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ABSTRACT: This study examines the behavioral aspect of improving the recommendation agent-consumer relationship, utilizing a model of internal information search for unplanned purchases prompted by a recommendation from a collaborative filtering agent. The model describes how consumers update their beliefs about a product upon receiving a recommendation and identifies the factors affecting the increase in the product's expected utility after the recommendation. A Monte Carlo simulation derives propositions regarding how these factors influence the effectiveness of recommendations. Broadly, the marginal value of recommendation depends on the preference structure of the recipient, the attributes of the product on which the recommendation is based, and the characteristics of the population of consumers. The major managerial implication is that retailers should include more information in recommendations when the products are less common or when there is a large variability of user tastes.

KEY WORDS AND PHRASES: Buying behavior, internal information search, marginal value of recommendation, Monte Carlo simulation, on-line product recommendations.

As a commercial vehicle, the Internet has opened a vast number of opportunities for businesses and consumers. The most frequently cited benefits for consumers are transparency of prices, lower search costs, and wider choice of products [3, 10]. On-line retailers benefit by obtaining information about customers that can facilitate customization of products and services to meet individual requirements. According to industry experts, personalizing the shopping experience is a very effective way for e-tailers to turn browsers into buyers [33]. Recommendation agents and other interactive decision aids can be used as a tool for mass customization [30]. As Häubl and Trifts show, recommendation agents enhance the shopping experience for consumers by increasing the quality of their consideration sets [15].

Another area of considerable interest to e-tailers is the use of interactive decision aids to stimulate unplanned consumer purchases. Given the high growth rate of on-line shopping, even a small percentage of impulse purchases can have significant economic implications for e-tailers. While the Internet lacks the sensory stimuli and instant gratification important for impulse purchases, some research suggests that the anonymity of the on-line purchase experience may encourage impulse buying [29]. A study by the Angus Reid Group in 2000 found that one in four on-line purchases was made on impulse [25].

What kind of information can stimulate consumers to make impulse purchases? According to Senecal and Nantel, consumers are influenced by

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both personal and impersonal information sources [31]. They identify three broad categories of on-line information sources that can influence consumers: (1) other consumers, (2) human experts, and (3) expert systems, including recommender systems. They note that information from "other consumers" may be perceived as less expert than the other two categories, but also as more trustworthy, based on the discounting principle of attribution theory put forth by Kelley [19].

This paper examines the effect of on-line product recommendations from collaborative filtering systems on consumers' interest in the recommended product. The study reported here was conducted in response to the call by Ariely, Lynch, and Aparicio for further research to identify consumers' requirements regarding recommendation quality [2]. More specifically, the study considers recommendations linked to particular purchases. For example, retailers like Amazon.com make recommendations of the form "Customers who bought this such-and-such also bought . . ." The object of the study is to understand how the increase in interest in the recommended product is moderated by (1) the characteristics of the consumers who make purchases in the product category, (2) the characteristics of the recommendation recipient, and (3) the attributes of the product the consumer is currently purchasing, based on which recommendation is made. An understanding of the moderating effect of these factors can help on-line retailers to devise effective recommendations. To this end, a model is proposed that explains how consumers evaluate the information they receive from a recommendation. The effectiveness of a recommendation is measured in terms of the increase in expected utility for the product upon receiving the recommendation. An exploratory Monte Carlo simulation study is performed to understand the effect of the factors influencing the value of product recommendations to consumers. The findings indicate that customizing the information in a recommendation can have a significant impact on consumers' interest in the recommended product.

West et al. cite evidence from earlier studies indicating that the way product information is organized can influence choice [34]. Greater interest in the recommended product will ultimately result in more unplanned purchases—and thus more sales for the e-tailer and more customer satisfaction. The findings of the present study will be managerially relevant in collaborative filtering and interactive decision aid technology for the development of optimal recommendation strategies. Since the study looks at the triggers of search for unsought products, its results supports the assertion by Lin, Hsu, Huang, and Hsu that an effective recommender agent should promote sales of unsought products [21]. Through such improvements, companies can enhance the consumer experience and nurture longer relationships.

Theoretical Framework

Consumer Behavior

The literature on marketing and economics has extensively studied product search. Studies of consumer search behavior generally follow either a normative, a behavioral, or a descriptive approach. DeSarbo and Choi provide an excellent summary and comparison of these three streams [9]. Peterson and Merino also discuss the literature on consumer information-search behavior [26]. Traditionally, search is modeled as comprising two sequential stages, internal search and external search. Internal search refers to consumer information search from memories that can be aroused by external cues, such as store promotions or recommendations received while shopping on-line. External search is primarily associated with reducing consumer uncertainty by collecting external information about a product's performance. In most cases, internal search precedes external search, because memory information is more accessible than external information. If the outcome of internal search strongly favors purchase of the product in question, the consumer may bypass the external search stage.

Hagerty and Aaker's theoretical model of the external search process shows that a consumer will search for information until its expected value exceeds the cost of the search [14]. The expected value of sample information is based on the consumer's beliefs before undertaking an active information search. Thus, external search increases as the consumer's involvement increases and search cost decreases. Moorthy, Ratchford, and Talukdar propose relative brand uncertainty as a third dimension, in addition to product involvement and search cost, that accounts for lack of information search in high-involvement categories even when the cost of information search is very low [23].

In contrast to the literature on external search behavior, this paper investigates the increase in the perceived value of a product driven by an external cue (e.g., a product recommendation). This may lead to an increase in internal search or impulse actions by consumers receiving the recommendation. The paper uses Piron's comprehensive definition of impulse buying as unplanned, the result of exposure to a stimulus, decided "on the spot," and involving an emotional/cognitive reaction [27]. Impulse action is manifested either as complete bypassing of the external search stage leading to a direct purchase of the recommended product, or as proceeding to an external search that would have not occurred in the absence of recommendations, as when a consumer sees a recommendation for an unfamiliar music CD and decides to sample some of its tracks. The last situation depicts information search for an impulse purchase. Impulse actions triggered by a recommendation are most likely to occur in product categories in which multiple items are often purchased on one buying occasion, like books, CDs, videos, or apparel.

Recommendations alter consumers' perceptions of the expected utility from a recommended product and may affect their eventual search and purchase behavior. As with impulse buys, the arousal may be high enough to induce an immediate purchase. On the other hand, some customers will completely disregard the recommendation, thus leaving their system of beliefs relatively unaltered. Anything in between these two extremes can be characterized as information search for impulse purchases. The focus in this paper is on how a recommendation triggers the internal information search process—in other words, on how recommendations alter consumers' beliefs.

Recommender Systems

The papers by Burke and by Huang, Chung, and Chen provide excellent summaries of the research on recommender systems [6, 17]. The reader is directed to tables 1, 2, and 3 in both papers for a taxonomy of recommender systems and examples of relevant research. By and large, recommender systems use information from three sources: user characteristics, product features, and behavior of similar users. Collaborative filters, the most widely used recommender systems, construct product recommendations from one of the three sources of information or any combination thereof. Systems of this kind all have three major deficiencies: the cold-start problem (a new product or new user), the sparsity problem (many products, few users), and the gray-sheep problem (users with unique tastes) [17]. Burke discusses the advantages of various hybrid systems and identifies areas unaddressed by researchers [6]. Because of the deficiencies of pure recommender systems, Huang, Chung, and Chen also see a hybrid approach based on both content and collaborative information as a better alternative [17].

Another problem faced by researchers and practitioners is the evaluation of collaborative filtering recommender systems [16]. According to Herlocker, Konstan, Terveen, and Riedl, the basic premise for evaluation should be the usefulness of the recommendation to the end user [16]. Two important dimensions of usefulness relevant to the present research are novelty and serendipity. These refer to the case when a recommendation helps the user to find a very interesting product that would not have been found otherwise. The present model can bring advances in this direction. As Schafer, Konstan, and Riedl point out, providing an explanation behind the recommendation is a promising tool that can increase its usefulness for the consumer [30]. Accordingly, the present research identifies ways that recommender system designers can incorporate explanation modes behind the recommendation. The value of a recommendation ultimately depends on the product and the users, but will be enhanced by the presence of information that can help consumers draw inferences about the population of users from which the recommendation originates.

Statement of the Problem

The discussion in this paper concerns a collaborative filtering type of recommender system. However, in practice, consumers are not aware of how recommendations are generated. Logging on to a retailer's site, a consumer decides to buy a product (e.g., a book or a CD), then learns that other purchasers of the same product have also bought certain other products from the same category. If these other products have not as yet aroused the consumer's interest, what would make the consumer now be willing to consider them? This question can be answered by modeling the consumer's interpretation of the information conveyed by a recommendation.

Consumers have beliefs about the products/brands available in a given category. If the expected utility for a product, based on these beliefs, is greater than some threshold (which varies depending on the individual), a consumer may initiate an external search or bypass a search and proceed to a purchase. Recommendations may alter the expected utility and in some cases increase it beyond the threshold. The shift in the consumer's beliefs on receiving a recommendation is the marginal value of recommendation, or MVR. A high MVR corresponds to a greater probability of purchasing the recommended product.

A consumer's information processing upon receiving a recommendation in the form just stated is modeled as shown below (*see Figure 1*):

1. Suppose that the focal individual, consumer 1, has negative expectations about the utility that would derive from product B and so instead buys product A. Based on this purchase, consumer 1 receives a recommendation for product B, stating that it has been purchased by another buyer of product A (consumer 2). For the purposes of discussion, the consumer's expected utility before receiving the recommendation is called the "pre-prior."
2. Consumer 1 is assumed to have perfect information about product A, the product purchased, but has no information about product B except what is captured in the pre-prior value. However, consumer 1 can try to infer the preference structure of consumer 2 based on the latter's purchase of product A.
3. Based on the inference about consumer 2's preference structure, consumer 1 infers the characteristics of product B. Thus, the recommendation has enabled consumer 1 to obtain an updated belief about B. This new belief is designated the "post-prior."

The terms "pre-prior" and "post-prior" emphasize that this is the process influencing the belief structure that triggers external information search, as described by other studies (e.g., [14]). The post-prior is the information the consumer uses to decide whether to proceed with external search and how much external search to conduct. If the post-prior is large enough, consumer 1 may purchase product B directly without any external search. If it is not large enough to lead to a purchase, it could induce an external search.

Formal Model

Economics and marketing researchers generally assume that products are characterized by different attributes. Every product has a combination of attribute levels, such as price, reviews, and the like. The attribute levels of a product are denoted by a p-dimensional vector $\mathbf{x}$, where p is the number of attributes that characterize a product category. Since the products in a product category differ from each other, one may assume that the x vector is drawn from a p-variate distribution with a probability density function $f(\mathbf{x})$. In the present application, $f(x)$ corresponds to a multivariate normal distribution with mean vector μ_x and a covariance matrix Σ. Many studies have made similar assumptions regarding the distribution of product attributes (e.g., [14]).

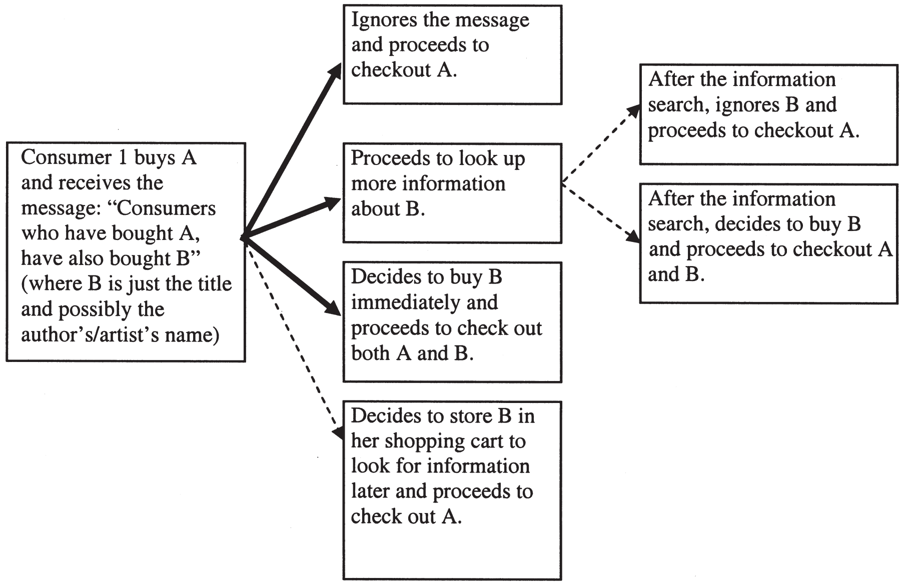

Figure 1. Consumer 1's Decision Process

Note that the model looks at what may lead the consumer to the outcomes indicated by the three bold arrows.

Consumers attach different weights to attributes. The composition of the attribute weights characterizes a consumer's preference structure. The vector of attribute weights can be represented by a p-dimensional vector $\mathbf{a}$. For any consumer, the attribute weights should sum to 1 for normalization. Again, to capture heterogeneity in consumer preferences, it is assumed that vector $\mathbf{a}$ is distributed $g(a \mid \Sigma a_i = 1)$ across individuals in the population. One distribution that satisfies the condition $\Sigma a_i = 1$ is the Dirichlet distribution, the multinomial version of the beta distribution [24]. A Dirichlet distribution was chosen to operationalize the distribution of the preference structure in the population of consumers for the following reasons: (1) As stated above, for any consumer the attribute weights need to sum to 1 for normalization, and the Dirichlet distribution satisfies this requirement. (2) The Dirichlet distribution is used in the marketing literature to model consumer heterogeneity in respect to probability of choosing a particular brand [5]. Given these precedents, it is used here to model the heterogeneity in preference structures across consumers in the population.

The utility a consumer j gets from consuming a product k is defined by the sum of the attributes of product k, weighted by consumer j's preferences for these attributes.

$$\begin{aligned} U_{jk} &= \mathbf{a}_j \cdot \mathbf{x}_k \\ &= \sum_{i=1}^{I} a_{ij} x_{ik}, \end{aligned} \tag{1}$$

where I is the total number of attributes characterizing the product.

If price is treated as one of the attributes, then U_{jk} can be thought of as net utility. Then the consumer would purchase k if U_{jk} is positive.

At the point of purchase, consumers presumably know the attribute levels of the product being purchased. Consumers also know their own attribute weights. In mathematical terms, one assumes that the consumer knows $\mathbf{a}_1$ and $\mathbf{x}_A$ with certainty. A consumer who receives a recommendation in the form stated earlier does not know:

1. How many individuals have bought products A and B, but only that at least one individual has bought both A and B. In this case, the consumer is assumed to believe that one individual (individual 2) has bought both A and B.
2. The attribute weights vector $\mathbf{a}$ of individual 2, $\mathbf{a}_2$.
3. The actual attribute levels of the recommended product B, $\mathbf{x}_B$.

It is assumed here that the consumer's beliefs about the distribution of attribute preferences in the population imply that the attribute preferences of individual 2, $\mathbf{a}_2$, can be drawn from the distribution of attribute preferences in the population. Recall that according to the model assumption, these attribute preferences follow a Dirichlet distribution. Correspondingly, the consumer expects $\mathbf{a}_2$ to be a random variable from the Dirichlet distribution. Similarly, given the consumer's belief about the distribution of product attributes in the category, it is assumed that the consumer perceives the attributes of the recommended product B, $\mathbf{x}_B$, to be drawn from the multivariate normal distribution described above.

In the absence of the recommendation, the consumer would have assumed that the attribute weights of any individual in the population, $\tilde{\mathbf{a}}$, are drawn from $g(\mathbf{a})$, and the attribute levels of any product, $\tilde{\mathbf{x}}$, are drawn from $f(\mathbf{x})$. (The ~ signifies that the variable is random and not known with certainty from the consumer's perspective.) Based on this, the consumer's pre-prior probability of any product being "good" would have been

$$\begin{aligned} p_{pre} &= P(\mathbf{a}_1 \cdot \tilde{\mathbf{x}} > 0) \\ &= P\left(\sum_i a_{i1}\tilde{x}_i > 0\right) \end{aligned} \tag{2}$$

and the pre-prior expected utility from any brand in the product category is given by

$$EU_{pre} = E(\mathbf{a}_1 \cdot \tilde{\mathbf{x}}). \tag{3}$$

The fact that someone else (consumer 2) bought product A implies that the utility consumer 2 derives from A is positive. The focal consumer tries to infer the attribute weights of consumer 2 based on this. The focal consumer cannot determine the attribute weights precisely. Let $\tilde{\mathbf{a}}_2$ be consumer 1's inferred attribute weights of the second consumer.

$$\tilde{\mathbf{a}}_2 = \tilde{\mathbf{a}} \big| \tilde{\mathbf{a}} \cdot \mathbf{x}_A > 0. \tag{4}$$

The consumer then proceeds to obtain the distribution of the attribute levels of the recommended product B based on the fact that consumer 2 also bought B.

$$\tilde{\mathbf{x}}_B = \tilde{\mathbf{x}} \big| \mathbf{a}_2 \cdot \tilde{\mathbf{x}} > 0. \tag{5}$$

Thus, after the recommendation, the consumer's post-prior probability is given by

$$p_{post} = P(\mathbf{a}_1 \cdot \tilde{\mathbf{x}}_B > 0) \tag{6}$$

and the post-prior expected utility is given by

$$EU_{post} = E(\mathbf{a}_1 \cdot \tilde{\mathbf{x}}_B). \tag{7}$$

The marginal value of the recommendation is a function of the difference between the pre-prior and the post-prior expressed either as probability or as expected utility. Expected utility is used to compute the marginal value of the recommendation.

Closed form solutions could not be obtained for the conditional distribution, $\tilde{\mathbf{x}}_B$, and thus for p_{post} and EU_{post}. The discussion here, however, is only interested in identifying the factors that influence the marginal value of recommendation. This can be achieved by a Monte Carlo simulation study. The purpose of the simulation is to outline how the different factors influence the effects of recommendations that would lead to propositions that can be tested experimentally. Ariely, Lynch, and Aparicio list several advantages of simulation studies, such as the precise specification and systematic manipulation of the variables of interest as well as a convenient framework for understanding the relationship between variables [2].

Monte Carlo Simulation

The model formulation encompasses six sets of factors that can influence the marginal value of a recommendation:

1. the attribute weights of the focal consumer, 1
2. the attribute levels of the focal product, A
3. the mean attribute weights of the population
4. the variance in the attribute weights across individuals in the population
5. the mean attribute levels of the products in the product category
6. the variance in the attribute levels across the products in the category.

The Monte Carlo simulation study investigates how the marginal value of a recommendation would change when these six factors are manipulated.

For simplicity, the study considers the case of three attributes (incorporating more attributes would complicate the simulation but would not change the direction of the results). As a measure of the value of the recommendation to the consumer, the simulation used the marginal value of recommendation defined by:

$$MVR = EU_{post} - EU_{pre}. \tag{8}$$

One would expect the recommendation to increase the expected utility as perceived by the consumer. The extent to which the recommendation is able to achieve this would be a measure of its effectiveness.

As stated earlier, the vector of the population attribute levels, $\tilde{\mathbf{x}}$, was drawn from a multivariate normal distribution with mean vector $\boldsymbol{\mu}_{\mathbf{x}}$ and variance-covariance matrix $\Sigma_{\mathbf{x}}$. The attribute levels of the focal brand A are obtained by making a random draw from the above multivariate normal distribution.

We draw $\tilde{\mathbf{a}}$ from a Dirichlet distribution. The shape parameters of the distribution determine both the mean and the variance across the attribute weights [35]. The attribute weights of the focal individual 1 are obtained from a random draw from the Dirichlet distribution mentioned above.

To ensure that the simulation study was representative of the entire space, extensive simulations were conducted over 950 different combinations of:

1. The mean attribute levels in the product category, $\boldsymbol{\mu}_{\mathbf{x}}$, obtained by making 950 random draws from a uniform distribution (independently for the three attributes).
2. 950 randomly generated variance-covariance matrices.
3. The shape parameters of the Dirichlet distribution, which determine the mean attribute weights (preference) in the population and the variance in attribute weights across individuals in the population (the extent to which the preference structure is shared in the population), obtained by making 950 independent draws from a uniform distribution.

Since the focal consumer 1 would buy the focal brand A only if it gives a positive utility, the draws that did not satisfy this condition were discarded. Out of the 950 simulations, 555 satisfied this condition. The Appendix describes the details of the simulation.

Propositions, Results, and Implications

A look at the existing theoretical base will help to shape expectations of the relationships with respect to factors affecting the value of recommendations. As pointed out by Huang, Chung, and Chen, electronic agents base recommendations on three sources: behavior of similar users, user characteristics, and product features [17]. Therefore, the factors are grouped accordingly. A regression analysis follows, based on the above 555 data points with the marginal value of recommendation (MVR) as defined by Equation (8) as the dependent variable. The results of this analysis along with descriptions of the variables are reported in Table 1. The matter of interest here is the effect of the variables under investigation and not the overall predictive value of the model.

The factors that influence MVR are grouped into the following categories:

1. Characteristics of the population of consumers
2. Characteristics of the recommendation recipient
3. Characteristics of the product the consumer is buying

Based on the results reported in Table 1a, where all variables are statistically significant, a series of propositions was formulated, explained below. Table 1b provides a description of how the variables are defined.

Characteristics of the Population of Consumers

Since collaborative filtering constructs recommendations based on the behavior of similar users, a key moderator of the effectiveness of a recommendation is the perceived similarity between consumers who purchase in the recommended product category. As Aksoy, Bloom, Lurie, and Cooil note, numerous studies in the psychology literature show that similarity between the message source and the recipient plays an important role in persuasion [1]. In particular, recipients are more likely to be influenced by sources that they perceive as similar to themselves. Feick and Higie have explored the interaction effects of preference heterogeneity and similarity [11]. They propose that in populations with high preference heterogeneity (the extent to which consumers have different tastes), the similarity effect will be stronger. This is because consumers under high preference heterogeneity seek different benefits from products, and a similar endorser communicates similar benefits. Thus, recommendation recipients who perceive the recommendation as based on consumers with high preference heterogeneity are likely to assume that there is a difference between their own preference structure and that of the consumers who were the basis for the recommendation. And following from this, they will be hesitant to trust the recommendation.

> *Proposition 1: All else being equal, there is a negative relationship between the focal consumer's perception of heterogeneity among the buyers of the focal product and the marginal value of recommendation.*
>
> *(Variable TOTVARA: The sum of the variances in the attribute weights in the population is used as a measure of the heterogeneity in preferences in the population.)*

The interpretation that follows is based on the theory presented above and the simulation results. Given a finite population of consumers, the more diverse

Dependent variable: MVR*

Proposition	Variable	Coefficient**	t	p
P1	TOTVARA	-0.062	-2.036	0.042
P2	DISTA	-0.070	-2.314	0.021
P3	POLA	0.191	6.546	0.000
P4	EUFIAVBR	-0.329	-10.915	0.000
P5	DISTX	-0.396	-10.061	0.000

Table 1a. Model Results.

Notes: *The full model's R^2 is 75.4%. **The standardized coefficients.

Variable	Formula	Description
TOTVARA	$\sum_{i=1}^{3} Var(a_i)$ $Var(a_i) = \alpha_i \left(\sum_{i=1}^{3} \alpha_i - \alpha_i \right) \Big/ \left(\sum_{i=1}^{3} \alpha_i \right)^2 \left\{ \sum_{i=1}^{3} \alpha_i + 1 \right\}$	Total variance in attribute weights across individuals in the population. The parameters α_i, $i = 1, 2, 3$ are the shape parameters of the Dirichlet distribution
DISTA	$\sqrt{\sum_{i=1}^{3} (a_{1i} - \bar{a}_i)^2}$ $\bar{a}_i = \alpha_i \Big/ \sum_{i=1}^{3} \alpha_i$	Distance of the focal individual (consumer 1) from the population mean
POLA	$-\prod_{i=1}^{3} a_{1i}$	Extent to which the focal individual (consumer 1) does not place equal weights on all the attributes and thus has a polarized preference structure
EUFIAVBR	$\sum_{i=1}^{3} a_{1i} \bar{x}_i$	Utility the focal individual (consumer 1) would derive from the average product (brand) in the category
DISTX	$\sqrt{\sum_{i=1}^{3} (x_{Ai} - \bar{x}_i)^2}$	Distance of the focal product (product A) from the mean of the product category

Table 1b. Description of the Variables.

they are, the less likely that the focal consumer would be getting a recommendation from somebody with similar taste. A consumer who knows that the focal product attracts customers with heterogeneous underlying preference structures would have fewer incentives to trust any given recommendation since it may have originated from an individual of dissimilar tastes. Intuitively, a consumer who is buying a product in an exclusive category (e.g., books on game theory) will find it easy to infer that other people who have bought in the same category have similar interests. Consequently, the recommended product would seem more attractive in the absence of any other information. On the other hand, if the consumer is buying a bestseller, it will not be trivial to infer the preferences of the other consumers who have bought the same bestseller.

Based on the regression result, the recommendation agent needs to make the population look more homogeneous in order to increase the value of the recommendation. This can be achieved, for example, by narrowing down the category. Consumers who bought a fiction book are likely to be more heterogeneous than consumers who bought a science-fiction book. Thus, while making the recommendation, the agent can specify the subcategory from which the recommendation is made. A way to circumvent the problem that bestsellers tend to be purchased by heterogeneous populations is by having the recommender system match the focal consumer to a group that has more than two commonly bought products. That is, instead of recommending product B based on a match with product A, the system would recommend product B based on a match with products A and C. In this way, the recommender system could specify a subcategory that is more credible to the focal consumer.

Characteristics of the Recommendation Recipient

The following theoretical review refers to propositions 2–4 regarding the characteristics of the recommendation recipient. Using the same theoretical underpinnings of similarity and judgment, Smith, Menon, and Sivakumar contend that consumers judge recommendations based on the perceived similarity between themselves and a peer recommender [32]. The effect would be stronger with recommendation recipients who consider themselves to be different from the "average" consumer. Theorizing on distinctiveness, McGuire shows that a person's distinctive traits in relation to the population are more salient than more commonly shared characteristics [22]. As a result, consumer distinctiveness is associated with more identification with and trust of a similar source [13]. This suggests that a recommendation will be of greater value if the focal consumer identifies with the distinctive group from which the recommendation is perceived to have originated. In addition, group affiliation can also influence consumer choice [36]. Based on various studies of peer influences, neighborhood effects, the bandwagon effect, and conformity, the authors contend that consumers who identify with a group often adopt its preferences [36]. Therefore, a recommendation will be more effective for consumers who perceive them as originating from a population of consumers who are similar to themselves and with whom they can identify. The effect would be especially relevant to recipients who perceive themselves as different from the general population.

Another aspect of the recommendation recipient's preference structure that can affect the value of a recommendation is the degree of polarization. In this case, a consumer is very passionate about one particular attribute, as is typical of noncompensatory decision-making processes. This is close to what some authors refer to as "extreme opinion" [12]. People generate high-intensity affective reactions when they place high importance on an item [20]. Since there is less ambiguity with extreme opinions, individuals' agreement on extreme evaluations is more important than their overall agreement [12]. Therefore, one may conjecture that consumers who exhibit a polarized preference structure or extreme opinions will extract a greater value from a recommendation if they assume that it is based on like-minded consumers.

While consumers may be influenced by recommendations originating from like-minded consumers, it is interesting to look at another type of buyer—the ones who buy heavily in a category. One could argue that these people derive a relatively high utility from the average product in the category and therefore may purchase many products. Since they are high-volume buyers, they tend to develop deeper product-category knowledge. Chandy et al. posit that ads are largely irrelevant for consumers who are highly knowledgeable about the advertised product [7]. Similarly, recommendation recipients who already have a higher expected utility from the category (either because they know the category well or are heavy buyers) may not perceive a significant improvement in their expected utility upon receiving the recommendation. This problem has been recognized by Ziegler et al., who point out that a recommendation that is very accurate may nonetheless prove to be unsatisfactory to the user [37]. For example, receiving recommendations for books by the same author is accurate, but not very exciting for a consumer who already knows about the author. Therefore, one would expect such a recommendation to be of less value to consumers who already expect a high utility from the product category prior to receiving the recommendation.

> *Proposition 2: All else being equal, there is a negative relationship between the recommendation recipients' perception of the distance between their preference structure and the average preference structure in the population and the marginal value of recommendation.*
>
> *(Variable DISTA: This variable is operationalized by measuring the Euclidean distance between the focal individual's attribute weights and the average attribute weights in the population.)*

The preceding proposition means that an individual who has exclusive tastes is less likely to trust a recommendation perceived as based on the preferences of other, "average" consumers. Imagine someone who is not a sci-fi fan buying the *Star Wars* trilogy. *Star Trek* might seem an obvious recommendation because it is very popular with *Star Wars* customers. In this instance, however, the focal consumer is more interested, say, in romances but would still receive a recommendation for *Star Trek*, or for some other sci-fi or a bestseller movie that would not be perceived as very valuable. This is equivalent to the problem of obvious choices in collaborative filtering [16].

Since the recommendation agent cannot manipulate the individual's preference structure, it can use the result from Proposition 1 to magnify the effect of the recommendation. For consumers who have more exclusive tastes, it is preferable to make the population look more homogenous and indicate that the recommendation is based on consumers with similar tastes. In the preceding example, if the recommender system has recorded the customer's previous purchases in the romance category and makes a recommendation based on the overlap of customers who have purchased romances and *Star*

Wars, then the recommender agent should explicitly state the origin of the recommendation.

Proposition 3: All else being equal, there is a positive relationship between the level of polarization in the recommendation recipient's preference structure and the marginal value of recommendation.

(Variable POLA: This variable is operationalized as the negative product of the attribute weights of the focal consumer. Recall that according to the formulation, the attribute weights sum to 1. Therefore, for the case with three attributes, the product would be the highest when each attribute weight = .33. This corresponds to the case when the consumer places equal weights on the three attributes and thus has nonpolarized attribute weights. As the degree of polarization increases, the product decreases in magnitude. Therefore the negative value of the variable is used.)

A polarized preference structure implies that the consumer places a high weight on one (or more) attribute(s) and a low weight on the other attributes. For such consumers, the lack of one attribute will probably not be compensated by other attributes. They are likely to be more involved in their purchase decisions than consumers who have less polarized preferences. A consumer with less polarized preferences might accept a lower-quality product at a lower price, but a consumer who is very particular about the quality of the product would not accept a cheaper substitute. Consumers with polarized preference structures have a higher *a priori* risk of choosing a wrong product. This interpretation is based on the "extreme opinion" theory presented above and the regression result. Consequently, if a recommendation allows these consumers to infer something more about the product attribute they cherish, it will be of greater value to them.

Managerially, an indication from the recommender system that the recommendation is based on a particular attribute can significantly increase the consumer's utility. If the recommendations are classified by attributes, the focal consumer is likely to perceive that recommendations in the particular attribute category are based on consumers who attach high value to that attribute. Subsequently, the consumer is more likely to respond to the recommendation. Thus, recommendations can be classified by attributes that will help consumers navigate toward the group of recommended products of greatest interest to them.

Proposition 4: All else being equal, there is a negative relationship between the recommendation recipient's expected utility from an average product in the category and the marginal value of recommendation.

(Variable EUFIAVBR: The variable is operationalized as the product vector of the focal individual's attribute weights and the mean vector of the product attributes.)

It is important to note that the way the model is formulated makes the preference for attributes monotonic. In other words, more of an attribute is always better. Attributes like price or ratings are examples where one would expect a monotonic preference structure. Given this formulation, one may infer that the consumers who derive a high utility from an average product (product with average levels of attributes) are high-volume buyers. (This conjecture is based on the model assumption that a consumer buys a product when the expected utility is positive, and a consumer whose utility threshold is lower will buy more products from a category.) Such consumers, in any event, are likely to buy many products. Thus, it is reasonable that they do not derive much more information from the recommendation. Another interpretation of the above result is the case when a consumer is well acquainted with some narrow category and derives high utility from an average product in that category (e.g., a collector of rare books; we thank an anonymous reviewer for this suggestion). In this case, the recommendation value would be low as well, because the consumer is already quite familiar with the category. The best recommendation might be for new arrivals.

Characteristics of the Product the Focal Consumer Is Buying

There is a vast literature on content-based recommender systems that use product characteristics to construct product recommendations [17]. The objective is to minimize the distance between product characteristics, thus increasing product similarity [18]. If the focal product triggering the recommendation is far from the average product in the category (e.g., a discontinued clearance product), the recommendation is likely to be less effective.

It is logical, in light of this, to ask how the recipient of the recommendation can judge the similarity between the recommended and focal products. Current technologies are able to reveal one or more attributes of the product. For example, consumers can listen to audio samples, watch video clips, read excerpts from books, try on a clothing item in a virtual dressing room, and so on. But would this always be adequate? Since the revealed information provides some context for the unfamiliar stimuli, consumers can engage either in assimilation or contrast processing of information [8]. The theory suggests that factors focusing on the similarity between the target and the context evoke assimilation, whereas factors highlighting differences result in contrast [4]. Cooke et al. show that when recommendation agents present item-specific information in a familiar context, consumers engage in contrast processing of the recommendation, resulting in lower evaluations [8]. If the revealed attribute for the recommended product is far from the corresponding one in the focal product, the recommendation is more likely to evoke contrast. Consequently, one would expect such a recommendation to be less effective in increasing the expected utility from the recommended product. The effect would be magnified for consumers who place high weight on the revealed attribute.

> *Proposition 5: All else being equal, there is a negative relationship between the distance between the attributes of the focal product and the mean attributes in the category and the marginal value of recommendation.*

(Variable DISTX: The Euclidean distance is used as a measure of how far the individual perceives the focal brand to be from the average product in the category.)

This result follows from a model based on attributes with monotonic preferences. If a consumer is buying a product that is far from the mean, it is more likely than otherwise to be high on the attributes. For example, the recommendation is likely to be of less value to a consumer buying a very popular book or CD at a discounted price. A consumer buying a book or CD because of its low price may assume that the recommended product does not have the same desirable characteristic. This result is similar to Proposition 2.

The managerial implication is also similar to Proposition 2. If the focal product is exclusive, it would be beneficial for the recommendation to signify that the recommended product is similar to the focal product. This means indicating a narrower subcategory.

A Special Case

As mentioned earlier, the model assumes that the recommendation does not give away any information other than $U_{2A} > 0$ and $U_{2B} > 0$. However, in reality, recommendations can give complete information about one or more attributes. Assume that the level of attribute 3 for product B, x_{3B}, is known with certainty. Since the level of attribute 3 is known, the consumer needs only to draw inferences about the remaining attributes of product B, $\tilde{\mathbf{x}}_{-3B}$. Given that the level of attribute 3 is x_{3B}, the distribution of the attributes of product B, with the exception of attribute 3, is denoted as $\tilde{\mathbf{x}}_{-3B|x_{3B}}$. It is here suggested that the consumer infers the distribution of the random variable $\tilde{\mathbf{x}}_{-3B|x_{3B}}$ as follows:

1. To obtain p_{pre}, use the same distribution of $\tilde{\mathbf{x}}$ as in the original model.
2. For p_{post}, first make draws from a multivariate normal distribution $\tilde{\mathbf{x}}_{-3B|x_{3B}}$ (this is the conditional distribution of the other attributes in the population, given the value of the known attribute).
3. Use this conditional distribution to perform the same procedure as in the original model (Equations 3–5) to obtain p_{post}. This step is based on the information that $U_{2A} > 0$ and $U_{2B} > 0$. The final p_{post} obtained reflects the marginal values of both items of information.

Propositions 6–7 are derived based on the results presented in Table 2a. As before, all the variables are statistically significant. Table 2b describes the definition of the variables.

Proposition 6: All else being equal, there is a negative relationship between the distance of the revealed attributes in the two products and the marginal value of recommendation.

(Variable ADSTX3FB: The variable is operationalized as the absolute distance between the revealed attribute of the recommended product and the corresponding attribute of the focal product.)

Dependent variable: MVR*

Proposition	Variable	Coefficient**	t	p
P6	ADSTX3FB	–0.356	–5.034	0.000
P6	CONTRST	0.351	8.177	0.000
P7	A3ADSTX3	–0.288	–3.681	0.000

Table 2a. Special Case Results.

*The full model's R^2 is 56.2%. **The standardized coefficients.

Variable	Formula	Description
ADSTX3FB	$\|x_{3B} - x_{3A}\|$	Absolute distance of the revealed attribute from the focal product's (attribute 3 of product A) corresponding attribute
CONTRST	$\|x_{3B} - x_{3A}\| * I$ $I = 1$ if $x_{3B} > x_{3A}$ $I = 0$ if $x_{3B} \leq x_{3A}$	The positive distance of the revealed attribute (attribute 3) from the focal product's (product A) corresponding attribute
A3ADSTX3	$a_{31} * \|x_{3B} - x_{3A}\|$	Interaction between the absolute distance of the revealed attribute and the focal brand's corresponding attribute (attribute 3 of product A) with the weight set by the focal individual (consumer 1) for this attribute

Table 2b. Description of the Variables.

Based on the contrast and assimilation theory mentioned earlier, the following interpretation of Proposition 6 is offered. The consumer looks at the recommendation in the context of the current product. If the recommended product has attributes similar to the current product, the consumer trusts the recommendation. However, if the recommended product has an attribute far from that of the corresponding attribute in the current product, the recommendation has a lower value. Therefore, it is better to reveal information about an attribute similar to the focal product rather than one far away, even if it is better. This occurs because consumers will tend to contrast it with the product they are familiar with [8]. Other researchers have similarly observed that consumers are more likely to trust recommender systems that provide some familiarity in the recommended product [16]. From a managerial perspective, this means that if the recommendation can reveal both the rating and the price of the product, it would be better to reveal only the attribute closer to the focal product even if it is not the best attribute.

The study also tested whether the distance effect was symmetric. (Variable *CONTRST:* The variable is operationalized by multiplying the absolute distance variable by a dummy variable indicating whether the distance is positive.) The results show that going farther on the negative side has a greater adverse effect than going farther on the positive side. This suggests that if finding a similar attribute is not possible, it is better to reveal a superior attribute in the recommended product. In managerial terms, if the recommended product is of much higher quality and price than the focal product, it would be better to reveal only the quality attribute. This would be true even if the price is not proportionally higher than the quality.

Proposition 7: All else being equal, revealing an attribute of the recommended product that is farther from the corresponding attribute of the focal product will have a greater adverse effect on the MVR of consumers who place a high value on that attribute.

(Variable A3ADSTX3: The variable is operationalized as the interaction between the absolute distance of the revealed attribute and the focal product's corresponding attribute with the weight set by the focal consumer for this attribute)

By implication, a recommendation revealing an attribute in the recommended product inferior to the corresponding one in the current product for a consumer who places a lower weight on that attribute could be better (in some cases) than one revealing a superior attribute greatly valued by the consumer. Armed with knowledge of a consumer's attribute preferences, a recommendation agent may be able to customize the recommendations in tune with the above proposition. This finding contradicts the popular belief that revealing the superior attribute is always better and is related to the contrast and assimilation theory discussed by Cooke et al. [8]. It means that a consumer is more likely to contrast the recommendation to the focal product if it reveals an attribute important to the consumer that is far from the focal product. For example, a consumer who sees price as the most important attribute and is recommended a product significantly cheaper than the focal product is more likely to contrast it to the focal product and assume that a lower price means bad quality, thus ignoring the recommendation. In this case, it would be better to recommend a product closer to the focal product even if the other attribute (e.g., quality) is slightly lower than the one of the focal brand.

Discussion and Further Research

The study summarized in this paper was intended to understand the factors that moderate the effectiveness of recommendations based on collaborative filtering. It showed that the usefulness of recommendations depends on:

- *The population of consumers*. The wider the population segment, the less likely that consumer will find "clones" of themselves, thus making the recommendations less valuable.
- *The preference structure of the recipient*. Recipients who favor one attribute at the expense of others will benefit more from the recommendation, whereas those who perceive their own taste as quite different from the mainstream will not benefit from the recommendation.
- *The utility the focal consumer derives from the product bought*. Consumers who derive high utility from their purchases will assume that the recommended product has the potential of delivering equally high utility. However, recommendation of yet another product would not enhance the expected utility for those already happy with the products in this category.

- *The attribute characteristics of the product the recommendation recipient is buying.* The less common the product, the less valuable the recommendation will be.
- *The similarity of the revealed product attribute to the corresponding attribute of the product the focal consumer has already bought.* Revealing an attribute that the consumer likes increases the credibility of the recommendation agent. The effect is most pronounced when the consumer values this attribute a lot.

A formal model was proposed to capture the behavior of recommendation recipients. This presented certain limitations: assumptions of rationality and stylized representation of a complex phenomenon. The propositions were based on a Monte Carlo simulation originating from certain distributional assumptions. This was admittedly a limitation of the study, and future research should investigate outcomes with different distributional assumptions. Going beyond simulations, it would also be useful to conduct an experimental study to validate the propositions.

The design recommendations presented in the paper are stylized, but industry practitioners will benefit from more details about the incorporation of the study results in a collaborative filtering system. An experimental study would clarify the interpretation of the propositions. Another helpful research area would be an investigation of the suitability of augmented recommendations to different product categories. *A priori*, they should be suitable for media products and apparel. However, any category in which customers tend to buy more than one product on one shopping occasion may be a good candidate.

The marginal value of recommendation may depend, in part, on the perceived number of consumers who have bought both A and B, an issue not addressed in the current study. It would be interesting to investigate whether the results are affected by the number of other buyers. For example, Amazon has begun to release information on the percentage of customers who view a particular item and buy it or other items.

Another possible direction of extension is to identify the optimal number of recommendations. The authors believe that the marginal value of recommendation would initially increase with the number of recommendations and then decrease beyond a certain point.

Conclusion

To the best of the authors' knowledge, this study is the first to provide a model of consumers' internal search for information triggered by an external cue. While the model presented was built in the context of on-line product recommendations, it is relevant to any recommendations received from "other consumers" [31]. It should be emphasized that the study in this paper does not prescribe how to construct better recommendation agents (this topic is discussed by Polat and Du [28]). Rather, it offers propositions on factors that affect the perceived value of recommendations in the eyes of the recipients. The propositions are based on a theoretical model and a simulation study. The next step would be to experimentally test the propositions.

Overall, increasing the usefulness of recommendations to consumers would help companies build better relationships with their customers. If consumers are aware that every purchase they make helps the intelligent agent to improve the customized recommendations, they will have more incentive to be loyal to a merchant. Offering customized recommendations may turn out to be one of the most important areas of differentiation among Internet retailers. Therefore, studying the moderators of recommendation effectiveness is likely to provide managerial insights of long-term value.

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Appendix

Steps in the Monte Carlo Simulation Study

The main objective of the simulation exercise is to understand how the effectiveness of a recommendation is moderated by specific product and consumer characteristics. The key steps in the simulation are as follows:

Step 1: Draw the mean vectors of the multivariate normal distribution corresponding to the distribution of attribute levels of the product category from a uniform distribution.

Step 2: Make one draw from this multivariate normal distribution and designate it as the attribute level for the focal product, $\mathbf{x}_A$.

Step 3: Draw the shape parameters of the Dirichlet distribution corresponding to the heterogeneity distribution of the preference structure in the population from a uniform distribution.

Step 4: Make one draw from this distribution and designate it as the preference structure of the focal consumer, $\mathbf{a}_1$.

Step 5: If the utility consumer 1 would derive from product A is less than zero, that is, $\mathbf{a}_1 \bullet A < 0$, discard the draw and proceed to Step 1 to make a new draw. Otherwise, proceed to Step 6. This ensures that the focal consumer derives a positive utility from the focal product and thus would buy the product.

Step 6: Make 1,000 draws each from the distributions of consumer preferences, $\tilde{\mathbf{a}}$, and product attributes, $\tilde{\mathbf{x}}$.

Step 7: Compute $\mathbf{a}_1 \bullet \tilde{\mathbf{x}}$ and compute the average of this across all 1,000 draws. This corresponds to the expected utility from the recommended product prior to receiving the recommendation, EU_{pre}.

Step 8: Compute $\tilde{\mathbf{a}} \bullet \mathbf{x}_A$ and retain only the draws for which the resultant utility is positive. This will yield the distribution of the preferences of consumers who could have bought product A, $\tilde{\mathbf{a}}_2 = \tilde{\mathbf{a}} \mid \tilde{\mathbf{a}} \bullet \mathbf{x}_A > 0$.

Step 9: Compute $\tilde{\mathbf{a}} \bullet \tilde{\mathbf{x}}$ and retain the combinations that yield positive utilities. This corresponds to the distribution of the attributes of the recommended product given that consumer 2 derived a positive utility from it, $\tilde{\mathbf{x}}_B = \tilde{\mathbf{x}} \mid \tilde{\mathbf{a}}_2 \bullet \tilde{\mathbf{x}} > 0$.

Step 10: Compute $\mathbf{a}_1 \bullet \tilde{\mathbf{x}}_B$ and the corresponding expected value. This is the expected value of the recommended product after receiving the recommendation, EU_{post}.

Repeat Steps 1 through 10.

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