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This article examines how a common form of decision assistance—recommendations that present products in order of their predicted attractiveness to a consumer—transforms decision processes during product search. Such recommendations induce a shift in consumers’ decision orientation in search from being directed at whether additional alternatives should be inspected to identifying the best alternative among those already encountered, which is common when choosing from predetermined sets of alternatives. That is, recommendations cause consumers to search in “choice mode.” Evidence from three studies provides support for such a transformation of search decisions, which manifests itself in two respects. First, compared with unassisted search, recommendations lead consumers to assess a product they encounter in their search by comparing it less with the best one discovered up to that point and more with other previously inspected alternatives. Second, recommendations transform how variability in product attractiveness affects stopping decisions such that greater variability causes consumers to search less, which is contrary to what is commonly observed in search without recommendations.

Keywords: product recommendations, product search, behavioral search models, consumer decision making

Searching in Choice Mode: Consumer Decision Processes in Product Search with Recommendations

Consumers increasingly have easy access to a vast number of products, services, and vendors. As a result, they often engage in an extensive search of the set of available alternatives to make a purchase. An effective means of assisting consumer search is to provide them with recommendations that sort alternatives in terms of their attractiveness. Such assistance may be provided by human advisors (e.g., sales assistants, financial advisors, real estate agents), but it is increasingly available in the form of recommendations that are generated automatically by information systems.

While prior research has investigated how product recommendations affect decision outcomes (Diehl 2005; Diehl, Kornish, and Lynch 2003; Fitzsimons and Lehmann 2004; Häubl and Murray 2003; Häubl and Trifts 2000), little is known about how such decision assistance might influence consumer decision processes during product search. The current research is an attempt to fill this gap. Our central thesis is that the presence of recommendations transforms the decision processes consumers use during sequential product search relative to searching without such assistance. When engaging in unassisted search, consumers’ natural decision orientation is characterized by considerations directed at determining, at each stage of the search, whether an additional alternative should be inspected (Adam 2001; Bikhchandani and Sharma 1996; Häubl, Dellaert, and...
Donkers 2010; Kim, Albuquerque, and Bronnenberg 2010; Weitzman 1979). In contrast, we propose that the presence of recommendations induces a decision orientation during search that is focused on comparing and identifying the best among the alternatives that have already been discovered. We refer to this phenomenon as “searching in choice mode.”

The hypothesized shift in decision orientation implies that consumer search behavior in the presence of product recommendations is partly governed by influences that are nonnormative in the context of search and are commonly observed when consumers choose from small predetermined sets of alternatives. To test this proposition, we examine how recommendations affect the two key decisions that consumers must make at each stage of a sequential product search: determining which of the alternatives that have already been inspected is the most attractive one (product comparison decision) and deciding whether to terminate the search or continue it by inspecting an additional alternative (stopping decision).

**PRODUCT RECOMMENDATIONS AND CONSUMER SEARCH**

We consider decision assistance in the form of recommendations whereby a consumer is presented with products in descending order of their (predicted) attractiveness to him or her. Such an ordered presentation of alternatives has important implications for consumer search (Brickman 1972; Shapira and Venezia 1981). Compared with unassisted search, the average attractiveness of the alternatives a consumer inspects is higher and the variability in the attractiveness of these alternatives is lower when searching with product recommendations. These properties are consistent with the more favorable decision outcomes that consumers have been shown to achieve when provided with such recommendations (Häubl and Trifts 2000; Xiao and Benbasat 2007).

The Consumer Product Search Process: Normative Model

Many purchase decisions involve a sequential search process during which the consumer inspects some of the (often numerous) candidate products available in the market, one at a time, with the aim of identifying the product that best matches his or her preference. We examine the case in which the attractiveness of a product is fully revealed to the consumer upon inspection, and any previously encountered products can be “recalled” (i.e., after inspected, a product remains accessible to the consumer as a candidate for purchase for the remainder of the search process). In search without recommendations, the consumer has no prior information about the alternatives, and all alternatives thus have the same expected attractiveness before inspection. In contrast, in search with recommendations, the order in which the alternatives are presented reflects their expected attractiveness.

Formal normative models of this type of product search have the reservation-value property, which indicates that, at each stage of the search process, when consumers determine whether the expected value of the most attractive to-be-inspected alternative exceeds some reservation value, this is equivalent to solving the global optimization problem of how many and which alternatives to inspect (e.g., Adam 2001; Bikhchandani and Sharma 1996; Weitzman 1979). When the uncertainty about the expected value is identical for each alternative at a given stage of the search, the decision whether to continue searching is a function of the cost of further search and the expected utility of the most attractive uninspected alternative. This expected utility is identical for all alternatives in unassisted search, but it decreases across stages in search with recommendations.

The search is continued if the cost of search is lower than the expected utility gain from inspecting the next alternative. When the search is terminated, the product with the highest utility among all inspected products is selected. This decision requires the consumer to determine the utility of the most attractive product encountered up to that point, which may be either the currently inspected product or the best previously encountered one.

This structure enables us to conceptualize the product search process as an iterative sequence of decision stages (see Figure 1), with each stage involving (1) a product comparison decision (to determine the most attractive alternative thus far) and (2) a stopping decision (to determine whether to end the search). The product comparison decision is represented by a standard choice model structure that applies both with and without recommendations. In line with random utility theory, we conceptualize the consumer’s evaluation of a given product during search in terms of an overall product utility (that is known to the consumer but not directly observable to the researcher) and that

![Figure 1: CONSUMER DECISIONS IN THE SEQUENTIAL PRODUCT SEARCH PROCESS](image)

Notes: At the initial stage of the search process (i.e., for the first inspected alternative), the product comparison stage is skipped.
maps the various attributes of the product into a single subjective utility value based on the consumer’s multiattribute preferences (McFadden 1986).

For the stopping decision, the normative model differs between the cases with and without recommendations (see Web Appendix A at http://www.marketingpower.com/jmr_webappendix). For unassisted search, the variability (or standard deviation) of the distribution from which the consumer’s utility value of the next-to-be-inspected alternative is drawn reflects the distribution of the values of all available alternatives. The range of possible values in the market is known to consumers, and they learn about the distribution of these values as they search (Häubl, Dellaert, and Donkers 2010). In contrast, in search with recommendations, the distribution of all possible utility values in the market is not directly relevant to the stopping decision. Consumers are presented with an ordering of the alternatives in terms of their attractiveness. Therefore, what is critical is the slope and accuracy of this ordering. The potential payoff to further search is determined by how quickly the expected attractiveness declines across alternatives (i.e., the slope of the ordering) and by how accurately consumers believe the order of recommended alternatives reflects their preferences. We formalize these two aspects of the sequence of alternatives as two components of variability: (1) the decrease in expected value over inspected alternatives that is inherent to search with recommendations and (2) the uncertainty about the expected value of the next-to-be inspected alternative as represented by the standard deviation of the distribution of that expected value (i.e., how “noisy” the ordering of the recommended alternatives is).

Thus, in the presence of recommendations, consumers anticipate a decrease in value, and they update their beliefs about the standard deviation of the expected value of the next-to-be-inspected alternative, in the course of their search. In line with random utility theory, we define both components of variability in terms of the consumers’ own subjective utility.

**Searching in Choice Mode: Recommendations Transform the Decision Process**

When presented with recommendations, consumers can expect to discover many attractive alternatives early on in their search. In contrast, in unassisted search, they are likely to encounter only a much smaller number of good alternatives, along with many unattractive ones. We propose that because recommendations selectively identify attractive alternatives, consumers anticipate that this form of decision assistance reduces the number of alternatives they need to inspect. This focus on fewer alternatives changes their expectation about the payoff from allocating decision effort to determining whether it is worth inspecting an additional alternative relative to the payoff from more thorough comparisons among alternatives already inspected (Lenton and Francesconi 2010; Payne, Bettman, and Johnson 1988). This anticipated difference in relative payoff parallels the phenomenon in consumer choice from small versus large sets, in which thorough evaluation of all alternatives in a large choice set may not be optimal when cognitive decision costs are taken into account (Hauser and Wernerfelt 1990; Roberts and Lattin 1991). When the choice set is large, a cursory initial assessment of the alternatives is typically followed by a more in-depth comparison of a small subset (Chakravarti, Janiszewski, and Ulkümen 2006; Ge, Häubl, and Elrod 2012).

We argue that the anticipated difference in the relative payoff of decision effort from search with and without recommendations also affects consumer decision processes during product search. In particular, our overarching hypothesis is that recommendations shift searchers’ decision orientation from being directed at determining whether an additional alternative should be inspected (which governs unassisted search) toward comparing and choosing among alternatives that have already been discovered. We should find evidence of such a choice mode in both the product comparisons and the stopping decisions that consumers make in product search.

According to normative models of sequential search, when consumers are deciding whether the current product is the most attractive one thus far, all previously encountered alternatives except the best one among them are irrelevant (Rosenfield, Shapiro, and Butler 1983; Weitzman 1979). Thus, the product comparison decision at a given search stage should be based only on the difference in attractiveness between the current product and the best previously inspected one.

In line with the proposed shift toward a choice mode, we hypothesize that the presence of recommendations transforms product comparison decisions in search such that, in addition to making the comparison with the best previously discovered alternative, consumers also assess the attractiveness of the current product more broadly by comparing it with other inspected alternatives. This implies that consumers also make product comparisons that include inferior alternatives they have encountered in the course of the search (e.g., Huber, Payne, and Puto 1982; Tversky and Simonson 1993).

H1: Searching with recommendations causes consumers to make broader comparisons among the set of inspected products than when searching without such assistance.

A key driver of consumers’ stopping decisions in product search is the amount of variability in the attractiveness of the available products. In normative models of (unassisted) search, greater variability in product attractiveness increases the reservation utility, thus reducing the probability that the search is terminated at a given stage (Rosenfield, Shapiro, and Butler 1983; Stigler 1961). Consequently, all else being equal, greater variability in attractiveness should lead consumers to inspect a larger number of products.

To examine the impact of variability in product attractiveness on consumers’ stopping decisions in search with recommendations, we must disentangle two components of this variability. First, when searching with recommendations, the expected attractiveness of the next-to-be-inspected alternative is always lower than that of the best one discovered up to that point. The greater the difference in expected attractiveness between consecutive to-be-inspected alternatives—and thus the greater the variability—the more likely the consumer is to stop searching at a given stage. This is a normative effect. The second component of the variability in product attractiveness is the consumer’s uncertainty about the attractiveness of the next-to-be-inspected alternative, taking into account the difference in expected attrac-
tiveness. Normatively, the greater this variability component, the less likely the consumer should be to stop searching at a given stage, because this implies a greater probability of encountering an attractive alternative through continued search.

However, the proposed shift toward a choice-oriented decision mode in search with recommendations suggests a change in how consumers respond to the component of variability associated with the uncertainty about the attractiveness of the next-to-be-inspected product. Prior work has shown that, when consumers are choosing from predetermined sets, less variability makes it more difficult to select their preferred alternative and, consequently, increases the likelihood of choice deferral (Dhar 1997; Dhar and Simonson 2003). Thus, we hypothesize that in search with recommendations, greater variability of the inspected alternatives around their expected attractiveness (i.e., lower accuracy of the recommendations) increases the probability of ending the search and thus causes consumers to stop sooner. This would be a behavioral effect and, indeed, contrary to the normative prediction.

In summary, we propose that the presence of recommendations changes how variability in product attractiveness influences consumers’ stopping decisions during search. Both the normative and the behavioral effect described previously imply a positive effect of variability on the probability of stopping at a given stage when searching with recommendations. However, only the behavioral effect is in line with the proposed shift toward a choice-oriented decision mode. (The empirical evidence we present next disentangles these two effects, thus providing the opportunity to isolate the behavioral effect.) We hypothesize that greater variability in the encountered products’ attractiveness makes it more likely for consumers to stop at a given stage when searching with recommendations, whereas it has the opposite effect in unassisted search.

\[ H_2: \text{While greater variability in product attractiveness leads consumers to stop later during unassisted search, it causes them to stop sooner when searching with recommendations.} \]

**STUDY 1**

As a first test of the hypothesized effects of recommendations on consumer product search decisions, we conducted a computer-based study (using the Internet) in which participants completed a task that resembled a common prepurchase product search activity and that concluded with the choice of one of the available alternatives. Participants viewed the descriptions of as many alternatives as they wished, one at a time, and the task concluded with them choosing one of the inspected alternatives. The study involved two conditions: one in which participants searched with recommendations and another in which they searched without such assistance. The available alternatives were presented in descending order of their predicted attractiveness to the participant in the recommendation condition, and they were presented in random order in the unassisted condition (for further details, see Web Appendix B at www.marketingpower.com/jmr_webappendix).

**Design and Procedure**

Participants were members of a panel of consumers maintained by a Dutch university. The consumers in this panel had been randomly selected from the population of the Netherlands. A total of 438 panel members completed this study in connection with one of two product categories—compact stereo systems (n = 217) or holiday home rentals (n = 231)—according to their interest (which was measured as part of another study one week earlier). While the majority of participants (n = 333) performed the task with product recommendations, approximately one-quarter (n = 115), selected at random, were assigned to an unassisted condition in which no such recommendations were available. The average age of participants was 45.5 years, 40.8% of them were female, and 48.5% held a bachelor’s or higher academic degree.

Participants first read detailed instructions that included descriptions of the six quality attributes used to characterize the products in the assigned category. This provided them with information about the range of possible products in the market. They then completed a ratings-based conjoint task designed to measure their multiattribute preference in the focal product category. This serves as a basis for determining the predicted attractiveness—or “utility”—of each alternative to each consumer.

During the search task, participants were presented with a list of 500 products based on a fractional factorial design to resemble a typical assortment of differentiated alternatives. In the recommendation condition, the alternatives in this list were sorted in descending order of their predicted attractiveness to participants. In the unassisted condition, the presentation order of the alternatives was randomized independently for each participant. In both conditions, participants were fully informed about how the presentation order was determined. The alternatives were identified by arbitrary numbers (determined at random for each participant). To inspect the detailed description of one of the products (all attribute levels and prices), participants had to click its number in the list. All alternatives remained available throughout the search, but it was only possible to view the description of one product at a time. Participants were asked to mark their “current favorite” (i.e., the best alternative they had found up to that point) at each stage of the search. (Doing so made it easier for them to subsequently locate that product again.) When they were ready to terminate their search and make their choice, participants were to go to the detailed description of their preferred alternative and click a link to indicate that they wanted to select that product.

**Analysis**

To examine the hypothesized effects on consumer search behavior, we estimated choice models characterizing the decisions that participants faced at each stage of the search process—whether the currently inspected product is the most preferred one that they have encountered thus far (i.e., the product comparison decision) and whether to end the search at that stage (i.e., the stopping decision). To test \( H_1 \), we estimated one product comparison model across both conditions (with and without recommendations). To test \( H_2 \), we estimated the stopping model for search with recom-
mendations. (The Appendix reports the econometric models and results.)

We operationalized the dependent variables in the models as follows. At each stage of the search, we observed whether participants marked the newly inspected alternative as their currently most preferred product. This served as the dependent variable in the product comparison model. We also observed, at each stage, whether participants chose to end their search at that point or inspect an additional alternative. This served as the dependent variable in the stopping model.

In the product comparison model, we use a standard utility specification and include as independent variables the difference in utility (1) between the currently inspected product and the best previously encountered one and (2) between the current product and the one inspected just before that. We used the interactions between each of these variables and the presence of recommendations to test H1.

In the stopping model, the independent variables are based on a reduced-form approach to representing reservation-utility-based stopping rules of search with learning. In the case of search with recommendations, these variables are (1) the maximum utility observed up to that point to capture the normative reservation-utility effect, (2) a random intercept to allow for heterogeneity in search cost across participants, (3) the predicted utility of the next-to-be-inspected alternative in the recommendation list, and (4) the standard error of the prediction of the expected utility of the next-to-be-inspected alternative (for details, see the Appendix). Variables 3 and 4 enable us to disentangle the normative and behavioral effects of variability in product attractiveness in search with recommendations that underlie H2.

### Results

To assess decision quality, we calculated a measure (Q_i) that compares the utility of the product a participant chooses (U_i.chosen) with that of the most attractive available product (U_i.best), each in terms of their improvement relative to the expected utility of a product selected at random from those that were available [Q_i = (U_i.chosen − U_i.random)/(U_i.best − U_i.random)]. Decision quality was substantially higher for participants who searched with recommendations (M = .82) than for those who searched without such assistance (M = .47, p < .001, t-test), consistent with previous findings (Häubl and Trifts 2000). The number of alternatives inspected was somewhat lower with recommendations (M = 12.6) than without (M = 14.3, p < .10, one-tailed Mann–Whitney test). Participants spent more time on a given alternative when searching with recommendations (M = 36.1 seconds) than in unassisted search (M = 33.4 seconds, p < .001, t-test), indicating greater effort per alternative in the presence of recommendations. Finally, participants chose an alternative that was presented higher up in the list when recommendations were provided: The median display position of the chosen product was 7 with recommendations and 12 in the absence of such assistance (p < .001, one-tailed Mann–Whitney test).

The model estimates support our hypotheses about how the presence of recommendations transforms consumer decision processes during search (see the Appendix for details and Tables 1 and 2). First, with regard to product comparison decisions, we observe the baseline normative effect that a higher utility of the currently inspected alternative relative to the best previously encountered one leads to a greater probability of the current alternative being selected as the most preferred one thus far (β = 12.7, p < .001). More
important, we find support for H1 in that the presence of product recommendations reduces the influence of the utility difference between the currently inspected product and the best previously encountered one on whether the current alternative is selected as the most attractive one thus far (β = −9.2, p < .001). Moreover, the presence of recommendations also amplifies the impact of (local) comparisons with alternatives other than the best previously encountered one on the product comparison decision (β = 4.2, p < .05). These findings provide support for the proposed shift in decision orientation toward a choice mode.

In connection with stopping decisions, the estimates for the model of search with product recommendations provide a test of H2. This hypothesis is supported in that, when searching with recommendations, greater uncertainty about the expected utility of the next-to-be-inspected alternative increases the probability of terminating the search at a given stage (β = 6.3, p < .05). This effect occurs beyond the increase in the probability of stopping due to a lower expected utility for the next-to-be-inspected alternative in search with recommendations (β = −4.3, p < .05). The negative effect of greater uncertainty about the expected utility of the next-to-be-inspected alternative is in contrast with what would be predicted by a normative model of search with recommendations, and it provides further evidence of the proposed shift toward a choice-oriented decision mode when searching with product recommendations.

Discussion

The findings of Study 1 provide strong support for the proposition that the presence of recommendations transforms consumer decision processes during product search. We conducted this study in a realistic setting in which product recommendations were based on participants’ own preferences. While such realism is desirable in terms of the external validity of our findings, it also has some downsides. Because the recommendations were based on participants’ idiosyncratic preferences, the composition of the searched set of products varied across participants and conditions. As a result, we cannot rule out the (remote) possibility that the findings of Study 1 might be due to the particular products inspected rather than the proposed shift in decision orientation. For example, the range of observed utility differences was more restricted in the recommendation condition, which may have made it more difficult to judge these differences than those in the unassisted condition, which in turn may have influenced how participants made their product comparison decisions. Moreover, for the stopping model, we were able to test the effect of variability in the recommendation condition but not between conditions because of the inherent difference in the underlying normative models. We address these limitations in Studies 2 and 3 (focusing on the product comparison and stopping decisions, respectively), in which the nature and sequence of the products inspected was identical across participants and conditions.

STUDY 2

Study 2 was designed to more directly examine the hypothesis that the presence of recommendations induces a shift in the search decision process from comparing the currently inspected alternative only with the best previously encountered one toward broader comparisons with other inspected alternatives (H1). We do so based on process evidence in the form of consumers’ tendency to reinspect previously seen alternatives other than the most attractive one, which is counter to the normative policy in cases in which product attractiveness is fully revealed upon first inspection.

As in Study 1, participants conducted sequential product searches that concluded with their choice of one of the inspected alternatives. The key manipulation in Study 2 was whether participants believed that the alternatives were sorted in terms of attractiveness. Moreover, to isolate the effect of sorting and to disentangle it from the possible effect of the set of alternatives having been prescreened to include only attractive ones (which is another aspect of product recommendations), we also manipulated participants’ beliefs about the latter. Indeed, the stream of inspected alternatives was identical in all conditions.

Design and Procedure

Participants were members of an Internet-based research panel maintained by a major North American university. Usable data were obtained from a total of 60 participants who completed the study over the Internet for a $3 payment. All participants were U.S. residents, their average age was 43.8 years, 68.3% were female, and 80.0% held a bachelor’s or higher academic degree.

Each participant performed the product search task in two categories: rental apartments and fitness club memberships. (Category order was determined at random for each participant.) Before beginning their search in one of the categories, participants were presented with descriptions of the five attribute dimensions used to characterize the alternatives in that category (see Web Appendix C at www.marketingpower.com/jmr_webappendix). The levels of all attributes were described numerically, using a scale from 1 (“very poor”) to 10 (“excellent”). Thus, all attributes were “vertical” in that the levels were strictly ordered in terms of their desirability. Participants were informed that all alternatives in a category were available at the same price.

In the search task, alternatives were revealed one at a time, and participants were free to inspect as many of these as they wanted before choosing one of the revealed alternatives. The information about the alternatives was arranged in an alternatives (rows) × attribute dimensions (columns) table. Because the objective of this study was to obtain process measures of reinspection behavior, only the description of one of the alternatives was displayed at any point in time, and those of all other previously revealed alternatives were masked. Participants were able to reinspect any of the latter by clicking on the corresponding masked row of the table, which was labeled “Click Here to See Alternative #.” Again.” When reinspected, a previously revealed alternative was eligible to be chosen. Thus, at each stage, participants could (1) end their search and choose the currently displayed alternative, (2) reinspect a previously seen alternative, or (3) continue their search by inspecting a new alternative. After every inspection of an alternative, participants indicated whether that alternative was the most attractive one they had encountered up to that point.

We manipulated two factors in a 2 × 2 between-subjects design: searchers’ beliefs as to whether the alternatives were sorted in descending order of attractiveness and their beliefs about the average attractiveness of these alternatives. We
manipulated beliefs about presentation order by either informing participants that the alternatives would appear roughly in descending order of their attractiveness (sorted) or not providing any information about the order of the alternatives (control). We manipulated beliefs about the level of attractiveness of the alternatives by either informing participants that the alternatives they were about to inspect were the most attractive ones available (screened) or not providing any information about the level of attractiveness (control). For both factors, the task instructions indicated that the attractiveness of the alternatives had been determined on the basis of a recent survey and reflected the preferences of typical consumers. We presented an identical set of alternatives in the same order in all four conditions. The sequence of encountered alternatives followed a mildly declining slope in terms of attractiveness to ensure that the sorted treatment was plausible. To motivate search, a random component was added to the attractiveness of each alternative, resulting in a noisy sorting in which the actual attractiveness of alternatives was not monotonically decreasing. Moreover, all attribute levels were favorable (i.e., above the midpoint of the scale) to ensure the credibility of the screened treatment.

We used two dependent variables to test the prediction that recommendations induce a shift in the search decision process toward comparisons of the current alternative with previously encountered alternatives other than the best one: (1) how frequently such alternatives were reinspected and (2) how much time was spent on these reinspections. For consistency across participants, product categories, and rounds of the search task, the values of these dependent variables are based on the first five informative inspections (the first two observations could not have been reinspections, by definition) for each participant and round.

Results

To account for the repeated measures structure of the data (participants completed two rounds of the search task), we estimated random-effects regression models for all dependent variables. The manipulation of beliefs about the overall level of attractiveness of the presented alternatives (i.e., screened vs. control) did not have a significant main or interaction effect on any of the dependent variables, and thus we do not discuss it further. Moreover, none of the effects reported here are qualified by product category or round of the search task.

Participants inspected fewer alternatives when they believed that these were sorted ($M = 7.7$) than when they did not ($M = 14.4$, $p < .01$). Moreover, they chose an alternative that appeared earlier on in the search sequence when they believed that the alternatives were sorted ($M = 3.3$) than when this was not the case ($M = 5.7$, $p < .05$). These findings are consistent with prior work (Häubl and Trifts 2000).

In support of H1, the belief that the alternatives were sorted in an order that reflected their attractiveness led to an increase in comparisons with alternatives other than the best previously encountered one. This manifested itself in both how frequently such alternatives were reinspected and the amount of time spent on these reinspections. First, the sorting manipulation caused the proportion of inspections that were reinspections of alternatives other than the most attractive one to increase from 5.1% to 15.0% ($\beta = .11$, $p < .05$).

Moreover, it also resulted in an increase in the proportion of the overall search time that was spent reinspecting alternatives other than the best previously encountered one from 4.5% to 12.1% ($\beta = .09$, $p < .05$).

Discussion

The process-level results of Study 2 provide clear support for the hypothesized shift toward broader comparisons among alternatives when consumer search is aided by recommendations. In line with the notion of searching in choice mode, believing that the set of alternatives reflected product recommendations led participants to more frequently reinspect alternatives other than the best previously encountered one. The findings of this study also identify consumers’ understanding that the alternatives are presented in descending order of attractiveness as the property of recommendation-assisted search that is driving this effect (as opposed to the prescreening of alternatives so that only attractive ones are included in the set presented to the consumer).

STUDY 3

The objective of Study 3 was to examine the predicted moderating effect of the presence of recommendations with respect to the impact of variability in product attractiveness on the stopping decision ($H_2$) in a more tightly controlled setting. Doing so enables us to rule out the possibility that the previously observed effect might have been due to the particular alternatives participants inspected in Study 1, which were based on personalized recommendations. In Study 3, we examined whether the proposed transformation of consumer decision processes during search can be observed even when we hold the specific stream of inspected alternatives constant and only manipulate consumers’ beliefs about whether the ordering of the alternatives reflects recommendations.

Participants again engaged in sequential product searches that concluded with their choice of one of the inspected alternatives. The unique aspect of Study 3 is the disentangling of (1) participants’ beliefs about whether the order of the alternatives was generated on the basis of recommendations and (2) the amount of variability in the attractiveness of the alternatives they encounter in the course of their search. Within each level of variability, the stream of inspected alternatives was identical across the two levels of belief about the ordering of alternatives. This allows a more conclusive test of our hypothesis that the presence of recommendations alters how consumers respond to the amount of variability in product attractiveness during search ($H_2$), in line with a shift toward a choice-oriented decision mode.

Design and Procedure

Participants were members of an Internet-based research panel maintained by a major North American university. A total of 169 members of this panel completed the study over the Internet. All participants were U.S. residents, their average age was 38.1 years, 72.8% of them were female, and 67.5% held a bachelor’s or higher academic degree.

The task and stimuli were similar to those used in Study 2. Each participant performed the product search task in four categories: rental apartments, all-inclusive beach resorts, fitness club memberships, and lake chalet rentals (in that order). All alternatives were characterized in terms of
five attribute dimensions (see Web Appendix C at www.
marketingpower.com/jmr_webappendix), with levels ranging from 1 (“very poor”) to 10 (“excellent”). All alternatives in a category were available at the same price.

In the search task, alternatives were revealed one at a time, and participants were free to inspect as many of these as they wished before choosing one of the revealed alternatives. The information about the alternatives was arranged in an alternatives (rows) \( \times \) attribute dimensions (columns) table. When revealed, alternatives remained visible on the screen. At each stage, participants could either (1) end their search and make their choice by selecting one of the revealed alternatives or (2) inspect a new alternative.

We manipulated two factors in a 2 \( \times \) 2 mixed design: searchers’ beliefs whether the alternatives were presented in descending order of attractiveness (between subjects) and the amount of variability in the attractiveness of the inspected alternatives (within subject). Although the presentation order was the same irrespective of this manipulation, we manipulated beliefs about presentation order by either informing participants that the alternatives would appear roughly in descending order of their attractiveness (sorted) or not providing any information about the order of the alternatives (control).

We manipulated variability in attractiveness as follows: First, for each of the categories, we selected four levels for each attribute over which the products could vary to create a set of 256 alternatives using a 4\(^5\) fractional factorial design. Then, we sorted these alternatives in terms of their overall utility according to an equal weighting of the five attributes and selected the middle 100. To induce different levels of variability, the initial sorting of these 100 alternatives was contaminated either slightly or more substantially by adding a random component to the overall utility of each alternative. This component had an expected value of zero, and we manipulated its standard deviation at two levels: 1.5% and 15.0% of the average overall utility for low and high variability, respectively. We then sorted the alternatives from least to most attractive according to these contaminated utilities. Each participant completed two rounds of the task in connection with each of the two levels of variability, and we manipulated the order of these treatments as an additional between-subjects factor such that participants were exposed to the levels of variability in either “low-high-low-high” or “high-low-high-low” order.

**Results**

On average, participants inspected 9.4 alternatives on each round of the search task. To examine how the two manipulated factors influenced the amount of search, we estimated a random-effects Poisson regression model with the number of alternatives participant inspected in a category as the dependent variable. The independent variables were main effects of beliefs about presentation order (sorted vs. control) and of variability in attractiveness (low vs. high), as well as the interaction between these two (to examine the predicted moderating role of recommendations with respect to the effect of variability on stopping). Because inclusion of the main effects of and interaction effects with product category and treatment order did not affect our substantive findings, we do not report these in the interest of expositional clarity.

The main effect of beliefs about the presentation order of the alternatives is significant (\( \beta = -.12, p < .01 \)): Participants searched less when they were informed that the order reflected recommendations in that the alternatives had been sorted according to their attractiveness. The main effect of the amount of variability in the attractiveness of the inspected alternatives is not significant. Critically, however, the interaction effect between beliefs about presentation order and the amount of variability in attractiveness is highly significant (\( \beta = -.15, p < .001 \)).

The nature of this interaction provides clear support for H\(_2\). In the control condition, in which participants were not provided any information about how the presentation order of the alternatives had been determined, lower variability led to a higher probability of stopping at a given stage and, thus, less search—in line with normative models of unassisted search. The mean number of alternatives inspected was 10.1 and 11.7 in the low- and high-variability conditions, respectively. In contrast, when participants believed that the alternatives were presented in an order that reflected their relative attractiveness, lower variability in attractiveness resulted in a lower probability of stopping at a given search stage and, thus, a greater number of inspected alternatives. The mean number of alternatives searched was 8.9 and 7.0 in the low and high variability conditions, respectively (see Figure 2). This reversal in the direction of the effect of variability in the attractiveness of encountered alternatives on the stopping decision is a clear demonstration of the shift in consumers’ decision orientation when searching with product recommendations toward a broader, more backward-looking evaluation of already inspected alternatives. Indeed, the results of this experiment show that the shift toward a choice-oriented decision mode resulting from (the mere belief that the order of inspected alternatives reflects) recommendations can actually dominate the natural orientation that characterizes consumer decision processes in unassisted search.

![Figure 2](image-url)

**Figure 2**

**EFFECTS OF VARIABILITY AND RECOMMENDATION BELIEFS ON AMOUNT OF SEARCH (STUDY 3)**

Notes: Average across all four product categories.
This conclusion is further corroborated by an analysis of the amount of time that participants took to inspect each alternative in the different conditions. The inspection time per alternative was longer in the sorted condition (M = 14.2 seconds) than in the control condition (M = 12.4 seconds, p < .10). This result is consistent with the notion that the presence of recommendations causes a shift toward a choice-oriented decision mode in that the latter involves a more in-depth comparison of (multiple) alternatives than is typically the case in unassisted search.

Discussion

The findings of Study 3 further demonstrate—in a more tightly controlled experimental setting than in Study 1—how the proposed shift toward a choice mode in product search with recommendations manifests itself in consumers’ stopping decisions. If consumers believe that the order in which products are presented to them is based on the attractiveness of these products, they are more inclined to stop searching when the uncertainty about the attractiveness of the next-to-be-inspected product is greater. This is in sharp contrast to the normative prediction based on search theory (Weitzman 1979) but fully consistent with our notion of a choice mode in that different alternatives among alternatives (in terms of their overall attractiveness) make it easier for consumers to identify the best alternative they have already inspected, thus reducing the inclination to defer their choice and continue searching. However, if consumers are not aware that the order of presentation reflects product attractiveness, greater variability reduces the probability of stopping and, thus, results in a larger number of inspected alternatives.

In summary, the evidence from Study 3 shows that (merely believing that one is) receiving recommendations to aid product search activates a choice mode, which transforms the way consumers respond to the stream of products they encounter while searching—in particular, whether the amount of variability in the attractiveness of the inspected alternatives has a positive or a negative effect on their inclination to stop searching. In this study, we were able to induce this effect by simply changing searchers’ beliefs about how the order of alternatives was determined, while controlling for the actual alternatives that were encountered.

GENERAL DISCUSSION

This article examines consumer decision processes during product search with recommendations and how the order in which alternatives are encountered reflects their attractiveness to the consumer. We propose that such recommendations transform searchers’ decision processes by inducing considerations that are more in line with choice from a predetermined set of alternatives (i.e., that cause consumers to search in choice mode). Evidence from three studies provides strong support for this perspective. When inspecting a new product in search with recommendations, consumers tend to make broader comparisons with previously encountered alternatives rather than only with the best alternative seen thus far. Moreover, in contrast to unassisted search, when searching with recommendations, greater variability in the expected attractiveness of the next-to-be-inspected alternative increases the probability of stopping the search at a given stage. Both these effects indicate a shift in decision mode from determining whether an additional alternative should be inspected toward comparing the alternatives that have already been discovered in the course of the search.

The presence of product recommendations affects not only the way consumers make their decisions in product search but also which of the available products they consider, which can also influence their ultimate product choice. In particular, recommendations cause consumers to rely less on the utility difference between a newly inspected product and the best previously encountered one and to make broader comparisons among the set of inspected products. Indeed, our findings show that, with recommendations, consumers shift their decision effort from whether to continue searching at each stage of the search to a more thorough comparison among alternatives already inspected (Lenton and Francesconi 2010; Payne, Bettman, and Johnson 1988). Recommendations also cause consumers to respond differently to variability in expected product attractiveness, with greater variability leading them to end their search sooner—in sharp contrast to normative models of search (and to what is typically observed empirically in unassisted search). This provides support for our proposition that choice deferral (Dhar 1997) also plays a role in consumer search with recommendations, such that the inspected alternatives are relatively more attractive and more similar than in search without recommendations.

Implications

The large body of literature on normative search behavior has increasingly been extended to also incorporate behavioral influences (Häubl, Dellaert, and Donkers 2010; Zwick et al. 2003). The current research is the first to show that these behavioral influences vary systematically as a function of the nature of the search task and environment. It demonstrates this phenomenon in connection with recommendations, which are an important decision support tool in many (physical or technology-mediated) search environments. Further research should examine other aspects that might have similar effects.

The findings of the current research also have important implications for firms that want to design decision environments that help consumers make better purchase decisions (Johnson et al. 2011). In particular, they suggest that the potential exists to further assist consumers in making better purchase decisions, even if they are already aided by product recommendations. This could be done, for example, by combining recommendations with tools designed to help consumers recall the subjectively most attractive alternative(s) they have encountered so far in their search (e.g., in the spirit of the product comparison matrices Häubl and Trifts [2000] use). Another possibility for assisting consumers in search with recommendations is to deliberately construct the set of the recommended products to facilitate choosing. This implies that alternatives may perhaps not always be ranked in terms of predicted attractiveness alone but that other considerations, such as the anticipated difficulty of making a choice, may also be taken into account in designing the recommended set of alternatives.

Limitations and Further Research

Some limitations of this research are worth noting. First, although we used a national consumer panel and closely
mimicked a real-world recommendation scenario in Study 1, as well as much more tightly controlled experimental paradigms in Studies 2 and 3, consumers’ actual search decisions might differ from what we observed. Despite the benefits of product recommendations, consumers might rely on these recommendations only in part, perhaps integrating them with information from other sources. Furthermore, it may not be the case in all search environments that consumers obtain full information about the utility of the product upon a single inspection in the search. Indeed, a promising avenue for further research is to study in more detail what type of heuristics or “rules” consumers use to integrate information from different sources when they make decisions with recommendations.

Second, it would be worthwhile to develop evaluation criteria that could be used to examine the extent to which consumers believe they make better purchase decisions when conducting their product search with recommendations than when shopping without such assistance. This is especially important because consumers do not always appreciate the benefits they obtain from the use of product recommendations (Häubl and Trifts 2000; Murray and Häubl 2009). It would be worthwhile to study in greater detail how different aspects of recommendations might result in different levels of satisfaction with the consumers’ search decision (e.g., by affecting experienced decision difficulty). Thus, although much additional research is needed in this area, the findings we report in this article represent a next step toward developing a deeper and more complete understanding of the psychological forces that govern consumer search behavior in the presence of decision assistance.

**APPENDIX: STUDY 1: ECONOMETRIC MODEL AND ESTIMATION RESULTS**

**Product Comparison Model**

In the product comparison model, consumer i’s decision at stage t as to which of the products encountered thus far is the most preferred is modeled as the probability that the utility of the currently inspected alternative (\(U_{it}\)) is greater than that of the most attractive one among all previously encountered alternatives (\(U_{it-1}\)). We express this probability as follows:

\[
P(\text{prefer}_{it}) = P(U_{it} > U_{it-1}) = P(U_{it} - U_{it-1} > 0),
\]

where \(P(\text{prefer}_{it})\) is the probability that the alternative observed at stage t is selected as the new most preferred alternative. For ease of coding, we model the probability that \(U_{it} - U_{it-1}\) is greater than zero rather than the probability that \(U_{it}\) is greater than \(U_{it-1}\), which is mathematically equivalent. If, along with their systematic components, the two utility terms in the product comparison model are assumed to contain random error components (\(e_{it}^{PC}\) and \(e_{it}^{maxPC}\), respectively) that are independently and identically Gumbel distributed, the binary logistic regression model arises.

The utility function expresses the independent variables that drive the consumer’s product comparison decision and that we hypothesize to be moderated by the presence of product recommendations (\(H_1\)).

1. \(\Delta U_{it}\): The difference in systematic utility between the current alternative and the most preferred among the previously encountered ones. For the purpose of model estimation, we designate the first inspected product as the most attractive one until another product is marked as the current favorite by the participant. (We also estimated the model for only those participants who had used the “current favorite” feature; the substantive findings were the same as those obtained for the full sample, which we report herein.)

2. \(\Delta L O C_{it}\): The difference in systematic utility between the current alternative and the one inspected immediately before it. This variable enables us to test \(H_1\) by investigating whether broader comparisons are made among multiple alternatives. In the estimation, we did not include cases in which the previously inspected product was the most preferred one (and thus \(\Delta L O C_{it}\) equal \(\Delta V_{it}\) to avoid potential biases).

We included these two independent variables in the model along with their interactions with a binary variable indicating the presence of recommendations (REC) to test for the latter’s hypothesized moderating effects (\(REC \Delta V_{it}\) and \(REC \Delta L O C_{it}\)). Also included in the product comparison model are an intercept (\(\alpha^{PC}\)) with a random error component (\(\nu_{it}^{PC}\)) that allows for heterogeneity in the intercept and that may be correlated across the product comparison and stopping models. We also include a variable indicating the presence of recommendations (coded 1 for search with recommendations and –1 for unassisted search) to capture a possible main effect of this manipulation.

\[
\begin{align*}
U_{it} - U_{it-1}^{max} &= \alpha^{PC} + \nu_{it}^{PC} + \beta_{AV} \Delta V_{it} + \beta_{ALOC} \Delta L O C_{it} \\
&+ \gamma_{AV} REC \Delta V_{it} + \gamma_{ALOC} REC \Delta L O C_{it} + \rho_{REC} REC + \epsilon_{it}^{PC} - e_{it}^{maxPC}.
\end{align*}
\]

**Stopping Model**

In the stopping model with recommendations, consumer i’s decision to either terminate the search at stage t or inspect an additional alternative is based on the probability that the maximum observed utility after the product comparison decision (\(U_{it}^{\text{max}}\)) exceeds the consumer’s (unobserved) reservation utility at that stage. Specifically, the reservation utility \(r_{it}\) is that value of for which the expected returns of inspecting the next product equal the cost of search and the consumer terminates the search if and only if the highest product utility observed up to that point exceeds the reservation utility (Rosenfield, Shapiro, and Butler 1983). Formally,

\[
P(\text{stop}_{it}) = P(U_{it}^{\text{max}} > r_{it}),
\]

where \(P(\text{stop}_{it})\) is the probability that the consumer chooses to terminate the search at stage t.

We capture the consumer’s reservation utility at a given stage in the model in a reduced form using a combination of several components. The first is an intercept (\(\alpha^{S}\)) with an individual specific error component (\(\nu_{it}^{S}\)) that captures unexplained heterogeneity in reservation utilities among consumers (e.g., due to unobserved differences in search costs). Moreover, we include the expected utility of the next-to-be-inspected alternative (\(\bar{u}_{it}\)) because, in the recommendation condition, a decrease in the expected utility for the next alternative influences the expected returns to search at a given stage (along with the maximum observed utility). In addition, we capture the impact of the amount of variability in the expected utility of the next-to-be-inspected alternative using the standard error of the prediction for the expected utility of the next-to-be-inspected alternative (\(\hat{\sigma}_{it}\)).
The standard error reflects how much variability exists around the expected value, and it is based on the set of utility values observed up to the current stage of the search. Thus, this measure reflects learning about variability in the expected utility of the next-to-be-inspected alternative. 

Jointly, \( \hat{u}_it \) and \( \hat{s}_it \) enable us to test the normative and behavioral effects underlying \( H_2 \), respectively. We capture the maximum utility observed (\( U_{it}^{max} \)) using a systematic component (\( V_{it}^{max} \)) and a random error component (\( e_{it}^{max} \)). Similarly, we also include a random error component for the reservation utility (\( e_{it}^r \)). These error components capture the possible effects of unobserved explanatory variables, as well as possible random measurement error. Thus, we express the utility (\( U_{it}^{max} - r_{it} \)) of stopping the search at stage \( t \) as follows:

\[
(A4) \quad U_{it}^{max} - r_{it} = \alpha e^t + V_{it}^{max} \beta_{max} + \beta_x \hat{u}_it + \beta_s \hat{s}_it + e_{it}^{max} - e_{it}^r.
\]

The consumer terminates the search if \( U_{it}^{max} - r_{it} \) is greater than zero. If it is assumed that the random error components for both the maximum observed utility and the reservation utility are independently and identically logistically distributed, the random coefficient binary logistic regression model arises.

We estimate the stopping model using observations beginning with the third inspected product because consumers have sufficient information (in terms of our model) to determine whether to continue searching only after observing at least two alternatives. More specifically, to capture consumers’ expectations of the variability effect of the decrease in expected utility from one alternative to the next, we model the consumer’s calculation of the expected utility of the next-to-be-inspected alternative. We do so using an individual-level ordinal least squares regression model that is updated at each search stage and describes the (negative) slope in the utility of the encountered products. The alternatives at the top of a recommendation list are those predicted to be the most attractive available products. The alternatives at the top of a recommendation list are those predicted to be the most attractive available products. The top-listed products represent the extreme tail of the distribution of utilities. The slope of this part of the utility distribution can be closely approximated by a linear function. Consumers attach a weight of zero to their initial prior because no information is available in advance about the utility of the first product in the recommendation list the variability around this utility.

More formally, if \( x_{it} \) denotes the order position (in the list) of the alternative inspected by consumer \( i \) at stage \( t \), \( x_{it} \) is the average observed order position, \( x_{it}^r \) and \( V_{it}^{max} \) represent the order position and systematic utility, respectively, of the alternatives inspected at stages \( k \) with \( k \) ranging from 1 to \( t \), and \( t > 2 \), and \( b_0 \) and \( b_1 \) are parameters in the regression model, the consumer’s prediction at stage \( t \) about the utility of the next-to-be-inspected alternative (\( \hat{u}_it \)) is expressed as follows:

\[
(A5) \quad \hat{u}_it = b_0 + b_1 \left( x_{i(t+1)}^r - x_{it} \right)
= \frac{1}{t} \sum_{k=1}^{t} V_k \cdot \frac{1}{t} \sum_{k=1}^{t} (x_{ik} - x_{it}) V_k \times \left( x_{i(t+1)}^r - x_{it} \right),
\]

We also capture the effect of consumers’ response to variability in the distribution describing the expected utility of the next-to-be-inspected alternative. We do this by including the standard error of the expected utility of the projection for the next-to-be-inspected alternative in the model:

\[
(A6) \quad \hat{s}_it = \sqrt{\frac{1}{t-2} \sum_{k=1}^{t} (x_{ik} - x_{it})^2}.
\]

**Results**

We estimated binary random effect logit models for both the product comparison and the stopping decisions using simulated maximum likelihood based on 200 Halton draws. The product comparison model incorporates both decisions with and without recommendations. We estimated separate models for the stopping decisions with and without recommendations.

**REFERENCES**


