Extraction of Hidden Information from Attribute-Based Product Recommendations

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ABSTRACT

We use a multi-method approach (analytical model and behavioral economics experiment) to investigate product recommendations based on less-important attributes (weak unique selling proposition). We consider multiple scenarios in which a recommender's level of *expertise* (knowledge about product attributes and their importance) and *bias* (preference for the firm as opposed to consumers) operate as cues for consumers to evaluate the recommender's message. We also consider two different processing strategies that consumers may adopt: focus on the differences between product attributes, or focus on both similarities and differences between attributes. Results show that optimal messaging behavior is a function of an interactive process involving recommender characteristics, consumer processing strategy, and the relative importance of product attributes to consumers. The results identify conditions that determine when weak USPs are likely to increase or decrease a consumer's propensity to buy the recommended product, and when a recommender may optimally communicate weak USPs or avoid sending such a recommendation.

Keywords: Product Recommendations, Advertising, Game Theory, Behavioral Economics

Advertisers strive to communicate superior attribute performance because such a strategy, known as Unique Selling Proposition (USP), communicates to consumers that if they buy the product they will obtain a unique benefit, “one that the competition either cannot or does not offer” (Reeves 1961, pp. 51-52). This approach has been widely prescribed as an effective reason-based persuasive technique (Brierley 2002; Shimp 2008) for how it influences the knowledge structure of consumers, directing the decision focus to a brand’s most positive attributes.

Ideally, a unique selling point should involve an attribute that is important enough to motivate consumers to buy the firm’s product over competing brands (Belch and Belch 2007; Reeves 1961). Because it is impossible for every product to outperform competitors on a set of important product attributes, some firms have resorted to communicating USPs based on less-important features, which constitute a weak USP. This idea is corroborated by Brierly (2002, p. 139), who asserts that “[c]reatives in ad agencies would go through the different benefits of the product until they could find something that is different about it. ... Whether the consumers were interested enough in these USPs to make them want to buy the product was of little relevance.” Implicit is the belief that regardless of their strength, USPs will generate positive consumer reactions.

The use of a potentially weak USP is illustrated by the Ford advertising campaign that claimed the F-150 truck had an advantage over direct competitors because of its bigger spring leaf mounting bolts (see Appendix A for screenshots from the Ford commercial). In one ad spot, a non-expert spokesperson attempts to communicate this feature by showing that the Ford bolt is larger than the Tundra’s. In another execution of the concept, celebrity endorser Mike Rowe from the TV series *Dirty Jobs* interacts with Paul, a spokesperson dressed as a mechanic (Rowe calls him Ford’s “resident expert”). When shown a tray of labeled parts, and asked to explain the difference between the F-150 bolt and four competitors’, Paul responds, “Ford’s bolt is bigger and stronger, Mike.”

Such a claim is a clear attempt to influence consumers by placing Ford at an advantage compared with its competitors, based on the size of its spring leaf bolt. However, these types of USP may not convince buyers in the way that Ford intended, as seen in an Internet comment posted on the anandtech.com forum: “I don't like the ford commercials. They are soo [sic] stupid. They had this one commercial with the guy from dirty jobs there. They had the leaf spring bolts from the

Ford F-150 and other trucks like the Nissan, Toyota etc. … They were showing how the bolts from the F-150 were the thickest of all other manufactures thus making the vehicle stronger LMAO." Consistent with the idea that the spring leaf bolt claim may be seen as a weak USP by one buyer segment, the post continued: "When do the leaf spring bolts in a truck ever fail. Anybody who has any basic education or eng[sic] knowledge would automatically smell bull [expletive]." Similarly, the F-150 advertisement posted on YouTube prompted one poster to comment that Toyota would not waste its time and effort focusing on a bolt, and that when comparing trucks, one should focus on engines, miles per gallon, and transmissions, not bolts.

Such anecdotal evidence reflects a conundrum that many firms face. On one hand, weak USP messages help to communicate a unique aspect of a product to consumers. On the other hand, consumers could make unfavorable inferences about undisclosed information, causing the weak USP message to backfire and end up placing the product at a disadvantage. If the spring leaf bolt claim was judged to be a weak USP by a large segment of the market, one might assume that consumers will not react as positively as Ford hoped.

To investigate this notion, our study develops, analyzes, and empirically tests a game theory model that looks at product recommendations in situations where one product dominates competitors' products on attributes of lesser importance (weak USPs). We focus on non-interactive forms of communication such as advertising, blogs, and interviews, and investigate how the characteristics of sender and receiver can mitigate or amplify the potential backlash from the use of weak USPs.

With respect to the message sender, two characteristics seem to be relevant, both in the evidence presented and in previous research (e.g., Austen-Smith 1994; Crawford and Sobel 1982) in activating higher-order rationality. These are *bias* (a recommender's focus on her own welfare versus consumer welfare), and *expertise* (the recommender's knowledge about the importance of product attributes). With respect to consumers, we investigate information-processing strategies that focus on similarities or differences in the attribute performance (Tversky 1977), and argue that the interaction between the recommender type and the consumer's choice of processing strategy can provide important consumer insights, including when a recommender should communicate superior performance based on less-important attributes, and how such messages affect consumers' likelihood to buy the recommended product.

This research addresses three main questions: 1) how consumers process and react to recommendations based on less-important attributes, and whether a recommender's bias and expertise will mitigate or amplify consumer responses to persuasion attempts; 2) how a consumers' processing strategies affect their overall perception of a product following a persuasion attempt based on less-important attributes; and 3) given an expected consumer response to persuasion attempts, what is the optimal recommendation strategy for a firm and which conditions support withholding or sending recommendations based on less-important attributes.

In terms of the first question, we found that consumers react both positively and negatively to weak USPs. For example, when a recommender is an unbiased novice, this may increase consumer intent to buy a product, while the recommendation of a biased expert may increase interest in buying a competing product. With respect to the second research question, we found that the processing strategy adopted by consumers can significantly affect their intent to buy a recommended product when the recommender uses a weak USP, except when the recommender is an unbiased novice. Regarding the third question, we determined that optimal messaging policy based on type of recommender and consumer processing strategy. In general, although both unbiased and biased expert recommenders may adopt distinct recommendation strategies, the outcome can lead recommenders to optimally withhold weak USP messages. We also found that a novice recommender's optimal strategy involves an even chance of sending weak and strong USPs (an interesting finding, since biased novice recommenders are generally aware that weak USPs can lead consumers to buy a competing brand). The rationale is that sometimes a novice recommender needs to bank on the *ex-post* chance that she is sending a strong USP.

The following sections present a review of the literature, the theoretical models developed, and propositions derived from analyzing the models, which were tested in an experiment that simulates a situation in which consumers and recommenders interact by making decisions about what information to disclose and which product to buy. We conclude by summarizing our findings, and discussing the theoretical and managerial implications stemming from our research.

Related Literature

The substantive issue of how consumers react to product recommendations, and how firms should respond to these reactions, has sparked much empirical research in marketing (Ansari, Essegaier, and Kohli 2000; Fitzsimons and Lehmann 2004; Kalra, Li, and Zhang 2011). Marketing researchers have also taken an interest in using game-theory tools to model information transmission (and persuasion games) in a variety of marketing phenomena. Godes and Mayzlin’s (2004) study shows how consumers provide product information via online communications. Bloomfield and Kadiyali (2005) investigates how sellers persuade buyers to accept unverifiable information by exaggerating verifiable information. Mayzlin (2006) examines online word-of-mouth communications, and identifies conditions under which online messages are persuasive. Chen and Xie (2008) studies online consumer reviews as a source of product information to identify how firms should combine this information with other proprietary information. Mayzlin and Shin (2011) investigate how firms may intentionally provide uninformative product advertising to encourage consumers to search for information on their own. Our paper adds to the emerging trend of game-theoretic modeling of information transmission by focusing on attribute-based product recommendations.

To address our research questions, we follow the basic framework of information disclosure models (Crawford and Sobel 1982; Green and Stokey 2007). These models show that when recommender and receiver have different goals, messages are uninformative “cheap talk.” We focus on situations where lying about a product feature is not a viable option, to learn whether the informed party may attempt to benefit from managing information disclosure in situations where the message content is verifiable (Fishman and Hagerty 1990; Seidmann and Winter 1997; Shin 1994). We also model situations in which recommender expertise affects overall effectiveness of messages when it comes to changing consumer preferences (Austen-Smith 1994; Benabou and Laroque 1992; Durbin and Iyer 2006; Ottaviani and Sørensen 2006).

Our paper differs from the current literature in three regards. First, while past studies have investigated selective disclosure of information of the same importance, we investigate disclose of information of varying importance. Second, previous research has considered experts to be those with knowledge of the actual information communicated and novices as those who lack this information. In our research, both types of recommender possess hard information, but the expert understands its relative importance, while the novice does not.[1] Third, we look at two processing approaches consumers may follow when making inferences about hidden attributes. Behavioral research indicates that consumers may or may not take into consideration attributes of equal value when evaluating products (Tversky 1977; also see Payne, Bettman and Johnson 1993 for a review). In the first processing approach, consumers infer that products in the market perform differently with respect to non-disclosed attributes — hereafter, a *dichotomous* processing strategy (e.g., "the F-150's cargo capacity must be better or worse than the Tundra's"). In the second processing approach, consumers infer that products in the market have different or equivalent performance of non-disclosed attributes— hereafter a *trichotomous* processing strategy (e.g., "the F-150's cargo capacity could be better, worse, or the same as the competing trucks").[2] This distinction is important because significant differences in product preference could arise depending on which process consumers adopt, as will become clear when we discuss the models.

Although a TV commercial is used to illustrate the context of this research, our model relates broadly to many forms of non-interactive marketing communication in which a recommender sends a message and consumers do not have the opportunity to probe the message or the source (i.e., consumers make a decision based only on the information they receive). This is a common situation when messages are sent via traditional media (TV, radio, print, blogs, interviews, etc.) but less so when messages are sent via highly interactive media (e.g., one-on-one interaction with a salesperson) which increase the consumer's ability to probe the message.

MODEL SETUP

In this section we consider the dichotomous information-processing model (the trichotomous information-processing model will be discussed in a later section).

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[1]In the Ford F-150 example, both recommenders have knowledge that the truck's bolt is bigger than the Tundra's. However, the ad also implies that Ford's "residential expert," dressed as a mechanic, understands that a larger bolt is important to the overall performance of a pickup truck better than a non-expert does.

[2]The behavioral literature usually refers to these processing strategies in terms of feature similarity (e.g., Tversky 1977). Consumers may focus on the dissimilarities between attribute values used to recommend the product (the hidden attribute is perceived as "better" or "worse"). Alternatively, consumers may focus on the dissimilarities and similarities of these attributes (the hidden attribute is perceived as "better," "equal," or "worse").

Product Utilities

Assume that there are two products in the market, indexed by $i \in \{1,2\}$.[3] These products have a set of attributes that can be partitioned into two subsets A_i^k $k \in \{L,H\}$. They have different *true utilities* U_i^*, which are a function of the relative value of the two attribute partitions, where partition A_i^H has a probability $\rho > 1/2$ of being more important than partition A_i^L. As a consequence, A_i^H is denominated "the more-important attribute partition." On the other hand, A_i^L receives the probabilistic weight $(1-\rho) < 1/2$ and is thus denominated "the less-important attribute partition." This assumption allows for a clear identification of strong USPs (those based on A_i^H) and weak USPs (those based on A_i^L). The partitions may be composed of single or multiple elements. In the Ford F-150 example, A_i^L could capture "spring leaf bolt" (a single element) or "spring leaf bolt and tow hook" (two elements), whereas A_i^H could capture a variety of other truck attributes such as "cargo capacity, horse power, and gas mileage" (multiple elements). Henceforth we will refer to "attribute partitions" simply as *attributes*, with the understanding that no generality is lost. This consideration nicely captures situations in which a company cannot communicate information about all relevant attributes of a product. Thus, information about a subset of attributes is communicated to consumers, while information about the remaining subset of attributes is withheld. An example of such situation is when advertising has limited bandwidth (as in Mayzlin and Shin 2011).[4]

To accommodate qualitative attribute comparisons with other products (e.g., "the Ford F-150 has bigger spring leaf bolts than the Toyota Tundra"), we define the *state space* of an attribute to be $W^K = \{A_1^k > A_2^k, A_1^k < A_2^k\}$. Given that there are two products and two attributes, four possible states of the world *w* are collected in the set $W = W^H \times W^L$, as shown in Figure 1.

We focus on situations in which the firm's product (product *i*, for example) dominates the other product, with respect to the less-important attribute only; hence the true state of the world

[3]We use the index *i* to refer to a given product and the index –*i* to indicate the "other product."

[4]A model in which talking about all attributes (full disclosure) is allowed can be accommodated by setting the attribute-importance parameter to 1 (ρ = 1).

is: $w^{*} = \{A_i^H < A_i^H, A_1^L > A_2^L\}$.[5]

Figure 1 - States of the world $w \in W$

		Attribute A_i^L	
		$A_1^L > A_2^L$	$A_1^L < A_2^L$
Attribute A_i^H	$A_1^H > A_2^H$	$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$\{A_1^H > A_2^H, A_1^L < A_2^L\}$
	$A_1^H < A_2^H$	$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$\{A_1^H < A_2^H, A_1^L < A_2^L\}$

To capture the probability of the state of each attribute, we define the random variables $X_i^k(\cdot)$ that map the state spaces W^K into the interval [0,1] of Real numbers as $X_i^k(x) = P\left(\left\{s \in \{A_i^k > A_{-i}^k, A_i^k < A_{-i}^k\} : s = x\right\}\right)$. Because each state space has only two elements, it follows that $X_{-i}^k(A_{-i}^k > A_i^K) = \left(1 - X_i^k(A_i^k > A_{-i}^K)\right)$.

Assuming that the utility derived from both attributes is additive, we can write the expected utility for product *i* as:

(1) $$U_i^* = \rho\, 1[A_i^H > A_{-i}^H] + (1-\rho)\, 1[A_i^L > A_{-i}^L],$$

where $1[\cdot]$ is the indicator function. Note that this formulation is consistent with a weighted-averaging information-integration model (Anderson 1981).

It follows that the expected utility for the products can be expressed as:

(2) $$U_i = \rho P(A_i^H > A_{-i}^H) + (1-\rho) P(A_i^L > A_{-i}^L).$$

In this dichotomous-information-processing version of product utilities, we do not explicitly model situations in which consumers consider attributes to be equal (such as when $A_1^H = A_2^H$). This specification still allows for consumers to perceive that the two products possess attributes with the same value, but this possibility is *knife-edged*. Two product attributes are perceived as equivalent when the probability that a given attribute of product 1 is better than that of product 2 is 1/2; for

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[5]The results for situations in which a firm's product dominates on a more-important attribute are straightforward: it is always optimal for the firm to disclose this information, and for the consumer to buy this product.

instance, when $P(A_1^H > A_2^H) = 1/2$. Later when we discuss the trichotomous processing strategy we consider an alternative utility specification in which consumers explicitly consider attributes with equal values ($A_1^k = A_2^k$).

Players and Messaging

There are two types of players in the market, the recommender and the consumer. Initially only the recommender knows the true value of product attributes. The recommender may then attempt to influence consumers by sending a message that favors one of the products. The recommender possesses two characteristics, bias and expertise, which are public knowledge. To capture bias, we use variable $b \in \{biased, unbiased\}$, where $b = biased$ indicates that the recommender has a clear association with a firm and will benefit if the firm sells the product she recommends; and $b = unbiased$ if the recommender has no association with the firm selling the product she is recommending. We assume that an unbiased recommender has some level of concern for consumer welfare and prefers that consumers select the best available product. A biased recommender, on the other hand, prefers that consumers select the product she benefits from. For the sake of brevity, the product favored by a biased recommender will be termed the "target product," adding that this label only has meaning when the recommender is biased.[6]

To capture the expertise of the recommender, we use variable $e \in \{expert, novice\}$, where $e = expert$ indicates that the recommender is an expert in the product category under consideration, and $e = novice$ indicates that the recommender is not an expert in the product category. In this research we assume that while both expert and novice recommenders know the value of the attributes (the state of the world *w*), it is the expert who understands the relative importance of attributes for overall product performance (attribute importance parameter ρ) while the novice does not (recall the examples from the F-150 spring leaf bolt campaign).

Prior to receiving information about a product, consumers cannot be sure about the relative

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[6]The qualitative results of the model are unchanged when consumers have a probabilistic perception about the type of a recommender (for instance, results for a *biased* recommender are similar to those for a recommender perceived by consumers as more likely to be *biased* than *unbiased*).

value of the attributes (that is, whether A_1^H performs better than A_2^H); thus, for both attributes A_i^L and A_i^H consumers have identical prior beliefs that a given attribute of product 1 has greater value than the same attribute of product 2 (i.e., 1/2):

$$P\left(A_1^k > A_2^k\right) = P\left(A_1^k < A_2^k\right) = 1/2, \text{ for } k \in \{H, L\}.$$

The recommender can send message *m* containing information about the relative value of an attribute (e.g., that the F-150 has bigger spring leaf bolts than the Tundra). There are two types of attribute dominance messages: "$a_i^L > a_{-i}^L$" and "$a_i^H > a_{-i}^H$," where message $m = a_i^L > a_{-i}^L$ is a verifiable message claiming that attribute A_i^L is better than attribute A_{-i}^L, and message $m = a_i^H > a_{-i}^H$ is a verifiable message claiming that attribute A_i^H is better than attribute A_{-i}^H (we use capital A to denote the *true value* of an attribute and lowercase *a* to denote a *message* about the attribute's value).

Upon receiving the message, consumers may update their prior beliefs about attributes and decide which product to buy. Consumers will likely select product 1 over product 2 if $E\left[U_1 \mid m,b,e\right] > E\left[U_2 \mid m,b,e\right]$. Therefore, the likelihood that consumers will purchase product 1 should be proportional to the probability $P\left(U_1 > U_2 \mid m,b,e\right)$. As this probability increases (decreases), so does the likelihood that the consumer will purchase product 1 (product 2). Since there are only two products in the market, $P\left(U_1 > U_2\right) = 1 - P\left(U_1 < U_2\right)$. Therefore, consumers will be indifferent about products when $P\left(U_1 > U_2\right) = P\left(U_1 < U_2\right) = 1/2$, and prefer product *i* when $P\left(U_i > U_{-i}\right) > 1/2$.

We assume that the recommender has the option of not sending a message, and that the consumers would not know if she had declined to send it. Such situations include but are not limited to many forms of non-interactive communication such as TV, radio, and print advertising, large conferences, interviews, etc. This implies that consumers cannot make inferences in lieu of a message; however, when consumers do receive a message, they note that the recommender may be using a "sanitization strategy" (Shin 1994, p. 63). In other words, consumers understand that recommenders can suppress unfavorable information, and account for this possibility when computing the posterior beliefs upon receiving a message.

If the recommender is known to be biased in favor of one product (i) and recommends the other product ($-i$), we assume that consumers would perceive this as credible evidence for assigning the best possible beliefs to product $-i$, and the worst possible beliefs to product i. This implies that $P\left(U_i < U_{-i}\right) = 1$, which is equivalent to $P\left(U_i > U_{-i}\right) = 0$.[7]

With this specification, we can use Expression (2) to establish the likelihood a consumer will purchase product *i* (see Appendix B for derivation):

(3) $$P\left(U_i > U_{-i} \mid m,b,e\right) = \rho\ P\left(A_i^H > A_{-i}^H \mid m,b,e\right) + \left(1-\rho\right)\ P\left(A_i^L > A_{-i}^L \mid m,b,e\right).$$

Notice that because ρ is a probability, it introduces stochastic noise and prevents all consumers from buying the same product with certainty whenever $A_i^H > A_{-i}^H$ (if ρ were deterministic, $A_i^H > A_{-i}^H$ would imply that $U_i > U_{-i}$ with probability 1, thus, consumers would definitely choose product *i*). It also allows for the interpretation that there is heterogeneity in how consumers see the importance of attributes (a proportion ρ of consumers sees one attribute as more important, while the rest $(1-\rho)$ see the other attribute as more important).

Finally, we assume that a small number of consumers do not account for the strategic behavior of the recommender. This assumption is not unrealistic, and filters out mixed-strategy equilibrium outcomes.[8] The existence of a single consumer who does not act strategically will guarantee pure-strategy messaging-behavior equilibrium in all states of the world.

ANALYSIS — DICHOTOMOUS UTILITY SPECIFICATION

When evaluating optimal recommender and consumer strategies, we look for the pure-strategy Perfect Bayesian Equilibrium in which consumer beliefs upon receiving a message are consistent with the recommender's optimal messaging behavior. The solution concept for the model is similar to a signaling game, and follows the principle of sequential rationality. We first analyze

[7]A biased recommender who claims that a competing product is better than the product for which she is biased would be seen by most consumers as overwhelmingly credible in favoring the competing product (see Durbin and Iyer 2006).

[8]For research that documents how people cope differently with persuasion attempts, depending on their "persuasion knowledge" see, for example, Friestad and Wright (1995) and Campbell and Kirmani (2000).

the end of the game and determine consumer belief formation given all possible types of recommenders and messages. We then use consumer beliefs to solve for the recommender's optimization problem. The result is the equilibrium recommender's messaging strategy and ensuing consumer beliefs about relative product qualities.

Consumer Beliefs

In this section we study the decision strategy of consumers. Lemma 1 states how consumers should react to product recommendations:

Lemma 1 *When the recommender sends a message about the more-important attribute, consumers will follow the recommendation with probability*

(4) $$P\left(U_i > U_{-i} \mid m = a_i^H > a_{-i}^H, b, e\right) = \rho + \left(1-\rho\right)\frac{P\left(m = a_i^H > a_{-i}^H \mid A_i^L > A_{-i}^L, b, e\right)P\left(A_i^L > A_{-i}^L\right)}{P\left(m = a_i^H > a_{-i}^H \mid b, e\right)}.$$

When the recommender sends a message about the less-important attribute, consumers will follow the recommendation with probability

(5) $$P\left(U_i > U_{-i} \mid m = a_i^L > a_{-i}^L, b, e\right) = \rho\frac{P\left(m = a_i^L > a_{-i}^L \mid A_i^H > A_{-i}^H, b, e\right)P\left(A_i^H > A_{-i}^H\right)}{P\left(m^A = a_i^L > a_{-i}^L \mid b, e\right)} + \left(1-\rho\right).$$

Proof See Appendix C.

Lemma 1 implies that when consumers receive a recommendation based on the more-important attribute, the probability that they will buy the product always increases. This is expected because even if consumers infer that there is no chance the recommended product dominates the other product on the less-important attribute, the probability consumers would buy the recommended product is ρ, which is necessarily greater than 1/2.

Conversely, when consumers receive a message regarding the less-important attribute, the probability that they will buy the recommended product may either increase or decrease (be greater or smaller than 1/2, depending on ρ). It decreases (increases) when consumers infer that the probability that the recommended product will dominate the other product on the more-important attribute is small (large).

The Recommender's Problem

The recommender will select the best messaging strategy conditioned on consumer beliefs, knowing that such beliefs are shaped by a combination of her own type and messaging strategy (according to Lemma 1).

The unbiased recommender prefers consumers to select the best product and aims to minimize the difference between true probability and the consumer's perceived probability that the best product dominates the other product. Thus, the unbiased recommender solves the problem:

(6) $\min_{m \in W} \left| P\left(U_1^* > U_2^*\right) - P\left(U_1 > U_2 \mid m, b = unbiased, e\right) \right|$ conditional on consumer beliefs.

The biased recommender prefers that consumers select the target product (e.g., product *i*) and aims to maximize the probability that consumers perceive product *i* to be the best. This means that the biased recommender solves the problem:

(7) $\max_{m \in W} P\left(U_i > U_{-i} \mid m, b = biased, e\right)$ conditional on consumer beliefs.

Following a Perfect Bayesian Equilibrium framework, we solve for the optimal recommender messaging strategy, taking into account both the recommender type and the "final" belief formed by consumers. Such beliefs ultimately dictate the likelihood that consumers will follow the recommendation. The next two sections present the equilibrium results.

Unbiased Recommender and Consumer's Purchase Strategy

The unbiased recommender cares about consumer utility. In this scenario, the equilibrium messaging strategy employed by the recommender and the ensuing posterior beliefs formed by consumers are given in the following proposition:

Proposition 1 *In the dichotomous specification, when a product dominates the competing product on the less-important attribute:*

- *An unbiased novice recommends based on the less-important attribute with probability* $1/2$, *in which case consumers buy the recommended product with probability* $1-\frac{\rho}{2}$.
- *An unbiased expert never recommends based on the less-important attribute; consequently, consumers cannot update their prior beliefs. However, if consumers receive this "out of equilibrium" message, the probability that they will buy the recommended product should be smaller than* $\frac{1}{2}+\frac{\rho}{2}$.

Proof See the Web Appendix.

The rationale for this proposition is that the unbiased novice recommender would prefer to provide the most useful information possible, but she does not know which attribute is more important; thus, the recommender will select an attribute at random. Because she has no interest in deception, strategic consumers will not make a negative inference regarding the value of the non-disclosed attribute; in this case, more information is beneficial, even if the message refers to a less-important attribute, since $1-\frac{\rho}{2} > \frac{1}{2}$ for all $\rho \in (\frac{1}{2},1)$. The increased likelihood to buy is driven exclusively by what consumers learn about the less-important attribute (the posterior on the more-important attribute remains unchanged).

Alternatively, the unbiased expert recommender can identify the important attribute and always send a message about A_i^H regardless of whether it favors product 1 or 2 since the attribute is diagnostic in determining product utility. Because a recommendation based on the less important attribute A_i^L is *out of equilibrium,* one could make only a coarse prediction that the likelihood that consumers will purchase the recommended product will be smaller than $\frac{1}{2}+\frac{\rho}{2}$.

Biased Recommender and Consumers' Purchase Strategy

A biased recommender will try to influence consumers to buy whichever product benefits the recommender the most (the target product). The equilibrium messaging strategy employed by the recommender and the posterior beliefs formed by consumers are formalized in the following proposition:

Proposition 2 *In the dichotomous specification, when the target product dominates the competing product on the less-important attribute:*

- *A biased novice always recommends the target product, in which case consumers will buy the target product with probability* $1-\frac{2\rho}{3}$.
- *A biased expert forgoes recommending the target product (never recommends it based on the less-important attribute); however, if consumers receive this "out of equilibrium" message, they will buy the target product with probability* $1-\rho$.

Proof See the Web Appendix.

The rationale for Proposition 2 is that a biased novice recommender will not know which attribute gives the target product the greater advantage since she lacks knowledge about the attribute's importance; however, when there is only one dominating attribute, the recommender can choose to talk about that specific attribute. When the target product does not dominate on either attribute, the recommender will naturally forgo providing information. Anticipating this, consumers will derive information based on the recommender's behavior. When consumers receive a recommendation based on the less-important attribute A_i^L, they decrease the posterior probability that the product is superior for attribute A_i^H; thus, the likelihood that they will select the target product is likely to decrease when ρ is large, since $1-\frac{2\rho}{3} < \frac{1}{2}$ for $\rho \in (\frac{3}{4},1)$. The intuition underlying this prediction is that when a recommender sends a message based on a certain attribute, she is imperfectly revealing information about the other attribute, thus the probability that the recommended product has greater value for the non-disclosed attribute decreases.

A biased expert has the ability to identify which attribute is more important. One would expect that the expert recommender would recommend based on A_i^L when the target product dominates on only the less-important attribute. However, this strategy will reveal that the product is dominated on attribute A_i^H and decrease the likelihood that consumers will purchase the product (the posterior would change from 1/2 to $1-\rho$). Consequently, a recommendation based on the less-important attribute A_i^L is out of equilibrium and should not be expected.

ANALYSIS — TRICHOTOMOUS UTILITY SPECIFICATION

In this section we consider that consumers may infer that the recommender does not disclose information about the important attribute because the information is not diagnostic to the decision at hand. In other words, consumers may infer that both products perform equally well on the hidden attributes and that this information will not shape a preference. We retain the model setup, extend the state-space for attribute values to be W^K $\{A_i^k > A_{-i}^k, A_i^k = A_{-i}^k, A_i^k < A_{-i}^k\}$, and redefine the random variables $X_i^k(\cdot)$ as $X_i^k(x) = P\left(\left\{s \in \{A_i^k > A_{-i}^k, A_i^k = A_{-i}^k, A_i^k < A_{-i}^k\} : s = x\right\}\right)$.

The true utility of a product is similar to that in Expression (1), but its expected utility now explicitly incorporates the possibility that $A_i^k = A_{-i}^k$:

$$(8)\quad \begin{aligned} U_i &= \rho\left[1\ X_i^H(A_i^H > A_{-i}^H) + \frac{1}{2}X_i^H(A_i^H = A_{-i}^H) + 0\ X_i^H(A_i^H < A_{-i}^H)\right] \\ &+ (1-\rho)\left[1\ X_i^L(A_i^L > A_{-i}^L) + \frac{1}{2}X_i^L(A_i^L = A_{-i}^L) + 0\ X_i^L(A_i^L > A_{-i}^L)\right] \end{aligned}.$$

With this specification, the likelihood that a consumer will purchase product *i* is given by (see Appendix B for derivation):

$$(9)\quad \begin{aligned} P(U_i > U_{-i}) &= \rho\ P\left(A_i^H > A_{-i}^H\right)P\left(A_i^L < A_{-i}^L\right) + (1-\rho)\ P\left(A_i^H < A_{-i}^H\right)P\left(A_i^L > A_{-i}^L\right) + P\left(A_i^H = A_{-i}^H\right)P\left(A_i^L > A_{-i}^L\right) \\ &+ P\left(A_i^H > A_{-i}^H\right)\left[P\left(A_i^L > A_{-i}^L\right) + P\left(A_i^L = A_{-i}^L\right)\right] + \frac{1}{2}P\left(A_i^H = A_{-i}^H\right)P\left(A_i^L = A_{-i}^L\right). \end{aligned}$$

Considering that there are three states of the world for each attribute, we assume that consumers' *prior beliefs* for each state of the world is 1/3, i.e.,

$$P\left(A_1^k > A_2^k\right) = P\left(A_1^k = A_2^k\right) = P\left(A_1^k < A_2^k\right) = 1/3, \text{ for } k \in \{H, L\}.$$

Here, consumers' belief formation is more tedious than in the previous dichotomous case since, in the trichotomous case, three probabilities must be computed rather than two. Given a message, the overall probability of selecting one product over another is calculated by computing random variables $X_i^k(x)$, for $x \in W^k$, $k \in \{H, L\}$.

When the recommender sends a message about the less-important attribute, the random variables $X_i^L(x)$ are directly computed from the information in the message ($X_i^L(A_i^L > A_{-i}^L) = 1$, $X_i^L(A_i^L = A_{-i}^L) = 0$, $X_i^L(A_i^L < A_{-i}^L) = 0$), while $X_i^H(x)$ is computed using the Bayesian rule:

$$(10)\qquad X_i^H(x) = P\left(x \mid m = a_i^L > a_{-i}^L, b, e\right) = \frac{P\left(m = a_i^L > a_{-i}^L \mid x, b, e\right)P(x)}{P\left(m = a_i^L > a_{-i}^L \mid b, e\right)}, \quad \text{for } x \in W^H.$$

When the message refers to the more-important attribute, the computation of random variables follows a similar rule:

$$(11)\qquad X_i^L(x) = P\left(x \mid m = a_i^H > a_{-i}^H, b, e\right) = \frac{P\left(m = a_i^H > a_{-i}^H \mid x, b, e\right)P(x)}{P\left(m = a_i^H > a_{-i}^H \mid b, e\right)}, \quad \text{for } x \in W^H.$$

Considering these conditional consumer beliefs, the problems for the recommender, given her type, are the same as those in expressions (6) and (7). (In order to avert redundancy, we have not rewritten them here.)

Once again, we follow a Perfect Bayesian Equilibrium framework to solve for the optimal recommender messaging strategy, taking into account both the recommender's type and the "final" belief formulated by consumers. The results are presented below.

Unbiased Recommender and Consumer's Purchase Strategy

The following proposition provides the equilibrium messaging behavior of an unbiased recommender and the respective consumer's belief formation:

Proposition 3 *In the trichotomous specification, when a product dominates the competing product on the less-important attribute:*

- *An unbiased novice recommends based on the less-important attribute with probability* $1/2$, *whereas an unbiased expert recommends based on the less-important attribute only if products do not differ for the more-important attribute. In either case, if consumers receive a recommendation based on the less-important attribute, they will buy the recommended product with probability* $1-\frac{\rho}{2}$.

Proof See the Web Appendix.

The rationale for Proposition 3 is similar to that of Proposition 1. The only difference is that, in the trichotomous specification, a message about attribute A_i^L sent by the expert recommender is not *out-of equilibrium*. Instead, it tells consumers that the products have the same value for the more-important attribute ($P(A_i^H = A_{-i}^H) = 1$); otherwise, the recommender would send a message based on attribute A_i^H. Therefore, consumers will make no negative inference regarding the value of the undisclosed attribute, and thus more information is always beneficial to consumers, even if the message refers to a less-important attribute, since $1-\frac{\rho}{2} > \frac{1}{2}$ for all $\rho \in (\frac{1}{2},1)$.

Biased Recommender and Consumer's Purchase Strategy

The proposition below gives the optimal messaging behavior for a biased recommender and the posterior beliefs formed by consumers:

Proposition 4 *In the trichotomous specification, when the target product dominates the competing product on the less-important attribute:*

- *A biased novice always recommends the target product, in which case consumers will buy the target product with probability* $1-\frac{3\rho}{5}$.

- *The strategy of the biased expert depends on the relative value of the attributes. If* $\rho < \frac{2}{3}$*, she recommends the target product based on the less-important attribute. If* $\rho > \frac{2}{3}$*, the recommender forgoes sending a recommendation. If consumers receive a recommendation to buy the target product based on the less-important attribute, they will buy the target product with probability* $1 - \frac{3\rho}{4}$

Proof See the Web Appendix.

The details underlying Proposition 4 are as follows. For the biased novice recommender, the logic is similar to that found in the dichotomous case. The biased novice recommender always recommends based on the less-important attribute, because that is the only attribute that favors the target product. However, in this case, the negative impact of a recommendation based on A_i^L is smaller than that predicted in the dichotomous case, since the probability that attributes may have the same value "soaks up" some of the negative inferences regarding attribute A_i^H.

For the biased expert, a major difference pertains. Although for the dichotomous case the biased-expert recommender never recommends based on the less-important attribute, for the trichotomous specification the recommender may do so, if the value of ρ is small enough (close to 1/2). The logic for this strategy is that, from the consumers' perspective, a recommendation based on the less-important attribute A_i^L does not automatically mean that the target product is dominated on the more-important attribute A_i^H. Consumers may attribute a positive probability that the products are actually equal on A_i^H. Consequently, if $\rho < 2/3$, the recommender is better off recommending the product based on the less-important attribute, and insuring that consumers will perceive the target product as better on attribute A_i^L even if this risks decreasing consumer beliefs that the target product is superior on attribute A_i^H. In other words, the recommender trades the definite perceived superiority on the less-important attribute for a perceived inferiority "with some increased probability" on the more-important attribute.

TESTABLE IMPLICATIONS OF THE MODEL

The dichotomous and trichotomous models make distinct predictions with respect to equilibrium recommendation messaging based on less-important attributes and how consumers should react to such recommendations. A summary of predictions is available in Table 1.

Insert Table 1 about here

EMPIRICAL TEST OF THE THEORY

To test the models' predictions, we used a computer-based laboratory experiment that was designed and deployed using the z-Tree software program (Fischbacher, 2007), which allows respondents to interact, playing the role of recommender or consumer. The study participants were undergraduates enrolled in the business program of a major West Coast university who were compensated for their time with a $15 gift card from the college bookstore. The total number of participants who played the role of recommender was 66; by study construction, 66 students played the role of consumer. The pairing of recommenders and consumers was random. The experiment was conducted in six sessions, and participants could not repeat a session.

To provide an incentive so that the economic utility of participants' actions were linked to their own decisions, before each session we announced that an additional $20 gift card would be given to participants who performed best in their assigned role (either consumer or recommender). The gift cards were awarded at the end of each experimental session (two cards per session) after processing the session results. Awarding the incentive provided the two sufficient conditions for a Microeconomics experiment postulated by Smith (1982): *nonsatiation*, since the participant's expected utility in dollars would increase (decrease) with a good (bad) performance; and *saliency*, given that individuals were informed of the award before each experimental session, and told whether they had won immediately following the session.

Stimuli, Procedures, and Experimental Design

Participants were greeted by the experimenter and told that they would play an interactive recommendation/product-choice game with multiple rounds. During each round, recommenders would send messages to consumers regarding five different products representing two brands of consumer electronics (Asus and MSI). Upon receiving a recommendation, consumers would rate their likelihood of buying products from each brand.

To manipulate *attribute importance*, participants were informed that the overall performance of the electronic products depended on two groups of features: functionality and user-friendliness. They were also told that one group of features was more important than the other. To manipulate recommender *expertise* regarding attribute importance, roughly half of the recommenders were informed of which set of attributes was more or less important (expert condition), while the other recommenders received no attribute information (novice condition). This manipulation assured that type of recommender would function as intended: the expert possessed information about attribute importance, while the novice did not. All consumers received information about the relative importance of attributes and the expertise of each recommender.[9]

To manipulate the degree of recommender *bias*, approximately half the recommenders were told that they cared about the welfare of the consumers (unbiased condition) while the other half were told they would receive a commission on the sales of a certain product/brand combination (biased condition). Participants were randomly assigned to the four possible combinations of recommender type resulting from fully crossing the expertise and bias factors. *Processing strategy* was manipulated by displaying products for which attributes were either better or worse (dichotomous condition), or better, equal, or worse (trichotomous condition). Participants were randomly assigned a role and matched with a participant playing the opposite role.

During each round, recommenders were shown a screen that displayed product information in a matrix format (see Figure 2, top panel): a description of the product (media player, HD camcorder, 3G router, etc.), which product/brand combination paid a commission (for biased recommenders), the "state of the world" (i.e., the realization of *w*), and an input field with radio buttons for making mutually exclusive selections: (a) send a message about functionality, (b) send a message about user-friendliness, or (c) send no message. While recommenders were making their decisions, consumers were shown a message asking them to wait while the other player completed an action.

[9]Whether consumers "believed" this information and acted accordingly is captured in the experimental results.

Upon receiving product recommendations, consumers were shown a screen (see Figure 2, bottom panel) that displayed recommender characteristics and product information in a matrix format. The matrix provided a description of the product, the product/brand combination that paid a commission to the recommender (only in the biased condition and if the recommender sent a message about the product), the recommended product, and an input field to rate the likelihood of selecting each brand. The rating was performed on an 11-point tradeoff scale ranging from 0% to 100%, in which participants could assign the likelihood of buying each product. A rating of 50% indicated that consumers were indifferent to purchasing any brand. A likely-to-buy rating of 90% for one brand translated to a 10% likely-to-buy rating for the other. While consumers were assigning ratings, recommenders were shown a message asking them to wait for the other player to complete an action. At the end of each round, recommenders received feedback on consumer decisions, while consumers received feedback about the state of the world.

Insert Figure 2 about here

During each round, recommenders and consumers acted upon 5 electronic products. All participants played each role, i.e., consumer *and* recommender. The order in which each role was played was randomly assigned. Once in a role, participants played 8 rounds before assuming the other role, and then played 8 more rounds of the game. Thus, the data comprised 8 rounds of 5 decisions each for 66 participants, for a total of 2,640 recommender decisions and an equal number of consumer decisions.

To prevent participants from learning whether a particular state of the world was more likely, the experimental software randomly selected one product attribute as better or worse than that of competing products (better, worse, or equal in the trichotomous case). Thus, the stimuli for the experiment featured all possible states of the world. Since we were interested in situations where products (or, in the biased-recommender condition, target products) were dominated on the more-important attribute and dominant on the less-important attribute, our target stimuli for recommenders were products that captured the state of the world: $w = \{A_i^H < A_{-i}^H, A_i^L > A_{-i}^L\}$. Stimuli for consumers were generated endogenously by the recommender's decision. As with the case of the recommender, the target stimulus for consumers was a recommendation based on the less-important attribute.

To summarize, the design was expertise (novice/expert) by bias (unbiased/biased) by processing strategy (dichotomous/trichotomous) between subjects design, with 8 rounds of 5 product recommendations, while the role (recommender/consumer) was a within-subjects manipulation. Participants were randomly assigned to the experimental conditions.

Analysis

Before describing the consumer choice and recommendation results, we report that an analysis of brand preference prior to recommendation showed no statistically significant preference for any brand name ($p > .40$). Thus, brand preferences are unlikely to systematically influence the reported results.

Consumer decisions. We modeled the recommender's decision using a Generalized Estimating Equation (GEE) model, an extension of the standard Generalized Linear Models that accounts for the possibility of unknown correlations between outcomes. This makes the model flexible enough to handle unmeasured dependence between outcomes, and consequently appropriate for longitudinal (panel) data analysis (Diggle et al. 2002).[10]

The expectation of consumer response is given by:

(12) $$y_{bes,t} = \alpha_{bes}^{C} + \beta_{bes}^{C}(t-1),$$

where y_{bes} is the consumer likelihood-to-buy rating given a product recommendation based on the less-important attribute by a recommender of a certain type (indexed by b = *bias*, e = *expertise*, s = processing strategy), t is the time (period), and β_{bes}^{C} is the trend coefficient for consumers. The parameter α_{bes}^{C} is a fixed effect for consumers, which is further decomposed according to the expressions in Propositions 1 to 4. For instance, if the recommender is an unbiased novice in the dichoto-

[10]A robustness check of the estimated results was performed by running a random coefficient model with a random factor that captured individual and time specific heterogeneity, including the autoregressive effect of error terms. This model is similar to Lindstrom and Bates (1990) which was shown to be adequate for repeated measures analyses. The results are very similar to those in Table 2, with a small reduction in standard errors, owing to the variance being soaked up by the random element. An additional reason for reporting the GEE estimation results is that the same procedure can be employed to estimate the binary logistic model that captures the recommenders' decisions.

mous condition, then $\alpha^{C}_{bes} = 1 - \frac{\rho_{bes}}{2}$. This allows us to estimate the overall effect of recommender type on consumer decisions, and also to estimate the parameter ρ_{bes} from the data as a latent variable. The estimates are reported in Table 2.

Recalling Table 1, it is notable that in three of the conditions, predictions depend on the magnitude of the attribute-importance parameter. For these conditions, we allowed for heterogeneous consumer perceptions of ρ_{bes} by estimating parameters for two different segments. We performed this segmentation by computing the maximum likelihood that a respondent belonged to a given segment. As a robustness check, we also provide the overall likelihood-to-buy ratings as estimated by the model with no period trend parameter. Notice that, in fact, there were no statistically significantly changes in the ratings across periods (all β^{C}_{bes} coefficients are non-significant).

Insert Table 2 about here

Recommender decisions. We modeled recommender decisions using a logistic linear model following the GEE approach for longitudinal data analysis described above. The expectation of recommender decisions is given by the relationship:

$$(13) \qquad \ln\left(\frac{P_{ebsm,t}}{1 - P_{ebsm,t}}\right) = \alpha^{R}_{besm} + \beta^{R}_{besm}(t-1),$$

where $P_{ebsm,t}$ represents the probability for sending certain type of recommendation, α^{R}_{besm} is the fixed effect for each condition, t is the period, and β^{R}_{besm} captures the effect of the recommenders learning about the effectiveness of each message across periods. The index m identifies the message sent by the recommender.

In this specification, statistically significantly values above (below) zero indicate the likelihood of observing a decision that was statistically significantly higher (smaller) than chance level (50%). Values that do not statistically significantly differ from zero indicate the likelihood of observing a decision at about chance level. The estimates are reported in Table 3.[11]

For recommender decisions that exhibit significant changes across periods, the results from

[11]Robustness checks performed were similar to those for the consumer decision model. The results of these analyses resemble those in Table 3.

the last period (period 8) are reported in Table 4. When β^{R}_{besm} is not statistically significant, the results from the intercept parameter can be used to empirically investigate the respondent's choice. As a robustness check, Table 3 also provides overall cell probabilities, generated by using a logistic analysis without a time trend parameter (but controls for serial dependency using the GEE method).

Insert Tables 3 and 4 about here

Discussion of Dichotomous Results

Overall, the results for the recommender's recommendations and consumers' responses in the dichotomous conditions aligned nicely with the theoretical predictions. The results are described in greater detail below.

Unbiased-novice condition. When consumers received a recommendation from an unbiased-novice recommender, the average likelihood to buy the recommended product was statistically significantly higher than the 50% chance level (M = 64.553%; σ = 3.382, p < .01).
For recommenders, the lack of statistical significance of α^{R}_{bes} for messages based on the more-important attribute ($\alpha^{R}_{bes\_more}$ = 0.097; σ = 0.446, p > .10) and the less-important attribute ($\alpha^{R}_{bes\_less}$ = -0.257; σ = 0.451, p > .10) showed that these decisions did not differ from the chance level. Conversely, the decision to forgo sending a recommendation was negative and statistically significant ($\alpha^{R}_{bes\_none}$ = -3.355; σ = 0.948, p < .01). The trend parameters β^{R}_{bes} did not reach statistical significance (all with p > .10), indicating a lack of carryover effects, or change in playing strategies over time. The overall cell probabilities further confirmed that respondents were indifferent about recommending a product based on the more- or the less-important attribute (neither differed statistically significantly from 50%), and chose not to forgo sending a message (statistically significantly below 50%). These results are fully consistent with the prediction (cell 1 in Table 1) that recommenders would have an even chance (50%) of recommending a product based on less-important attributes, and that given such a message, the likelihood of consumers buying the recommended product would increase.

Unbiased-expert condition. The theoretical model allows for only a coarse prediction of how consumers would react when they received a recommendation based on the less-important attribute from an unbiased expert (see discussion in the proof of Proposition 1). Nevertheless, a small number of such recommendations were empirically verified, which we report for the sake of completeness: The data showed that consumers were indifferent about the two brands (M = 50.607%; σ = 7.907, $p > .10$). A theoretically sound explanation for these observations is that consumers did not update their posteriors given the "out of equilibrium" message.

For recommenders, all parameters α^{R}_{bes} were statistically significantly different from chance (50%), and the values of these parameters were consistent with the predictions. Recommenders chose to provide information based on the more-important attribute ($\alpha^{R}_{bes\_more}$ = 1.519; σ = 0.438, $p < .01$), and neither to provide information on the less-important attribute ($\alpha^{R}_{bes\_less}$ = -2.564; σ = 0.612, $p < .01$) nor forgo sending a message ($\alpha^{R}_{bes\_none}$ = -2.108; σ = 0.502, $p < .01$). The only statistically significant trend involved recommendations based on the less-important attribute, which showed a small increase over time ($\beta^{R}_{bes\_less}$ = 0.208; σ = 0.125, $p < .05$). Because this trend was statistically significant, we analyzed the outcomes in the last period (see Table 3). These results show that despite some small differences, recommenders continued to recommend a product by communicating information about the more-important attribute ($\alpha^{R}_{bes\_more,\, last\_period}$ = 0.868; σ = 0.384, $p < .05$), but chose not to provide information about the less-important attribute ($\alpha^{R}_{bes\_less,\, last\_period}$ = -1.107; σ = 0.434, $p < .01$) or to forgo sending a message ($\alpha^{R}_{bes\_none,\, last\_period}$ = -2.544; σ = 0.547, $p < .01$). Consistent with the theoretical predictions (cell 2 in Table 1), the overall choice probabilities in the last period confirmed that recommenders chose to send messages based on the more-important attribute (statistically significantly above 50%), while avoiding the other two strategies (statistically significantly below 50%).

Biased-novice condition. When consumers received a recommendation from a biased novice recommender, predictions depended on the magnitude of ρ. In this condition, we identified two consumer segments who rated the importance of each attribute as different from one another. In one segment, the magnitude of ρ_{bes} was moderately large ($\rho_{moderate}$ = 0.845; σ = 0.077, p < .01) and consumer choices did not differ statistically significantly from the 50% chance level ($M_{moderate}$ = 46.972%; σ = 3.47, p > .10). In the other segment, the magnitude of ρ_{bes} was very large (ρ_{large} = 0.999; σ = 0.052, p < .01), and the likelihood of consumers buying the product was statistically significantly below the 50% chance level (M_{large} = 33.812%; σ = 11.72, p < .01).

For both segments, the recommender was more likely to recommend based on the less-important attribute than any other decision: a recommendation based on the less-important attribute was either above or at the 50% chance level, whereas other types of recommendation were all statistically significantly below chance level. These results are in line with the theoretical predictions (cell 3 in Table 1).

Biased-expert condition. When consumers received a recommendation from a biased expert recommender, their average likelihood of buying the target product was statistically significantly lower than the 50% chance level (overall rate = 30.465%; σ = 6.036, p < .01).

Initially, recommenders attempted to influence consumers to buy the target product by sending recommendations based on the less-important attribute ($\alpha^R_{bes\_less}$ = 0.794; σ = 0.411, p < .01). They did not send messages based on the more-important attribute ($\alpha^R_{bes\_more}$ = -2.537; σ = 0.690, p < .01) nor forgo sending a message ($\alpha^R_{bes\_none}$ = -0.944; σ = 0.420, p < .01). However, the statistical significances of the trend parameter showed a decline in the trend of sending messages based on the less-important attribute ($\beta^R_{bes\_less}$ = -0.658; σ = 0.160, p < .01) and an increase in the trend of forgoing sending a message ($\beta^R_{bes\_none}$ = 0.507; σ = 0.133, p < .01). This pattern of data is consistent with recommenders' choices converging to the optimal theoretical predictions. During the last period (Table 4), recommenders avoided sending messages based on the more-important attribute ($\alpha^R_{bes\_more,\ last\_period}$ = -2.345; σ = 0.784, p < .01), ceased sending a message based on the less-important attribute ($\alpha^R_{bes\_less,\ last\_period}$ = -3.810; σ = 0.869, p < .01), and opted to forgo sending a message ($\alpha^R_{bes\_none,\ last\_period}$ = 2.607; σ = 0.664, p < .01). This result is corroborated by the choice probabilities that show recommenders chose to forgo sending a message (statistically significantly above 50%), and avoided the other two strategies (statistically significantly below 50%). These results indicate that recommenders initially attempted to persuade consumers with a recommendation based on the less-important attribute. As predicted, however, consumers formed the (out-of-equilibrium) belief that a recommendation based on the less-important attribute reveals the product to be inferior on the more-important attribute, and thus inferior overall. Consequently, recommenders adjusted their recommendation strategy and converged to the theoretical prediction, i.e., they forwent sending a message (cell 4 in Table 1).

Discussion of Trichotomous Results

Unbiased-novice condition. When consumers received a recommendation from an unbiased novice recommender, the likelihood to buy the recommended product was statistically significantly higher than the 50% chance level (M = 63.922%; σ = 1.399, p < .01), as predicted. For recommenders, the lack of significance on the intercept parameter showed that responses based on either the more- ($\alpha^{R}_{bes\_more}$ = 0.127; σ = 0.333, p > .10) or less-important attribute ($\alpha^{R}_{bes\_less}$ = -0.419; σ = 0.330, p > .10) did not differ from chance level. The decision to forgo providing advice was statistically significant ($\alpha^{R}_{bes\_none}$ = -2.493; σ = 0.653, p < .01). The overall cell probabilities further confirm that respondents were indifferent about recommendations based on the more- and less-important attributes (neither differed statistically from 50%), and decided not to forgo sending a message (statistically significantly below 50%).

These results are fully consistent with our predictions (cell 5 in Table 1) that recommenders would have an even chance (50%) of recommending based on the less-important attribute, and that given such a message, consumer likelihood to buy would increase.

Unbiased-expert condition. In contrast with the dichotomous case, consumer reactions to the recommendation of an unbiased expert can be theoretically predicted in the trichotomous case. The experimental results supported the prediction: likelihood to buy the target product was statistically significantly higher than the 50% chance level (M = 60.354%; σ = 4.228, p < .01).

For recommenders, all the intercepts are statistically significant and in the predicted direction.

Recommenders chose to provide information based on the more-important attribute ($\alpha^R_{bes\_more}$ = 0.870; σ = 0.457, $p < .05$), and not to provide information based on the less-important attribute ($\alpha^R_{bes\_less}$ = -0.886; σ = 0.462, $p < .05$) or forgo sending a message ($\alpha^R_{bes\_none}$ = -5.600; σ = 1.865, $p < .01$). The overall choice proportions of the last period confirm that recommenders chose to send messages based on the more-important attribute (statistically significant above 50%), and avoided the other two strategies (statistically significant below 50%). These results fully support our theoretical predictions (cell 6 in Table 1).

Biased-novice condition. For consumers, predictions depended on the magnitude of ρ. We identified two segments of consumers with different perceptions about the relative importance of attributes. In one segment, the magnitude of ρ_{bes} was moderately high (ρ_{moderate} = 0.816; σ = 0.102, p <.01) and consumer responses were not statistically significantly different from the 50% chance level (M_{moderate} = 55.416%; σ = 2.81, p >.10). In the other segment, the magnitude of ρ_{bes} was very large (ρ_{large} = 0.999; σ = 0.114, $p < .01$) and the likelihood to buy decreased significantly (M_{large} = 34.804%; σ = 3.22, $p < .01$).

For both segments, the recommender was more likely to recommend based on the less-important attribute (both intercepts were statistically significantly higher than the 50% chance level) than employ any other strategy (all other decisions were statistically significantly below the 50% chance level). These results fully support the predictions in cell 7 of Table 1.

Biased-expert condition. Since predictions depended on the magnitude of the attribute-importance parameter ρ, we divided consumers in two segments. In one segment, the magnitude of ρ_{bes} was moderately large (ρ_{moderate} = 0.603; σ = 0.027, p <.01) and consumer responses were statistically significantly different from the 50% chance level (M_{moderate} = 54.917%; σ = 1.34, p <.05). Recommenders matched with these consumers were more likely to send a recommendation based on the less-important attribute than any other option ($M_{\text{moderate\_less}}$ = 64.138% is statistically significantly greater than both $M_{\text{moderate\_more}}$ = 29.993% and $M_{\text{moderate\_none}}$ = 6.762% – both p values $\leq$ .01). In the other segment, the magnitude of ρ_{bes} was large (ρ_{large} = 0.835; σ = 0.034, $p < .01$) and responses were not statistically significantly different from chance level (M_{large} = 50.753%; σ = 2.374, p > .05). Recommenders matched with these consumers were more likely to forgo sending a recommendation than sending other message ($M_{\text{large\_none}}$ = 53.605% is statistically significantly greater than both $M_{\text{large\_more}}$ = 19.686% and $M_{\text{moderate\_less}}$ = 27.458% – both p values < .01).

These results are in-line with the theoretical predictions (cell 8 of Table 1) that relatively low values of ρ_{bes} are associated with higher likelihood that a recommender will send a weak USP recommendation and that consumers will buy the product, while the converse behavior is more likely to happen for relatively low values of ρ_{bes}. The lack of statistical significance for the trend parameters β^{C}_{bes} and β^{R}_{besm} indicated there was no change in playing strategies over time.

CONCLUSION

This paper investigates marketers' use of weak USPs via non-interactive communication channels to recommend products. We identify how the bias and expertise of the recommender and the consumer processing strategy jointly determine when such a messaging strategy is viable. The multi-method research approach follows the framework of strategic information disclosure for verifiable messages, and extends the literature by (*a*) considering that the recommender may be strategic in disclosing messages about attributes of varying importance; (*b*) investigating recommenders with varying knowledge about the importance of the attributes; and (*c*) considering consumers who form inferences about non-disclosed attributes according to two information-processing strategies: a focus on *differences* (dichotomous) or a focus on *differences and similarities* (trichotomous). We tested these theoretical predictions using a behavioral economics experiment that allowed for a sequential interaction between participants playing the roles of recommender and consumer.

The results produced answers to our three research questions. First, we found that consumers may react positively and negatively to a weak USP, depending on the type of recommender. For instance, consumers will be more likely to buy a recommended product when the recommender is an unbiased novice, but more likely to prefer the competing product when the recommender is a biased expert. Second, we found that the consumers' processing strategy affects how consumers react to recommendations. Responses to weak USPs are generally less negative (and may even be positive) when products are believed to have similar performance on non-disclosed attributes. Third, we found that the dyad recommender characteristics and consumer processing strategy jointly determine the recommender's optimal messaging strategy, as described below.

In general, the expert recommender optimal strategy involves refraining from sending a weak USP, regardless of bias. However, the overall profiles of strategies may differ: an unbiased expert will always send a strong USP for the product that dominates on the important attribute since this is the most efficient way to help consumers, but a biased expert will withhold sending a message because any truthful message could increase the likelihood that consumers will buy the competing product. The only exception is when consumers adopt a trichotomous processing strategy (focusing on both similarities and differences) and the difference in importance between attributes is small. In such cases, the biased expert may risk possible negative inferences regarding the more important attribute to gain assured dominance of the less-important attribute. We also found that the optimal strategy of an unbiased novice is to always make a recommendation (either weak or strong USP). This was expected since any recommendation will increase the probability that consumers will buy the best product. On the other hand, the optimal strategy for a biased novice is to recommend the target product (using weak or strong USP). This was surprising, given that a biased novice is aware that a weak USP causes negative consumer response. The rationale for this strategy is that sometimes the recommender needs to bank on the *ex-post* chance of sending a strong USP.

Managerial and Policy Implications

Our research shows that firms must take into account many issues when communicating information to consumers, especially when their products dominate only on lesser-important attributes, as judged by the target market. In such situations, firms should pay careful attention to who recommends their products. Common wisdom suggests that firms should hire knowledgeable people to recommend or endorse products. To illustrate, the website Celebrity Healthlink claims that it helps companies "find and hire a medical expert or celebrity as a health product endorser or media product spokesperson" with the objective of creating "credible, performance-driven endorsements." Our findings indicate that under certain conditions, a novice recommender will be more persuasive than an expert, particularly if consumers deem the recommender to be biased.

Our results also show that when a recommender is biased, consumers will be less likely to buy the product after receiving a weak USP message than if no information were received at all. Recommendation from a biased sender are only beneficial for a firm when consumers believe undisclosed attributes of the product would perform equally well, and when the dominance of a more-important attribute over a less-important attribute is only marginal. Therefore, a firm should not blindly disclose information that favors its product over competing products. Under certain conditions, withholding information may be the better strategy. We do not mean to imply that a firm should avoid promoting its products, but rather that other forms of promotional activities (such as advertisements that focus on symbolic or affective benefits) may be more profitable.

Finally, the findings of this research may provide insights to policymakers. Bustillo and Zimmerman (2009) report that some government agencies have focused on tightening regulation of Internet-based product recommendations, given the proliferation of bloggers who receive compensation to promote products on their websites. These regulators have proposed that firms and bloggers be held accountable for misleading claims, and that paid bloggers disclose when they receive compensation to promote a product (i.e., disclose their degree of bias). Although such regulations are steps toward improving consumer welfare, our research suggests that the disclosure of recommender characteristics such as expertise should be considered, since they may shape recommender and consumer behavior in important ways.

Caveats and Future Research

Our model assumes that consumers know the true characteristics of a recommender, but we acknowledge there may be times when this is not the case. Our predictions must therefore be governed by what consumers perceive the expertise and bias of the recommender to be. One example is the “Anything Goes Deal” promotional campaign that was conducted by Domino’s Pizza, where the company released a series of videos on YouTube to surreptitiously call attention to its $9.99 pizza (PR Newswire 2007). In this situation, a biased recommender could be perceived to be unbiased and, as a result, consumer behavior predictions might follow those for an unbiased recommender. As stated in the setup, the qualitative results of the model do not change when consumers are not completely sure of a recommender’s characteristics and can only make a probabilistic assessment of her level of bias and expertise. In such cases, the magnitude of the effects would be attenuated, but the directional effects would remain in line with consumer beliefs about a recommender's characteristics.

From the recommender standpoint, the model assumes that consumer processing strategy is known by both recommender and consumer. One might ask what would happen if consumers used a different processing strategy than the one expected by the recommender. In a single-shot interaction, players would follow optimal strategies for what they believe to be in operation, regardless of the actual processing strategy followed by most consumers in the market.

If the game were to be repeated, however, then, according to *ex-post* outcomes, results could change depending on observed outcomes. If different beliefs about processing strategies are inconsequential to the equilibrium outcome, players should not change their strategies. If players observed a result different than the one expected for an assumed processing strategy, they might revise their beliefs about a consumer processing strategy and adjust their play in subsequent periods. Given enough periods, players' beliefs would converge to the "true value" and reach a stationary equilibrium (see Aumann and Heifetz 2002, p. 1671). Because we obtained empirical support for our theoretical predictions, this caveat should not detract from the merit of our research.

In the theoretical model, we assumed that the relative importance of attributes was the same for all consumers. If consumers had heterogeneous perceptions of attribute importance, the qualitative results of the model would not change, provided that perceptions were not diffuse. To improve our understanding of the impact of such perceptions on equilibrium messaging behavior, further research could investigate scenarios in which consumer perceptions are diffuse. Nevertheless, because importance of attribute was modeled as a probabilistic parameter, our model may be seen as accommodating two heterogeneous groups of consumers (one that gives more importance to one subset of attributes, and one that gives more importance to other attributes).

We also considered a firm's choice of recommender type not to be rationalized by consumers. Our empirical results do not show evidence of this highly sophisticated rational strategy. However, future studies may wish to investigate situations in which the adoption of such a strategy occurs.

Finally, our research focused on two key recommender characteristics. Follow-up studies of attribute-based product recommendations might investigate how recommender characteristics such as likability and trustworthiness of the source of the message. Another interesting element would be the effect of a recommender's history of past messages on subsequent recommendations for the same or different brands.

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Table 1 - Testable implications of the model

Processing Strategy	Recommender type	Player	Testable implication	Cell
Dichotomous	Unbiased Novice	Recommender	Even chance (50%) to recommend based on the less-important attribute	1
		Consumer	Likelihood to buy increases	
	Unbiased Expert	Recommender	Unlikely to recommend based on the less-important attribute	2
		Consumer	Any change except for a large increase in the likelihood to buy	
	Biased Novice	Recommender	Likely to recommend the target product	3
		Consumer	If ρ is small: likelihood to buy increases moderately If ρ is large: likelihood to buy decreases moderately	
	Biased Expert	Recommender	Likely to forgo sending a recommendation	4
		Consumer	Likelihood to buy decreases greatly	
Trichotomous	Unbiased Novice	Recommender	Even chance (50%) of recommending based on the less-important attribute	5
		Consumer	Likelihood to buy increases	
	Unbiased Expert	Recommender	Unlikely to recommend based on the less-important attribute	6
		Consumer	Likelihood to buy increases greatly	
	Biased Novice	Recommender	Likely to recommend the target product	7
		Consumer	If ρ is small: likelihood to buy increases moderately If ρ is large: likelihood to buy decreases moderately	
	Biased Expert	Recommender	If ρ is small: likely to recommend the target product If ρ is large: likely to forgo sending a recommendation	8
		Consumer	If ρ is small: likelihood to buy increases moderately If ρ is large: likelihood to buy decreases moderately	

Table 2 – Consumers' Decisions Estimates

Processing Strategy	Recommender Type	Estimated ρ_{bes} Parameter	S.D.	Intercept α^{C}_{bes} Parameter	S.D.	Period β^{C}_{bes} Parameter	S.D.	Overall Choice Ratings Parameter	S.D.
Dichotomous	Unbiased Novice	0.709**	0.051	66.956**	5.523	-0.714	1.298	64.553**	3.382
	Unbiased Expert	0.720**	0.072	51.420	8.736	-0.212	0.919	50.607	7.907
	Biased Novice	0.795** 0.993**	0.052 0.176	56.362 30.805**	5.021 8.887	-2.780 0.919	1.195 2.146	46.972 33.812**	3.205 5.430
	Biased Expert	0.695**	0.028	34.860**	6.320	-3.640	2.940	30.465**	6.036
Trichotomous	Unbiased Novice	0.721**	0.044	63.394**	2.429	0.153	0.574	63.922**	1.399
	Unbiased Expert	0.792**	0.124	66.067**	5.975	-1.648	1.140	60.354**	4.228
	Biased Novice	0.743** 0.999**	0.047 0.054	52.903 32.176**	5.208 4.845	0.668 0.740	1.201 1.120	55.416* 34.804**	2.635 2.859
	Biased Expert	0.603** 0.835**	0.027 0.034	58.530* 50.741	3.478 3.214	-1.169 0.004	1.216 0.786	54.917* 50.753	1.337 2.374

Note:

* $p \leq .05$, ** $p \leq .01$. Number of observations = 886.

Significances are with respect to chance level (ratings significantly different from 50%).

Estimates for the Intercept (α^{C}_{bes}), Period (β^{C}_{bes}), and Overall Choice Ratings are reported as percentages.

Table 3 – Recommenders' Decisions

Processing Strategy	Recommender Type		Recommender Decision	Intercept α^R_{besm} Parameter	S.D.	Period β^R_{besm} Parameter	S.D.	Overall Cell Probability (%) Parameter	S.D.
Dichotomous	Unbiased Novice		More	0.097	0.446	-0.012	0.107	51.450	6.312
			Less	-0.257	0.451	0.045	0.108	47.402	6.366
			None	-3.355**	0.948	-0.447	0.413	1.199**	1.191
	Unbiased Expert		More	1.519**	0.438	-0.093	0.097	76.423**	3.906
			Less	-2.564**	0.612	0.208*	0.125	14.517**	3.845
			None	-2.108**	0.502	-0.062	0.124	8.883**	2.613
	Biased Novice	ρ: .795	Bias	1.985**	0.402	-0.088	0.090	84.087**	4.611
			Other	-3.090**	0.737	-0.250	0.237	2.201**	1.401
			None	-2.380**	0.472	0.144	0.111	13.707**	3.558
		ρ: .993	Bias	0.196	0.423	0.041	0.102	58.281	10.795
			Other	-1.542**	0.554	0.053	0.128	20.524**	4.126
			None	-0.937*	0.505	-0.118	0.130	21.130**	7.134
	Biased Expert		More	-2.537**	0.690	0.027	0.175	7.929**	3.527
			Less	0.794*	0.411	-0.658**	0.160	31.735*	8.205
			None	-0.944*	0.420	0.507**	0.133	60.826	9.856
Trichotomous	Unbiased Novice		More	0.127	0.333	-0.041	0.081	49.675	4.614
			Less	-0.419	0.330	0.047	0.080	43.610	4.491
			None	-2.493**	0.653	-0.039	0.165	6.748**	2.804
	Unbiased Expert		More	0.870*	0.457	0.155	0.125	79.134**	4.470
			Less	-0.886*	0.462	-0.187	0.131	19.338**	5.250
			None	-5.600**	1.865	0.348	0.346	1.566**	1.538
	Biased Novice	ρ: .743	Bias	3.430**	1.148	-0.301	0.212	88.827**	5.043
			Other	-4.665**	1.840	0.247	0.341	2.746**	1.868
			None	-3.843**	1.434	0.324	0.259	8.832**	3.337
		ρ: .999	Bias	1.105*	0.641	-0.044	0.148	72.122*	10.326
			Other	-2.885**	1.229	-0.616	0.680	1.545**	1.183
			None	-1.349*	0.708	0.091	0.159	26.457*	10.896
	Biased Expert	ρ: .603	More	-0.833	0.817	-0.005	0.191	29.993	11.837
			Less	0.322	0.736	0.084	0.181	64.138	14.360
			None	-2.063**	0.782	-0.219	0.262	6.762**	3.475
		ρ: .835	More	-1.025*	0.519	-0.122	0.138	19.686**	5.118
			Less	-0.381	0.392	-0.192	0.108	27.458**	4.899
			None	-0.596	0.381	0.226*	0.097	53.605	5.474

Note:

* $p \le .05$, ** $p \le .01$. Number of observations = 1312.

Significances are with respect to chance level (significantly different from zero in the Intercept and Period cells, and significantly different from 50% in the Overall Cell Probabilities cells).

Table 4 – Last Period Recommender's Decisions for the conditions with Statistically Significant Changes across Periods

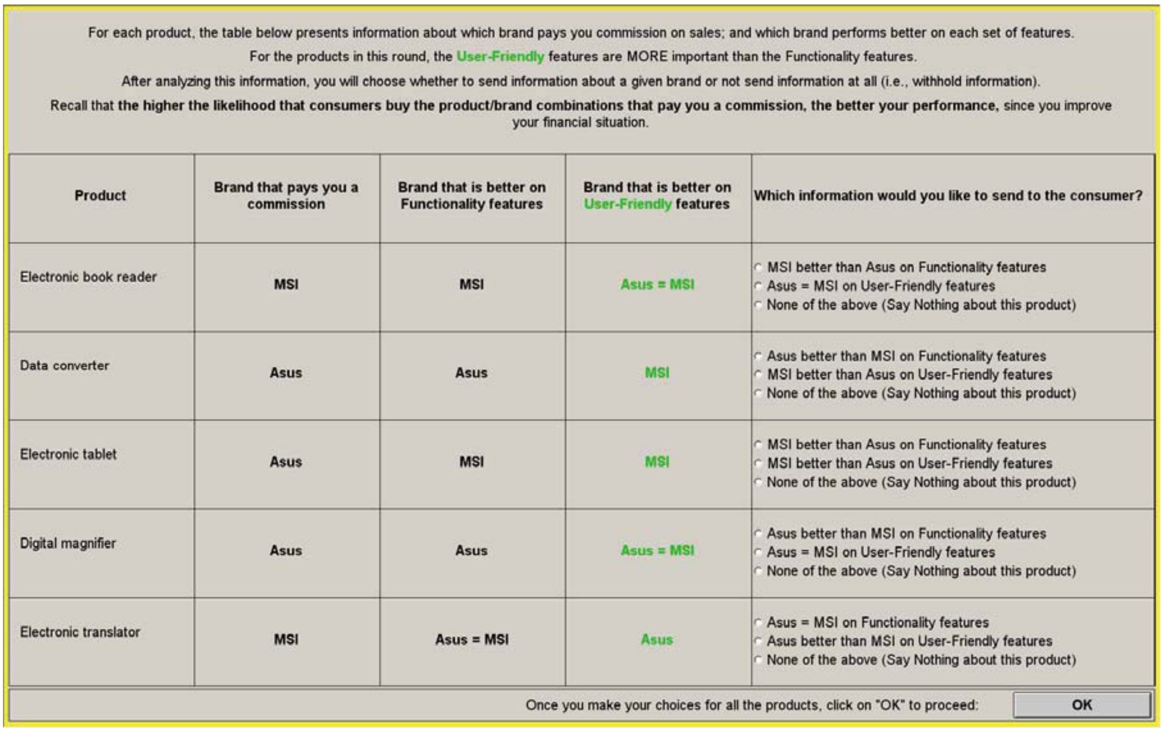
Processing Strategy	Recommender Type	Recommender Decision	Last Period Log Odds		Last Period Cell Probabilities (%)	
			Parameter	S.D.	Parameter	S.D.
Dichotomous	Unbiased Expert	More	0.868*	0.384	70.4*	7.33
		Less	-1.107**	0.434	24.8**	8.94
		None	-2.544**	0.547	7.3**	4.67
	Biased Expert	More	-2.345**	0.784	8.7**	8.60
		Less	-3.810**	0.869	2.2**	2.85
		None	2.607**	0.664	93.1**	3.21

Note:

* $p \leq .05$, ** $p \leq .01$. Number of observations = 205.

Significances are with respect to chance level (significantly different from zero in the Log Odds cells, and significantly different from 50% in the Cell Probabilities cells).

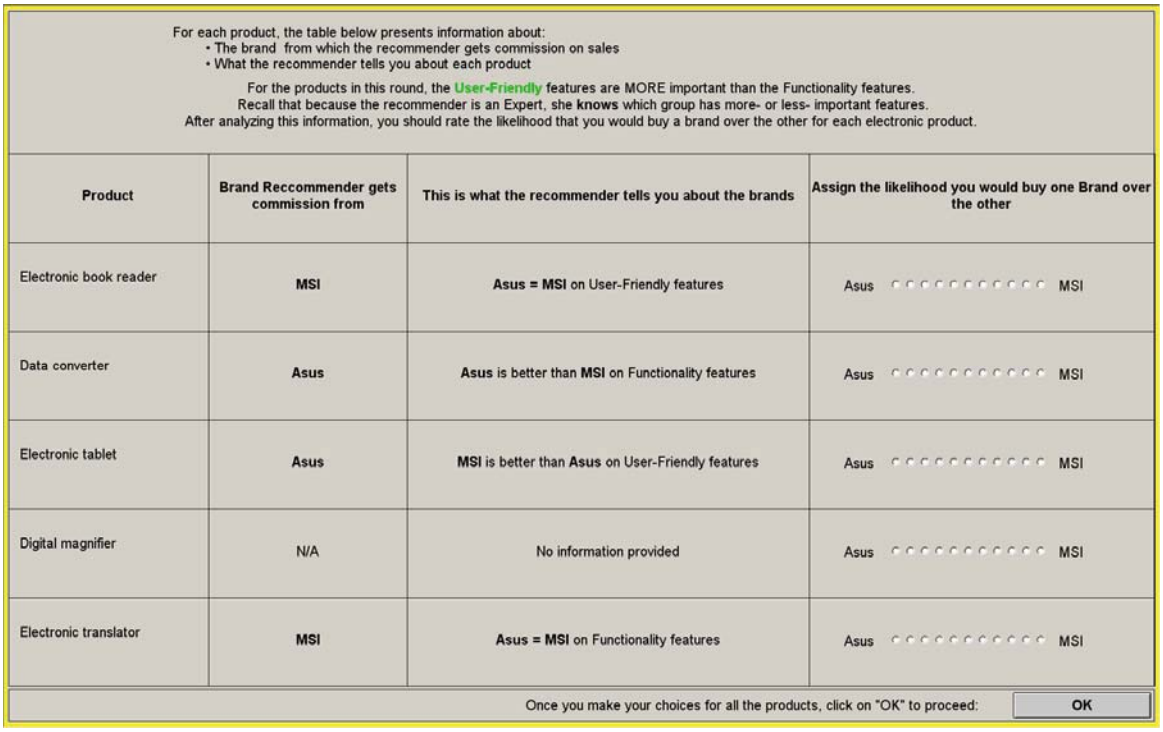
Figure 2 - Example of Recommender and Consumer Stimuli



For each product, the table below presents information about which brand pays you commission on sales; and which brand performs better on each set of features.
For the products in this round, the User-Friendly features are MORE important than the Functionality features.
After analyzing this information, you will choose whether to send information about a given brand or not send information at all (i.e., withhold information).
Recall that **the higher the likelihood that consumers buy the product/brand combinations that pay you a commission, the better your performance**, since you improve your financial situation.

Product	Brand that pays you a commission	Brand that is better on Functionality features	Brand that is better on User-Friendly features	Which information would you like to send to the consumer?
Electronic book reader	MSI	MSI	Asus = MSI	MSI better than Asus on Functionality features Asus = MSI on User-Friendly features None of the above (Say Nothing about this product)
Data converter	Asus	Asus	MSI	Asus better than MSI on Functionality features MSI better than Asus on User-Friendly features None of the above (Say Nothing about this product)
Electronic tablet	Asus	MSI	MSI	MSI better than Asus on Functionality features MSI better than Asus on User-Friendly features None of the above (Say Nothing about this product)
Digital magnifier	Asus	Asus	Asus = MSI	Asus better than MSI on Functionality features Asus = MSI on User-Friendly features None of the above (Say Nothing about this product)
Electronic translator	MSI	Asus = MSI	Asus	Asus = MSI on Functionality features Asus better than MSI on User-Friendly features None of the above (Say Nothing about this product)

Once you make your choices for all the products, click on "OK" to proceed: OK



For each product, the table below presents information about:
- The brand from which the recommender gets commission on sales
- What the recommender tells you about each product

For the products in this round, the User-Friendly features are MORE important than the Functionality features.
Recall that because the recommender is an Expert, she **knows** which group has more- or less- important features.
After analyzing this information, you should rate the likelihood that you would buy a brand over the other for each electronic product.

Product	Brand Reccommender gets commission from	This is what the recommender tells you about the brands	Assign the likelihood you would buy one Brand over the other
Electronic book reader	MSI	**Asus = MSI** on User-Friendly features	Asus MSI
Data converter	Asus	**Asus** is better than **MSI** on Functionality features	Asus MSI
Electronic tablet	Asus	**MSI** is better than **Asus** on User-Friendly features	Asus MSI
Digital magnifier	N/A	No information provided	Asus MSI
Electronic translator	MSI	**Asus = MSI** on Functionality features	Asus MSI

Once you make your choices for all the products, click on "OK" to proceed: OK

APPENDIX

A Advertising Screenshots

B Consumers' likelihood to follow the recommendation

We suppress conditioning in this derivation. Since states of the world $w \in W$ are mutually exclusive, we use Expression (2) to write that:

$$P\left(U_i > U_{-i}\right) = \sum_{w \in W} P(\rho\ 1[A_i^H > A_{-i}^H] + \left(1-\rho\right)\ 1[A_i^L > A_{-i}^L] > \rho\ 1[A_{-i}^H > A_i^H] + \left(1-\rho\right)\ 1[A_{-i}^L > A_i^L])\ P(w).$$

We directly compute this probability by imputing the value of the indicator function in each state of the world, verifying the probability that $U_i > U_{-i}$ in that state, and multiplying this probability by the probability of that state.

When consumers adopt a dichotomous processing strategy, this probability is:

$$\begin{aligned}P\left(U_i > U_{-i}\right) &= 1\ P(A_i^H > A_{-i}^H)\ P(A_i^L > A_{-i}^L) + \rho\ P(A_i^H > A_{-i}^H)\ \left(1 - P(A_i^L > A_{-i}^L)\right) \\ &+\ (1-\rho)\ \left(1 - P(A_i^H > A_{-i}^H)\right)\ P(A_i^L > A_{-i}^L) + 0\ \left(1 - P(A_i^H > A_{-i}^H)\right)\left(1 - P(A_i^L > A_{-i}^L)\right) \\ &=\ \rho\ P(A_i^H > A_{-i}^H) + \left(1-\rho\right)\ P(A_i^L > A_{-i}^L).\end{aligned}$$

When consumers adopt a trichotomous processing strategy, this probability is:

$$\begin{aligned}P\left(U_i > U_{-i}\right) &= 1\ P(A_i^H > A_{-i}^H)\ P(A_i^L > A_{-i}^L) + 1\ P(A_i^H > A_{-i}^H)\ P(A_i^L = A_{-i}^L) \\ &+1\ P(A_i^H = A_{-i}^H)\ P(A_i^L > A_{-i}^L) + 0\ \left(1 - P(A_i^H > A_{-i}^H)\right)\left(1 - P(A_i^L > A_{-i}^L)\right) \\ &+0\ P(A_i^H = A_{-i}^H)\ \left(1 - P(A_i^L > A_{-i}^L)\right) + 0\ \left(1 - P(A_i^H > A_{-i}^H)\right)P(A_i^L = A_{-i}^L) \\ &+\rho\ P(A_i^H > A_{-i}^H)\ \left(1 - P(A_i^L > A_{-i}^L)\right) + (1-\rho)\ \left(1 - P(A_i^H > A_{-i}^H)\right)\ P(A_i^L > A_{-i}^L) \\ &+\frac{1}{2} P(A_i^H = A_{-i}^H)\ P(A_i^L = A_{-i}^L).\end{aligned}$$

This probability can be simplified as:

$$\begin{aligned}P\left(U_i > U_{-i}\right) &= \rho\ P\left(A_i^H > A_{-i}^H\right)P\left(A_i^L < A_{-i}^L\right) + (1-\rho)\ P\left(A_i^H < A_{-i}^H\right)P\left(A_i^L > A_{-i}^L\right) + P\left(A_i^H = A_{-i}^H\right)P\left(A_i^L > A_{-i}^L\right) \\ &+P\left(A_i^H > A_{-i}^H\right)\left[P\left(A_i^L > A_{-i}^L\right) + P\left(A_i^L = A_{-i}^L\right)\right] + \frac{1}{2}P\left(A_i^H = A_{-i}^H\right)P\left(A_i^L = A_{-i}^L\right).\end{aligned}$$

C Proof of Lemma 1

When consumers receive a recommendation based on an attribute, the true value of this attribute becomes known with certainty; thus:

$$P\left(A_i^H > A_{-i}^H \mid m = a_i^H > a_{-i}^H, b, e\right) = 1, \quad P\left(A_i^L > A_{-i}^L \mid m = a_i^L > a_{-i}^L, b, e\right) = 1.$$

However, consumers can make inferences about the attribute that was not communicated in the message; hence, they update their priors by applying Bayes' rule:

$$P\left(A_i^H > A_{-i}^H \mid m = a_i^L > a_{-i}^L, b, e\right) = \frac{P\left(m = a_i^L > a_{-i}^L \mid A_i^H > A_{-i}^H, b, e\right) P\left(A_i^H > A_{-i}^H\right)}{P\left(m^A = a_i^L > a_{-i}^L \mid b, e\right)}.$$

$$P\left(A_i^L > A_{-i}^L \mid m = a_i^H > a_{-i}^H, b, e\right) = \frac{P\left(m = a_i^H > a_{-i}^H \mid A_i^L > A_{-i}^L, b, e\right) P\left(A_i^L > A_{-i}^L\right)}{P\left(m^A = a_i^H > a_{-i}^H \mid b, e\right)}.$$

By using the expressions above, one can compute the strategic consumers' perceived probability that the recommended product is better than the competing product. When consumers receive information about A_i^H, the probability is:

$$P\left(U_i > U_{-i} \mid m = a_i^H > a_{-i}^H, b, e\right) = \rho + (1-\rho) \frac{P\left(m = a_i^H > a_{-i}^H \mid A_i^L > A_{-i}^L, b, e\right) P\left(A_i^L > A_{-i}^L\right)}{P\left(m = a_i^H > a_{-i}^H \mid b, e\right)}.$$

When consumers receive the information about A_i^L, this probability is:

$$P\left(U_i > U_{-i} \mid m = a_i^L > a_{-i}^L, b, e\right) = \rho \frac{P\left(m = a_i^L > a_{-i}^L \mid A_i^H > A_{-i}^H, b, e\right) P\left(A_i^H > A_{-i}^H\right)}{P\left(m^A = a_i^L > a_{-i}^L \mid b, e\right)} + (1-\rho). \quad \blacksquare$$

Extraction of Hidden Information from Attribute-Based Product Recommendations

Online Appendix

PROOF OF PROPOSITIONS 1 TO 4

Proof of Proposition 1

We use game theoretical arguments to prove this proposition. We start with the **unbiased-expert recommender**.

Recall that there are four states of the world (in the set W). In each of these states, it is possible to recommend based on A_i^H (it is possible to say either that $m = a_1^H > a_2^H$ or that $m = a_1^H < a_2^H$). Because the recommender does not favor any particular product and because information about A_i^H is more diagnostic than information about A_i^L, the recommender will always recommend the product that is superior in A_i^H. In this case, consumers can use Expression (4) to update the posterior beliefs to: $p\left(U_i > U_{-i} \mid m = a_i^H > a_{-i}^H, b = unbiased, e = expert\right) = \rho\, 1 + \left(1-\rho\right)\, \frac{1}{2} = \frac{1}{2} + \frac{\rho}{2} > \frac{1}{2}$.

Hence, for each state of the world, the expert recommender's optimal message is as follows:

State of the world	Message by an unbiased expert recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m = a_1^H < a_2^H$
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	$m = a_1^H < a_2^H$

Consumers will only expect messages based on A_i^H. A message about A_i^L is out of equilibrium and any out-of-equilibrium beliefs so that:

$$p\left(U_i > U_{-i} \mid m = a_i^H > a_{-i}^H, b = unbiased, e = expert\right) < \frac{1}{2} + \frac{\rho}{2}$$ is admissible.[1]

Now we proceed to the **unbiased-novice recommender**. This recommender does not know

[1] This out-of-equilibrium beliefs follows the very common-sense notion that, on itself, a message about the less-important attribute cannot be more diagnostic than a message about the more-important attribute.

which attribute is more important. Therefore, for each state of the world, the recommender will select A_i^H or A_i^L with probability $\frac{1}{2}\rho+\frac{1}{2}(1-\rho)=\frac{1}{2}$ (i.e, at random with equal probability).

Hence, for each state of the world, the recommender's optimal message is as follows:

State of the world	Message by an unbiased novice recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m=a_1^H > a_2^H$ or $m=a_1^L > a_2^L$ with equal probability
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m=a_1^H > a_2^H$ or $m=a_1^L < a_2^L$ with equal probability
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m=a_1^H < a_2^H$ or $m=a_1^L > a_2^L$ with equal probability
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	$m=a_1^H < a_2^H$ or $m=a_1^L < a_2^L$ with equal probability

Consumers have no basis for updating the value of the less-important attribute due to strategic behavior by the recommender.) Hence, when the recommender recommends based on A_i^L, consumers will only update the value of this attribute and follow the recommendation with probability $\rho\ \frac{1}{2}+\left(1-\rho\right)\ 1=1-\frac{\rho}{2}>\frac{1}{2}$. ■

Proof of Proposition 2

We start with the **biased-expert recommender**. In this scenario, consumers know that $b=biased$ and $e=expert$; thus, for simplicity, we will drop these variables from all conditional probability expressions.

Recall that a small number of consumers do not consider the strategic behavior of the recommender; hence, messages b and e are irrelevant for these consumers and they cannot update the posterior on non-disclosed attributes. For notational purposes we define λ (which is close to zero) to be the proportion of these "naïve" consumers and $P^N\left(\ \cdot\ \mid m,b,e\right)=P\left(\ \cdot\ \mid m\right)$ to be the probability assessment they make. Furthermore, we compute that when naïve consumers receive information about A_i^H, the probability that they would purchase the target product is:

(o1) $$P^N\left(U_i > U_{-i} \mid m=a_i^H > a_{-i}^H, b, e\right)=\rho\ 1+\left(1-\rho\right)\ \frac{1}{2}=\frac{1}{2}+\frac{\rho}{2}>\frac{1}{2}.$$

On the other hand, when they receive information about A_i^L, the probability is:

(o2) $$P^N\left(U_i > U_{-i} \mid m=a_i^L > a_{-i}^L, b, e\right)=\rho\ \frac{1}{2}+\left(1-\rho\right)\ 1=1-\frac{\rho}{2}>\frac{1}{2}.$$

Without loss of generality, consider that the recommender favors product 1. With the above definitions we can rewrite π to be the utility of the recommender according to expression (7) as:

(o3)
$$\pi = \max_{m \in W} \left\{ \lambda \ P^N \left(U_1 > U_2 \mid m \right) + (1-\lambda) P\left(U_1 > U_2 \mid m \right) \right\}.$$

We are interested in knowing the recommender's optimal choice of message, m, and the consumer's belief formation given the recommender's messaging strategy. Recall that there are four states of the world (in the set W). Therefore, the recommender's expected utility, considering all the states of the world, is:

(o4)
$$E\left[\pi\right] = \begin{pmatrix} E\left[\pi \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right] + E\left[\pi \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right] \\ +E\left[\pi \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right] + E\left[\pi \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right] \end{pmatrix} \div 4.$$

The recommender thus maximizes $E\left[\pi\right]$ with respect to m for each state of the world.

Next, consider the consumer's belief formation. $P^N \left(U_1 > U_2 \mid m \right)$ is updated according to expressions (o1) and (o2). $P\left(U_1 > U_2 \mid m \right)$ is updated according to Lemma 1.

When the state of the world is $\{A_1^H > A_2^H, A_1^L > A_2^L\}$, the recommender cannot lie; thus: $P\left(m = a_1^H < a_2^H \mid \{A_1^H > A_2^H, A_1^L > A_2^L\} \right) = 0$ and $P\left(m = a_1^L < a_2^L \mid \{A_1^H > A_2^H, A_1^L > A_2^L\} \right) = 0$. The recommender can send the messages $m = a_1^H > a_2^H$ and $m = a_1^L > a_2^L$ with some probability (the unknown variable we want to determine); hence we define:
$P\left(m = a_1^H > a_2^H \mid \{A_1^H > A_2^H, A_1^L > A_2^L\} \right) \equiv X_1$ and $P\left(m = a_1^L > a_2^L \mid \{A_1^H > A_2^H, A_1^L > A_2^L\} \right) \equiv X_2$. Because the recommender only sends one message, these probabilities are mutually exclusive, and we can write $X_1 = 1 - X_2$.[2]

When the state of the world is $\{A_1^H > A_2^H, A_1^L < A_2^L\}$, due to the "no-lie" assumption, we immediately have $P\left(m = a_1^L > a_2^L \mid \{A_1^H > A_2^H, A_1^L < A_2^L\} \right) = 0$ and

[2] This expression considers that when the product favored by the recommender dominates the other product in both attributes, the recommender will never forego the opportunity to recommend the product; hence $X_1 + X_2 = 1$. This turns out to be true, and for simplicity we are skipping this part of the proof. This statement can be verified by defining a variable F for "forego" and considering that $X_1 + X_2 + F = 1$. After following the same steps we use in the remainder of the proof, one would reach the conclusion that $F = 0$.

$P\left(m = a_1^H < a_2^H \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right) = 0$. Furthermore, because the recommender cannot recommend the “other product” or she will face the worst possible beliefs, we also have $P\left(m = a_1^L < a_2^L \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right) = 0$. Hence, the recommender can only send message $m = a_1^H > a_2^H$ or forego the opportunity (she will not recommend the product); thus we define $P\left(m = a_1^H > a_2^H \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right) \equiv X_3$.

When the state of the world is $\{A_1^H < A_2^H, A_1^L > A_2^L\}$, for the same reasons in the previous paragraph, it is immediately evident that $P\left(m = a_1^H > a_2^H \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$, $P\left(m = a_1^H < a_2^H \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$, and $P\left(m = a_1^L < a_2^L \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$. Therefore, the recommender can only send message $m^A = a_1^L > a_2^L$ or forego the opportunity; thus we define $P\left(m = a_1^L > a_2^L \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) \equiv X_4$.

When the state of the world is $\{A_1^H < A_2^H, A_1^L < A_2^L\}$, the recommender forgoes the opportunity to recommend a product; thus the probability of each message is zero: $P\left(m = a_1^H > a_2^H \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$, $P\left(m = a_1^L > a_2^L \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$, $P\left(m = a_1^H < a_2^H \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$, and $P\left(m = a_1^L < a_2^L \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) = 0$.

Given the above conditional probabilities, the overall probabilities (for all states of the world) that the recommender will speak about an attribute are: $P\left(m = a_1^H > a_2^H\right) = \frac{1 - X_2 + X_3}{4}$, $P\left(m = a_1^L > a_2^L\right) = \frac{X_2 + X_4}{4}$, $P\left(m = a_1^H < a_2^H\right) = 0$, and $P\left(m = a_1^L < a_2^L\right) = 0$.

Furthermore, the probability of receiving a message about one attribute, given the state of the other attribute, are: $P\left(m = a_1^H > a_2^H \mid A_1^L > A_2^L\right) = \frac{1 - X_2}{2}$, $P\left(m = a_1^H > a_2^H \mid A_1^L < A_2^L\right) = \frac{X_3}{2}$, $P\left(m = a_1^L > a_2^L \mid A_1^H > A_2^H\right) = \frac{X_2}{2}$, and $P\left(m = a_1^L > a_2^L \mid A_1^H < A_2^H\right) = \frac{X_4}{2}$.

By plugging these probabilities into Expressions (4) and (5) from Lemma 1, we obtain: $P\left(U_1 > U_2 \mid m = a_1^H > a_2^H\right) = \rho + (1-\rho)\frac{1 - X_2}{1 - X_2 + X_3}$, $P\left(U_1 > U_2 \mid m = a_1^L > a_2^L\right) = \rho\frac{X_2}{X_2 + X_4} + (1-\rho)$.

Now that we know $P^N(U_1 > U_2 \mid m)$ and $P(U_1 > U_2 \mid m)$, we can use Expression (o3) to write the conditional profit expression for all states of the world ($E[\pi \mid w]$ for all $w \in W$):

$$E\left[\pi \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right] = (1-X_2)\left\{\lambda\left(\frac{1}{2}+\frac{\rho}{2}\right)+(1-\lambda)\left[\rho+(1-\rho)\frac{1-X_2}{1-X_2+X_3}\right]\right\}$$
$$+X_2\left\{\lambda\left(1-\frac{\rho}{2}\right)+(1-\lambda)\left[\rho\frac{X_2}{X_2+X_4}+(1-\rho)\right]\right\},$$

$$E\left[\pi \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right] = X_4\left\{\lambda\left(1-\frac{\rho}{2}\right)+(1-\lambda)\left[\rho\frac{X_2}{X_2+X_4}+(1-\rho)\right]\right\}+(1-X_4)\frac{1}{2},$$

$$E\left[\pi \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right] = X_3\left\{\lambda\left(\frac{1}{2}+\frac{\rho}{2}\right)+(1-\lambda)\left[\rho+(1-\rho)\frac{1-X_2}{1-X_2+X_3}\right]\right\}+(1-X_3)\frac{1}{2},$$

$$E\left[\pi \mid \{A_1^H < A_2^H, A_1^L < A_2^L\}\right] = \frac{1}{2}.$$

Now we are ready to maximize $E[\pi]$ (Expression (o4)) with respect to the unknown probabilities X_2, X_3, and X_4. It is sufficient to inspect the First Order Conditions:

The derivative $\frac{\partial E[\pi]}{\partial X_2} = -\frac{(2\rho-1)\lambda}{8}$ is negative; thus $X_2^* = 0$ and $X_1^* = 1 - X_2^* = 1$. The derivative $\frac{\partial E[\pi]}{\partial X_3} = \frac{\rho\lambda + (2\rho-1)(1-\lambda)}{8}$ is positive; thus $X_3^* = 1$. Lastly, the derivative $\frac{\partial E[\pi]}{\partial X_4} = \frac{(1-\rho)\lambda + (1-2\rho)(1-\lambda)}{8}$ is negative because λ is a very small number; hence, $X_4^* = 0$.

Thus, for each state of the world, the recommender's optimal message is as follows:

State of the world	Message by a biased expert recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	"no message"
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	"no message"

Therefore, a message about A_1^L is out of equilibrium. To compute consumers' reaction if they were to receive such an out-of-equilibrium message, we "force" $X_4 = 1$, which would imply that $P\left(m = a_1^L > a_2^L \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) \equiv X_4 = 1$, and consequently it would reveal that the target product is dominated in the more important attribute. This would be consistent with consumers forming out-of-equilibrium beliefs of $P\left(U_1 > U_2 \mid m^A = a_1^L > a_2^L\right) = \rho\ 0 + (1-\rho)\ 1 = (1-\rho)$.

Now we proceed to the **biased-novice recommender**. This type of recommender does not know which attribute is more important. Thus she perceives the utility of the products as follows:

$$E\left[U_i\right] = \frac{\rho\ A_i^H + (1-\rho)\ A_i^L}{2} + \frac{(1-\rho)\ A_i^H + \rho\ A_i^L}{2} = \frac{A_i^H + A_i^L}{2} \qquad \text{for } i = 1,2.$$

By recognizing that the above expression is <u>mathematically identical</u> to the utility expectations for the Biased Expert Recommender when $\rho = \frac{1}{2}$ (i.e., $\frac{A_i^H + A_i^L}{2} = \frac{1}{2} A_i^H + \left(1 - \frac{1}{2}\right) A_i^L$), we can bypass the steps in the proof of proposition 3 and directly plug the value $\rho = \frac{1}{2}$ into the first-order conditions of the Biased Expert Recommender's problem and determine that:

The derivative $\frac{\partial E[\pi]}{\partial X_2} = 0$; thus the recommender is indifferent to selecting any number for X_2 and consequently for X_1. This implies that she will speak about each attribute at random, with equal probability ($X_1^* = X_2^* = 1/2$). The derivative $\frac{\partial E[\pi]}{\partial X_3} = \frac{\lambda}{16}$ is positive; thus $X_3^* = 1$. Lastly, the derivative $\frac{\partial E[\pi]}{\partial X_4} = \frac{\lambda}{16}$ is positive; thus $X_4^* = 1$.

Hence, for each state of the world, the recommender's optimal message is as follows:

State of the world	Message by a biased novice recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$ or $m = a_1^L > a_2^L$ with equal probability
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	"no message"

By applying these probabilities to Expression (5), we compute the likelihood that consumerswill select the recommended product given a message about A_i^L :

$$P\left(U_1 > U_2 \mid m^A = a_1^L > a_2^L\right) = \rho\ \frac{1}{3} + (1-\rho)\ 1 = 1 - \frac{2\rho}{3}. \quad \blacksquare$$

Proof of Proposition 3

We use game theoretical arguments to prove this proposition. We start with the **unbiased-expert recommender**.

In the trichotomous specification there are nine states of the world, and messages stating that products perform equally on a given attribute ($m = a_i^k = a_{-i}^k$) are also possible. Because the recommender does not favor any particular product, for each state of the world she will disclose the information that is most beneficial to consumers. In cardinal order, this means: disclose information about A_i^H ($m = a_i^H > a_{-i}^H$) whenever a product dominates in the more-important attribute. Next, disclose information about A_i^L ($m = a_i^L > a_{-i}^L$) whenever a product dominates only in the less-important attribute. Lastly, when a product has equal performance on both attributes, the recommender will be indifferent to messages $m = a_1^H = a_2^H$ and $m = a_1^L = a_2^L$; thus, she will pick one of these message at random (with equal probability).

Hence, for each state of the world, the expert recommender's optimal message is as follows:

State of the world	Message by an unbiased expert recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L = A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H = A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$
$\{A_1^H = A_2^H, A_1^L = A_2^L\}$	$m = a_1^H = a_2^H$ or $m = a_1^L = a_2^L$ with equal probability
$\{A_1^H = A_2^H, A_1^L < A_2^L\}$	$m = a_1^L < a_2^L$
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m = a_1^H < a_2^H$
$\{A_1^H < A_2^H, A_1^L = A_2^L\}$	$m = a_1^H < a_2^H$
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	$m = a_1^H < a_2^H$

Different from the dichotomous specification, here strategic consumers can update their priors on non-disclosed attributes based on a message about A_i^L . By realizing that the recommender will only recommend based on A_i^L when $A_1^H = A_2^H$, the probability that strategic consumers will follow a recommendation given a message about the less-important attribute is 1 (the product dominates in the less important attribute and is equal in the more-important attribute).

Now we proceed to the **unbiased-novice recommender**. This recommender does not know which attribute is more important. Therefore, for all states of the world in which there are differences in both attributes A_i^H and A_i^L , the recommender will randomly disclose information based on one of these attributes at random (either $m = a_i^H > a_{-i}^H$ or $m = a_i^L > a_{-i}^L$ with equal probability). For states of the world in which there is a performance difference in one of the attributes, the novice recommender will do better by recommending based on that attribute, regardless of the actual importance of the attribute ($m = a_i^H > a_{-i}^H$ if product *i* dominates on A_i^H or $m = a_i^L > a_{-i}^L$ if product *i* dominates on A_i^L). Lastly, when a product has equal performance on both attributes, the recommender will be indifferent to messages $m = a_1^H = a_2^H$ and $m = a_1^L = a_2^L$; thus, she will pick either message at random (equal probability).

Hence, for each state of the world, the recommender's optimal message is as follows:

State of the world	Message by an unbiased novice recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$ or $m = a_1^L > a_2^L$ with equal probability
$\{A_1^H > A_2^H, A_1^L = A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$ or $m = a_1^L < a_2^L$ with equal probability
$\{A_1^H = A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$
$\{A_1^H = A_2^H, A_1^L = A_2^L\}$	$m = a_1^H = a_2^H$ or $m = a_1^L = a_2^L$ at random
$\{A_1^H = A_2^H, A_1^L < A_2^L\}$	$m = a_1^L < a_2^L$
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m = a_1^H < a_2^H$ or $m = a_1^L > a_2^L$ with equal probability
$\{A_1^H < A_2^H, A_1^L = A_2^L\}$	$m = a_1^H < a_2^H$
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	$m = a_1^H < a_2^H$ or $m = a_1^L < a_2^L$ with equal probability

As in the expert recommender case, strategic consumers can consider the behavior of the recommender to extract some information about the non-disclosed attribute.

Upon receiving a message about A_i^L, strategic consumers can update their priors. By considering that $P(A_1^H > A_2^H) = P(A_1^H = A_2^H) = P(A_1^H < A_2^H) = 1/3$, $P(m = a_i^L > a_{-i}^L) = 2/9$, $P(m = a_i^L > a_{-i}^L \mid A_i^H > A_{-i}^H) = 1/6$, $P(m = a_i^L > a_{-i}^L \mid A_i^H = A_{-i}^H) = 1/3$, and $P(m = a_i^L > a_{-i}^L \mid A_i^H < A_{-i}^H) = 1/6$; and by applying Bayes rule, one can compute the posteriors:

$P(A_i^H > A_{-i}^H \mid m = a_i^L > a_{-i}^L) = \frac{(1/6)(1/3)}{2/9} = \frac{1}{4}$, $P(A_i^H = A_{-i}^H \mid m = a_i^L > a_{-i}^L) = \frac{(1/6)(1/3)}{2/9} = \frac{1}{2}$,

$P(A_i^H < A_{-i}^H \mid m = a_i^L > a_{-i}^L) = \frac{(1/6)(1/3)}{2/9} = \frac{1}{4}$.

However, this updating does no better than not updating at all (it only strengthens the belief that the performance on attribute A_i^H is the same). Therefore, we conclude that when the unbiased novice recommends based on the less-important attribute, strategic consumers will follow the recommendation with probability $1-\frac{\rho}{2}>\frac{1}{2}$. ■

Proof of Proposition 4

We start with the **biased-expert recommender**. In this scenario, consumers always receive the message that $b = biased$ and $e = expert$; thus, for simplicity, we will drop these variables from all conditional probability expressions. In addition, without loss of generality, consider that the recommender favors product 1.

Recall that a small number of consumers do not account for the strategic behavior of the recommender, hence we redefine π from expression (7) as:

(o5) $$\pi = \max_{m \in W} \left\{ \lambda \; P^N \left(U_1 > U_2 \mid m \right) + (1-\lambda) P\left(U_1 > U_2 \mid m \right) \right\},$$

where λ and P^N are defined as in the Proof of Proposition 2.

We are interested in knowing the recommender's optimal choice of message, m, and the consumer's belief formation given the recommender's messaging strategy. Recall that there are **nine** states of the world (in the set W). Therefore, the recommender's expected utility, considering all the states of the world, is:

(o6)

$$E[\pi] = \frac{\begin{gathered} E\left[\pi \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right] + E\left[\pi \mid \{A_1^H > A_2^H, A_1^L = A_2^L\}\right] + E\left[\pi \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right] \\ + E\left[\pi \mid \{A_1^H = A_2^H, A_1^L > A_2^L\}\right] + E\left[\pi \mid \{A_1^H = A_2^H, A_1^L = A_2^L\}\right] + E\left[\pi \mid \{A_1^H = A_2^H, A_1^L < A_2^L\}\right] \\ + E\left[\pi \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right] + E\left[\pi \mid \{A_1^H < A_2^H, A_1^L = A_2^L\}\right] + E\left[\pi \mid \{A_1^H < A_2^H, A_1^L < A_2^L\}\right] \end{gathered}}{9}$$

The recommender thus maximizes $E[\pi]$ with respect to m for each state of the world.

Next consider the consumer's belief formation. $P^N\left(U_1 > U_2 \mid m\right)$ is updated according to expressions (o1) and (o2). $P\left(U_1 > U_2 \mid m\right)$ is updated according to expressions (10) and (11).

The recommender cannot lie, thus when the state of the world is $\{A_1^H > A_2^H, A_1^L > A_2^L\}$, she can send the messages $m = a_1^H > a_2^H$ and $m = a_1^L > a_2^L$ with some probability (the unknown variable we want to determine) while all other messages have zero probability; hence we define: $P\left(m = a_1^H > a_2^H \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right) \equiv X_1$ and $P\left(m = a_1^L > a_2^L \mid \{A_1^H > A_2^H, A_1^L > A_2^L\}\right) \equiv X_2$. Because the recommender only sends one message, these probabilities are mutually exclusive, and we can write $X_1 = 1 - X_2$.[3]

When the state of the world is $\{A_1^H > A_2^H, A_1^L = A_2^L\}$, she can send the messages $m = a_1^H > a_2^H$ and $m = a_1^L = a_2^L$ with some probability while all the other messages have zero probability; hence we define: $P\left(m = a_1^H > a_2^H \mid \{A_1^H > A_2^H, A_1^L = A_2^L\}\right) \equiv X_3$ and $P\left(m = a_1^L = a_2^L \mid \{A_1^H > A_2^H, A_1^L = A_2^L\}\right) \equiv X_4$, and we can write $X_3 = 1 - X_4$.

Similarly, when the state of the world is $\{A_1^H = A_2^H, A_1^L > A_2^L\}$, she can send the messages $m = a_1^H = a_2^H$ and $m = a_1^L > a_2^L$ with some probability while all the other messages have zero probability; hence we define: $P\left(m = a_1^L > a_2^L \mid \{A_1^H = A_2^H, A_1^L > A_2^L\}\right) \equiv X_5$ and $P\left(m = a_1^H = a_2^H \mid \{A_1^H = A_2^H, A_1^L > A_2^L\}\right) \equiv X_6$, and we can write $X_6 = 1 - X_5$.

When the state of the world is $\{A_1^H > A_2^H, A_1^L < A_2^L\}$, the recommender cannot recommend the "other product" or she will face the worst possible beliefs, thus $P\left(m = a_1^L < a_2^L \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right) = 0$. Due to the "no-lie" assumption the other messages except $m = a_1^H > a_2^H$ also have zero probability. Hence, the recommender can only send message $m = a_1^H > a_2^H$ or forego the opportunity; thus we define $P\left(m = a_1^H > a_2^H \mid \{A_1^H > A_2^H, A_1^L < A_2^L\}\right) \equiv X_7$.

For the same reasons in the previous paragraph, when considering the sates of the world

[3]This expression considers that when the product favored by the recommender dominates the other product in both attributes, the recommender will never forego the opportunity to recommend the product; hence $X_1 + X_2 = 1$. This turns out to be true, and for simplicity we are skipping this part of the proof. This statement can be verified by defining a variable F for "forego" and considering that $X_1 + X_2 + F = 1$. After following the same steps we use in the remaining of the proof, one would reach the conclusion that $F = 0$.

$\{A_1^H < A_2^H, A_1^L > A_2^L\}$, $\{A_1^H < A_2^H, A_1^L = A_2^L\}$, $\{A_1^H = A_2^H, A_1^L < A_2^L\}$ we define the respective probabilities $P\left(m = a_1^L > a_2^L \mid \{A_1^H < A_2^H, A_1^L > A_2^L\}\right) \equiv X_8$, $P\left(m = a_1^L = a_2^L \mid \{A_1^H < A_2^H, A_1^L = A_2^L\}\right) \equiv X_9$, and $P\left(m = a_1^H = a_2^H \mid \{A_1^H = A_2^H, A_1^L < A_2^L\}\right) \equiv X_{10}$.

When the state of the world is $\{A_1^H = A_2^H, A_1^L = A_2^L\}$ only messages stating that the product has the same performance are possible, and we define $P\left(m = a_1^H = a_2^H \mid \{A_1^H = A_2^H, A_1^L = A_2^L\}\right) \equiv X_{11}$ and $P\left(m = a_1^L = a_2^L \mid \{A_1^H = A_2^H, A_1^L = A_2^L\}\right) \equiv X_{12}$. Because these messages are mutually exclusive we write $X_{12} = 1 - X_{11}$.

Lastly, when the state of the world is $\{A_1^H < A_2^H, A_1^L < A_2^L\}$, the recommender forgoes the opportunity to recommend a product (she will not recommend the product); thus the probability of any messages is zero.

Given the above conditional probabilities, the overall unconditional probabilities (for all states of the world) that the recommender will speak about an attribute are: $P\left(m = a_1^H < a_2^H\right) = 0$, $P\left(m = a_1^L < a_2^L\right) = 0$, $P\left(m = a_1^H > a_2^H\right) = \frac{2 - X_2 - X_4 + X_7}{9}$, $P\left(m = a_1^L > a_2^L\right) = \frac{X_2 + X_5 + X_8}{9}$, $P\left(m = a_1^H = a_2^H\right) = \frac{1 - X_5 + X_{10} + X_{11}}{9}$, and $P\left(m = a_1^L = a_2^L\right) = \frac{1 + X_4 + X_9 - X_{11}}{9}$.

Furthermore, the probability of receiving a message about one attribute, given the state of the other attribute, are: $P\left(m = a_1^H > a_2^H \mid A_1^L > A_2^L\right) = \frac{1 - X_2}{3}$, $P\left(m = a_1^H > a_2^H \mid A_1^L = A_2^L\right) = \frac{1 - X_4}{3}$, $P\left(m = a_1^H > a_2^H \mid A_1^L < A_2^L\right) = \frac{X_7}{3}$, $P\left(m = a_1^H = a_2^H \mid A_1^L > A_2^L\right) = \frac{1 - X_5}{3}$, $P\left(m = a_1^H = a_2^H \mid A_1^L = A_2^L\right) = \frac{X_{11}}{3}$, $P\left(m = a_1^H = a_2^H \mid A_1^L < A_2^L\right) = \frac{X_{10}}{3}$, $P\left(m = a_1^L > a_2^L \mid A_1^H > A_2^H\right) = \frac{X_2}{3}$, $P\left(m = a_1^L > a_2^L \mid A_1^H = A_2^H\right) = \frac{X_5}{3}$, $P\left(m = a_1^L > a_2^L \mid A_1^H < A_2^H\right) = \frac{X_8}{3}$, $P\left(m = a_1^L = a_2^L \mid A_1^H > A_2^H\right) = \frac{X_4}{3}$, $P\left(m = a_1^L > a_2^L \mid A_1^H = A_2^H\right) = \frac{1 - X_{11}}{3}$, and $P\left(m = a_1^L > a_2^L \mid A_1^H < A_2^H\right) = \frac{X_9}{3}$.

By plugging these probabilities into the Bayes formula for $P\left(U_1 > U_2 \mid m\right)$, we obtain:

$P\left(U_1 > U_2 \mid m = a_1^H > a_2^H\right) = \rho + (1 - \rho)\frac{-3 + 2X_2 + X_4}{2(-2 + X_2 + X_4 - X_7)}$,

$P\left(U_1 > U_2 \mid m = a_1^H = a_2^H\right) = \frac{\rho}{2} + \left(1-\rho\right)\frac{2 - 2X_5 + X_{11}}{2(1 - X_5 + X_{10} + X_{11})}$,

$P\left(U_1 > U_2 \mid m = a_1^L > a_2^L\right) = \rho \frac{2X_2 + X_5}{2(X_2 + X_5 + X_8)} + \left(1-\rho\right)$,

$P\left(U_1 > U_2 \mid m = a_1^L = a_2^L\right) = \rho \frac{1 + 2X_4 - X_{11}}{2(1 + X_4 + X_9 - X_{11})} + \frac{\left(1-\rho\right)}{2}$.

With these expressions, we can write the conditional profit expressions for all states of the world ($E\left[\pi \mid w\right]$ for all $w \in W$) and maximize Expression (o6) with respect to the unknown probabilities X_1 to X_{12}. X_4. It is sufficient to inspect the First Order Conditions:

The derivative $\frac{\partial E\left[\pi\right]}{\partial X_2} = -\frac{(2\rho - 1)\lambda}{18}$ is negative; thus $X_2^* = 0$ and $X_1^* = 1 - X_2^* = 1$. The derivative $\frac{\partial E\left[\pi\right]}{\partial X_4} = -\frac{\rho\lambda}{18}$ is negative; thus $X_4^* = 0$ and $X_3^* = 1 - X_4^* = 1$. The derivative $\frac{\partial E\left[\pi\right]}{\partial X_5} = \frac{(1-\rho)\lambda}{18}$ is positive; thus $X_5^* = 1$ and $X_6^* = 1 - X_5^* = 0$. The derivative $\frac{\partial E\left[\pi\right]}{\partial X_7} = \frac{(2\rho - 1) + (1-\rho)\lambda}{18}$ is positive; thus $X_7^* = 1$. The derivative $\frac{\partial E\left[\pi\right]}{\partial X_8} = \frac{1 - (2-\lambda)\rho}{18}$ is negative since λ is an infinitesimal small number; thus $X_8^* = 0$. The derivative $\frac{\partial E\left[\pi\right]}{\partial X_9} = -\frac{(1-\lambda)\rho}{18}$ is negative; thus $X_9^* = 0$. The derivative $\frac{\partial E\left[\pi\right]}{\partial X_{10}} = -\frac{(1-\lambda)(1-\rho)}{18}$ is negative; thus $X_{10}^* = 0$. Lastly, the derivative $\frac{\partial E\left[\pi\right]}{\partial X_{11}} = 0$, thus this first order condition is automatically satisfied for any value of X_{11}^* and X_{12}^*.

However, to be a PBN, we need to assure that players have no incentive to deviate. This only occurs when the state of the world is $\{A_1^H < A_2^H, A_1^L > A_2^L\}$ and the recommender changes X_8^* from 0 to 1 (i.e., send the message $m = a_1^L > a_2^L$). By incorporating this incentive, consumers have to believe that when they receive the message $m = a_1^L > a_2^L$, the probability that the real state of the world is $\{A_1^H = A_2^H, A_1^L > A_2^L\}$ or $\{A_1^H < A_2^H, A_1^L > A_2^L\}$ are equal. By incorporating this belief, we find that the recommender only send the message $m = a_1^L > a_2^L$ if $p\left(U_1 > U_2 \mid m = a_1^L > a_2^L\right) \geq \frac{1}{2}$. This only occurs when ρ is such that $\frac{1}{2}\left(\rho\ \frac{1}{2} + \left(1-\rho\right)\ 1\right) + \frac{1}{2}\left(\rho\ 0 + \left(1-\rho\right)\ 1\right) \geq \frac{1}{2} \ \Rightarrow \rho < \frac{2}{3}$.

Hence, for each state of the world, the recommender's optimal message is as follows:

State of the world	Message by a biased expert recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L = A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H = A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$ if $\rho < \frac{2}{3}$, otherwise "no message"
$\{A_1^H = A_2^H, A_1^L = A_2^L\}$	"no message"
$\{A_1^H = A_2^H, A_1^L < A_2^L\}$	"no message"
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$ if $\rho < \frac{2}{3}$, otherwise "no message"
$\{A_1^H < A_2^H, A_1^L = A_2^L\}$	"no message"
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	"no message"

With these determinations, we are ready to compute two probabilities that consumers will select the recommended product given a message about A_i^L. If $\rho < \frac{2}{3}$, the probability is

$P\left(U_1 > U_2 \mid m = a_1^L > a_2^L\right) = \frac{1}{2}\left(\rho\ \frac{1}{2} + (1-\rho)\ 1\right) + \frac{1}{2}\left(\rho\ 0 + (1-\rho)\ 1\right) = 1 - \frac{3\rho}{4}$. If $\rho > \frac{2}{3}$, the message is out of equilibrium. If consumers were to receive this message, consumers still have to believe that probabilities are equal that the real state of the world is either $\{A_1^H = A_2^H, A_1^L > A_2^L\}$ or $\{A_1^H < A_2^H, A_1^L > A_2^L\}$. This would be consistent with consumers forming the same out-of-equilibrium beliefs of $P\left(U_1 > U_2 \mid m^A = a_1^L > a_2^L\right) = 1 - \frac{3\rho}{4}$, which is smaller than $\frac{1}{2}$ for $\rho > \frac{2}{3}$.

Now we proceed to analyze the **biased novice recommender**. As in the Proof of Proposition 2 we can we can directly plug the value $\rho = \frac{1}{2}$ into the first-order conditions to the Biased Expert Recommender's problem to determine that:

The derivative $\frac{\partial E[\pi]}{\partial X_2} = 0$; thus the recommender is indifferent to selecting any number for X_2 and consequently for X_1. This implies that she will speak about each attribute at random ($X_1^* = X_2^* = 1/2$). Similarly, the derivative $\frac{\partial E[\pi]}{\partial X_{11}} = 0$, which imply that ($X_{11}^* = X_{12}^* = 1/2$).

The derivatives $\frac{\partial E[\pi]}{\partial X_4} = -\frac{1-\lambda}{36}$, $\frac{\partial E[\pi]}{\partial X_9} = -\frac{1-\lambda}{36}$, $\frac{\partial E[\pi]}{\partial X_{10}} = -\frac{1-\lambda}{36}$ are negative; thus $X_4^* = 0$,

$X_9^* = 0$, $X_{10}^* = 0$. Because $X_4^* = 0$, we conclude that $X_3^* = 1$.

The derivatives $\frac{\partial E[\pi]}{\partial X_7} = \frac{\lambda}{36}$, $\frac{\partial E[\pi]}{\partial X_8} = \frac{\lambda}{36}$ are positive; thus $X_7^* = 1$, and $X_8^* = 1$.

Lastly, the solutions for the first order condition $\frac{\partial E[\pi]}{\partial X_5} = 0$ are $X_5 = 1 + X_{11} \pm X_{11} \frac{\sqrt{\lambda(1-\lambda)}}{\lambda}$.

Since this expression is always greater than one we have that $X_5^* = 1$.

Hence, for each state of the world, the recommender's optimal message is as follows:

State of the world	Message by a biased novice recommender
$\{A_1^H > A_2^H, A_1^L > A_2^L\}$	$m = a_1^H > a_2^H$ or $m = a_1^L > a_2^L$ at random
$\{A_1^H > A_2^H, A_1^L = A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H > A_2^H, A_1^L < A_2^L\}$	$m = a_1^H > a_2^H$
$\{A_1^H = A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$
$\{A_1^H = A_2^H, A_1^L = A_2^L\}$	$m = a_1^H = a_2^H$ or $m = a_1^L = a_2^L$ at random
$\{A_1^H = A_2^H, A_1^L < A_2^L\}$	"no message"
$\{A_1^H < A_2^H, A_1^L > A_2^L\}$	$m = a_1^L > a_2^L$
$\{A_1^H < A_2^H, A_1^L = A_2^L\}$	"no message"
$\{A_1^H < A_2^H, A_1^L < A_2^L\}$	"no message"

Notice that in this case, there is no incentive for players to deviate from this equilibrium. Therefore, we can use the determinations in the table above and compute the likelihood that consumers will select the recommended product given a message about A_i^L:

$$P\left(U_1 > U_2 \mid m^A = a_1^L > a_2^L\right) = \rho \, \frac{2}{5} + \left(1-\rho\right) \, 1 = 1 - \frac{3\rho}{5}. \quad \blacksquare$$