Should Recommendation Agents Think Like People?

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Electronic recommendation agents have the potential to increase the level of service provided by firms operating in the online environment. Recommendation agents assist consumers in making product decisions by generating rank-ordered alternative lists based on consumer preferences. However, many of the online agents currently in use rank options in different ways than the consumers they are designed to help. Two experiments examine the role of similarity between an electronic agent and a consumer, in terms of actual similarity of attribute weights and perceived similarity of decision strategies, on the quality of consumer choices. Results indicate that it helps consumers to use a recommendation agent that thinks like them, either in terms of attribute weights or decision strategies. When agents are completely dissimilar, consumers may be no better, and sometimes worse off, using an agent's ordered list than if they simply used a randomly ordered list of options.

Keywords: *decision making; electronic commerce; recommendation agents; personalization; information search*

As traditional shelf space concerns cease to be a limitation in the digital marketplace, consumers may be overloaded with product choices (Lurie 2004). The availability of information brings with it issues about how to manage it and present it effectively to consumers. One of the ways that online vendors assist consumers in their product choices is to offer electronic recommendation agents as part of their service to consumers (Haübl and Trifts 2000). As relatively low-cost "virtual salespeople," these agents sort through vast amounts of information and, on the basis of prespecified criteria, return ranked product alternative lists that consumers can use to make decisions. Despite their promise as aids to help consumers in increasingly

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information-rich environments, electronic decision aids may not prove to be a panacea. In fact, there is limited research on whether using recommendation agents actually improves the quality of consumer decisions (Haübl and Trifts 2000).

One reason why electronic recommendation agents may be of limited help to consumers is that they often generate recommendations in ways that are different from those of the consumers they are designed to help. Specifically, the way in which electronic agents generate recommendations may differ from the way in which consumers evaluate products on two dimensions. First, electronic recommendation agents often use attribute weights that are different from consumers' own weights, and second, they may use decision strategies that are disparate from the simple heuristics often used by consumers. If differences between the decision weights and strategies of an electronic agent and a consumer are extreme, following an agent's recommendations may lead to very different choices than those a consumer would make by himself or herself. This may lead to choices and satisfaction levels that are no better, and perhaps worse, than not using an agent at all.

This article investigates the impact of similarity in the *decision-making process* (i.e., the attribute weights and decision strategies) of an agent and consumer on the perceived benefits and costs of using an agent, the amount of information search in which consumers engage, the extent to which consumers conform to an agent's recommendations, the quality of consumers' decisions, as well as their loyalty to a Web site. In demonstrating the important role that similarity can play in how consumers interact with recommendation agents, this research provides guidance about a critical design feature of these agents that prior research has overlooked.

The Impact of Electronic Recommendation Agents

Electronic recommendation agents may be one way for marketers to enhance e-service (Rust 2001). Recent research on e-service has focused on understanding aspects of e-service that are critical in effectively interacting with consumers (Rust and Lemon 2001), factors influencing consumer perceptions of Web site attributes (Zeithaml, Parasuraman, and Malhotra 2000), measurement of e-service quality (Parasuraman, Zeithaml, and Malhotra 2005; Wolfinbarger and Gilly 2003), and understanding what e-service means in different contexts and industries, among others.

Although there is evidence that recommendation agents have the potential to reduce the prices paid by consumers (Diehl, Kornish, and Lynch 2003) and improve decision quality (e.g., Ansari, Essagier, and Kohli 2000; Ariely, Lynch, and Aparicio 2004; Haübl and Trifts 2000; West 1996), other research (e.g., Benbasat and Nault 1990; Todd and Benbasat 1992) suggests that there may be potential negative effects of using these agents. According to the economics of information (Stigler 1961), consumers should search until the marginal benefits no longer outweigh the marginal costs of search. More important, recommendation agents can both raise the benefits and lower the costs of search. For example, ordering alternatives according to individual preferences increases the probability that optimal alternatives are among the first viewed. It also lowers cognitive costs associated with examining options, by eliminating the effort expended on examining inferior or less suitable options (Chu and Spires 2000; Russo 1977). By performing resource-intensive information-processing tasks that liberate individuals from excess cognitive effort, agents can enhance the quality of consumers' decisions (Haübl and Trifts 2000).

On the other hand, recommendation agents may lead individuals to focus more on reducing cognitive effort than increasing decision quality (Einhorn and Hogarth 1978; Kleinmutz and Schkade 1993). This phenomenon of deferring to the agent is potentially problematic, especially in situations where there are no clear "dominant" alternatives (i.e., alternatives that are equal to or superior to all other alternatives on all attributes, which therefore should be preferred regardless of attribute weights or decision strategy; Payne, Bettman, and Johnson 1993). Furthermore, sorting through, and choosing from, a recommendation list that does not reflect one's preference structure may actually involve more effort than going through an unordered (random) list of alternatives. In other words, recommendation agents may actually increase cognitive load for consumers and at the same time reduce decision quality.

The Role of Similarity

Research suggests that similarity plays an important role in persuasion. In particular, endorsers who are perceived as similar to their audience are more influential in changing attitudes and opinions (Haas 1981; Miller 1984; Simons, Berkowitz, and Moyer 1970; Woodside and Davenport 1974); perceived similarity between negotiators increases the number of cooperative responses (Mathews, Wilson, and Monoky 1972); and similarity between buyers and sellers increases the likelihood of a sale (Evans 1963), increases salesperson trust and influence (Busch and Wilson 1976), and increases the likelihood of opinion change about a brand (Brock 1965). Research also suggests that similarity may be important in human-machine interactions as well. In particular, computers that behave in ways that are similar to humans may elicit more cooperative behavior from consumers (Moon 2000).

One dimension of similarity between agents and consumers is the degree to which consumer preferences for different attributes are incorporated in the sorting and presentation of alternatives. Although some agents provide recommendations that have little or no correlation with consumer preferences, others provide recommendations that are highly correlated with consumer preferences (Diehl, Kornish, and Lynch 2003). On one end of this continuum are agents, like mySimon.com, that provide randomly ordered alternative lists that do not incorporate any consumer preference information. Other agents, like Amazon.com, indirectly elicit attribute importance information through collaborative filtering (cluster algorithms) based on other consumers' choices, which may or may not be concordant with the consumer's own utility function. On the other end of the continuum are recommendation agents, such as activebuyersguide.com, where attribute importance weights are directly elicited and used to rank alternatives.

Another dimension of similarity is the degree to which recommendation agents use decision-making strategies that are similar to those used by consumers. Consumers employ a variety of decision-making strategies when choosing among products (Payne et al. 1993). These include compensatory decision strategies, such as the weighted additive model (WADD), as well as simplifying heuristics such as elimination by aspects (EBA; for a review, see Payne, Bettman, and Johnson 1988). Although the weighted additive decision rule usually leads to the (normatively) best decision (Payne, Bettman, and Johnson 1988), research suggests that consumers often use simplifying heuristics, particularly when choosing among multiple alternatives, and that, depending on relative attribute weights, such heuristics can lead to high-quality choices (Payne 1976; Payne, Bettman, and Johnson 1988). In addition to varying in terms of the incorporation of consumer attribute weights, recommendation agents can vary in the degree to which they are similar to consumers' preferred decision-making strategies. For example, activebuyers.com allows consumers to set minimum levels for attributes, thereby using an EBA rule. Other recommendation agents, such as Yahoo's SmartSort (shopping .yahoo.com/smartsort), use a WADD rule to develop recommendations.

The degree to which consumers believe their attribute weights and preferred decision strategy are incorporated into the recommendation process may influence perceptions about the degree of personalization/customization, a critical dimension of e-service (Parasuraman, Zeithaml, and Berry 1988; Parasuraman, Zeithaml, and Malhotra 2005; Zeithaml, Parasuraman, and Malhotra 2000). Wolfinbarger and Gilly (2003) also included this dimension in their 14-item e-TailQ scale for the measurement of customer perceptions of e-tailing quality. However, there has been limited research on how the degree of personalization of product recommendations via such electronic agents affects consumer choices.

Given that a recommendation agent may be thought of as an online salesperson (Alba et al. 1997), perceived similarity between the agent and consumer may be an important determinant of consumer usage of agent recommendations in choice. In particular, if an agent is perceived to behave in ways that are similar to the consumer, such as using similar attribute weights or decision strategies, persuasion should increase and consumers should be more likely to conform to the recommendations of the agent. Increased similarity should also lead to more focused search and potentially increase decision quality.

This suggests that a key determinant of the effectiveness of recommendation agents may be the extent to which an agent and a consumer's decision-making processes are aligned (Hoch and Schkade 1996). If similarity has the potential to influence conformity to the agent's recommendation, and therefore decision quality, what makes an agent particularly "good"? Is either attribute weight or decision strategy similarity sufficient? Conversely, what characteristics make an agent "bad"? Does dissimilarity in either attribute weights or decision strategy make an agent bad, or is dissimilarity on both features required? One way to define a good agent is one whose use leads to higher decision quality; likewise, a bad agent may be defined as one whose use leads to lower decision quality. Based on the assumption that similarity matters, the following propositions are set forth regarding agent-consumer similarity and decision quality:

Proposition 1: Decision quality should increase as attribute weight similarity increases.

Proposition 2: Decision quality should increase as decision strategy similarity increases.

Proposition 3: Decision quality should be higher when attribute weight and/or decision strategy are similar, compared to when both aspects of the decision-making process are dissimilar.

The next section describes the basic method used in the preliminary and main studies. Following the results of the preliminary study, formal hypotheses are developed regarding the role of decision process similarity in decision quality. Next, the main study, results, and finally conclusions and implications are presented.

BASIC METHOD

The recommendation agent in the preliminary and main studies made recommendations about a database of

32 cellular phones. This category was chosen because cell phones were of particular interest to our sample population (undergraduate students) and is a category characterized by a wide range of products and features. Each cell phone in the database was identified by a randomly generated three-letter combination, and the phones were defined by four attributes—low price, light weight, long talk time, and long standby time—that could take on values ranging from 1 to 10. These attributes were chosen on the basis of those of real cell phone models listed on Web sites such as www.cellmania.com, www.point.com, as well as cell phone manufacturers' Web sites. Among the 32 alternatives, 10 were nondominated, and 22 were dominated (Haübl and Trifts 2000). Appendix A shows the attribute levels for the 32 alternatives used in the two studies.

Participants searched and chose cellular phones from an online Web site created specifically for this research using the *Authorware* software program.[1] A fictitious Web site name, Shopper's Universe, was used to control for prior beliefs. After reading information about Shopper's Universe, participants were asked to imagine that they planned to buy a cellular phone for themselves.

PRELIMINARY STUDY

The preliminary study examined the role of similarity by testing both the main and interaction effects of attribute weight and decision strategy similarity on decision quality. The preliminary study also had the supplementary objective of testing the stimuli used to investigate hypotheses in the main study.

Design and Procedure

The preliminary study used a 2 (attribute weight similarity: high or low) × 2 (perceived decision strategy similarity: high or low) between-subjects design in which attribute weight similarity was manipulated and perceived decision strategy similarity was measured. Seventy-nine undergraduate students participated in the preliminary study for course credit. The recommendation agent used a WADD to generate a ranked listing of recommended cell phones.

Attribute weight similarity. Attribute weight similarity was manipulated by adding a random number to the participant's own attribute weights. In the condition of high attribute weight similarity, this number ranged from –1 to +1. In the condition of low attribute similarity, this number ranged from –9 to +9.[2] Thus, the weights and resultant list were most different from the consumer's own preferences in the condition of low attribute similarity. Before evaluating the agent's recommendations, participants were shown how the attribute importance weights used by the agent (stated as belonging to other consumers) compared with their own weights.

Decision strategy similarity. Perceived decision strategy similarity was assessed as follows: Before commencing search, respondents were given a description of the WADD used by the agent to generate recommendations. Individual differences in the perceived similarity of the agent's decision strategy to participants' own preferred strategy were then measured on a 7-point semantic differential scale with end points 1 (*not at all similar*) and 7 (*very similar*) that asked participants the extent to which they thought the weighted additive method used by the computer program was similar to their preferred way of generating a ranked list. Results of the 101 participants revealed a bimodal distribution, and participants were divided into two groups (similar decision strategy, dissimilar decision strategy), with 22 persons who answered 4 on the scale deleted from the analysis, resulting in a final sample size of 79 participants.

Dependent variables. Process measures including perceived benefits and costs, conformity to recommendations, and time spent searching for product information (Moorthy, Ratchford, and Talukdar 1997) were measured. Main dependent variables included objective and subjective decision quality. Scale items for these measures are listed in Appendix B. Manipulation check and covariate questions, including participants' subjective knowledge of the product category (Flynn and Goldsmith 1999), their tendency to seek information from others in making product choices (Bearden, Netemeyer, and Teel 1990), and their experience in purchasing products on the Internet, were also measured.

Results

Manipulation check. Participants indicated how similar the attribute weights used by the recommendation agent to generate the ranked alternative listing were to their own attribute weights (on a 7-point semantic differential scale with endpoints 1 [*not at all similar*] and 7 [*very similar*]). Participants in the condition of high attribute weight similarity ($M = 5.51$) were significantly more likely to indicate that the attribute weights used by the agent were similar to their own weights compared with participants in the dissimilar condition ($M = 4.19$), $F(1, 77) = 17.88$, $p < .01$.

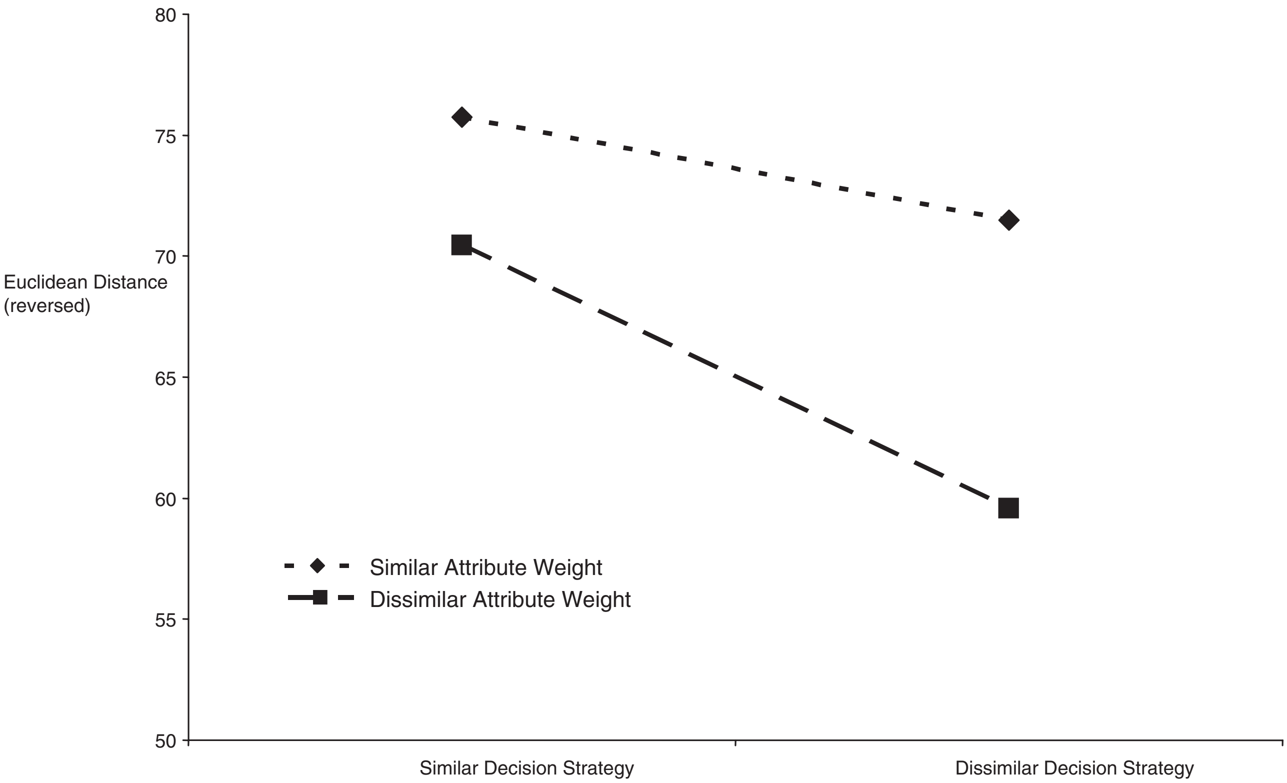
Objective decision quality. Objective decision quality was measured by calculating, for each participant, the Euclidean distance (reversed) in utility between their chosen alternative and the alternative with the highest utility. Table 1 indicates the results. Although Propositions 1 and 2 are not supported, Proposition 3 is supported. There

TABLE 1
Preliminary Study Means, Main, and Interaction Effects

		Similar Attribute Weights		*Dissimilar Attribute Weights*		
		Similar Decision Strategy	*Dissimilar Decision Strategy*	*Similar Decision Strategy*	*Dissimilar Decision Strategy*	*Results*
Notation		$\overline{X}_{11}$	$\overline{X}_{12}$	$\overline{X}_{21}$	$\overline{X}_{22}$	
Perceived benefits		4.87	4.97	4.76	4.14	
		(1.29)	(1.21)	(1.17)	(1.16)	
Perceived costs[a]		3.50	3.16	3.51	4.24	
		(0.95)	(1.19)	(1.00)	(1.06)	
Amount of information search	Time spent examining alternatives[b]	85.05	69.74	86.73	88.10	
		(57)	(43)	(58)	(48.70)	
Conformity to agent's recommendation	Likelihood of following agents recommendation	0.50	0.35	0.27	0.33	
		(0.50)	(0.49)	(0.46)	(0.48)	
Decision quality	Euclidean distance—(reverse scored)	75.76	71.48	70.45	59.57	Proposition 1: $(\overline{X}_{11} + \overline{X}_{12}) > (\overline{X}_{21} + \overline{X}_{22})$
		(22)	(18.62)	(25.16)	(26.51)	Proposition 2: $(\overline{X}_{11} + \overline{X}_{21}) > (\overline{X}_{12} + \overline{X}_{22})$
						Proposition 3: $(\overline{X}_{11} + \overline{X}_{12} + \overline{X}_{21})/3 > (\overline{X}_{22})$*
	Subjective decision quality	5.44	5.33	5.44	4.89	Proposition 1: $(\overline{X}_{11} + \overline{X}_{12}) > (\overline{X}_{21} + \overline{X}_{22})$
		(0.85)	(0.97)	(0.82)	(1.27)	Proposition 2: $(\overline{X}_{11} + \overline{X}_{21}) > (\overline{X}_{12} + \overline{X}_{22})$
						Proposition 3: $(\overline{X}_{11} + \overline{X}_{12} + \overline{X}_{21})/3 > (\overline{X}_{22})$*

NOTE: Standard deviations are in parentheses.
a. Gender is a significant covariate.
b. Amount of online search per month is a significant covariate.
*$p < .05$.

FIGURE 1
Preliminary Study: Effect of Similarity on Euclidean Distance (reversed) in Utility



NOTE: Higher numbers indicate higher objective decision quality.

were no significant main-effect differences between the similar and dissimilar attribute weight conditions (M = 73.47 vs. 64.10), $F(1, 75) = 2.69$, *ns*, and similar and dissimilar decision strategy conditions (M = 73.49 vs. 65.80), $F(1, 75) = 2.74$, *ns*. However, when some aspect of the process was similar (either attribute weights or decision strategy), decision quality remained high relative to when both aspects of the decision process were disimilar. Figure 1 shows that, when *both* attribute weights and decision strategy were dissimilar, a large decline in decision quality was observed. Participants in the doubly dissimilar cell chose alternatives that were much more distant from their preferences (M = 59.57) than participants for whom some aspect of the decision-making process was similar (M = 72.79), $F(1, 75) = 5.00$, $p < .04$.

Subjective decision quality. Subjective decision quality was measured by averaging responses to five 7-point items regarding participants' beliefs about the quality of their choice (Cronbach's $\alpha = .84$; see Appendix B). As with the objective decision quality measure, results indicate no significant main-effect differences between participants in the similar and dissimilar attribute weight conditions (M = 5.38 vs. 5.12), $F(1, 75) = 0.90$, *ns*, and similar versus dissimilar decision strategy conditions (M = 5.44 vs. 5.12), $F(1, 75) = 2.04$, *ns*. At the same time, and in line with the objective decision quality results, subjective decision quality was lower when both attribute weights and decision strategies were dissimilar (M = 4.89) than when there was some aspect of the process that was similar (M = 5.39), $F(1, 75) = 3.86$, $p < .05$. Whereas Propositions 1 and 2 are not supported, Proposition 3 is supported. To better understand these differences, we compared the perceived benefits and costs of using the agent, amount of information search, as well as conformity to the agent's recommendations when either attribute weights or decision strategies were similar versus when neither of these aspects were similar.

Perceived benefits and costs of using a recommendation agent. The perceived benefits of using the recommendation agent were measured by averaging six 7-point Likert-type items (Cronbach's α = .82). Perceived costs were measured by averaging three 7-point scales (Cronbach's $\alpha = .79$; see Appendix B). Results indicate that perceived benefits are higher when the agent used similar attribute weights or a similar decision strategy than when neither of these aspects were similar ($M = 4.88$ vs. 4.14), $F(1, 75) = 5.70$, $p < .05$. A parallel pattern was observed for perceived costs where similarity on at least one dimension led to lower perceived costs than when neither dimension was similar ($M = 3.37$ vs. 4.24), $F(1, 74) = 9.90$, $p < .01$.

Amount of search and conformity to the agent's recommendation. Amount of search was measured as the amount of time in seconds spent examining alternatives. Conformity to the agent's recommendations was measured as the percentage of participants who chose the top-ranked alternative in the different conditions. An economics-of-information argument would suggest that, because the marginal benefits of search are higher when alternatives are not ordered according to one's preferences, which is more likely when the agent uses different attribute weights and different decision strategies, lower agent similarity should increase search. This, in turn, should lead to lower conformity with the agent's recommendation because consumers are more likely to find another alternative that better meets their preferences. Interestingly, there was no significant difference in the amount of time spent searching when the agent used either similar attribute weights or a similar decision strategy than when neither of these dimensions were similar ($M = 79.41$vs. 88.10), $F(1, 74) = 0.33$, *ns*. Participants were also, surprisingly, equally likely to follow the recommendations of an agent that was similar on at least one dimension than when neither of these dimensions were similar ($M = 38\%$ vs. 33%), $\chi^2(1) = 0.14$, *ns*.

Discussion

The results of the preliminary study provide initial insights into how similarity between an electronic recommendation agent and consumer affects decision quality. Propositions 1 and 2 suggested that attribute weight similarity and perceived decision strategy similarity influence decision quality independently. These propositions were not supported. In particular, using an agent that was similar in either attribute weights or decision strategy led to decisions of equal quality as using an agent that was similar on both of these aspects. Proposition 3, however, was supported by results that show that when both attribute weights and decision strategies are dissimilar, there was a significant decline in decision quality. These decision quality results are buoyed by perceived benefits and costs measures that show a decrease in the perceived benefits and an increase in the perceived costs of using an agent when both attribute weights and decision strategies are dissimilar.

Surprisingly, despite the fact that perceived benefits were lower and perceived costs were higher when both attribute weights and decision strategies were dissimilar, results show that participants did not significantly increase search and were just as likely to conform to the agent's recommendations. This suggests that when faced with a bad agent, even if they recognize that the agent is bad, consumers may seek to reduce cognitive effort rather than increase decision quality through additional search (Einhorn and Hogarth 1978; Kleinmutz and Schkade 1993). This deference to a bad agent can lead to declines in decision quality.

ARE RECOMMENDATION AGENTS BETTER THAN RANDOM LISTS?

Although using an agent that is dissimilar in terms of both attribute weights and decision strategies leads to poorer decisions than if either dimension is dissimilar, these decisions may still be better than an unordered list. At the same time, given that providing attribute weights is time-consuming for the consumer, and providing a recommendation agent may be costly for a company, it is important to assess whether electronic recommendation agents do better than an unordered list. Two cases may be examined. The first compares an agent that is similar in terms of either attribute weights or decision strategies with an unordered list; the second compares an agent that is similar on neither of these dimensions with an unordered list.

Similar Agent Versus an Unordered List

Using an agent that incorporates similarity in attribute weights and/or decision strategy increases the probability that the consumer's most preferred alternatives are listed first; this suggests that the perceived benefits should be higher and perceived costs lower than when the agent provides an unordered listing (i.e., where there is a zero rank order correlation between list position and expected utility (Diehl, Kornish, and Lynch 2003)). In addition, low marginal benefits to additional search should reduce information search, increase conformity to the agent's recommendations, and increase decision quality relative to using an agent that provides an unordered listing.

Hypothesis 1: Decision quality will be higher when either attribute weights or decision strategies are similar than when using an unordered listing.

Doubly Dissimilar Agent Versus an Unordered List

The second question is whether using no agent at all is better or worse for the consumer compared with using an agent that is dissimilar in terms of both attribute weights and decision strategies. The answer to this question depends on how the consumer uses the agent's recommendation list. One possible response is that consumers may believe that the benefits of following the recommendations of a dissimilar agent are still higher than making their own evaluation. They may therefore search less, conform to the recommendations more, and end up making worse choices for themselves than if they had used an unordered listing.

Hypothesis 2a: Using an agent that is dissimilar in both attribute weights and decision strategies will lead to lower quality decisions than using an agent that provides an unordered list of alternatives.

Alternatively, consumers may adapt to this situation (Payne, Bettman, and Johnson 1993) by changing their behavior. In particular, when faced with a bad agent, they may increase their search and be less likely to conform to the agent's recommendations. This argument suggests that decision quality will be no worse than when using an unordered list. The following competing hypothesis is proposed:

Hypothesis 2b: Using an agent that is dissimilar in both attribute weights and decision strategies will lead to equal quality decisions as when using an agent that provides an unordered list of alternatives.

MAIN STUDY

A second study was conducted to see if results of the preliminary study would replicate and to test Hypotheses 1 and 2. In the preliminary study, perceptions of decision strategy similarity were measured after participants had completed the choice task. It is possible that these perceptions may have been affected by the choice task, making it difficult to assign a causal relationship between decision strategy similarity and choice quality. Accordingly, the main study experimentally manipulates, rather than measures, perceived similarity of the decision strategy. In addition, we were interested in how agent similarity affects satisfaction, repurchase intentions, and word of mouth in addition to search and choice. The main study includes these additional measures.

Design and Procedure

A 2 (attribute weight similarity: similar or dissimilar) × 2 (decision strategy similarity: similar or dissimilar) plus unordered between-participants experimental design was used for the study. Participants were randomly assigned to one of five conditions. One hundred ten undergraduate students participated in the study for course credit. In all conditions except the unordered condition, the recommendation agent used a WADD to generate a ranked listing of recommended cell phones. In the unordered condition, alternatives were presented in random order, which was varied for each participant.

Attribute weight similarity. Attribute weight similarity was manipulated as in the preliminary study.

Decision strategy similarity. Decision strategy similarity was manipulated by changing participants' perceptions that the WADD decision strategy used by the agent was or was not the ideal decision strategy for them. After learning how the WADD algorithm used by the recommendation agent works, participants in the similar decision strategy condition were told that a survey indicated that 99% of students at the university preferred WADD as their decision strategy. In the dissimilar decision strategy condition, participants were told that survey results indicated that 99% of students *did not* prefer WADD as their decision strategy.

Unordered condition. Participants in the unordered condition did not read about the WADD model before making a choice. To create similar levels of cognitive load, participants in the unordered condition were given a filler task of comparable length in which they read a section from "How Advertising Works" (Vakratsas and Ambler 1999). Participants were told that the text on advertising was for a different study. After reading this passage, participants were asked to choose from a randomly generated list and then to specify importance weights for the four attributes at the end of the task.

Dependent variables. The perceived benefits of using the agent (Cronbach's α = .72), the perceived costs of using the agent (Cronbach's α = .87), information search, conformity to the agent's recommendations, objective choice quality, and subjective choice quality (Cronbach's α = .89) were measured as in the preliminary study. In addition to the main dependent variables, measures of satisfaction with the Web site, repurchase intentions, and intentions to recommend the Web site to others were collected (see Appendix B). The effectiveness of the experimental manipulations were also assessed along with cognitive load.

Results

Manipulation checks. The manipulation of attribute weight similarity was assessed as in the preliminary study by asking participants to indicate how similar the attribute weights used by the recommendation agent were to their own attribute weights using a 7-point scale. Results indicate that participants in the condition of similar attribute weight believed that the attribute weights used by the agent were significantly closer to their own weights than participants in the condition of dissimilar attribute weight (M = 5.18 vs. 4.30), $F(1, 86) = 8.36$, $p < .01$.

The manipulation of decision strategy similarity was assessed through a 7-point scale (with endpoints 1 [*not at all similar*] and 7 [*very similar*]) where participants were asked to assess (a) the degree to which they believed WADD was similar to other students' preferred way of ranking and (b) the degree to which they believed WADD was similar to their own preferred way of ranking. Results show that participants in the condition of high decision strategy similarity were significantly more likely than those in the condition of low decision strategy similarity to believe that the WADD was similar to other students' preferred way of ranking (M = 4.25 vs. 3.59), $F(1, 86)$ = 13.06, $p < .01$, as well as to their own preferred way of ranking alternatives (M = 4.32 vs. 3.95), $F(1, 85) = 11.76$, $p < .01$. There was no significant main or interaction effect of attribute weight similarity on perceived decision strategy similarity.

Cognitive load. Cognitive load was measured by taking the average of two 7-point scales (r = .80) asking participants how difficult and effortful they found reading the explanation of how the algorithm (how advertising) works. Results suggest that the filler task used in the unordered condition created levels of cognitive load equivalent to that of the other conditions as there were no significant differences in perceived difficulty across conditions, $F(4, 105)$ = 1.52, *ns*.

Separate analyses were conducted on each of the dependent variables to test Proposition 3, which predicted differences between a similar agent and a doubly dissimilar agent; Hypothesis 1, which predicted differences between a similar agent and an unordered list; and Hypothesis 2, which predicted differences between a doubly dissimilar agent and an unordered list.

Proposition 3: Similar agent versus doubly dissimilar agent. Table 2 reports the means and tests for the main study. As in the preliminary study, perceived benefits were higher when either attribute weights or decision strategies were similar relative to when neither of these aspects were similar (M = 4.84 vs. 4.14), $F(1, 104) = 7.96$, $p < .01$. A parallel pattern was observed for perceived costs where some similarity led to lower perceived costs than if neither dimension was similar (M = 2.99 vs. 3.86), $F(1, 105)$ = 7.74, $p < .01$.

As in the preliminary study, despite the fact that perceived benefits were lower and perceived costs were higher when both attribute weights and decision strategy were dissimilar, results show that participants restrained their search and conformed to the recommendations of the doubly dissimilar agent. In particular, there was no significant difference in the amount of time spent examining products by those who used agents that were similar on at least one dimension and those who used an agent that was similar on neither dimension (M = 73.36 vs. 93.68), $F(1, 105) = 2.65$, *ns*. Likewise, participants were equally likely to follow recommendations generated by an agent with some similarity versus an agent with dissimilar attribute weights and decision strategy (36% vs. 18%), $\chi^2(1) = 2.51$, *ns*. Figure 2 shows that objective choice quality, as measured by reversed Euclidean distance, was lower when both attribute weights and decision strategies were dissimilar compared to when at least one of these dimensions was similar (M = 62.41 vs. 73.70), $F(1, 105) = 4.11$, $p < .05$. Results for subjective decision quality also parallel those of the preliminary study. Double dissimilarity led to lower subjective evaluations of choice (M = 4.71 vs. 5.30), $F(1, 105) = 6.06$, $p < .02$ compared to some similarity. These results provide additional support for Proposition 3.

Parallel effects were found for the loyalty and satisfaction measures. Table 3 shows mean loyalty intentions and Web site satisfaction for the main study. Results indicate that there is a higher likelihood to come back to the Web site, $F(1, 104) = 7.94$, $p < .01$, higher likelihood to recommend the Web site to friends, $F(1, 105) = 3.36$, $p < .05$ (one-tailed), and higher satisfaction with the Web site, $F(1, 105) = 19.34$, $p < .01$, when the agent is similar (M = 3.97, 3.76, and 4.62, respectively) compared to when it is doubly dissimilar (M = 2.86, 3.00, and 3.18, respectively).

Similar agent versus an unordered list. As expected, perceived benefits are higher when using an agent that is similar on at least one dimension (M = 4.84) compared with using an unordered listing (M = 4.11), $F(1, 104)$ = 6.73, $p < .01$. Likewise, perceived costs are lower (M = 2.99 vs. 3.92), $F(1, 105) = 7.74$, $p < .01$, as is amount of information search (M = 73.36 vs. 114.27), $F(1, 104)$ = 10.78, $p < .01$. Conformity to the agent's recommendations is higher (36% vs. 5%), $\chi^2(1) = 8.21$, $p < .01$, when some similarity is present.

Hypothesis 1 proposed that decision quality should be higher when some similarity is present. In support of Hypothesis 1, objective decision quality, measured in terms of the Euclidean distance (reversed) in utility between chosen and highest utility alternative, is higher when the agent is similar on at least one dimension than when choosing from an unordered list (M = 73.70 vs. 64.74), $F(1, 105) = 2.60$, $p < .05$ (one-tailed). At the same time, participants were subjectively *equally* happy with their choices (M = 5.30 vs. 5.33), $F(1, 102) = 0.01$, *ns*. Hypothesis 1 is therefore partially supported.

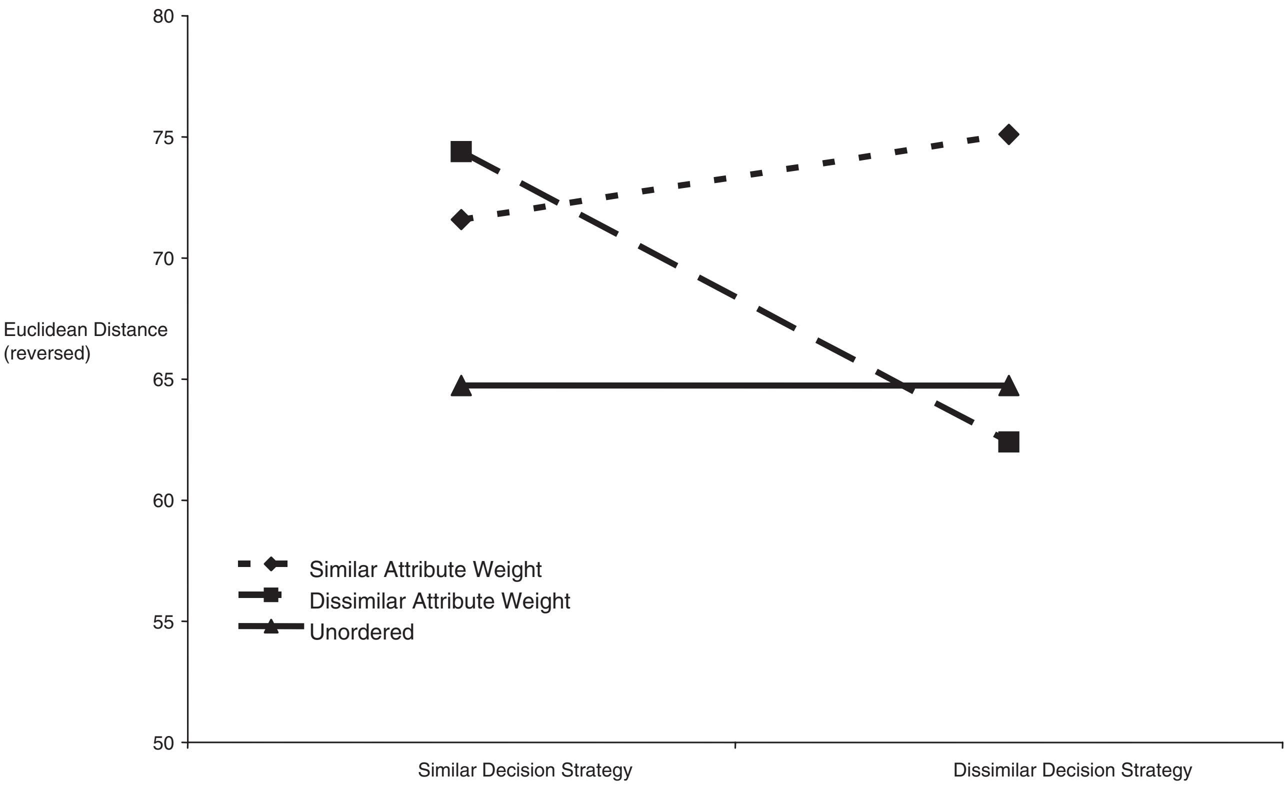
Results for the loyalty and Web site satisfaction measures are in line with the subjective decision quality results. In particular, participants who used an agent that was

TABLE 2
Main Study Means and Hypotheses

		Similar Attribute Weights		*Dissimilar Attribute Weights*			
		Similar Decision Strategy	*Dissimilar Decision Strategy*	*Similar Decision Strategy*	*Dissimilar Decision Strategy*	*Unordered*	*Hypotheses*
Notation		$\overline{X}_{11}$	$\overline{X}_{12}$	$\overline{X}_{21}$	$\overline{X}_{22}$	$\overline{X}_{00}$	
Perceived benefits[a]		4.86	4.81	4.85	4.14	4.11	
		(0.78)	(0.98)	(0.86)	(0.88)	(1.46)	
Perceived costs		2.68	3.39	2.9	3.86	3.92	
		(1.11)	(1.39)	(1.21)	(1.64)	(1.36)	
Amount of information search	Time spent examining alternatives	79.73	78.91	61.45	93.68	114.27	
		(45.40)	(45.26)	(34.50)	(66.43)	(55.60)	
Conformity to agent's recommendation	Likelihood of following agents recommendation[b]	0.27	0.50	0.32	0.18	0.05	
		(0.45)	(0.50)	(0.46)	(0.40)	(0.20)	
Decision quality	Euclidean distance—(reverse scored)	71.59	75.11	74.39	62.41	64.74	Proposition 3: $(\overline{X}_{11} + \overline{X}_{12} + \overline{X}_{21})/3 > (\overline{X}_{22})$*
		(18.27)	(21.12)	(21.33)	(30.21)	(20.20)	Hypothesis 1: $(\overline{X}_{11} + \overline{X}_{12} + \overline{X}_{21})/3 > (\overline{X}_{00})$*
							Hypothesis 2a: $(\overline{X}_{00}) > (\overline{X}_{22})$
							Hypothesis 2b: $(\overline{X}_{00}) = (\overline{X}_{22})$*
	Subjective decision quality	5.25	5.13	5.52	4.71	5.33	Proposition 3: $(\overline{X}_{11} + \overline{X}_{12} + \overline{X}_{21})/3 > (\overline{X}_{22})$*
		(0.81)	(1.14)	(0.78)	(1.18)	(0.88)	Hypothesis 1: $(\overline{X}_{11} + \overline{X}_{12} + \overline{X}_{21})/3 > (\overline{X}_{00})$
							Hypothesis 2a: $(\overline{X}_{00}) > (\overline{X}_{22})$*
							Hypothesis 2b: $(\overline{X}_{00}) = (\overline{X}_{22})$

NOTE: Standard deviations are in parentheses.
a. Information-seeking tendency is a significant covariate.
b. Information-seeking tendency, amount of online search per month, and gender are significant covariates.
*$p < .05$.

FIGURE 2
Main Study: Effect of Similarity on Euclidean Distance (reversed) in Utility



NOTE: Higher numbers indicate higher objective decision quality.

TABLE 3
Main Study Web Site Loyalty and Satisfaction

	Similar Attribute Weights		*Dissimilar Attribute Weights*		
	Similar Decision Strategy	*Dissimilar Decision Strategy*	*Similar Decision Strategy*	*Dissimilar Decision Strategy*	*Unordered*
Notation	$\overline{X}_{11}$	$\overline{X}_{12}$	$\overline{X}_{21}$	$\overline{X}_{22}$	$\overline{X}_{00}$
Likelihood to come back to Web site	4.45	3.73	3.73	2.86	3.45
	(1.50)	(1.85)	(1.64)	(1.55)	(1.44)
Likelihood to recommend Web site to friend	3.91	3.55	3.82	3.00	3.91
	(1.60)	(1.79)	(1.59)	(1.82)	(1.47)
How well the Web site met expectations	4.77	4.36	4.73	3.18	4.05
	(1.06)	(1.36)	(1.07)	(1.78)	(1.21)

NOTE: Standard deviations are in parentheses.

TABLE 4
Main Study Market Share Analysis (in percentages)

	ABC (price = 10)[a]	*BBC (price = 3)*	BCD (price = 10)	IJK (price = 9)	*ZAB (price = 5)*	*Total*
Some similarity	7.6 (5)[b]	18.2 (12)	15.2 (10)	24.2 (16)	10.6 (7)	75.8 (50/66)
Both dissimilar	0.0 (0)	31.8 (7)	0.0 (0)	18.2 (4)	18.2 (4)	68.2 (15/22)
All conditions	8.2 (9)	19.1 (21)	12.7 (14)	18.2 (20)	10.9 (12)	69.1 (76/110)

a. Alternatives in italics indicate higher priced alternatives. Higher numbers indicate lower prices.
b. Numbers in parentheses indicate the frequency with which the alternative was chosen.

similar on at least one dimension were as likely to return to the Web site, $F(1, 104) = 1.22$, *ns*, as likely to recommend the Web site to friends, $F(1, 105) = 0.54$, *ns*, and as satisfied with the Web site, $F(1, 102) = 3.00$, *ns*, when using the similar ($M = 3.97$, 3.76, and 4.62, respectively) and unordered lists ($M = 3.45$, 3.91, and 4.05, respectively).

Doubly dissimilar agent versus an unordered list. Results show that participants perceived the benefits ($M = 4.14$ vs. 4.11), $F(1, 104) = 0.09$, *ns*, and costs ($M = 3.86$ vs. 3.92), $F(1, 105) = 0.02$, *ns*, associated with use of a double dissimilar agent and no agent as approximately equal. The amount of time spent searching also did not vary significantly between those who used a doubly dissimilar agent and an unordered list ($M = 93.68$ vs. 114.27), $F(1, 105) = 1.82$, *ns*. Results show that participants using a double dissimilar agent were not significantly less likely to follow the recommendations of an unordered agent ($M = 18\%$ vs. 5%), $\chi^2(1) = 2.03$, *ns*.

Hypothesis 2 (a) proposed that using a doubly dissimilar agent might actually lead participants to make worse choices than when using an unordered list. Hypothesis 2b made the alternative prediction that choice quality would be equivalent for those using a doubly dissimilar agent and those using an unordered list because participants may recognize that the agent is bad and ignore the agent's recommendations. Results show that objective decision quality is not significantly different between those who used a doubly dissimilar agent and those who used an unordered list ($M = 62.41$ vs. 64.74), $F(1, 105) = .11$, *ns*. Subjective evaluations of choice, however, are quite different between the two cases. Despite the fact that participants do equally well in terms of the objective measure, they are happier with their choices using no agent at all than a doubly dissimilar agent ($M = 5.33$ vs. 4.71), $F(1, 105) = 4.46$, $p < .05$. Hypothesis 2b is therefore supported in terms of objective decision quality, but Hypothesis 2a is supported in terms of subjective decision quality.

Results for the loyalty and Web site satisfaction measures are also in line with the subjective decision quality results, but statistical significance was achieved only for the Web site satisfaction measure. For the two loyalty measures, differences between the doubly dissimilar and unordered conditions for the two loyalty intention measures were not statistically significant (likelihood to come back, $F(1, 104) = 1.81$, *ns*, and likelihood to recommend to friend, $F(1, 105) = 0.81$, *ns*). However, directional support was found for these measures. In particular, participants who did not use an agent indicated a higher likelihood to use Shopper's Universe again and to recommend it to a friend ($M = 3.45$ and 3.91) than participants who used a doubly dissimilar agent ($M = 2.86$ and 3.00). Satisfaction with the Web site was significantly higher, $F(1, 105) = 4.64$, $p < .05$, for participants who used the unordered list than those who used the dissimilar agent ($M = 4.05$ vs. 3.18).

Market share analysis. Results from both the preliminary and main studies suggest that consumers adapt to the choice environment, which in this case is the quality of agents' recommendations, and sacrifice accuracy to reduce effort (Payne, Bettman, and Johnson 1988, 1993). In particular, even though the perceived benefit and cost measures indicate a clear skepticism toward the recommendations provided by the bad agent, individuals limit their information search and conform more than expected to the agent's recommendations. To gain greater insights into the process through which agent similarity affects choice outcomes, we examined the characteristics of products chosen when there was similarity in one (or both) aspects of the decision-making process versus when there was dissimilarity in both aspects. Table 4 compares choice proportions in the different conditions of the main study. Results show that alternatives ABC, BBC, BCD, IJK, and ZAB were the most frequently chosen, with a combined share of 69% across all five conditions. Further examination revealed that three of these were low-price alternatives (ABC, BCD, IJK) and two were relatively high-price alternatives (BBC and ZAB). Examining choice among these five most popular alternatives shows that when either attribute weight or decision strategy were similar, low-price alternatives were chosen 62% (31/50) of the time, but when both aspects of the agent's decision process were dissimilar, this figure dropped to 26.7% (4/15), $\chi^2(1) = 5.79$, $p < .02$. This analysis suggests that double dissimilarity may lead to more heuristic processing where high price

TABLE 5
Main Study: The Best (Minimum BIC) Latent Class Model for Decision Quality

	Group 1	*Group 2*	*Group 3*
Cluster size	0.491	0.273	0.240
Decision quality—Euclidean distance reversed (dependent variable)			
Mean	66.2	98.8	43.2
Active predictors of group membership			
1. Some similarity			
Percentage with some similarity	65	70	39
2. Amount of information search (actual time in seconds)			
Percentage per time group			
≤40	11	23	35
41-64	14	20	32
65-89	20	20	19
90-123	25	20	9
126-311	29	17	5
Mean time	103	79	57
Inactive covariates			
1. Perceived effort			
Percentage per effort group			
5-7	24	20	19
4	18	10	24
3	30	27	26
2	19	37	23
1	9	7	8
Mean effort	3.5	3.1	3.4
2. Perceived time			
Percentage per perceived time group			
5-7	28	27	22
4	21	23	19
3	27	7	28
1-2	24	43	31
Mean perceived time	3.7	3.3	3.4
Percentage similar attribute weight	46	43	23
Percentage similar decision strategy	44	43	27
Percentage unordered condition	22	10	27

NOTE: The profiles are described in terms of all of the covariates, but some similarity and information search (actual time) are the only significant and active predictors of group membership.

is potentially viewed as a signal of high quality, thereby reducing search. This leads to lower quality decisions.

Latent class analysis. It is possible that some of these findings can be explained by the existence of latent groups of customers who respond differently to agent recommendations.[3] For example, it is possible that there is a group of consumers who conform to agent recommendations (both good and bad) and another group that selectively follows agent recommendations and spends more time searching. However, reanalyzing the decision quality results, using time spent searching as a covariate, did not reveal a significant role for amount of information search in predicting decision quality ($p = .15$), and its inclusion did not change the conclusions of that analysis.

To further investigate the existence of different customer response patterns, a general search for the best latent class grouping of customers was conducted. Candidate predictors included indicator variables for attribute weight similarity, decision strategy similarity, some similarity (i.e., either attribute weight and/or decision strategy similarity), assignment to the unordered condition, as well as amount of information search (in seconds) and the Likert-type measures of perceived effort and perceived time spent (Items 2 and 3 in the Perceived Costs Scale listed in Appendix B). Details on this latent class analysis and the search for the optimal model are provided in Appendix C.

The best fitting model revealed three latent classes. Significant variables were some similarity with the agent ($p = .025$) and amount of time spent searching ($p = .01$). The remaining variables were not significant in predicting latent class membership. Group 2 (27% of the participants) made the best decisions in terms of Euclidean distance reversed (M = 98.81), while Group 3 (24% of the participants) made the worst decisions (M = 43.16). Participants in Group 1 made decisions that were of intermediate quality (M = 66.20). Table 5 describes the characteristics of the three groups. A majority (70%) of members of Group 2, the best decision makers, used an agent that was either similar in attribute weights and/or in decision strategies, whereas a minority (39%) of members of Group 3, the worst decision makers, used such an agent. Those in the group that made the best decision spent an average of 79 seconds searching, whereas those who made the worst decisions only spent 57 seconds searching. Those in Group 1, who made decisions of intermediate quality, also had a large percentage (65%) of participants who used an agent with some similarity. Interestingly, they spent much more time making decisions than the other groups ($M = 103$ seconds), suggesting that time on task is not a straightforward predictor of decision quality. Although there were slight differences, perceptions of time and effort did not significantly differ among the three groups.

The results of the latent class analyses generally support the earlier ANOVA results. Participants who used agents that were either similar in attribute weights and/or in decision processes tended to make the better decisions than participants who used agents that were not similar on either dimension.

DISCUSSION AND LIMITATIONS

Results of the preliminary and main studies suggest that similarity between electronic recommendation agents and consumers matters. Hence, agents *should* think like the people they are attempting to help if the goal is to assist consumers in making better choices. Although it is not crucial that the agent be similar on all dimensions of the decision process, dissimilarity in both attribute weights and decision strategies can have negative effects for consumer welfare. When there is similarity in either attribute weights or decision strategies, choice quality is higher and search is reduced. In addition, Web site loyalty and satisfaction increase. However, using an agent that is doubly dissimilar increases perceived costs, reduces choice quality, and lowers Web site loyalty. Because consumers tend to defer to the agent, regardless of whether or not its recommendations are good, search is constrained and choice quality declines. The choice share analysis suggests that, rather than leading to greater effort by the consumer to make a good decision, agent dissimilarity leads to the use of price as a signal of quality and reduces the effort consumers expend to make a choice.

The main study also examined how electronic recommendation agents compare to unordered lists. Interestingly, results were different for objective and subjective choice quality. Subjective decision quality is as high for consumers using an unordered list as for consumers using an agent that is similar on at least one dimension although objective decision quality is lower. On the other hand, objective decision quality is as high for consumers using an unordered list as for those that use an agent that is dissimilar in terms of both attribute weights and decision strategies although subjective choice quality is higher. Hence, the results indicate that some similarity seems to lead to better objective decisions in all cases when compared to using no agent or a doubly dissimilar agent. At the same time, using an unordered list is better than using a doubly dissimilar agent, at least in terms of subjective decision quality.

Before discussing the implications of this research, it is important to point out its limitations. First, a single product category was employed. Although cell phones seem like a particularly appropriate product category for our participants, using agents for other categories that vary in product risk or product complexity can affect decision quality in different ways (Swaminathan 2003). Second, only a limited number of relevant attributes were used. Inclusion of other attributes could ultimately change their relative importance by their mere inclusion into the evaluation process (Haübl and Murray 2003). Finally, incentives to make the best choice were not provided in these experiments. Incentives could increase consumers' motivation to spend more time on the decision and affect choice quality. Although the results of the latent class analysis do not support a main-effect-of-incentives argument, in that those who spent the most time on the decision did not make better decisions, it is possible that incentives could influence search behavior in the similar and dissimilar conditions differentially. Future research could explore the impact that incentives have on search and choice for different levels of agent similarity.

Because similarity of the decision-making process is the central focus of this research, it is important to elaborate on the implications of how similarity was manipulated. In both the preliminary and main studies, these manipulations involved a mixture of actual and perceived similarity. In both studies, *actual* attribute weight similarity was manipulated, whereas *perceived* decision strategy similarity was either measured (preliminary study) or manipulated (main study). Future research could explore the differential impacts of actual and perceived similarity of the decision-making process. One option is to assess decision strategy similarity through unobtrusive process-tracing measures (as opposed to the self-report measures used in this research).

Although there are many other types of decision strategies that a recommendation agent could use, such as elimination by aspects (EBA) or use of lexicographical rules (Payne, Bettman, and Johnson 1988), the recommendation agent used in this research employed a WADD model. This model was used mainly because it has been found to lead to the normatively best choice (Payne, Bettman, and

Johnson 1988). Kahn and Baron (1995) suggested that there may be situations, such as when there is reluctance to make difficult trade-offs, in which consumers defer to electronic agents and prefer them to use a different decision-making process from the one they use. Future research could explore the impact of decision strategy similarity for recommendation agents using different types of decision strategies besides WADD and for choice sets that vary in the extent to which they require consumers to trade-off attributes.

Finally, student participants were used in this research, which limits the ability to assertively generalize the findings to other populations. Regardless of these limitations, however, this research proposes interesting results that should be interpreted within the context and boundaries of the design of the studies.

CONCLUSIONS AND IMPLICATIONS

Electronic recommendation agents offer an opportunity for companies to improve e-service and provide consumers with virtual salespeople at much lower cost. This research suggests that consumer acceptance and use of such agents may depend on the extent to which they are seen as generating recommendations in ways that reflect consumers own decision-making processes.

In this research, decision-making similarity was deconstructed into two components: similarity of attribute weights and perceived similarity of decision strategies. The results show that similarity of attribute weights and perceived similarity of decision strategies have important implications for decision quality, Web site loyalty, and satisfaction. Results show that consumers make better decisions using a similar agent but believe they make better choices using no agent at all than when using a doubly dissimilar agent.

These results have important implications for the design of electronic recommendation agents. In particular, agents that recommend products according to the preferences of other dissimilar consumers (i.e., through collaborative filtering) may not be as effective as those that provide recommendations based on individual attribute importance weights and preferred decision strategies (Ansari, Essagier, and Kohli 2000). This suggests that marketers may wish to allow consumers to indicate attribute importance weights and preferred decision strategies. If consumers are unwilling, or unable, to indicate these preferences, another approach is either to unobtrusively observe consumers to learn consumers' preferences and mimic their decision-making strategies or give them the option of choosing among several decision rules. Ariely (2000), for example, found that allowing the consumer to control information search can lead to choices that better match preferences. Sponsors of electronic agents should strive to match at least one aspect of the agents attribute weights and/or decision strategy with those of the consumer; if this is not possible, reconsider whether it makes sense to provide consumers with electronic recommendation agents that employ the preferences of (potentially) dissimilar others. Results from this research suggest that providing consumers with an unordered list may be better, at least subjectively, than providing recommendations from a dissimilar agent.

Helping consumers make better choices has important implications for product return rates. If an individual is not happy with the choice made, the probability of returning the product to the vendor increases leading to higher operating costs for the firm. Good choices lead to satisfaction, which is also important for loyalty and retention of customers.

These results have implications for not only decision aids in the online environment but those that exist in the offline environment as well. For example, *Consumer Reports* ratings of products and *Business Week* rankings of business schools may impose preference structures and decision strategies that may not be similar to those of consumers. This research suggests that such dissimilarity may have serious consequences for decision quality.

This research only examines one dimension of agent similarity, similarity in decision making. Other aspects of similarity such as the effect of other dimensions of the degree of humanness of the agent should be explored. Future research could also examine potential interactions between the effects of information source (e.g., experts versus other consumers) and those of decision making and attribute weight similarity. Given that agents may only be one source of information in consumers decision-making processes (Ratchford, Talukdar, and Lee 2001), it is also important to examine the impact that multiple sources of information (or multiple agents) have on decision-making processes and decision quality. Cross-cultural comparisons may also reveal important differences in preferences for information sources with implications for decision quality.

Moreover, the results of this research can provide guidance for the design of agents in the business-to-business context. This is especially important given the large ratio of business-to-business transactions relative to consumer transactions. As the interface between marketers and consumers becomes increasingly virtual, an understanding of providing e-service through online agents will be of increasing importance.

APPENDIX A
Alternatives in the Database

Alternative	*Low Price*	*Low Weight*	*Long Talk Time*	*Long Standby Time*	*Number of Dominating Alternatives*[a]
AAB	5	10	2	5	3
ABB	*3*	*6*	*10*	*3*	*0*
ABC	*10*	*6*	*5*	*6*	*0*
BBC	*3*	*10*	*8*	*9*	*0*
BCC	3	10	8	6	1
BCD	*10*	*10*	*4*	*5*	*0*
CCD	3	7	5	4	5
CDD	1	10	2	5	6
DCE	1	7	6	10	2
DDE	1	6	4	2	20
EFG	9	7	4	2	2
FGH	9	3	3	3	5
GHI	*5*	*3*	*8*	*3*	*0*
HIJ	1	4	1	1	27
IJK	*9*	*7*	*6*	*10*	*0*
JKL	9	10	4	5	1
KLM	1	9	4	7	2
LMN	*1*	*9*	*6*	*10*	*0*
MNO	7	7	4	3	7
NOP	7	10	4	5	2
OPQ	*7*	*7*	*7*	*6*	*0*
PQR	3	1	8	4	4
QRS	1	4	5	3	10
RST	1	5	1	1	26
STU	*7*	*8*	*4*	*7*	*0*
TUV	1	10	4	5	5
UVW	*5*	*8*	*5*	*2*	*0*
VWX	5	5	3	8	2
WXY	1	3	4	2	22
XYZ	1	8	5	1	4
YZA	1	8	3	3	9
ZAB	5	7	6	10	1

NOTE: Items in italics indicate nondominated alternatives.
a. The number of alternatives that dominate this alternative.

APPENDIX B
Scale Items

Perceived Benefits (1 = *strongly disagree*, 7 = *Strongly Agree*)

1. I believe that the listing generated by the agent is designed to help me make the best decision possible.
2. I believe that the listing generated by the agent is designed to help me avoid making a poor choice.
3. I believe that the listing generated by the agent provides an accurate reflection of how other consumers feel about the product.
4. I believe that the listing generated by the agent provides an unbiased reflection of how other consumers feel about the product.
5. I believe that the cell phone listing based on other consumers opinions provides an accurate ordering of how good the alternatives are.
6. I believe that the cell phone listing based on other consumers opinions provides an unbiased ordering of how good the alternatives are.

Perceived Costs

1. How difficult was the task of searching for and choosing a cell phone for yourself? (1 = *very difficult*, 7 = *not difficult at all*) Reverse coded
2. How would you rate the amount of effort it took to complete this task of searching for and choosing a cell phone for yourself? (1 = *no effort at all*, 7 = *a lot of effort*)
3. How would you rate the amount of time it took to complete this task of searching for and choosing a cell phone for yourself? (1 = *no time at all*, 7 = *a lot of time*)

Subjective Decision Quality

1. How satisfied are you with the choice that you have made? (1 = *not at all satisfied*, 7 = *very satisfied*)
2. How confident are you with the choice that you have made? (1 = *not at all confident*, 7 = *very confident*)
3. Please indicate your interest in the alternative you chose. (1 = *not at all interested*, 7 = *very interested*)
4. How well do you think that the cell phone you chose fits your preferences? (1 = *does not fit my preferences well*, 7 = *fits my preferences well*)
5. How much do you think you would like the cell phone you chose? (1 = *not at all*, 7 = *very much*)

Loyalty Intentions

1. How likely are you to use Shoppers Universe again? (1 = *very unlikely*, 7 = *very likely*)
2. How likely are you to recommend Shoppers Universe to a friend? (1 = *very unlikely*, 7 = *very likely*)

Web Site Satisfaction

1. How well do you think the Web site that you used met your expectations of helping you make a good decision? (1 = *worse than expected*, 7 = *better than expected*)

APPENDIX C
The Latent Class Model

In this analysis, the dependent variable, y_i, is decision quality (Euclidean distance, reverse scored). The *M* customer groups were found by maximizing the likelihood represented by the joint distribution of *M* latent classes across the 110 observations in the main study,

$$L = \prod_{i=1}^{110} \sum_{m=1}^{M} p(m \mid \mathbf{z}_i, \theta_i) f_m(y_i), \tag{C1}$$

where $p(m\mathbf{z}_i, \theta_i)$ is the probability that a participant with covariate vector $\mathbf{z}_i$ is in customer group *m*, $m = 1, \ldots, M$ (these probabilities are represented as a logistic function of the covariates using parameters θ_i), and $f_m(y_i)$ is the normal density within cluster *m*, with arbitrary mean and variance that varies by cluster. (Vermunt and Magidson 2002 consider general models of this type.) The best model was found by first using all candidate covariates and searching for the number of groups that minimized the Bayesian Information Criterion (BIC; Bozdogan 1987; Schwarz 1978). Up to six latent classes were considered. The solution with three groups minimized BIC, and the value of BIC increased as one moved away from this three-group solution. Next, a backward stepwise selection of covariates was conducted based on models that used only the three customer groups. The best three-group model was then compared with the best models based on from one to six groups, where in each case the best combination of covariates was found by backward selection. Overall, the best model was still the three-customer-group solution reported in Table 5.

NOTES

1. Special thanks to Kristin Diehl for guidance with Authorware.

2. After adding the random number, the resultant weight was constrained to be between 1 and 10.

3. Thanks to an anonymous reviewer for this suggestion.

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