SMART VERSUS KNOWLEDGEABLE ONLINE RECOMMENDATION AGENTS

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This paper studies how smart recommendation agents (those that filter and integrate information and offer feedback to customers) influence consumer decision making in online stores, in comparison to recommendation agents that are merely "knowledgeable" of the alternative options that exist in a product assortment. The cognitive cost model is used to propose hypotheses that link information search and alternative evaluation with two shopping environment influences that are typical of online settings. A study that simulates search and evaluation in a Web-based choice environment is conducted to test the hypotheses. The results offer insights into how the "feedback" provided by a recommendation agent on the product options available may have an effect on search and evaluation in an online store.

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As a result of the rapid growth of e-commerce, consumer purchase decisions are increasingly being made in computer-mediated environments. Data from the census bureau for the first quarter of 2007 show an 18% increase from the same period a year ago, compared to a 3% increase for total retail sales (http://www.census.gov/mrts/www/data/html/07Q1.html). Online or Web-based stores offer consumers immense choice and great convenience. They provide a shopping experience that is highly realistic, through the use of enhanced graphics, video, and zoom capabilities that have become possible with the availability of broadband internet connections (Tedeschi, 2004).

Yet, finding products that meet consumer needs in these stores is not an easy task. The large product assortments in online stores can overwhelm consumers. The limited processing ability of consumers is no match for the vast amount of information available on the typical online merchant's Web site. Therefore, most Web-based stores have a recommendation agent available to facilitate the purchase decision (Iacobucci, Phipps, & Bodapati, 2000; Smith, 2002). These recommendation agents are variously referred to as shopping assistants or as shopbots and can be provided by the merchant or an interested third party in the form of a product comparison site (Liedtke, 2005).

Data from Pew Internet Life and Nielsen/NetRatings indicate high usage of the Internet for shopping and the use of third-party product comparison sites for researching products (Bausch & Fan, 2006). There is evidence that customers will pay more for products in online settings when a recommendation agent is able to match their preferences to the right mix of product attributes (Saranow, 2005). Hence, there is an increased emphasis on designing recommendation agents that are appropriate for variety of Web-based environments (Tsai, 2004).

Being able to consider a variety of options and being able to do so quickly are often mentioned as the main reasons for shopping online. But, the desire to accomplish both goals represents the "paradox of choice" in a Web-based store (Tamaki, 2005). The more alternatives consumers consider, the more likely they are to make a quality decision. How do consumers reconcile the desire for finding what they need with the objective of saving time? Do they consider fewer alternatives and maintain the focus on saving time or do they maintain the focus on locating the product they want and take the time that is needed to do so? And how does a smart recommendation agent influence the trade-off?

A recommendation agent or shopbot that can match consumer specified criteria to the product assortment offered by the merchant can help consumers save time while also considering a wide variety of alternatives. Both consumers and merchants have an interest in making the matching process function effectively (Saranow, 2005). For consumers, finding products that closely match needs boosts customer satisfaction. For merchants, providing products that satisfy consumer needs creates loyal customers (Tedeschi, 2005).

Yet, the matching process may not work well for several reasons. Consumers may overspecify preferences in the pursuit of the ideal product. They may also become unsure of appropriate selection criteria as they are exposed to new products. Merchants may suggest selection criteria that direct consumers to products offered by them. They may also use recommendation agents to move slow moving products or provide product assortments that include many similar alternatives to increase the likelihood of a match (Schuman, 2005). Third-party electronic decision aids may direct consumers toward sponsored products.

What happens when the matching process does not work well and no acceptable alternatives are found? A "knowledgeable" recommendation agent may suggest that selection criteria be modified, whereas a "smart" recommendation agent may do the same and also display alternatives that are the "closest matches" to the current selection criteria. In both instances, consumers will need to respecify selection criteria and search again, but in the latter instance, the "smart" recommendation agent has given them valuable feedback on the available alternatives (Hodkinson, Kiel, & McColl-Kennedy, 2000).

The distinction between "knowledgeable" and "smart" recommendation agents has been previously noted in the literature (Maes, 1999; Russo, 1987). As the label suggests, a "knowledgeable" recommendation agent is merely informed about or conversant with the alternatives in the product assortment offered by the merchant. When it is used to query the relational database of alternatives available, it only presents those options that exactly meet specified selection criteria. If no acceptable options are found, it indicates so by displaying a "no matches found" or equivalent message. A "smart" recommendation agent has the same information filtration capability as the "knowledgeable" agent but goes a step further by also suggesting alternatives that nearly (i.e., almost) meet the selection criteria. In other words, it has both an information filtration and integration capability (West, Ariely, Bellman, Bradlow, Huber, Johnson, Kahn, Little, & Schkade, 1999).

Another way of thinking about the difference between the two types of recommendation agents is that the "smart" recommendation agent can also use "fuzzy" cut-offs[1] on the selection criteria, whereas the "knowledgeable" agent can only rely on "crisp" cut-offs when offering product recommendations to the consumer. The ability of a computer-assisted decision aid to use "fuzzy" criteria is normally associated with artificial intelligence, hence, the choice of the label "smart" to denote this kind of a recommendation agent. Previous research has found that consumers do not always like to receive unsolicited recommendations from recommendation agents[2] (Fitzsimons & Lehmann, 2004). Hence, it is important to understand how the identification and presentation of "closest matches" influence search and evaluation in an online setting.

An important behavioral difference between the two types of recommendation agents relates to how consumers "learn" about the product options available, which typically occurs when they discover that their ideal product is not available. Often the initial selection criteria used by consumers in online settings corresponds to more of a "wish list" of features sought than a realistic assessment of what may be available in the marketplace (e.g., consider the car shopper who seeks a luxury SUV that gets more than 30mpg and costs less than $35,000 on Cars.com). Stated another way, the initial attribute selection criteria may be somewhat akin to an "opening bid" in a negotiation. Once consumers find that their ideal product is not available (or perhaps does not even exist), they modify their selection criteria to learn more about the product options available.

The feedback given by the "smart" recommendation agent may help consumers know more about available alternatives while also indirectly suggesting what selection criteria to use. Thus, the difference between a "knowledgeable" and "smart" recommendation agent is that the latter facilitates learning on the part of the consumer (Marchionini, 1995). How do consumers respond to the feedback offered by a "smart" recommendation agent? Do they use it to search more efficiently? Also, does the use of a "smart" recommendation agent lead to more satisfaction? The purpose of this research is to examine differences in information search and alternative evaluation that may be attributed to the use of a "smart" recommendation agent. A comparative design is adopted to allow the study findings relating to the use of "smart" and "knowledgeable" recommendation agents to be compared with a view toward understanding the role of feedback during search and evaluation in online settings (Olson & Widing, 2002). The "smart" recommendation agent used in the study is characterized by an electronic decision aid that can provide feedback in the form of "closest matches" when no matching alternatives are found in the relational database of available alternatives. In contrast, the "knowledgeable" recommendation agent has no feedback mechanism.

Two task environment influences that are present in online stores are varied to highlight the predicted differences in search and evaluation behavior. These are the number of available alternatives in the relational database of alternatives searched by the recommendation agent and the amount of time available for the shopping task. Typically, the merchant has control over the first, while the second is under the control of the consumer. Both relate to the attractiveness of online shopping, namely, being able to search a variety of options, but also being able to do so quickly (Tamaki, 2005).

The research has implications for understanding how consumers use recommendation agents or shopbots in online stores. Recent findings from Comscore and Jupiter research show a marked increase in online sales (Aksoy, 2006; Lipsman, 2006). But, the findings

[1] We thank Reviewer 1 for suggesting the use of the terms "fuzzy" and "crisp" in this context.

[2] We thank Reviewer 2 for bringing this finding to our attention.

also suggest that many consumers are not satisfied with the online purchase experience. One possible avenue to increase satisfaction that has been noted in these studies is the provision of "smart" recommendation agents (Prince, 2005).

CONCEPTUAL BACKGROUND

The Cognitive Cost (CC) model may be used to understand how recommendation agents affect the search and evaluation behavior of consumers in Web-based choice environments. Recall that the Cognitive Cost (CC) model proposes that consumers maintain a focus on accuracy, but also consider the cognitive costs associated with the attainment of that goal. In other words, consumers make a trade-off between accuracy and effort reduction (Bellman, Johnson, Lohse, & Mandel, 2006; Benbasat & Todd, 1996; Payne, Bettman, & Johnson, 1988). Most of the research on the CC model suggests that the effort/accuracy trade-off is uneven with consumers focusing more on effort reduction than on accuracy.

Research findings seem to significantly support the CC model in physical store (i.e., bricks-and-mortar) environments. Consumers are more concerned with saving time and effort, because the benefits of such a focus are immediate and tangible. In contrast, the benefits of making a better decision are delayed and ambiguous (Chu & Spires, 2000). Do these conclusions also extend to Web-based store environments? And is there a difference in the focus on effort reduction between the "smart" and "knowledgeable" recommendation agents? Accuracy in the current context refers to finding the product that best meets needs or optimizing the "fit" between the consumer's selection criteria and the alternatives available in the product assortment.

Clearly, effort reduction is likely to be an important goal for consumers while using both types of agents. Thus, the key issue is the importance of that goal in relation to the desire for optimizing the "fit" between the recommendations made by the agent and the needs of the consumer. Hence, the distinction between the two recommendation agents essentially relates to how consumers behaviorally respond to the "feedback" provided by the two types of agents. When there are "exact matches" between the consumer's selection criteria and the alternatives available in the product assortment, there is no difference in the feedback provided by the two types of agents. Only when "exact matches" are not found does a difference arise. For a "knowledgeable" agent using "crisp" cut-offs on the selection criteria the cognitive load of criteria re-specification and continued search falls on the consumer. However, when a "smart" agent employs "fuzzy" cut-offs, there is an attempt to reduce the cognitive load on the consumer by first presenting her with product options based on a respecification of the criteria by the agent. Whether the consumer chooses to terminate search by selecting one of the "closest matching" options or continuing search is likely to depend on important task influences in the shopping environment, such as the depth of the product assortment and the amount of time allocated to the shopping task by the consumer, which are examined in the study.

Thus, the main difference between the two types of recommendation agents comes down to whether the consumer accepts the reduction in cognitive burden offered by the recommendation agent when it uses "fuzzy" cut-offs to present "closest matches" to the stated selection criteria after no "exact matches" have been found. Obviously, factors such as trust and competence in the recommendation agent (Maes, 1994) will have a bearing on that decision, but are controlled for this study. Hence, when there is a greater focus on effort reduction, one of the "closest matching" options presented by the recommendation agent is likely to be accepted and search terminated. But, when there is a greater focus on optimizing the "fit" between selection criteria and the product options available, criteria are likely to be re-specified and search continued.

We propose that the focus on effort reduction will be maintained in the case of the "smart" agent because consumers will use the feedback mechanism in it to further reduce effort. There is evidence that decision aids in offline environments are mainly used to reduce effort (Todd & Benbasat, 1993) and only rarely to counter the consumer's natural tendency to use a less effortful strategy (Todd & Benbasat, 2000). But, in the case of the "knowledgeable" recommendation agent we propose that there will be a subtle shift in emphasis from effort reduction to seeking a better product "fit" between selection criteria and available options. Empirical research on consumer decisions in online settings where recommendation agents similar to the "knowledgeable" agent used in this study have provided evidence of decision quality improvement (Dellaert & Haubl, 2005; Haubl & Trifts, 2000).

HYPOTHESES DEVELOPMENT

The hypotheses attempt to understand how consumers behaviorally respond to the two types of recommendation agents examined in this study. Specifically, the theoretical mechanism built into the Cognitive Cost model (i.e., that individuals trade-off effort versus accuracy while making decisions) is used to hypothesize how information search and consideration set formation is likely to be affected by the properties of the "knowledgeable" and "smart" recommendation agents. We attempt to distinguish between two scenarios, one where there is greater focus on effort reduction (and less on seeking better product "fit") versus where there is a greater focus on seeking better product "fit" (and less on effort reduction). Although we are unable to empirically calibrate the relative shift in emphasis in effort reduction for the two types of recommendation agents, we are able to offer differing predictions on how search and evaluation may be affected by the use of the two types of recommendation agents.

We propose that the feedback mechanism in a "smart" recommendation agent will primarily be used to maintain a focus on effort reduction (Maes, 1994). When such a mechanism is unavailable as in the case of the "knowledgeable" recommendation agent a shift toward seeking better product "fit" is likely for the reason mentioned earlier. A focus on effort reduction implies less search (Haubl & Trifts, 2000). Hence, the use of a "smart" recommendation agent will lead to a reduced level of search in comparison to the use of a "knowledgeable" recommendation agent.

Information search in an online setting where a recommendation agent is available normally has two aspects to it. First, is the number of alternatives that are examined during the search process, which is the traditional measure of search in an online setting (Haubl & Trifts, 2000; Diehl, 2005). However, there is an important second aspect of search in Web-based environments, namely, the number of search queries elicited from the relational database containing the alternative set. Taken together, the two measures of search better reflect the interactive (i.e., iterative) nature of search in a Web-based choice environment. We hypothesize that a focus on effort reduction in the case of the "smart" recommendation agent will lead to both fewer alternatives being examined and fewer search queries being conducted.

> **H1A:** The use of a "smart" recommendation agent will lead to fewer alternatives being examined in comparison to the use of a "knowledgeable" recommendation agent.

> **H1B:** The use of a "smart" recommendation agent will lead to fewer search iterations being performed in comparison to the use of a "knowledgeable" recommendation agent.

The focus on effort reduction in the case of the "smart" recommendation agent will also lead to more items being considered during alternative evaluation, because larger consideration sets are known to be associated with a greater level of consumer uncertainty (Roberts & Lattin, 1991). Stated another way, a smaller consideration set implies that the consumer knows what she wants and is consistent with a focus on seeking a better product "fit." By contrast, larger consideration set suggests that the consumer is unsure of what the best choices are and, hence, selects several alternatives (including similar ones) as a hedge against making an inappropriate choice. Hence, the use of a "smart" recommendation agent will lead to more alternatives being considered in comparison to the use of a "knowledgeable" recommendation agent. Previous research on whether the use recommendation agents leads to larger or smaller consideration sets is mixed. Although there is evidence that the use of a recommendation agent reduces consideration set size (Haubl & Murray, 2006; Haubl & Trifts, 2005), there are also findings that suggest that it increases size (Pereira, 2000) or has no effect (Pedersen, 2000).

The formation of a consideration set is a dynamic process. Alternatives selected for inclusion in the set may be eliminated from further consideration as other more attractive options are found during search. In other words, items may be added and then deleted or retained in an electronic "shopping cart" as the search process unfolds. Hence, there are two dimensions of alternative evaluation that need to be considered. First, is the size of the consideration set at the end of the search process. Second, is the total (i.e., cumulative) set of items that are placed in the "shopping cart" during the consideration phase, regardless of whether they are part of the final consideration set. We hypothesize that a focus on effort reduction in the case of the "smart" recommendation agent will lead to both a larger consideration set at the end of the search process and a larger total (i.e., cumulative) set of alternatives being considered during the evaluation phase.

H2A: The use of a "smart" recommendation agent will lead to a larger final consideration set in comparison to the use of a "knowledgeable" recommendation agent.

H2B: The use of a "smart" recommendation agent will lead to larger total set of alternatives being considered during the evaluation phase in comparison to the use of a "knowledgeable" recommendation agent.

In addition to the effects on information search and alternative evaluation, a focus on effort reduction in the case of the "smart" recommendation agent will also effect perceptions of the amount of cognitive resources spent during search and whether these resulted in a better product "fit" between the alternative selected and needs. Based on the Cognitive Cost model, there is a trade-off between effort and accuracy. Thus, perceptions relating to the cognitive resources expended and the corresponding product "fit" obtained will be concurrently affected. We hypothesize that the use of a "smart" recommendation agent will lead to perception of lower cognitive effort, whereas the use of a "knowledgeable" recommendation agent will lead to a perception of having obtained a better product "fit" between selection criteria and the product options available.

H3: Perceived cognitive effort will be lower from the use of a "smart" recommendation agent in comparison to the use of a "knowledgeable" recommendation agent.

H4: Perceived product fit will be higher from the use of a "knowledgeable" recommendation agent in comparison to the use of a "smart" recommendation agent.

As noted earlier, there is potential shift in emphasis to seeking a better product "fit" when a "knowledgeable" recommendation agent is used in a Web-based choice environment. But, will the shift in emphasis to making a better decision also influence satisfaction with search? Research indicates that the web environment generally offers the potential for greater satisfaction with search (Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer, & Wood, 1997). Furthermore, the ability to control the flow of information has been linked to greater satisfaction (Ariely, 2000). Although it is possible that the focus on seeking a better product "fit" will have a positive influence on satisfaction with search, empirical findings suggest that satisfaction with search is more related to perceptions of effort saved (Bechwati & Xia, 2003) and the availability of additional recommendations (Swearingen & Sinha, 2002). We hypothesize that the use of a "smart" recommendation agent will lead to a higher satisfaction with search in comparison to the use of a "knowledgeable" recommendation agent.

H5: Satisfaction with search will be higher from the use of a "smart" recommendation agent in comparison to the use of a "knowledgeable" recommendation agent.

The two task environment influences identified earlier, namely, the number of available alternatives and the amount of time available, may shed further light on how the search and evaluation behavior of consumers in an online setting is differentially effected depending on whether a "smart" or a "knowledgeable" recommendation agent is used. As mentioned earlier, the merchant has control over the number of alternatives made available, while the consumer controls the amount of time spent evaluating them. Both relate to the attractiveness of online shopping, namely, being able to consider a large number of alternatives, while also being able to save time (Lohse, Bellman, & Johnson, 2000).

What happens when more time is available? Do consumers using a "smart" recommendation agent shift focus from effort reduction to seeking a better product "fit" because of the increased time available? Likewise, what happens when there are more options available? Do consumers using a "smart" recommendation agent increase their focus on effort reduction due to the larger number of options?

We propose that the feedback mechanism in a "smart" recommendation agent will be less beneficial as the amount of time available increases (Payne, Howes, & Reader, 2001; Hoch & Ha, 1986) and, hence, consumers will reduce their focus on effort reduction and direct their attention to seeking a better product "fit," leading to an increase in both the number of alternatives examined and the number of search iterations performed.

> **H6A:** As time available increases, the use of a "smart" recommendation agent will lead to more alternatives being examined in comparison to the use of a "knowledgeable" recommendation agent.

> **H6B:** As time available increases, the use of a "smart" recommendation agent will lead to more search iterations being performed in comparison to the use of a "knowledgeable" recommendation agent.

In contrast, we propose that the feedback mechanism in a "smart" recommendation agent will be more beneficial as the number of available alternatives increases (Payne, Howes, & Reader, 2001; Rowley, 2000) and therefore consumers will increase their focus on effort reduction, which will lead to both a larger consideration set at the end of the search process and a larger total (i.e., cumulative) set of alternatives being considered during the evaluation phase.

> **H7A:** As the number of available alternatives increases, the use of a "smart" recommendation agent will lead to a larger final consideration set in comparison to the use of a "knowledgeable" recommendation agent.

> **H7B:** As the number of available alternatives increases, the use of a "smart" recommendation agent will lead to larger total set of alternatives being considered during the evaluation phase in comparison to the use of a "knowledgeable" recommendation agent.

METHOD

Study Design

A study that simulated consumer decision making in a Web-based environment was conducted to test the hypotheses. The scenario consisted of students choosing an apartment to rent near a hypothetical university. The Web environment was characterized by the availability of either a "smart" or a "knowledgeable" recommendation agent that could be used to search a relational database of available rental apartments. Apartments were profiled using photographs and written descriptions.

The study employed a 2 recommendation agent ("smart", "knowledgeable") $\times$ 2 number of alternatives (many, few) $\times$ 2 time available (more, less) design. The first factor is the primary construct of interest in the study, whereas the other two factors represent important task environment influences in online settings. The "smart" recommendation agent condition corresponded to when the electronic decision aid recommended a list of alternatives based on "closest matches" when no alternatives that matched the selection criteria specified by the user were found. The "knowledgeable" recommendation agent condition corresponded to when no recommendations were provided if no alternatives were found, but a "no matches found" message was displayed instead.

The selection of rental apartments as the product category was based on a number of considerations. First, the product category is familiar to student subjects. Second, alternatives in the product category can be objectively evaluated. Third, attribute importance normally differs across individuals leading to preference heterogeneity.

Procedure

Subjects were instructed to role-play a student transferring to another university who needed to find an apartment. They were asked to search and evaluate the relational database of available alternatives and create a list of apartments they would seriously consider for rental on arrival at the new campus. Both the "smart" and "knowledgeable" recommendation agent conditions were simulated by creating apartment profiles similar to those at apartment search sites (e.g., http://www.apartments.com). Profiles for apartments were constructed using a fractional factorial design based on attributes such as rent, location, number of bedrooms, and the number and type of amenities. Each profile described the apartment on twenty attributes. Unrealistic and dominated alternatives were eliminated.

A "search page" provided the interface between the recommendation agent and the relational database.

Subjects used this page to specify selection criteria and query the relational database about apartments that met these criteria. If apartments that met selection criteria were found, a screen listed them with hyperlinks to the corresponding apartment profiles. If no apartments that met selection criteria were found, a "no matches found" message was displayed in the "knowledgeable" recommendation agent condition, while a list of "closest matches" was displayed in the "smart" recommendation agent condition. Hyperlinks gave the subject the ability to: (1) return to the list of apartments that met selection criteria or to the "closest matches" when no apartments met selection criteria, (2) return to the search page and change selection criteria, or (3) add the apartment to their list of apartments for later consideration.

The number of alternatives available was set at 30 in the "few" alternatives condition and at 99 for the "many" alternatives condition based on guidelines provided in previous research (Haubl & Trifts, 2000; Widing & Talarzyk, 1993). A pretest indicated that subjects were able to complete the task in both conditions. In a second pretest, subjects completed the experimental task with a certain number of alternatives (many or few) with no time constraint. The time available conditions were then created by multiplying the median time for task completion in each manipulation by 0.90 for the "less" and by 0.70 for the "more" time available conditions based on guidelines provided in earlier studies (Ben-Zur & Breznitz, 1981; Payne Bettman & Johnson, 1988).

One hundred twenty undergraduate students participated in the study. Subjects were randomly assigned to the experimental conditions with approximately 15 subjects per cell. Each experimental session involved a single participant. The incentives for participation included extra course credit and a chance to win a $100 lottery. Subjects first undertook a training task to familiarize themselves with the features of the recommendation agent. Then, for the main task, subjects used the recommendation agent to create a "shopping cart" consisting of "apartments that they would seriously consider." Subjects were told that they could modify the "shopping cart" during the session, but were not told how many apartments were available or how many apartments they should select for later consideration.

Measures

As mentioned earlier, we used two measures of information search. The first measure corresponds to the traditional measure of search in online settings. However, there is an important second aspect of search in Web-based environments, namely, the number of search queries elicited from the relational database containing the alternative set. Hence, we used a second measure to capture this aspect of search. Taken together, the two measures of search are intended to better reflect the interactive (i.e., iterative) nature of search in a Web-based choice environment.

Number of Alternatives Examined. The number of unique alternatives examined (i.e., inspected) was determined by an inspection of the log file of the Web server.

Number of Search Iterations. The number of search iterations was calculated by counting the number of queries in the log file of the Web server.

Similarly, we used two measures of alternative evaluation. The first measure corresponded to the size of the consideration set at the end of the search process. However, there is a second measure of alternative evaluation that is relevant in Web-based environments, namely, the total set of items that enters the "shopping cart" at any stage, regardless of whether they are part of the final consideration set.

Size of Final Consideration Set. The number of items found in the "shopping cart" at the conclusion of the search process. The measure was computed from the log file of the Web server.

Total Set of Items Considered. The cumulative set of items that were placed in the "shopping cart" at any point of time during the search process, regardless of whether they were contained in the final consideration set or not. The measure was calculated from the log file of the Web server.

Perceived Cognitive Effort. A self-report measure that focused on the cognitive effort that an individual believed they expended during the search process [adapted from Cooper-Martin (1993)]. Individuals indicated their beliefs on five 9-point Likert-type statements such as "I thought very hard about which apartments to choose," and "I concentrated a lot while making my choices," with anchor-points "strongly agree/strongly disagree." The average of the summated items formed the measure, with higher scores indicative of greater cognitive effort. Reliability for the measure was 0.77.

Perceived Product "Fit." A self-report measure that captured the extent to which the individual believed they had found the best alternative that matched their needs [adapted from Cooper-Martin (1993)]. Individuals indicated their agreement on three 9-point Likert-type statements such as "It was very important to me to choose the best apartment," with anchor-points "strongly agree/strongly disagree." The average of the summated items formed the measure, with higher scores indicative of a better product "fit" with needs.

Satisfaction with Search. A self-report measure of the individual's satisfaction with various aspects of the search process (Widing & Talarzyk, 1993). Individuals indicated their beliefs on three 9-point Likert-type statements, such as "the strategy you used in your search for apartments was..." with anchor-points "confusing/not at all confusing." The average of the summated items formed the measure, with higher scores indicative of more satisfaction with search. Reliability for the measure was 0.88.

Tables 1 and 2 provide means, ranges, and correlations for the dependent variables in the study.

RESULTS

Manipulation Checks

An ANOVA model with the perceived number of available alternatives as a dependent variable and the number of available alternatives (many vs. few), amount of time available (more vs. less), and type of recommendation agent ("smart" vs. "knowledgeable"), as the independent variables was used to assess the manipulation. As expected, a significant main effect for the number of alternatives manipulation (many vs. few) was found [$F(1,122) = 4.72$, $p < .05$]. More alternatives were perceived to be available by subjects in the many alternatives condition ($\bar{x} = 6.6$) than in the few alternatives condition ($\bar{x} = 5.9$). Furthermore, there was a marginally significant main effect for the amount of time available (more vs. less) manipulation [$F(1, 122) = 3.42$, $p < .10$]. More alternatives were perceived to be present in the more time available condition ($\bar{x} = 6.0$) than in the less time available condition ($\bar{x} = 6.6$). Therefore, the manipulations were assessed to be successful. Table 3 provides the cell means and standard deviations for the dependent variables in the study.

Hypotheses Results

Number of Alternatives Examined. The main effect for type of recommendation agent was significant [$F(1, 118) = 35.49$, $p < .05$]. Inspection of the marginal means showed that the amount of search

TABLE 1 Means and Standard Devistions for Dependent Variables

	MEANS		STANDARD DEVIATIONS	
	SMART RECOMMENDATION AGENT	KNOWLEDGEABLE RECOMMENDATION AGENT	SMART RECOMMENDATION AGENT	KNOWLEDGEABLE RECOMMENDATION AGENT
Number of Alternatives Examined (H1A)	9.82	6.09	4.62	3.05
Number of Search Iterations (H1B)	7.61	9.74	5.06	4.82
Size of Final Consideration Set (H2A)	4.30	3.77	1.69	1.41
Total Set of Alternatives Considered (H2B)	5.21	4.38	1.93	1.74
Perceived Cognitive Effort (H3)	6.67	6.48	0.68	0.65
Perceived Product Fit (H4)	5.63	6.19	1.49	1.49
Satisfaction with Search (H5)	7.41	6.95	0.91	1.30

TABLE 2 Correlations among Dependent Variables

	NUMBER OF ALTERNATIVES EXAMINED (H1A)	NUMBER OF SEARCH ITERATIONS (H1B)	SIZE OF FINAL CONSIDERATION SET (H2A)	TOTAL SET OF ALTERNATIVES CONSIDERED (H2B)	PERCEIVED COGNITIVE EFFORT (H3)	PERCEIVED PRODUCT FIT (H4)	SATISFACTION WITH SEARCH (H5)
Number of Alternatives Examined (H1A)	—						
Number of Search Iterations (H1B)	.01						
Size of Final Consideration Set (H2A)	.51**	−.06	—				
Total Set of Alternatives Considered (H2B)	.61**	−.09	.76**	—			
Perceived Cognitive Effort (H3)	.08	−.02	.01	−.02	—		
Perceived Product Fit (H4)	−.12	−.00	−.20*	−.15	.03	—	
Satisfaction with Search (H5)	.04	−.29**	.12	.09	.15	−.01	—

**Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

TABLE 3 Cell Means and Standard Deviations

	SMART RECOMMENDATION AGENT				KNOWLEDGEABLE RECOMMENDATION AGENT			
	MANY ALTERNATIVES AVAILABLE		FEW ALTERNATIVES AVAILABLE		MANY ALTERNATIVES AVAILABLE		FEW ALTERNATIVES AVAILABLE	
	LESS TIME AVAILABLE	MORE TIME AVAILABLE	LESS TIME AVAILABLE	MORE TIME AVAILABLE	LESS TIME AVAILABLE	MORE TIME AVAILABLE	LESS TIME AVAILABLE	MORE TIME AVAILABLE
Number of Alternatives Examined (H1A)	9.73 (2.43)	13.87 (5.18)	8.00 (3.92)	7.80 (4.09)	6.11 (2.63)	5.47 (3.10)	6.33 (3.11)	6.53 (3.56)
Number of Search Iterations (H1B)	6.60 (3.58)	11.53 (7.46)	5.81 (2.46)	6.60 (3.54)	8.22 (3.87)	9.88 (6.49)	9.93 (4.22)	11.20 (4.09)
Size of Final Consideration Set (H2A)	4.13 (1.85)	5.33 (2.02)	4.06 (1.34)	3.67 (1.05)	4.00 (1.33)	3.82 (1.47)	4.00 (1.60)	3.20 (1.21)
Total Set of Alternatives Considered (H2B)	5.13 (2.23)	6.40 (1.92)	5.06 (1.65)	4.27 (1.39)	4.72 (1.36)	4.53 (2.07)	4.33 (1.68)	3.87 (1.85)
Perceived Cognitive Effort (H3)	6.48 (0.62)	6.87 (0.71)	6.53 (0.86)	6.80 (0.51)	6.48 (0.73)	6.65 (0.74)	6.35 (0.57)	6.43 (0.55)
Perceived Product Fit (H4)	5.57 (1.63)	5.07 (1.16)	6.07 (1.51)	5.80 (1.59)	6.39 (1.42)	6.05 (1.82)	6.70 (1.34)	5.61 (1.32)
Satisfaction with Search (H5)	7.28 (0.78)	7.39 (1.04)	7.80 (0.89)	7.16 (0.86)	6.80 (1.16)	7.33 (1.12)	7.45 (1.22)	6.21 (1.45)

Note: Entries are cell means with standard deviations shown in parentheses.

was significantly *more*, and not less as predicted in the "smart" recommendation condition ($\bar{x} = 9.82$) than in the "knowledgeable" recommendation agent condition ($\bar{x} = 6.09$). Thus, **H1A** is not supported. The interaction effect for the amount of time available $\times$ type of recommendation agent interaction was marginally significant [$F(1, 118) = 3.14$, $p < .10$]. Furthermore, in the contrast comparisons, the number of alternatives examined when a "smart" recommendation agent was used were more ($t = -1.71$, $p < .05$) in the more time available condition ($\bar{x} = 10.83$) than in the less time available condition ($\bar{x} = 8.84$). Thus, **H6A** is supported.

Number of Search Iterations. The main effect for type of recommendation agent was significant [$F(1, 118) = 6.21$, $p < .05$]. Inspection of the marginal means showed that the amount of search was significantly less ($t = 2.42$, $p < .05$) in the "smart" recommendation condition ($\bar{x} = 7.61$) than in the "knowledgeable" recommendation agent condition ($\bar{x} = 9.74$). Thus, **H1B** is supported. The interaction effect for the amount of time available x type of recommendation agent interaction was not significant. But, in the contrast comparisons, the number of search iterations performed when a "smart" recommendation agent was used was significantly more ($t = -2.27$, $p < .05$) in the more time available condition ($\bar{x} = 9.07$) than in the less time available condition ($\bar{x} = 6.19$). Thus, **H6B** is partially supported.

Size of Final Consideration Set. The main effect for type of recommendation agent was significant [$F(1, 118) = 4.22$, $p < .05$]. Inspection of the marginal means showed that the size of the final consideration set was significantly more ($t = -1.90$, $p < .05$) in the "smart" recommendation condition ($\bar{x} = 4.30$) than in the "knowledgeable" recommendation agent condition ($\bar{x} = 3.77$). Thus, **H2A** is supported. The interaction effect for the number of available alternatives x type of recommendation agent interaction was not significant. But, in the contrast comparisons, the number of alternatives in the final consideration set when a "smart" recommendation agent was used was significantly higher ($t = -2.05$, $p < .05$) in the more alternatives available condition ($\bar{x} = 4.73$) than in the few alternatives available condition ($\bar{x} = 3.87$). Thus, **H7A** is partially supported.

Total Set of Alternatives Considered. The main effect for type of recommendation agent was significant [$F(1, 118) = 7.39$, $p < .05$]. Inspection of the marginal means showed that the total set of alternatives was significantly more ($t = -2.53$, $p < .05$) in the "smart" recommendation condition ($\bar{x} = 5.21$) than in the "knowledgeable" recommendation agent condition ($\bar{x} = 4.38$). Thus, **H2B** is supported. The interaction effect for the number of available alternatives $\times$ type of recommendation agent interaction was not significant. But, in the contrast comparisons, the number of alternatives retained for later consideration when a "smart" recommendation agent was used was significantly higher ($t = -2.28$, $p < .05$) in the more alternatives available condition ($\bar{x} = 5.77$) than in the few alternatives available condition ($\bar{x} = 4.68$). Thus, **H7B** is partially supported.

Perceived Cognitive Effort. The main effect for type of recommendation agent was not significant. Inspection of the marginal means showed that perceived cognitive effort did not significantly differ between the "smart" recommendation condition ($\bar{x} = 6.67$) and the "knowledgeable" recommendation agent conditions ($\bar{x} = 6.48$). Thus, **H3** is not supported.

Perceived Product "Fit." The main effect for type of recommendation agent was significant [$F(1, 100) = 3.79$, $p < .05$]. Inspection of the marginal means showed that perceived product "fit" was significantly higher ($t = 1.94$, $p < .05$) in the "knowledgeable" recommendation condition ($\bar{x} = 6.19$) than in the "smart" recommendation agent condition ($\bar{x} = 5.63$). Thus, **H4** is supported.

Satisfaction with Search. The main effect for type of recommendation agent was significant [$F(1, 118) = 5.67$, $p < .05$]. Inspection of the marginal means showed that satisfaction with search was significantly higher ($t = -2.29$, $p < .05$) in the "smart" recommendation condition ($\bar{x} = 7.41$) than in the "knowledgeable" recommendation agent condition ($\bar{x} = 6.95$). Thus, **H5** is supported.

Even though only 8 of the 11 hypotheses or subhypotheses received full or partial support, the picture that emerges is that the use of a "smart" recommendation agent results in less iterative search, a larger consideration set, reduced perceptions of cognitive resources spent and product "fit" obtained, but more satisfaction. Thus, the "feedback" mechanism that is an inherent part of these recommendation agents does decrease effort, but does not necessarily help consumers find products that better fit their needs. In contrast, the lack of the same mechanism in "knowledgeable" recommendation agents increases effort but does help consumers find products that are better matched to their needs.

Interestingly, the findings show that when there is more time, more search iterations are undertaken but that does necessarily lead to more alternatives being examined for information. Likewise, when there are more product options available, more alternatives are examined but not because more search iterations have been performed. Hence, the two measures of search when taken together provide a richer description of the dynamics of interactive (i.e., iterative) search that is typical in online settings.

GENERAL DISCUSSION

Overall, the study findings indicate that the Cognitive Cost (CC) model can be used to explain differences between how consumers use a "smart" recommendation agent in comparison to a "knowledgeable" recommendation agent. The findings highlight important consumer behavior differences between the two types of agents. When a "smart" recommendation agent is used, consumers conduct less search and consider more alternatives. But, the reverse is true when a "knowledgeable" recommendation agent is used. The difference in search and evaluation behavior may be attributed to the feedback mechanism that is usually built into a "smart" recommendation agent, but is normally absent from a "knowledgeable" recommendation agent. Consumers have the option of using the feedback provided by interacting with a recommendation agent to either make a better decision or to save effort. Within the confines of this study, it appears that consumers generally tend to use feedback to accomplish the latter goal.

The results suggest that use of a "smart" recommendation agent enables consumers to maintain a focus on effort reduction. However, the use of a "smart" recommendation agent leads to a partial shift in focus to seeking a better product "fit," when more time is available. Thus, the good news is that consumers can shift focus from effort reduction to seeking a better product "fit," because the amount of time spent in an online store is under their control. But, the bad news is that merchants can "neutralize" the change in focus by making more alternatives available. Nevertheless, the use of "smart" recommendation agents offers the potential to create more satisfied customers, because satisfaction with search is higher, regardless of whether they are used to reduce effort or seek products better suited to needs.

Interestingly, consumers continue to maintain the focus on seeking a better product "fit" even when two task environment factors that could potentially shift the focus to effort reduction, namely, the number of available alternatives and the amount of time available are varied. Hence, somewhat ironically, consumers may be better off when a merchant or a third-party product comparison site provides a "knowledgeable" recommendation agent.

MANAGERIAL IMPLICATIONS

Web-based choice environments are characterized by large product assortments through which consumers seek to navigate quickly. The amount of product information and the lack of time to process it can overwhelm consumers. An electronic decision is almost essential for information processing in these environments. The ubiquitous presence of recommendation agents in e-commerce environments has created a need to better understand how their use can affect consumer behavior (in both intended and unintended ways). The properties of recommendation agents can influence how consumers navigate through the product assortment in an online store.

Overall, our findings indicate that "smart" recommendation agents may be more effective in helping consumers make less effortful decisions in comparison to "knowledgeable" recommendation agents. But, the findings also show that if consumers are willing to spend the extra time, they can make less effortful *and* more accurate decisions while using a "smart" recommendation agent. As mentioned earlier, one of the main attractions of online shopping is being able to search a variety of options and find the product that best fits needs. It is the task of recommendation agents to make the matching process function smoothly.

It is important to understand whether the closest matching feature in the "smart" agent facilitates or impedes the process by which consumers learn about the product options available. A part of that understanding comes from how consumers respond to the lack of feedback on what may be available when they encounter the proverbial "no matches found" message. Online product search rarely terminates in response to a "no matches found" message from the recommendation agent. Rather, it prompts a respecification of the search criteria (so that they are less stringent) with the expectation that some options (albeit less satisfactory than those originally sought) may be found. So even in the case of the "knowledgeable" agent there is deterioration in the matching capability. The only difference is that in the case of the "smart" agent the closest matching options are agent-generated, potentially saving the consumer the cost of conducting additional (iterative) search.

Based on work in the human-computer interaction (HCI) area, it seems that the concept of "information scent" may be an important driver of how agent-assisted search is conducted (Pirolli & Card, 1999). Thus, although iterative online search is sensitive to the errors and frustrations encountered by consumers, it also reflects the "information scent" that may be driving search. For example, how many (revised) queries are submitted, and how and when the selection criteria embedded in the queries is expanded or restricted is likely to be a function of the "information scent" that has been developed (and is being followed) a consumer.

Recommendation agents are often closely tied to the environments in which they are used because they are frequently designed for those environments (Olson & Widing, 2002). Thus, marketers may need to build in more flexibility into their recommendation agents so that they perform well under different task environment conditions (Montgomery, Hosanagar, Krishnan, & Clay, 2004). Consumers who want to make quick purchase decisions should be able to do so, as should consumers who want to me more thorough in their product selections. As noted earlier, consumers will pay more when a recommendation agent is able to match their preferences to the right mix of attributes. Anecdotal reports in the business press suggest that there is a movement toward the development of "flexible" recommendation agents, despite the increasing cost of designing such shopbots (Perez, 2002; Reda, 2002).

Future Research

The findings presented here only apply to a "smart" recommendation agent that can provide feedback, but cannot "learn" consumer preferences. Such a recommendation agent is appropriate when (1) preferences are well formed; (2) attributes are mostly digital (or can be readily digitized); (3) human-computer interactivity is (relatively) low; and (4) trust (in the decision aid) is not an issue.

Thus, the first area for future research is to relax these boundary conditions and study "advisor" recommendation agents that can provide feedback but also "learn" consumer preferences (West et al., 1999) and then provide personalized recommendations. Thus, an "advisor" recommendation agent is appropriate when (1) preferences are not well formed; (2) attributes are mostly nondigital (or cannot be readily digitized); (3) human-computer interactivity is (relatively) high; and (4) trust (in the decision aid) is an issue.

A comparison of the respective conditions best suited for "smart" and "advisor" type recommendation agents shows that they may be mapped by two underlying (and somewhat orthogonal) dimensions, (a) competence (of the decision aid) and (b) trust (in the decision aid) (Maes, 1994). A comparison of the two types of recommendation agents on these dimensions seems to indicate that "smart" type decision aids score higher on trust and lower on competence, and "advisor" type decision aids score higher on competence but lower on trust. In conclusion, the study seeks to contribute to the expanding literature on how consumers search for and evaluate products while shopping online. Specifically, it responds to calls for using cognitive models to understand how consumers search and evaluate products online (Alba et al., 1997; Haubl & Trifts, 2000).

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