simply the non-compensatory single-attribute based, filtering link mechanism found in most RAs while the advanced option offers a multi-attribute checkbox filtering mechanism. This limited ability to personalize the RA roughly translates into personalization which is based on the degree of preference dictation as stated in Proposition 8.1.3. However, an important distinction between our proposition and Price Grabber's implementation is that Price Grabber does not provide any guidance for choosing between the basic and the advanced options. The resulting deficiency from such an explicit choice of RA interface may inject unnecessary confusion in the user, thus triggering unwarranted negative affection with the RA. Whilst it is entirely possible that users find such an explicit choice flexible and convenient, our basic position remains that the next generation RA should be “smart” enough to understand the needs, and in this case the degree of preference dictation, and provide the correct interface customized to the user’s cognitive behavior. This, we argue, should be achieved in a subtle and/or non-obtrusive manner.

Furthermore, RA personalization through a hybrid use of need-based/feature-based and/or compensatory/non-compensatory approaches, is not observed in any of the current commercial RAs despite suggestions by numerous researchers (Stolze and Nart 2004; Adomavicius and Tuzhilin 2005). The implication of the lack of such a feature is non-trivial. Specifically, an RA that provides only a particular preference elicitation mechanism or decision-strategy may limit its usefulness to a specific subset of customers out of all potential visitors to the websites. For instance, a novice shopper may find a feature-based RA unhelpful in helping him to find the desired products, resulting in purchase-avoidance as suggested in Proposition 3.1. Hence, to ensure that the deployed RA can capture maximum potential revenue, appropriate personalization service through offering hybrid features should be applied.

The review of current commercial RAs as reflected in Table 4 suggests that much more research is needed to advance our understanding of an effective RA design framework that can more effectively assist consumers to make purchases. While design traits such as decision strategy based screening and option framing have adequate support, further theorizing is required before we can empirically test new propositions such as RA personalization. To this end, the unified RA framework proposed in this paper serves as an excellent guide.

D.5.2 BOUNDARY

While we have proposed a rather exhaustive set of RA features, we feel we cannot embed some areas of research into the agent design framework as we seek to keep our conceptual framework manageable. In this light, it is imperative that we first highlight the potential limitations in the proposed agent design framework before evaluating the current RA implementations against the proposed RA features, and discussing the implications of our research. Towards this end, two areas of research pose challenges to our agent framework: decisions involving multiple entities and preferences over time.

Research in consumer behavior and social psychology indicates that people seldom make decisions in isolation. They interact with others, who themselves have different decision strategies and preferences. Particularly, shopping is one such activity with a very high need for social interaction. People like to shop with friends and close ones in a social and collaborative environment, rather than in isolation. While socializing may be one reason for shopping collaboratively, there might be several others. People may shop together when the consumption of the product is not at the individual-level, such as the purchase of a living room sofa set (Corfman and Lehmann 1987); when the purchase is associated with significant financial resource commitment, such as acquiring a house; or when it is one with social implications such as accountability; and even when the product familiarity is low (Anderson 2003).

Regardless of the motivation behind shopping collaboratively, research in consumer behavior indicates that those who shop in groups may cover larger areas of stores, purchase more, and spend more money than when shopping alone (Sommer, Wynes, and Grinkley 1992). It is also observed that in many cases, the mere expectation of talking to others about products and their consumption experience can influence attitudes towards the product and induce preference shifts

(Schlosser and Shavitt 2002). Conversely, a consumer may defer buying decisions when there is no one to seek reassurance and advice from, regarding potential purchases.

While the proposed features allow consumers to simulate the use of the product, (i.e., preference discovering), and include additional information (e.g., expert rating) and guidance (decisional-guidance) which could alleviate the need for assurance (Ariely et al. 2004), they fail to meet the very basic requirement of any kind of collaborative activity – to communicate. In this regard, our agent framework should be extended to address the principles governing the need of the consumer to communicate and seek social assurance, that is, acknowledgement and approval from shopping partners (Tetlock 1991).

However, depending on the magnitude of such needs and the intrusiveness of the communication mode, such as prominently displaying additional information in an attempt to sway the consumer's preference for a particular product, individuals may choose to ignore the social needs and focus on addressing their internal needs. To some extent, some consumers may even choose to ignore certain information or contradict the recommendations given (Fitzsimons and Lehmann 2004). Indeed, the desire for autonomy and freedom of choice is sufficiently prevailing to precipitate the paradoxical moment at which results are judged not by whether the objective is met, but by the manner in which they are attained.

A second area of research that presents a challenge to our framework is the consumption choices that have consequences over time. For instance, Simonson (1990) observes that consumer choice could be influenced by whether a consumer simultaneously chooses to procure multiple items in a category for sequential consumption or sequentially makes the same number of choices over a period of time. Particularly, choices made simultaneously increase the amount of choice variety. In addition, Simonson and Winer (1997) stress that when the number of items to be purchased within a product category increases, consumers would have a higher propensity to acquire items that they would not have purchased when procured in a smaller quantity. In another example illustrating the consequences of time on purchase decision, Wertenbroch (1998) observes that consumers do exhibit a propensity to rationalize their purchase quantities, such as buying a pack rather than a box of cigarettes each time, despite the presence of quantity discounts.

These two areas of research -- social needs and preferences over an extended time -- reveal gaps in our framework that are not filled. In both cases, perceptual principles such as the need for opinions from close ones during shopping, and the making of simultaneous or sequential purchases, seem intertwined to a certain extent. Thus, extended research that further develops these aspects of agent design is needed.

D.5.3 IMPLICATIONS FOR RESEARCH

This study contributes to several streams of literature. First, prior studies have provided variations of online RAs to address the decision-difficulty problem (e.g., Häubl and Murray 2003; Grenci and Todd 2002), most of these solutions are somewhat disparate and piecemeal in nature, addressing only partial stages of the online consumer decision-making process. Furthermore, no study on RAs has formally examined decisional-support in the context of decision-difficulty and purchase-avoidance. This study has contributed to the cumulative knowledge by postulating ways in which RAs could be designed to assist consumers in alleviating purchase-avoidance through reducing decision-difficulty. In this regard, we have incorporated and extended the current state of our knowledge on consumer behavior literature to embrace agent design.

Second, much of prior research in consumer behavior has focused on the cognitive aspects of decision-making and many of the previous DSS and Human-Computer Interaction (HCI) studies, particularly those on RAs, attempt to develop and evaluate different underlying algorithms that address these cognitive difficulties (Xiao and Benbasat 2007). Our research has attempted to establish the notion of decision-difficulty as a composite of cognition and emotion, and further related decision-difficulty to purchase-avoidance. To this end, we have formalized six factors of decision-difficulty, which are considerably relevant to decision-aiding research and could further inform researchers who are embarking on consumer-based decision-support study.

Third, presented through the supports for three stages of the consumer decision-making process (Black et al. 2001), we have proposed a unified blueprint for an RA framework (see Figure 1) that encompasses more than 20 propositions concerning RA design. Our study draws mainly from behavioral theories which are highly relevant yet rarely applied in IS and HCI literature, such as the Feature Integration Theory (Quinlan 2003), the Construal Level Theory (Trope and Liberman 2003) and Category Learning Theories (Ashby and Maddox 2005), and we use these theories to relate them to existing DSS empirical studies. To this end, our study constitutes one of the first attempts to propose a set of theoretical-driven propositions governing RA design. By integrating the various streams of behavioral literature and decision-support literature, our study provides a nuanced understanding of the limitations of current RA implementations, introduces potential future RA design features, and offers a slew of research opportunities.

Fourth, this study also implicitly derives four underlying principles of RA design:

a. **Consumers must find it easy to learn and articulate their preferences**. Consumers often shop for products without well-constructed preferences (Bettman et al. 1998). Hence, they often seek to learn about a particular product type (acquiring product knowledge), the options offered, and their own preferences by interacting with an RA. However, unless the RA gains sufficient knowledge about consumers' preferences, it will not be able to accurately model their preferences and hence provide appropriate product information and guidance. This predicament has raised the question of how the RA should help consumers to learn about themselves and at the same time surface their inner, unrevealed preferences. To our knowledge, many previous studies (e.g., Haübl and Trifts 2000; Grenci and Todd 2000) suffer from the implicit assumption that consumers would learn about their preferences as they scroll through product attributes and specify their preferences. We explicitly violate this assumption by questioning how an RA could be used to alleviate knowledge uncertainty (i.e., a state of mind when a consumer is unsure of the knowledge to identify and evaluate the product options) and preference uncertainty (i.e., a state of mind of when a consumer is unsure whether he prefers one product option to another). In reviewing extant consumer psychology literature, we propose the inclusion of a preference discovery feature using a default option and simulating the use of a product to address the issue of knowledge uncertainty. In addition, we suggest solving the problem of preference uncertainty with a feature of preference framing that encourages consumers to make explicit tradeoffs between attributes such as pricing and safety.

b. **Consumers must perceive it to be undemanding to further reduce the choice sets derived from the learning stage.** Consumers often suffer from information structure overload in which they might not be cognitively capable to process all the product options extracted (Iygengar and Lepper 2000). Particularly, when the information structure is complex, the amount of effort to evaluate individual extracted options could be overwhelming. Hence, consumers often revert to purchase-avoidance (Anderson 2003) or adopt simplifying heuristics (Bettman et al. 1998; Payne et al. 1993). A milestone paper on screening is by Haübl and Trifts (2000) who observe that the inclusion of screening and comparison features could have a positive impact on both the quality and efficiency of purchase decisions. Building on this observation, we propose the inclusion of multiple-attribute screening (non-compensatory) and the addition of inclusion-screening from an option framing feature (compensatory) to reduce the size of the choice set. There are three distinctive differences between our research and studies such as that of Haübl and Trifts (2000). First, they focus on a problem-focus coping strategy in which consumers do not have a 'no-choice' option, i.e., of not making a choice. Previous research on no-choice options suggests that consumers might behave differently when they are aware of the presence of such options (Dhar and Simonson 2003; Dhar 1997). This study does explicitly take the no-choice option into consideration. Second, Haübl and Trifts (2000) only seek to highlight the positive aspects of screening features without explicitly considering the different impacts of varying screening features that are non-compensatory in nature. This study classifies screening features according to the number of attributes available for each screening attempt. Third, our study proposes both non-compensatory and compensatory approaches toward reducing the sizes of the choice sets as opposed to the mainly non-compensatory strategy of Haübl and Trifts (2000).

c. **Consumers must recognize the best matching option without suffering from extensive choice conflicts**. Our review of previous consumer psychology and decision-making literature suggests that consumers often abandon the initial purchase intention through the lack of convincing reasons for justifying a purchase (Anderson 2003; Simonson 1990). This study proposes a decision-guidance approach. Decision-guidance explicitly offers external informational and suggestive guidance to assist consumers to make informed decisions. In our knowledge, no previous research has made a similar combination of propositions on technological feature design. We are confident that this feature could address cognitive difficulty in evaluating options and emotional difficulty in finding sufficient justifications for making a purchase.

d. **Consumers must feel comfortable with the use of an RA**. To achieve this objective, we propose RA personalization. There are three main categories pertaining to previous research on personalization. The first category emphasizes the application of personalization technology and its commercial values, and includes studies which show the usage of personalization agents in the area of information dissemination (Leob 1992; Light and Maybury 2002) and search engines (Manber et al. 2000). The second category stresses privacy issues arising from personalization (Kobsa 2002; Stewart and Segars 2002). The third category focuses on the generation of personalized content derived from data-mining technologies based on customers' transactions (Perkowitz and Etzioni 2000; Eirinaki and Vazirgiannis 2003). Research in this area has concentrated on computational procedures to sort out transactions and personal profiles, and builds and adds onto the extant body of personalization literature by proposing that a hybrid model that takes into consideration learning, matching and evaluation supports could potentially alleviate decision-difficulty. To this end, we have proposed several ways of integrating RA features, which are yet to be explored theoretically.

D.5.4 IMPLICATIONS FOR PRACTICE

In addition to the theoretical contributions of the normative agent design prescriptions, we have presented summaries and propositions that may offer prescriptive guidelines to practitioners concerning the implementation of an RA. Particularly, RAs could be implemented within an online storefront managed by a merchant or an intermediary that seeks to assist consumers in sourcing for the best products available in the market. In this light, the implications of our research should be informative to both merchants and intermediate service providers.

For the merchants, this paper proposes the inclusion of a default option which could address the difficulty of preference elicitation, which in turn could influence the propensity for purchase-avoidance (e.g., shopping cart abandonment). In many in-store purchases, merchants could utilize an in-house RA to present consumers with a default option. This default option should generate an initial reference or anchor point that could subsequently be used to manage how consumers articulate their preferences (e.g., the minimum attribute values for screening), especially for unfamiliar products. Extending this notion of providing a default option further, merchants could utilize the recommendation to invoke consumer interest in a product by framing a default option that provides a satisfactory product choice (a reference option) and subsequently present them with a slightly better option (core option). The default option, in this case, serves as the initial anchor point for evaluating the other options in the choice set.

Upon the completion of the preference elicitation, the RA would then search for and extract product options that satisfy the articulated preferences. The next task is to further reduce the choice set to a smaller consideration set. With respect to this matching process, most of the existing RAs often rely on the use of an attribute-screening feature. In addition, as we proposed in our discussion on the propositions, merchants and service providers could further broaden the shopping cart concept by explicitly providing the inclusion-screening feature that allows consumers to “co-opt” product options. To the extent that people tend to be more sensitive to utility losses incurred by deleting an option, it is plausible that the inclusion-screening feature could alleviate such concerns. Indeed, inclusion creates a conflict between utility gain and effort loss that is more tolerable and acceptable compared to exclusion that entails decision conflict between utility loss and effort gain.

Our review also presents managerial guidance to RA service providers, i.e., the intermediaries. We propose that the context in which options are evaluated could significantly influence consumers’ perceived decision-difficulty, which in turn might affect consumers’ propensity for purchase-avoidance. Presenting consumers with a large number of alternatives, for instance, might not be to their advantage, as they have to make explicit tradeoffs among the attributes when determining which option to choose. To this end, a larger tradeoff size increases decision-difficulty by intensifying the approach-avoidance conflicts of attribute tradeoffs (e.g., brand and price) as reported by Chatterjee and Heath (1996). Service providers could reduce decision-difficulty by altering the presentation of attributes that consumers are more comfortable with by delineating preferences. We proposed that an RA could reduce such difficulty by framing trade-offs of important core attributes against less valued attributes (Janiszewski et al. 2003). The agent can subsequently compute the importance of the core attributes.

Conversely, service providers could also discourage consumers from delineating preferences that could induce future regrets -- such as acquiring a poorly serviced car at a relatively low price but later regretting the excessive repair and maintenance costs -- by explicitly framing the trade-offs of certain attributes to be more cognitively difficult or emotionally laden. To the extent that the existence of the service providers depends on customer satisfaction both during and after a sale, it is imperative that they should be cautioned on how attribute tradeoffs are framed.

D.6 CONCLUSION

Electronic commerce is at an important defining moment currently. As the dust from the dot-com bust settles, as computer and Internet penetration is increasing inexorably around the world, electronic commerce has the potential to grow exponentially beyond our imagination. Among many technological developments, such as Web 3.0, the RA has perhaps the greatest potential to facilitate and realize this growth in electronic commerce. The purpose of this article is, hence, to present readers with a progressive view of how RAs could be built and designed. Towards this end, we have proposed a conceptual model delineating the relationship between decision-difficulty and purchase-avoidance, and identified six factors related to decision-difficulty. Building on this conceptual model, we further propose a research framework demarcating seven RA design artifacts in alleviating decision-difficulty.

Although the studied approaches and problems represent a diversity of contributions from multiple disciplines, many of our theoretical-based propositions towards designing an agent inform us about the central problems associated with online shopping. Towards this end, we anticipate that a broad array of intriguing research opportunities and solutions remain on how an RA, (i.e., a Recommendation Agent, and not a Restricted Agent), could be designed to address these challenges. From this perspective, we would like to emphasize that our research is not restricted to RA design, but also delves insightfully into decision-aiding design in general, given the enormous number of online decision contexts in which RAs can be deployed and used. Indeed, understanding consumer decision processes and how technology could be designed to address problems faced by consumers such as decision-difficulty, will continue to be a major focus of IS. Hence, this study hopes to provide the rallying call for more efforts to be devoted to this area of research.

Table 4. Review of Commercial RA Implementations

	PL	*PD*	*PF*	*DSS*	*OF*	*DG*	*RAP*
CNET Shopper.com	●	◒	◒	●	●	◒	○
DealTime	○	◒	◒	●	●	◒	○
Froogle	○	○	◒	◒	◒	○	○
MSN Shopping	○	○	◒	●	●	◒	○
Price Grabber	○	◒	◒	●	●	◒	◒
Buyer Zone (buyerzone.com)	◒	○	◒	○	◒	○	○
AOL Shopping	○	◒	◒	●	●	◒	○
BizRate	◒	○	◒	●	●	◒	○
Expedia.com	◒	◒	◒	●	○	○	○
mySimon	○	◒	◒	●	●	◒	○
NetMarket	◒	◒	◒	●	●	○	○
Shopping.com	◒	◒	◒	●	●	◒	○
PCFinder	○	◒	◒	◒	◒	○	○
Amazon	◒	◒	◒	●	◒	◒	○
Yahoo! SmartSort	◒	○	◒	●	◒	●	○

PL – Product Learning (e.g. analogical, discursive or imagery); PD – Preference Discovery (e.g. product learning, default options or instant information cue); PF – Preference Framing (e.g. need-based, feature-based or framing of important attributes against less valued); DSS – Decision Strategy based Screening (e.g. compensatory, non-compensatory or single attribute screening); OF – Option Framing (e.g. inclusion screening or presenting attributes of alignable differences); CC – Choice Composition (e.g. branded product); DG – Decision Guidance (e.g. Inclusion of feedback or explanation that fits the cognitive ability of consumers); RAP – RA Personalization (e.g. product knowledge level, cognitive ability or degree of preference dictation).

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