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Consumers' response to weak unique selling propositions: Implications for optimal product recommendation strategy

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ABSTRACT

We use a multi-method approach (analytical model and behavioral experiment) to investigate product recommendations based on less-important attributes (weak unique selling proposition, USP). 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.

Results show that optimal messaging behavior is a function of an interactive process involving recommender characteristics 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 might optimally communicate weak USPs or avoid sending such a recommendation.

1. Introduction

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 promotional approach has long been used in traditional advertising, and more recently in advertising via social media influencers on platforms such as YouTube, Instagram, and Twitter (Antunes, 2021).

Ideally, a unique selling point should involve an attribute that is important enough to motivate consumers to buy the firm's product over that of competing brands (Belch & Belch, 2017; Reeves, 1961). However, given that it is virtually 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, or a weak USP. This idea is corroborated by Brierley (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 in this statement is the belief that, regardless of their strength, USPs will generate positive consumer reactions.

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The use of a potentially weak USP can be illustrated by Ford's advertising campaign, which claimed that the F-150 truck had an advantage over direct competitors because of its bigger spring leaf mounting bolts (see Online Appendix W-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 that of Tundra. 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. Although some consumers might find this feature to be somewhat important, it is unlikely a typical consumer will regard this feature among the most important ones to bear in mind when buying a pickup truck. For instance, Consumer Reports[1] lists cab size, truck bed, access, towing, axel ratios, fuel economy, ride, drivetrain, and safety features as the attributes one should consider when buying a pickup truck. In all likelihood, the rear spring bolt is a relatively less important feature.

The fact that Ford chose to highlight an attribute of lesser importance in a major national campaign conforms with the suggestion that agency creatives are indeed under pressure to find an advantage over competitors, regardless of whether this advantage is relevant to consumers. One caveat stemming from the use of such weak USPs is that they might not persuade buyers to favor Ford over its competitors. In fact, this claim could even backfire, with some customers questioning this choice, as illustrated by this 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." In response to this comment, and in line with the intent of the advertiser, another poster stated "Wrong! What you fail to realize is that most people can not identify with a larger leafspring as they have never seen one before, but they know what a bolt is. And guess what, a large bolt must mean that the truck is built bigger as everyone knows you don't need a large bolt for a small weak leafspring." In response, the first poster added "If you watched the ad they referred directly about leaf spring bolts and gave the audience the perspective as... Bigger bolts ===== Stronger more dependable vehicle. Bullshit..." Consistent with the idea that the spring leaf bolt claim might be seen as a weak USP by a 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[2] reflects a conundrum that many firms face. On the 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 about other important attributes, causing the weak USP message to backfire, and ultimately putting the product at a disadvantage.

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

With respect to the message sender, we focus on two characteristics that are deemed to be relevant based on the anecdotal evidence presented in the opening example and in previous research (e.g., Austen-Smith, 1994; Crawford & Sobel, 1982) regarding activating higher-order rationality: *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 need to acknowledge that they might not have firm beliefs about their preferences, and that a group of consumers might have heterogeneous preferences (e.g., Chakraborty & Harbaugh, 2014); thus, consumers may not have a deterministic perception about the importance of each attribute.

The consideration of these elements will enable us to address three main questions: (1) how do consumers process and react to recommendations based on less-important attributes, and do a recommender's bias and expertise mitigate or amplify consumer responses to persuasion attempts? (2) How does the relative importance of attributes affect consumers' 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 under which conditions would a firm be better off by withholding or sending recommendations based on less-important attributes?

[1] https://www.consumerreports.org/cro/cars/pickup-trucks/buying-guide/index.htm (accessed August 7, 2019).

[2] This type of ad focusing on a specific set of attributes is not uncommon. Another example in the trucks category is the advertising "Chevrolet Mobile Office," in which a Chevrolet spokesperson tells a group of people that the Chevy Silverado should be better than a Ford F-150 because the Silverado has built-in 4G LTE capabilities, while the F-150 does not.

In addressing the first question, we found that consumers might react either positively or negatively to weak USPs. For example, when a recommender is an unbiased novice, this may increase consumer intent to buy a product, whereas the recommendation of a biased expert might increase a consumer's interest in buying a competing product. In terms of the second research question, we found that the relative weight of an attribute is particularly relevant when the recommender is a biased novice, in which case the magnitude of this weight might affect consumers intent to buy the recommended product when the recommender uses a weak USP, except when the recommender is an unbiased novice. Regarding the third question, we determine the optimal messaging policy based on type of recommender. 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 underlying this finding 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 model developed and propositions derived from analyzing the model, 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.

1.1. Related literature

Marketing scholars have been studying promotion via USP communication for quite some time. This communication approach has been recommended as an effective reason-based persuasive technique (Andrews & Shimp, 2017; Brierley, 2002; Vakratsas & Ambler, 1999) for its influence on the knowledge structure of consumers, as it directs the decision focus to a products's most positive attributes. The approach is known to be extensively used in promotional campaigns through traditional advertising (Laskey, Day, & Crask, 1989; Niu & Wang, 2016), and more recently through social media influencers (Antunes, 2021). It can also be present in product recommendations by peers (Peluso, Bonezzi, De Angelis, & Rucker, 2017), user generated content (Colicev, Kumar, & O'Connor, 2018; Marchand, Hennig-Thurau, & Wiertz, 2017), and automatic item framing (Gai & Klesse, 2019).

However, the literature also reports that consumers may not always react as intended by the advertiser or recommender, in particular, if consumers rationalize that a message is crafted with the intention to persuade them (Campbell & Kirmani, 2000; Fitzsimons & Lehmann, 2004). This contributed to the interest by researchers in understanding how consumers react to product recommendations.

From a theoretical perspective, product recommendations using an USP in which a sender (a recommender) attempts to influence a receiver (customers) occurs through a process of communication that involves information transmission or disclosure (Crawford & Sobel, 1982). In this line, Bloomfield and Kadiyali (2005) investigate how sellers persuade buyers to accept unverifiable information by exaggerating verifiable information. Mayzlin (2006) examines online word-of-mouth communications and identifies the conditions under which online messages are persuasive. Chen and Xie (2008) study online consumer reviews as a source of product information to identify how firms should combine this information with other proprietary information. Kopalle and Lehmann (2015) show that if firms are not constrained by regulations or other forms of legal action, it is optimal for them to overstate claims about their products. Gardete and Bart (2018) show that, when the sender's preferences are known by the consumers, communication is informational only when the sender is not well informed. The central idea across these papers is that, under certain conditions, the strategic provision of information can influence the behavior of prospective consumers according to the objectives of the communicator, thus influencing consumer welfare.

The theoretical literature has also studied the specific issue of information disclosure to consumers. Guo (2009) considers the possibility of direct information disclosure to consumers or indirect disclosure via retailers and shows that indirect disclosure can lead to more information revelation. Kuksov and Lin (2010) find that, in vertically differentiated competitive markets, a low-quality firm could have stronger incentives to provide information that resolves consumer uncertainty about product quality. Iyer and Singh (2017) investigate the voluntary disclosure of product safety information to consumers via certification and show that the disclosure of negative information can be optimal if it helps reduce consumer moral hazard. Cui and Shin (2018) study the disclosure of inventory information to consumers as a way to entice those consumers who are hopeful that their more desired products are still in stock. They find that partial disclosure of information is optimal and that full unraveling of information might not occur.

Under the umbrella of information transmission and disclosure, our work focuses on the issue of disclosure of a subset of product attributes. In this realm, Mayzlin and Shin (2011) analyzed the strategy of firms regarding the provision of information about some of the attributes of their products via advertising. They show that, when the communication bandwidth is limited, a firm might intentionally provide uninformative advertising about product attributes to encourage consumers to search for information on their own. Ghosh and Galbreth (2013) show that consumer attentiveness and consumer information search costs can regulate the optimal quality disclosure strategies of competing firms. They show that firms should disclose less quality information when there are relatively more consumers who are previously informed about only one of the competing products in the market or when consumer search costs are large. Our research shows a related result in that a firm might prefer not to provide quality information about product attributes (or equivalently to provide only uninformative advertising), albeit as a result of a different objective: to prevent consumers from forming relatively more positive inferences about the attributes of competitors' products.

Research in persuasion has investigated the role of information transmission in persuading consumers. Kamenica and Gentzkow (2011) examine a Bayesian persuasion model in which a sender (recommender) chooses a signal to reveal to a receiver and provide general conditions for the existence of a signal that benefits the recommender. The underpinnings of our model are similar to those in this research with the key difference being that in Kamenica and Gentzkow (2011) the recommender knows the preferences of the receiver whereas in our model we also consider the case in which the receiver might not know this information. More recently, Chakraborty and Harbaugh (2014) study a seller's communication to consumers regarding unverifiable information about product attributes in a model in which the buyer is privately informed about her preferences and the seller has private information about the product. The seller tries to sway consumers to buy its product, regardless of whether it is the best option for consumers. Our paper differs from this work by considering verifiable instead of unverifiable information, by examining both recommenders who are informed and not informed about consumer preferences, and by examining both recommenders who always want to sway consumers to a specific product and recommenders who want to direct consumers to buy the best product. Additionally, we contribute to the literature by presenting empirical experimental evidence that tests and supports the findings from the theoretical model.

In the domain of communication of product-attribute information to consumers, a somewhat related paper by Carpenter, Glazer, and Nakamoto (1994) finds that consumers can derive meaning and value from an attribute even if it is objectively irrelevant for product performance. The underlying behavioral mechanism in their work relates to consumers creating value from information about an attribute, not about consumers diagnosing which brand has a superior product given the revealed information about the relative performance of an attribute. Another related paper by Zhu and Dukes (2017) shows that firms decide which attributes to emphasize in their communication efforts. They show that, depending on the degree of differentiation between firms, the communication strategy might focus on the same strong attributes or lead to asymmetric strategies in which firms focus on different attributes to reduce competition. In that research, however, the strategic force is not asymmetric information (in which firms have knowledge about product attributes that consumers do not), but rather about driving consumers' limited focus to certain attributes in an attempt to shape consumer preferences. The experimental evidence in our research supports the information transmission mechanism we put forward, which explains the sender's and receiver's strategies in a way that cannot be accommodated by these two contributions described above.

2. Model setup

2.1. Product attributes and consumer utility

To formalize our model of product recommendation, assume that there are two agents in the economy: a recommender and a representative consumer. Initially, the recommender knows more about the characteristics of the products and about his type (expert or novice, which will be explained below), whereas the consumer only has priors about the product characteristics, but he knows his preferences and the type of the recommender. The recommender may attempt to influence consumers by revealing information about the products to the consumer, who subsequently chooses one of the products in the market given the information received and the type of the recommender.

For the sake of simplicity, we assume that the consumer wants to choose the best of two available products indexed by $i \in \{1, 2\}$. We use the index j to represent the other product: $j = 3 - i$. For instance, the consumer might choose between two pickup trucks in the same category (such as F150 and Tundra). These products have a set of attributes that can be partitioned into two subsets, indexed by $k \in \{L, H\}$. 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 the attribute partitions to be $W^k = \{k_1 > k_2,\ k_1 < k_2\}$. Given that there are two products and two attribute partitions, four possible states of the world w are collected in the set $W = W^L \times W^H$, as shown in Fig. 1. These states of the world are exogenously given (presumably as an outcome of previous R&D by the producer of each product).

The partitions can be composed of single or multiple elements. In the Ford F-150 example, L could capture the spring leaf bolt (a single element) or both the spring leaf bolt and tow hook (two elements), whereas H could capture a variety of other truck attributes, such as cab size, axel ratios, and fuel economy (multiple elements). Henceforth, we will refer to attribute partitions simply as *attributes*, with the understanding that no generality is lost. This partitioning effectively 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, whereas information about the remaining subset of attributes is withheld. An example of such situation is when advertising has limited bandwidth (as in Mayzlin & Shin, 2011), in which consumers can have limited attention (as in Ghosh & Galbreth, 2013, and Zhu & Dukes, 2017), or when a sender might suppress unfavorable information by using a sanitization strategy (as in Shin, 1994).[3]

[3] As it will become clear later, a model in which a recommender talking about all attributes (full disclosure) is allowed or required can be accommodated by adjusting parameters in our model by assuming that $\rho = 1$ (θ is an *almost surely constant random variable* with probability $P(\theta = 1) = 1$).

		Attribute L	
		$L_1 > L_2$	$L_1 < L_2$
Attribute H	$H_1 > H_2$	$\{H_1 > H_2,\ L_1 > L_2\}$	$\{H_1 > H_2,\ L_1 < L_2\}$
	$H_1 < H_2$	$\{H_1 < H_2,\ L_1 > L_2\}$	$\{H_1 < H_2,\ L_1 < L_2\}$

Fig. 1. States of the world $\boldsymbol{w} \in \boldsymbol{W}$.

Similar to Mayzlin and Shin (2011), we assume that the consumer utility from both attributes is additive and can be expressed as:[4]

$$U_i^* = U_0 + \theta V 1[H_i > H_j] + (1-\theta)V 1[L_i > L_j], \quad (1)$$

where U_0 is the basic utility for the product and $1[\cdot]$ is the indicator function which is used to indicate whether a set of attributes of product i dominates those of product j, and V is the added utility provided by relatively superior product attributes. In this specification, the utility for a product that is inferior in both dimensions is $U_i^* = U_0$, the utility for a product that dominates only on attribute H is $U_i^* = U_0 + \theta V$, the utility for a product that dominates only on attribute L is $U_i^* = U_0 + (1-\theta)V$, and the utility for a product that dominates on both dimensions is $U_i^* = U_0 + V$.[5]

To model heterogeneity in consumer preferences, we assume that θ is a random variable drawn from a binomial distribution f with support $\Theta = \{0, 1\}$ and parameter ρ ($\theta \sim Binomial(1, \rho)$), where $\theta = 0$ represents $H \prec L$ (attribute H is less important or preferred than attribute) and $\theta = 1$ represents $H \succ L$ (attribute H is more important or preferred than attribute L). Without loss of generality, we assume that $\rho > 1/2$; thus, we can denominate H as the more-important attribute and L the less-important attribute. This implies that the representative consumer considers the attribute H to be superior with probability ρ (which is greater than 1/2), and attribute L to be superior with probability $1-\rho$ (which is smaller than 1/2). This assumption means that, in terms of expected value, attribute H provides greater utility to the representative consumers than attribute L does, and thus it allows for a clear identification of strong USPs (those based on H) and weak USPs (those based on L). Note, however, that because θ is a random variable, this specification implies that the representative consumer epitomizes a market in which there is some degree of uncertainty about consumer preferences.[6]

Notice that, although we do not explicitly model situations in which consumers consider attributes of different products to be equal, our model specification still enables consumers to perceive that the two products possess attributes with the same value. This occurs when the probability that a given attribute of product 1 is better than that of product 2 is 1/2; for instance, when $P(H_1 > H_2) = 1/2$.

Before receiving information about a product, consumers cannot be sure about the state of the world. Thus, for both attributes L and 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):

$$P(k_1 > k_2) = P(k_1 < k_2) = 1/2, \text{ for } \in \{H, L\}.$$

2.2. The recommender and messaging

The recommender may attempt to influence consumers by sending 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). The recommender can vary in terms of favoring one of the products (biasness) and knowledge about the importance of the attributes to consumers (expertise).

To capture biasness, we assume that the recommender can be of two types collected in the set $\mathrm{B} = \{\underline{b}, \bar{b}\}$, where $\bar{b}$ denotes a *biased* recommender who has some association with a particular product and favors recommending this product for purchase more than she favors the welfare of the consumers, perhaps because the recommender receives conflicted payments, spiffs, or a higher than industry standards commission from sales of that particular product. Thus, a biased recommender

[4] This model is not only compatible with that of Mayzlin and Shin (2011), but it is also compatible with a weighted-averaging information-integration model (Anderson, 1981).

[5] For instance, if ρ were to be 0.7, the expectation of the random variable θ would also be 0.7, and a product that dominates a competing product in terms of the more-important attribute would provide utility $U_i = U_0 + 0.7V$, whereas a product that dominates in terms of the less-important attribute would provide utility $U_i^* = U_0 + 0.3V$.

[6] With the proper contextualization, this specification could also capture a market in which consumers may have heterogeneous preferences for different attributes. For details, see Web Appendix W-D.

prefers that consumers select the product she favors over competing alternatives. Conversely, $\underline{b}$ denotes an *unbiased* recommender who either has no association with any of the products or receives the same level of payments from every product. Additionally, she has at least some level of concern about the welfare of consumers; thus, she prefers that consumers select the best available product. For the sake of brevity, the product favored by a biased recommender will be termed the *target product*, a label that only has practical meaning when the recommender is biased. Thus, our model predicts that the biased recommender maximizes its own utility whereas the unbiased recommender maximizes the consumer's utility. The biasness of the recommender is public knowledge, in line with the FTC recommendations that "if there's a connection between an endorser and the marketer that consumers would not expect and it would affect how consumers evaluate the endorsement, that connection should be disclosed" (Federal Trade Commission, 2017).

To capture expertise, we assume that the recommender's expertise can be collected in the set $E = \{\underline{e}, \bar{e}\}$, where $\bar{e}$ indicates that the recommender is an expert in the product category under consideration and understands what attributes should be important for consumers (i.e., knows the parameters of the distribution f of a consumer's preferences), and $\underline{e}$ indicates that the recommender is not an expert (a novice) in the product category and does not know what attributes should be important for consumers (does not know the parameters of f). This modeling assumption addresses the concern presented by Brierley (2002) that sometimes marketers focus on a product's unique attributes without considering whether such differences were actually relevant. Thus, our model considers that the expert recommender knows the parameters of the distribution f of consumer preferences whereas the novice recommender does not. The expertise of the recommender is public knowledge to capture situations in which recommenders may be identified by consumers either as a regular consumers, or as experts (such as a race-car driver or a medical doctor) who should know what are truly important attributes for each product.

As in Mayzlin and Shin (2011), we assume that, due to limited bandwidth (perhaps due to communication costs or consumers' attention bandwidth), the recommender can transmit information about only one of the attributes. We model this by assuming that the recommender can either send a message m that product i dominates the other product on attribute k or not send a message. Hence, the recommender has three types of actions detailed in Table 1.

This message space indicates that either the recommender talks about one of the attributes or the recommender might decide not to send a message. Not sending a message is equivalent to the adoption of a sanitization strategy (Shin, 1994, p. 63). Practical examples could be a firm deciding not to do product-attribute advertising, perhaps by not advertising at all or by using some form of non-informational advertising (for instance, Omega advertising that its watches are used by the fictional 007 character James Bond).

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

With this specification, we can use Expression (1) to establish the likelihood a consumer will purchase product i (see Appendix A for derivation):

$$P(U_i > U_j|m,b,e) = \rho P(H_i > H_j|m,b,e) + (1-\rho)P(L_i > L_j|m,b,e). \tag{2}$$

Additionally, if the recommender is known to be biased in favor of one product (i) and recommends the other product (j), we assume that consumers would perceive this as credible evidence for assigning the best possible beliefs to product j and the worst possible beliefs to product i. This implies that $P(U_i < U_j) = 1$, which is equivalent to $P(U_i > U_j) = 0$. This is consistent with previous literature, which notes that, if a biased recommender claims that a competing product is better than the product she favors in some dimension, this action should be seen by most consumers as overwhelmingly credible when favoring the competing product (see, for instance, Durbin & Iyer, 2009).

Lastly, we assume that the majority of consumers is *strategic* and account for the strategic behavior of the recommender when revising their beliefs about product attributes, whereas a small proportion λ of consumers is *naïve* and do not do so. This assumption about two different types of consumers goes in line with previous models (e.g., Inderst & Ottaviani, 2012; and Kartik, Ottaviani, & Squintani, 2007) that assume that the market has a proportion of naïve consumers who do not properly account for the strategic incentives behind the information they receive. This assumption is also supported by behavioral research that documents that people cope with persuasion attempts, informational content, and advertising differently depending on individual characteristics (see, for instance, Campbell & Kirmani, 2000; Feick & Gierl, 1996; Friestad & Wright, 1994). This assumption has the additional benefit of allowing the filtering out of mixed-strategy equilibria by adopting the intuitive criterion of Cho and Kreps (1987).[7]

In summary, both the expert and the novice recommender know their type and possess hard information about the product, but only the expert recommender knows which attribute is likely to be more important to consumers. On the other hand, the representative consumer initially does not have information about the product, but knows its own preferences and the type of the recommender. The recommender may disclose information about one of the attributes to lead consumers

[7] Other approaches could be adopted to reach the same equilibrium outcome, such as imposing restrictions on off-equilibrium beliefs.

Table 1
Possible actions of the recommender.

Recommender's action	Description
$m = m_{i,H}$	Message that product i dominates product j on attribute H
$m = m_{i,L}$	Message that product i dominates product j on attribute L
$m = \varnothing$	No message

to buy a particular product, whereas the consumer receives the information, updates its priors about the product, and purchases the product that maximizes his or her own utility. With this specification, we now proceed to conduct the analysis of the model.

3. Model analysis

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 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.

3.1. Consumer choice and 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*

$$P\left(U_i > U_j | m = m_{i,H}, b, e\right) = \rho + (1-\rho)\frac{P\left(m = m_{i,H} | L_i > L_j, b, e\right)P\left(L_i > L_j\right)}{P\left(m = m_{i,H} | b, e\right)}. \tag{3}$$

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

$$P\left(U_i > U_j | m = m_{i,L}, b, e\right) = \rho\frac{P\left(m = m_{i,L} | H_i > H_j, b, e\right)P\left(H_i > H_j\right)}{P\left(m = m_{i,L} | b, e\right)} + (1-\rho). \tag{4}$$

Proof. See Appendix A.

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 that the recommended product dominates the other product on the less-important attribute, the probability consumers would buy the recommended product is, 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 can 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).

3.2. 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).

An unbiased recommender prefers that consumers 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:

$$\min_{m \in W}\left|P(U_1^* > U_2^*) - P(U_1 > U_2 | m, e, b = \underline{b})\right|, \tag{5}$$

conditional on consumer beliefs (from Lemma 1).

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 of the two products. This means that the biased recommender solves the problem:

$$\max_{m \in W} P\left(U_i > U_j | m, e, b = \bar{b}\right), \tag{6}$$

conditional on consumer beliefs (from Lemma 1).

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.

We now proceed to present the equilibrium results. Recall that since the objective of the research is to investigate weak USPs, we focus on the state of the world $w = \{H_i < H_j, L_i > L_j\}$.

3.3. Unbiased expert recommender

The unbiased expert recommender (e.g., dedicated to objective product testing, such as an independent industry analyst, an expert professor, or an organization such as Consumer Reports) cares about the consumers' utility. As an expert, she can choose to disclose the information that would most benefit consumers. The equilibrium messaging strategy employed by the recommender and the ensuing posterior beliefs formed by consumers are given by the following proposition:

Proposition 1. *The unbiased expert recommender speaks only about the more-important attribute, and consumers will follow the recommendation with probability* $\frac{1+\rho}{2} > \frac{1}{2}$.

The rationale underlying this result is that the message about the more important attribute (H) is the most diagnostic in determining the utility of the product; hence, the unbiased expert recommender always sends a message about that attribute (regardless of whether it favors product 1 or 2). Therefore, the choice of attribute by the recommender conveys neither positive nor negative information regarding the relative value of the less-important (undisclosed) attribute. Nevertheless, by following the recommendation (i.e., by buying the product with the highest utility in attribute H), consumers are likely to select the product with the highest *true utility* for their own tastes. Accordingly, the likelihood that consumers would follow the recommendation and buy the recommended product always increases, since $\frac{1+\rho}{2} > \frac{1}{2}$ for all $> \frac{1}{2}$.

Notice that, because an unbiased expert never recommends based on the less important attribute (L), such recommendation is *out of equilibrium*. Hence, if consumers were to receive this type of message from an unbiased expert recommender, they should not update their priors (disregard the information) and have an even chance of selecting either product.

3.4. Unbiased novice recommender

Similar to the previous case, when the recommender is an unbiased novice (e.g., a non-expert friend or a relative) she intends to help consumers by providing the most useful piece of information possible. However, the unbiased novice recommender does not know which attribute is more important, which alters the equilibrium messaging strategy employed by the recommender and the posterior beliefs formed by consumers. The equilibrium, in this case, is formalized in the proposition below:

Proposition 2. *The unbiased novice recommender speaks about each attribute with equal probability. When she recommends based on the more-important attribute, consumers will follow the recommendation with probability* $\frac{1+\rho}{2}$. *When she recommends based on the less-important attribute, consumers will follow the recommendation with probability* $\frac{2-\rho}{2}$.

Proof. See Appendix A.

The rationale for this proposition is as follows. As the unbiased novice recommender cannot identify which attribute is more important, she evidently cannot adopt the strategy of focusing exclusively on the attribute that will benefit consumers the most. From her view point, the weak scenario $\{H_i < H_j, L_i > L_j\}$ is indistinguishable from the scenario $\{H_i > H_j, L_i < L_j\}$. From the recommender standpoind, recommending a product based on attribute H or attribute L will produce the same expected response on consumers; hence, she is indifferent between recommending based on either attribute and selects the attribute at random.

However, consumers receiving a recommendation from an unbiased novice recommender know the importance of the attributes and infer the overall utility of the products based on the recommendation. Because the unbiased novice recommender has no interest in being deceptive, consumers do not make any negative inference regarding the value of the non-disclosed attribute, but they cannot make any positive inference either. Ultimately, consumers benefit most by following the recommendation since any unbiased information increases the probability of identifying the best product. Consequently, the likelihood that consumers would buy the recommended product always increases since both $\frac{1+\rho}{2}$ and $\frac{2-\rho}{2}$ are greater than $\frac{1}{2}$ for all $> \frac{1}{2}$. Nevertheless, there is a possibility that the recommender unintentionally advocates the product with inferior *true utility* and that consumers fall prey to this "honest mistake."

The underlying rationale for the above is as follows. Ex-ante, before information being sent, the recommender considers what might happen depending on whether she sends a recommendation. If she does not send a recommendation, the consumer sticks to its priors and has an even chance of selecting each product. As a result, consumers will select the best product with probability $\frac{1}{2}$. Conversely, if the recommender sends a message, from her viewpoint, she has an even chance of sending information about the more- or the less-important attribute. If, by chance, she sends a message about the more-important attribute, she will help consumers by greatly increasing the likelihood they will select the best product. Alternatively, if, by chance, she sends a message about the less-important attribute, she will harm consumers to a slight extent by slightly decreasing the likelihood they will select the best product. Ex-ante, the recommender always sends the recommendation as the even chance of a great improvement in the chance of selecting the best product overpowers the even chance of a small decrease in the chance of selecting the best product. For the same reason, ex-ante, the consumer will follow the recommendation. Ex-post, however, in the weak USP scenario, 50% of the time the recommender will recommend the worse product and steer consumers towards buying the product that does not maximize their utility.

3.5. Biased expert recommender

When the recommender is a biased expert (e.g., an expert hired by the product manufacturer to endorse a product, such as an engineer or a sommelier), she tries to influence consumers to buy the product in which she has vested interest. Because she is an expert, she can identify which attribute is more important, and she can be strategic in her decision of recommending a product based on the attribute that is more, or less, important. She can also be strategic in her decision and adopt the sanitization strategy of not issuing any attribute-based product recommendation.

The equilibrium messaging strategy the recommender employs and the posterior beliefs consumers form are given by the following proposition:

Proposition 3. *A biased expert forgoes recommending the target product (never recommends it based on the less-important attribute) and consumers should buy the product according to their prior perceptions about it.*

Proof. See Appendix A.

To better understand this proposition, first recall that the focus of this research is in situations in which the target product dominates only in terms of the less-important attribute (L). One could expect that, in this scenario, the biased expert recommender would recommend a product based on attribute L, as it would cast the recommender's favored product as the superior option on that dimension. However, because consumers make rational inferences, such a recommendation would reveal that the target product is inferior with respect to the most important attribute H; consequently, such a message would decrease the likelihood that they will purchase the product (the posterior would change from $\frac{1}{2}$ to $1-\rho$). Because of this, the best action for the recommender is to refrain from issuing any attribute-based recommendation, which will cause consumers to choose either product with equal probability.

3.6. Biased novice recommender

As in the previous case, a biased novice recommender (e.g., a non-expert celebrity or an endorser hired by the firm based on their fame, likability, or looks) will attempt to persuade consumers to buy her favored product. However, because she is a novice in the product category, she can only do so with limited efficiency. The equilibrium messaging strategy employed by the recommender and the posterior beliefs formed by consumers are expressed below:

Proposition 4. *A biased novice always recommends the target product based on the less-important attribute, in which case consumers will buy it with probability* $\frac{3-2\rho}{3}$.

Proof. See Appendix A.

To understand this proposition, recall that, even though the proposition refers to the situation in which the target product dominates only on the less-important attribute ($w = \{H_i < H_j, L_i > L_j\}$), from the point view of the players, all states of the world are possible.

The recommender always recommends the product, because he or she does not know whether the target product dominates in terms of the less- or the more-important attribute. Still, it is worth taking the gamble of recommending the product and having an even chance of a substantial increase in the likelihood consumers would buy the product (if it were to dominate in terms of the more-important attribute H) and a moderate decrease in the likelihood that consumers would buy the product (if it were to dominate in terms of the less-important attribute L).

From the point of view of consumers, if they receive a recommendation based on the less-important attribute L (which will end up being the ex-post outcome), they decrease the posterior probability that the product is also superior on attribute H, but to a lesser extent than they would if the recommender was an expert. This is expected because, ex-ante, consumers need to take into account the possibility that the state of the world could be one in which the target product dominates the competing product in both attributes. In other words, the information revealed about the more important attribute is imperfect.

Interestingly, because of the reduction in the magnitude of negative inferences about the undisclosed attribute H, it is possible that, upon receiving a recommendation based on attribute L, the likelihood that consumers would buy the product might increase or decrease, depending on the magnitude of ρ. This occurs because the posterior $\frac{3-2\rho}{3}$ is smaller than $\frac{1}{2}$ if $\rho \in \left(\frac{3}{4}, 1\right)$, but it is greater than $\frac{1}{2}$ if $\rho \in \left(\frac{1}{2}, \frac{3}{4}\right)$.

3.7. Summary of the implications of the model

The analytical model makes 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 2.

We now proceed to test our main theoretical results.

4. 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 either the role of recommender or the consumer. The study participants were 66 undergraduate students 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. Participants were randomly assigned to the role of recommender or consumer, which an equal amount assigned to each role. The pairing of recommenders and consumers was also randomized. The experiment was conducted in six sessions, and participants could not repeat a session.

To provide an incentive and thus create implications for a participant's economic utility, we announced before each session that an additional $20 gift card would be given to participants who performed best in their assigned role as a consumer or a recommender.[8] The gift cards were awarded at the end of each experimental session (two cards per session) after processing the session results. The objective of the incentive was to meet the following 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 were told whether they had won immediately following the session.

4.1. 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 own 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 the *expertise* of the recommender regarding attribute importance, roughly half of the recommenders were informed which set of attributes was more or less important for consumers (expert condition), whereas the other recommenders did not receive such information (novice condition). All consumers received information about the relative importance of attributes and the expertise of each recommender.

To manipulate the degree of recommender *bias*, we told approximately half of the recommenders that they should care about the welfare of the consumers (unbiased condition), whereas we told the other half that 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.

On each round, recommenders were shown a screen that displayed product information in a matrix format (see Online Appendix OL-B, top panel). The screens described the product (media player, HD camcorder, portable printer, etc.), specified which product/brand combination paid a commission (for biased recommenders), defined the "state of the world" (i.e., the realization of w), and provided an input field with radio buttons for making mutually exclusive selections. The buttons indicated as follows: (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.

Upon receiving product recommendations, consumers were shown a screen (see Web Appendix W-B, bottom panel) that displayed the recommender's 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

[8] For consumers, performance was measured based on their responses about the likelihood of buying each product, with higher scores given to consumers who assigned a higher likelihood to buy the superior product. For recommenders, performance was measured based on the likelihood consumers would buy the target product (in the case of the biased recommender) or the superior product (in the case of the unbiased recommender).

Table 2
Testable implications of the model.

Recommender type	Player	Testable implication	Cell
Unbiased Expert	Recommender	Likely to recommend based on the more-important attribute	1
	Consumer	Even chance (50%) of selecting any product.	
Unbiased Novice	Recommender	Even chance (50%) to recommend based on the less-important attribute	2
	Consumer	Likelihood to buy increases	
Biased Expert	Recommender	Likely to forgo sending a recommendation	3
	Consumer	Likelihood to buy decreases greatly	
Biased Novice	Recommender	Likely to recommend the target product based on the less-important attribute	4
	Consumer	If ρ is small:likelihood to buy increases moderately	
		If ρ is large:likelihood to buy decreases moderately	

selecting each brand. The rating was performed on an 11-point 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, whereas consumers received feedback about the state of the world.

During each round, recommenders and consumers made decisions about five electronic products. The data comprised eight rounds of five decisions for each participant, for a total of 1320 recommender decisions and an equal number of consumer decisions, for a total of 2620 decisions.

As a way of preventing participants from learning whether a particular state of the world was more likely to occur, the experimental software randomly selected one product attribute as better or worse than that of competing products. Thus, the stimuli for the experiment featured all possible states of the world. Since we were interested in situations in which 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 $w = \{H_i < H_j, L_i > L_j\}$. Stimuli for consumers were generated endogenously according to 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 a two expertise (novice/expert) by two bias (unbiased/biased) by two role-order counterbalance (recommender first/consumer first) by two roles (recommender /consumer) with eight replicate rounds by five product recommendations mixed design. The expertise, bias, and role-order counterbalance factors were manipulated between subjects; and the remaining factors were manipulated within subjects. Participants were randomly assigned to the eight between-subjects experimental conditions.

4.2. Analysis

Before we describe the consumer choice and recommendation results, we report that, in a pre-study with the same population, 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, Heagerty, Liang, & Zeger, 2002).

The expectation of consumer response is given by:

$$y_{be,t} = \alpha^C_{be} + \beta^C_{be}(t-1), \tag{7}$$

where $y_{be,t}$ 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*), t is the time (period), and β^C_{be} is the trend coefficient for consumers. The parameter α^C_{be} 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, then $\alpha^C_{be} = \frac{2-\rho_{be}}{2}$. This enables us to estimate the overall effect of recommender type on consumer decisions and the parameter ρ_{be} from the data as a latent variable. The estimates are reported in Table 3.

According to Table 3, in the bias novice condition, the prediction depends on the magnitude of the attribute-importance parameter ρ_{be}. For this condition, we allowed for heterogeneous consumer perceptions of ρ_{be} 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, Table 3 also provides the overall likelihood-to-buy ratings as estimated by the model with no period trend parameter. Notice that, in fact, there were no statistically significant changes in the ratings across periods (all β^C_{be} coefficients are non-significant).

Table 3
Consumers' decisions.

Recommender Type	Weigth ρ_{be}			Intercept α^C_{be}			Trend β^C_{be}		Overall Choice Ratings		
	Parameter		S.D.	Parameter		S.D.	Parameter	S.D.	Parameter		S.D.
Unbiased Expert	0.720	**	0.072	51.420		8.736	−0.212	0.919	50.607		7.907
Unbiased Novice	0.709	**	0.051	66.956	**	5.523	−0.714	1.298	64.553	**	3.382
Biased Expert	0.695	**	0.028	34.860	**	6.320	−3.640	2.940	30.465	**	6.036
Biased	0.795	**	0.052	56.362		5.021	−2.780	1.195	46.972		3.205
Novice	0.993	**	0.176	30.805	**	8.887	0.919	2.146	33.812	**	5.430

Notes: Estimates refer to consumer responses to product recommendations based on the less-important attribute.
Number of valid observations = 886.
Significances are with respect to chance level (ratings significantly different from 50%): * $p \leqslant .05$, ** $p \leqslant .01$.
Estimates for the Intercept (α^C_{be}), Trend (β^C_{be}), and Overall Choice Ratings are reported as percentages.

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 that of Lindstrom and Bates (1990), which was shown to be adequate for repeated measures analyses. The results are very similar to those in Table 3, with a small reduction in standard errors, owing to the variance being absorbed by the random element. An additional reason for reporting the GEE estimation results is that the same procedure can be employed to estimate the logistic model that captures the recommenders' decisions.

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

$$ln\left(\frac{P_{eb,mt}}{1-P_{eb,mt}}\right) = \alpha^{R}_{be,m} + \beta^{R}_{be,m}(t-1), \tag{8}$$

where $P_{eb,mt}$ represents the probability for sending recommendation m at period t, $\alpha^R_{be,m}$ is the fixed effect for each condition, and $\beta^R_{be,m}$ captures the effect of the recommenders learning about the effectiveness of each message across periods.

In this specification, statistically significant 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 4.[9] The table 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). As an additional robustness check, we also estimated a multinomial logistic GEE model (Touloumis, Agresti, & Kateri, 2013), which supports these results (the analysis is available in Online Appendix W-C).

To check recommender decisions that exhibit significant changes across periods, the results from the last period (period 8) are reported in Table 5. When $\beta^R_{be,m}$ 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 4 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).

4.3. Results discussion

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

Unbiased-expert condition. The theoretical model allows only for 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 $\alpha^R_{\underline{b}\bar{e},m}$ 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 ($\alpha^R_{\underline{b}\bar{e},more}$ = 1.519; σ = 0.438, p < .01), and opted neither to provide information on the less-important attri-

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

Table 4
Recommenders' decisions.

Recommender Type		Recommender Decision	Intercept α^{C}_{be}			Trend β^{C}_{be}			Overall Cell Probability		
			Parameter		S.D.	Parameter		S.D.	Parameter		S.D.
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
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
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
Biased Novice	ρ: 0.795	More	−2.708	**	0.645	−0.241		0.189	3.053	**	2.026
		Less	1.803	**	0.235	−0.098	*	0.048	80.916	**	5.655
		None	−2.320	**	0.186	0.169		0.077	16.030	**	4.220
	ρ: 0.993	More	−2.252	*	1.070	0.197		0.246	18.310	**	2.805
		Less	0.442		0.306	0.062		0.099	63.380	**	6.861
		None	−1.006	*	0.598	−0.196	*	0.089	18.310	**	4.930

Note:Number of valid observations = 1245.
* $p \leqslant .05$, ** $p \leqslant .01$. Significances are with respect to chance level (significantly different from zero in the Intercept and Trend cells, and significantly different from 50% in the Overall Cell Probabilities cells).

Table 5
Last Period Recommender's Decisions

Recommender Type		Recommender Decision	Estimated Last Period Log Odds			Last Period Cell Probability (%)		
			Parameter		S.D.	Parameter		S.D.
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
Unbiased Novice		More	0.016		0.036	51.5		2.00
		Less	0.058		0.039	47.3		2.63
		None	−6.484	**	0.788	1.2	**	0.93
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
Biased Novice	ρ: 0.795	More	−4.398	**	1.266	3.1	**	2.02
		Less	1.116	*	0.494	80.9	**	5.65
		None	−1.133	*	0.513	16.0	**	4.22
	ρ: 0.993	More	−0.874		0.706	18.3		6.58
		Less	0.878		0.605	63.4		6.86
		None	−2.377	**	0.202	18.3	**	4.93

Note: Estimated log odds constructed from the trend of decisions, culminating in the last period. Cell probabilities are the actual share of choices in the last period.
Number of observations = 1245.
* $p \leqslant .05$, ** $p \leqslant .01$. 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).

bute ($\alpha^{R}_{\underline{b}\bar{e},less} = -2.564$; $\sigma = 0.612$, $p < .01$) nor forgo sending a message ($\alpha^{R}_{\underline{b}\bar{e},none} = -2.108$; $\sigma = 0.502$, $p < .01$). The only statistically significant trend involved recommendations based on the less-important attribute, which showed a small increase over time ($\beta^{R}_{\underline{b}\bar{e},less} = 0.208$; $\sigma = 0.125$, $p < .05$). Because this trend was statistically significant, we analyzed the outcomes in the last period (see Table 5). These results show that, despite some small differences, recommenders continued to recommend a product by communicating information about the more-important attribute ($\alpha^{R}_{\underline{b}\bar{e},more,last\_period} = 0.868$; $\sigma = 0.384$, $p < .05$), but chose not to provide information about the less-important attribute ($\alpha^{R}_{\underline{b}\bar{e},less,last\_period} = -1.107$; $\sigma = 0.434$, $p < .01$) or to forgo sending a message ($\alpha^{R}_{\underline{b}\bar{e},none,last\_period} = -2.544$; $\sigma = 0.547$, $p < .01$). Consistent with the theoretical predictions (cell 2 in Table 1), the overall choice probabilities in the last period confirmed that unbiased expert 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%).

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 ($M = 64.553\%$; $\sigma = 3.382$, $p < .01$).

For recommenders, the lack of statistical significance of $\alpha^R_{\underline{b}\,\underline{e},m}$ for messages based on the more-important attribute ($\alpha^R_{b\underline{e},more}$ = 0.097; σ = 0.446, p > .10) and the less-important attribute ($\alpha^R_{b\underline{e},less}$ = −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 ($\alpha^R_{b\underline{e},none}$ = −3.355; σ = 0.948, p < .01). The trend parameters $\beta^R_{b\underline{e},m}$ did not reach statistical significance (all with p > .10), indicating a lack of carryover effects or a change in the 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 2 in Table 2) that unbiased novice 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.

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 ($\alpha^R_{\bar{b}e,less}$ = 0.794; σ = 0.411, p < .01). They did not send messages based on the more-important attribute ($\alpha^R_{\bar{b}e,more}$ = −2.537; σ = 0.690, p < .01) nor did they forgo sending a message ($\alpha^R_{\bar{b}e,none}$ = −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 ($\beta^R_{\bar{b}e,less}$ = −0.658; σ = 0.160, p < .01) and an increase in the trend of forgoing sending a message ($\beta^R_{\bar{b}e,none}$ = 0.507; σ = 0.133, p < .01). This pattern of data is consistent with the recommenders' choices converging to the optimal theoretical predictions. In the last period (Table 5), recommenders avoided sending messages based on the more-important attribute ($\alpha^R_{\bar{b}e,more,last\_period}$ = −2.345; σ = 0.784, p < .01), ceased sending messages based on the less-important attribute ($\alpha^R_{\bar{b}e,less,last\_period}$ = −3.810; σ = 0.869, p < .01), and opted to forgo sending a message ($\alpha^R_{\bar{b}e,none,last\_period}$ = 2.607; σ = 0.664, p < .01). This result is corroborated by the choice probabilities indicating that 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 biased expert 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 (cell 3 in Table 2), i.e., they forwent sending a message.

Biased-novice condition. When consumers received a recommendation from a biased novice recommender, predictions depended on the magnitude of $\rho_{\bar{b}\,\underline{e}}$. In this condition, we identified two consumer segments whose participants rated the importance of each attribute as different from one another. In one segment, the magnitude of $\rho_{\bar{b}\,\underline{e}}$ was moderately large ($\rho_{\bar{b}\,\underline{e},moderate}$ = 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 $\rho_{\bar{b}\,\underline{e}}$ was very large ($\rho_{\bar{b}\,\underline{e},large}$ = 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 biased novice recommender was more likely to choose the alternative to recommend based on the less-important attribute than any other alternative. More specifically, 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 4 in Table 2).

5. Conclusion

This paper investigates marketers' use of weak USPs via unidirectional communication channels to recommend products to potential consumers, a topic that has been relevant to promotions via traditional advertising, and is gaining increasing more importance given the growth of promotional activities via social media incluencers, who nowadays use internet platforms to reach thousands, and in some case millions of followers.

We identify how the bias and expertise of the recommender jointly determine when such a messaging strategy is viable and the subsequent expected response from consumers. 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 might 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. We tested the theoretical predictions using an experiment that allowed for a sequential interaction between participants playing the roles of recommender and consumer.

With respect to consumers' optimal responses, our results show that consumers might 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 they are more likely to buy the competing product (the product not being recommended) when the recommender is a biased expert.

With respect to the recommenders, we found that, in general, the expert recommender's optimal strategy involves refraining from sending a weak USP, regardless of bias. However, the overall profiles of strategies might differ; an unbiased expert will always send recommendation based on a strong USP for the product that dominates on the important attribute, since this is the most efficient way to help consumers. A biased expert, however, will withhold sending a message, because any truthful message could increase the likelihood that consumers will buy the competing product. We also found that the optimal strategy of an unbiased novice is always to 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. Alternatively, the optimal strategy for a biased novice is to recommend the target product (using a weak or a strong USP). This was surprising, given that a biased novice is aware that a weak USP causes negative consumer responses (consumers are more likely to buy the competitor's product). The rationale for this strategy is that sometimes the recommender needs to bank on the *ex-post* chance of sending a strong USP.

Our findings allow us to shed light on the value of expertise on the magnitude of the influence of recommendations on consumers' likelihood to choose the recommended product. When the recommender is unbiased, both the welfare of the recommender and the consumers increase with expertise. With higher expertise, the recommender will be able to provide information that is more helpful to consumers (i.e., about the more-important attribute), and consumers would be more likely to buy the recommended product. Conversely, in the biased recommender case, a recommender's higher expertise could be detrimental to recommenders, as it essentially "shuts down" her recommendations to consumers, who will select products according to their prior beliefs. Interestingly, our findings also show (see Proposition 4) that the effect of lack of expertise is ambiguous for recommenders (it can be either beneficial or detrimental depending on the parameters), but it is always positive for consumers, as they can adjust their decisions for the recommender's biasness. In sum, when the recommender is unbiased, expertise is universally more valuable (more beneficial), whereas when the recommender is biased, expertise is less valuable (less beneficial) for consumers and may also be less beneficial to the recommender.

One could, of course, propose that there are other candidate explanations for the substantive phenomena of firms relying on weak USPs in an attempt to persuade consumers. One such explanation is the theory that consumers can attribute meaning to irrelevant attributes (Carpenter et al., 1994). According to this theory, brands can gain an advantage over competitors by differentiating based on attributes that appear to create a significant advantage, even if at close examination those attributes are less important or even irrelevant. If firms believe that consumers would attribute (unwarranted) meaning to less-important attributes, they may continue to use weak USPs. However, this explanation is more plausible when there is no clear dominance in terms of more important, concrete, attributes and consumers need to rely on cues to infer the superiority of a given product.

Other potential alternative explanations might be related to Persuasion theory. The attempt to communicate reasons to persuade a consumer can be interpreted as a compliance issue from a persuasion standpoint. Individuals and companies acting as persuaders often attempt to increase compliance with their requests by offering reasons, legitimate or placebic, as to why one should behave in line with the request. Key, Edlund, Sagarin, and Bizer (2009) demonstrates how providing any reason, legitimate or placebic, for a request can lead people to comply with that request. In addition, once a reason is offered, additional reasons should increase persuasion and compliance, or, at a minimum, not negatively influence the persuasion attempt (Petty & Cacioppo, 1984). However, given a competitive environment, it is unlikely that consumers would receive USP-based recommendation from a single source which could dilute the effect of number of reasons provided.

Although these theories can explain why firms will choose to adopt USP advertising strategies, none of these explanations can explain the pattern of behavior in the strategic interaction between recommenders and consumers that we predict and observe, in the sense that our predictions and observed results are non-monotonic both in terms of biasness and expertise, and that we predict and observe conditions under which it is optimal for a recommender to forego sending USP messages.

5.1. 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 company 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. Thus, firms that are aware that their product are dominated in terms of important attributes may be better off by selecting recommenders that score high on characteristics other than expertise. For instance, if a firm decides to promote via social media influencers, it would be beneficial to connect with influencers that attract followers because of characteristics such as humor, joviality, creativity, and aesthetics.

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 is received at all. Therefore, a firm should blindly encourage reviewers, expert recommenders, or promoters to disclose information that favors its product over competing products. However, under certain conditions, companies may do better by bypassing these types of promotional strategies. We do not mean to imply that a firm should avoid promoting its products, but rather that other forms of promotional activities (such as uninformative advertisements that focus on symbolic or affective benefits) might be more profitable.

Finally, the findings of this research could provide valuable insights to policymakers. Bustillo and Zimmerman (2009) report that some government agencies have focused on tightening the 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 should be held accountable for misleading claims and that paid bloggers should disclose when they receive compensation to promote a product (i.e., disclose their degree of bias). Although such regulations facilitate progress toward improving consumer welfare, our research suggests that the disclosure of recommender characteristics such as expertise should be considered, since they can shape recommender and consumer behavior in important ways.

5.2. Caveats and future research

Our model assumes that consumers know the true characteristics of a recommender, but we acknowledge that there are times when this is not the case. Our predictions must, therefore, be governed by the perceived expertise and bias of the recommender. 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.

In addition, if consumers did not have a solid knowledge or prior belief about the recommender, they could make inferences about the recommender's type, which would change the equilibria identified in our model. Furthermore, we 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 might investigate situations in which consumers do not know the type of recommender and/or adopt high rationalization about the choice of recommender's type.

Our research focused on two key recommender characteristics: bias and expertise. Follow-up studies of attribute-based product recommendations could 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.

In addition, our model assumed that the recommender cannot lie as it is often the case in regulated markets (e.g., truth in advertising regulations), and that strategic consumers do apply rationality to infer whether the recommended or the target product is the best product. We acknowledge that there might be real-world situations in which these assumptions do not hold. For instance, a recommender could misrepresent the truth, and consumers might believe in the recommendation and blindly follow follow it. We do not provide a formal analysis of this scenario in this research, but we expect that if such situation occurs: 1) an unbiased expert would still lead consumers to buy the best product; 2) an unbiased novice would be indifferent between remaining silent and recommending at random, and consequently consumers would have a fifty-fifty chance of buying the best product; and 3) both the biased expert and the biased novice would adopt the strategy of always recommending the target product based on weak attributes or made-up arguments, and consumers would always buy the target product (i.e., the worse product). We encourage researchers to further investigate situations such as the ones described above.

Finally, our model considered that consumers perceive that two products possess attributes with the same value when the probability that a given attribute of a product is better than that of the competing product is 1/2. We investigated a model that explicitly considers that attributes could be better, equally good, or worse. The analysis, which is in Section W-E of the Web Appendix, shows that the majority of the directional effects go in the same direction as in the current version of our model, but their magnitudes are attenuated. This give us confidence on the generalizability of our findings.

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Appendix A. Mathematical derivations

A.1. Consumers' likelihood to purchase a product

We suppress conditioning in this derivation. Since states of the world $w \in W$ are mutually exclusive, we use Expression (1) to write that:

$$P(U_i > U_j|m,b,e) = E\Bigg[\sum_{w \in W} P\big(U_0 + \theta VE\big[1\big[H_i > H_j\big]|m,b,e\big] + (1-\theta)VE\big[1\big[L_i > L_j\big]|m,b,e\big] > U_0 + \theta VE\big[1\big[H_i < H_j\big]|m,b,e\big] + (1-\theta)VE\big[1\big[L_i < L_j\big]|m,b,e\big]\big)P(w|m,b,e)\Bigg].$$

We compute the expectation by imputing the value of the indicator function in each state of the world, verifying the probability that $U_i > U_j$ in that state, and multiplying this probability by the probability of that state, and by considering that $E[\theta] = \rho$:

$$P(U_i > U_j|m,b,e) = \rho P(H_i > H_j|m,b,e) + (1-\rho)P(L_i > L_j|m,b,e).$$

A.2. Proof of Lemma 1

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

$$P(H_i > H_j|m = m_{i,H},b,e) = 1, P(L_i > L_j|m = m_{i,L},b,e) = 1.$$

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

$$P\big(H_i > H_j|m = m_{i,L},b,e\big) = \frac{P\big(m = m_{i,L}|H_i > H_j,b,e\big)P\big(H_i > H_j\big)}{P\big(m = m_{i,L}|b,e\big)};$$

$$P(L_i > L_j|m = m_{i,H},b,e) = \frac{P(m = m_{i,H}|L_i > L_j,b,e)P(L_i > L_j)}{P(m = m_{i,H}|b,e)}.$$

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 attribute H, the probability is:

$$P\big(U_i > U_j|m = m_{i,H},b,e\big) = \rho + (1-\rho)\frac{P\big(m = m_{i,H}|L_i > L_j,b,e\big)P\big(L_i > L_j\big)}{P\big(m = m_{i,H}|b,e\big)}.$$

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

$$P\big(U_i > U_j|m = m_{i,L},b,e\big) = \rho\frac{P\big(m = m_{i,L}|H_i > H_j,b,e\big)P\big(H_i > H_j\big)}{P\big(m = m_{i,L}|b,e\big)} + (1-\rho).$$

A.3. Proof of Proposition 1

We use game theoretical arguments to prove this proposition.

We need to identify the equilibrium message m and the probability consumers will find product i better than product j. 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 attribute H (it is possible to say either that $m = m_{1,H}$ or that $m = m_{2,H}$). Because the recommender does not favor any particular product and because information about attribute H is more diagnostic than information about attribute L, when the state of the world is $w = \{H_i < H_j, L_i > L_j\}$, the recommender will always recommend the product that is superior in attribute H (in this case, product j) which means that that the equilibrium recommendation is $m^* = m_{j,H}$. In this case, consumers can use the expressions in Lemma 1 to compute the posterior beliefs to:

$$P^*\left(U_j > U_i | m = m_{j,H}, \underline{b}\,\bar{e}\right) = \rho + (1-\rho)\frac{1}{2} = \frac{1+\rho}{2} > \frac{1}{2}.$$

Consumers will only expect messages based on attribute H. A message about attribute L is out of equilibrium and any out-of-equilibrium belief so that: $P\left(U_i > U_j | m = m_{i,L}, \underline{b}\,\bar{e}\right) < \frac{1+\rho}{2}$ is admissible.[10]

A.4. Proof of Proposition 2

As in the Proof of Proposition 1, we can use game theoretical arguments to identify the equilibrium message m and the probability consumers will find product i better than product j.

The unbiased-novice recommender would like to steer the consumer to the best product, but she does not know which attribute is the most important, in the eyes of the recommender, recommending based on attribute H or L will produce the same result. Therefore, for each state of the world, the recommender will select to recommend based on attribute H or L with probability $\rho\frac{1}{2} + (1-\rho)\frac{1}{2} = \frac{1}{2}$ (i.e, at random with equal probability). The recommender will still send a recommendation because any information will help consumers diagnose which product is the best, and this is better from the recommender point of view than withholding information. Given this, when consumers receive a message about an attribute, they have no basis to update their posteriors about the other attribute due to strategic behavior by the recommender. Therefore, when the state of the world is $w = \{H_i < H_j, L_i > L_j\}$, the equilibrium message is $m^* = m_{j,H}$ or $m^* = m_{i,L}$ with equal probability.

Consumers, however, know which attribute is more or less important, and thus their behavior will differ if they receive a recommendation based on attribute H or L. On the one hand, if the recommender recommends based on the more-important attribute H (i.e., $m^* = m_{j,H}$) consumers will update the value of this attribute and buy the recommended product with probability $P^*\left(U_j > U_i | m = m_{j,H}, \underline{b}\,\underline{e}\right) = \rho + (1-\rho)\frac{1}{2} = \frac{1+\rho}{2} > \frac{1}{2}$. On the other hand, if the recommender recommends based on attribute L (i.e., $m^* = m_{i,L}$) consumers will follow the recommendation with probability $P^*\left(U_i > U_j | m = m_{i,L}, \underline{b}\,\underline{e}\right) = \frac{1}{2} + (1-\rho) = \frac{2-\rho}{2} > \frac{1}{2}$.

A.5. Proof of Proposition 3

In this scenario, consumers know that $b = \bar{b}$ and $= \bar{e}$; thus, for simplicity, we will drop these variables from all conditional probability expressions.

The biased expert recommender knows the parameters of the distribution of consumer preferences and thus it access the probability consumers will select the target product directly from Expression (2):

$$P(U_i > U_j | m) = \rho P(H_i > H_j | m) + (1-\rho)P(L_i > L_j | m). \tag{A1}$$

Let $P^N(\cdot|m)$ denote the probability assessment the proportion λ of naïve consumers form. When naïve consumers receive information about attribute H, the probability that they would purchase the target product is:

$$P^N\left(U_i > U_j | m = m_{i,H}\right) = \rho 1 + (1-\rho)\frac{1}{2} = \frac{1}{2} + \frac{\rho}{2} > \frac{1}{2}. \tag{A2}$$

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

$$P^N\left(U_i > U_j | m = m_{i,L}\right) = \rho\frac{1}{2} + (1-\rho)1 = 1 - \frac{\rho}{2} > \frac{1}{2}. \tag{A3}$$

Without loss of generality, consider that the recommender favors product 1. We can thus rewrite π to be the recommender's utility according to Expression (6) as:

$$\pi = \max_{m \in W}\left\{\lambda P^N(U_1 > U_2 | m) + (1-\lambda)P(U_1 > U_2 | m)\right\}. \tag{A4}$$

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:

$$E[\pi] = \begin{pmatrix} E[\pi|\{H_1 > H_2, L_1 > L_2\}] + E[\pi|\{H_1 > H_2, L_1 < L_2\}] \\ +E[\pi|\{H_1 < H_2, L_1 > L_2\}] + E[\pi|\{H_1 < H_2, L_1 < L_2\}] \end{pmatrix} \div 4. \tag{A5}$$

[10] This out-of-equilibrium beliefs follow 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.

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

Next, consider the consumer's belief formation. $P^N(U_1 > U_2|m)$ is updated according to expressions (A2) and (A3), whereas $P(U_1 > U_2|m)$ is updated according to Lemma 1.

When the state of the world is $\{H_1 > H_2,\ L_1 > L_2\}$, the recommender cannot lie; thus: $P\left(m = m_{2,H}|\{H_1 > H_2, L_1 > L_2\}\right) = 0$ and $P\left(m = m_{2,L}|\{H_1 > H_2, L_1 > L_2\}\right) = 0$. The recommender can send the messages $m = m_{1,H}$ and $m = m_{1,L}$ with some probability (the unknown variable we want to determine); hence we define: $P\left(m = m_{1,H}|\{H_1 > H_2,\ L_1 > L_2\}\right) \equiv X_1$ and $P\left(m = m_{1,L}|\{H_1 > H_2,\ L_1 > L_2\}\right) \equiv X_2$. Because the recommender only sends one message, these probabilities are mutually exclusive, and we can write $X_1 = 1 - X_2$.

When the state of the world is $\{H_1 > H_2,\ L_1 < L_2\}$, due to the "no-lie" assumption, we immediately have $P\left(m = m_{1,L}|\{H_1 > H_2,\ L_1 < L_2\}\right) = 0$ and $P\left(m = m_{2,H}|\{H_1 > H_2,\ L_1 < L_2\}\right) = 0$. Furthermore, because the recommender cannot recommend the "other product" or she will face the worst possible beliefs, we also have $P\left(m = m_{2,L}|\{H_1 > H_2,\ L_1 < L_2\}\right) = 0$. Hence, the recommender can only send message $m = m_{1,H}$ or forego the opportunity to send a message ($m = \varnothing$); thus we define $P\left(m = m_{1,H}|\{H_1 > H_2,\ L_1 < L_2\}\right) \equiv X_3$.

When the state of the world is $\{H_1 < H_2,\ L_1 > L_2\}$, for the same reasons in the previous paragraph, it is immediately evident that $P\left(m = m_{1,H}|\{H_1 < H_2,\ L_1 > L_2\}\right) = 0$, $P\left(m = m_{2,H}|\{H_1 < H_2,\ L_1 > L_2\}\right) = 0$, and $P\left(m = m_{2,L}|\{H_1 < H_2,\ L_1 > L_2\}\right) = 0$. Therefore, the recommender can only send message $m = m_{1,L}$ or forego the opportunity to send a message ($m = \varnothing$); thus we define $P\left(m = m_{1,L}|\{H_1 < H_2,\ L_1 > L_2\}\right) \equiv X_4$.

When the state of the world is $\{H_1 < H_2,\ L_1 < L_2\}$, the recommender forgoes the opportunity to recommend a product; thus the probability of each message is zero: $P\left(m = m_{1,H}|\{H_1 < H_2,\ L_1 < L_2\}\right) = 0$, $P\left(m = m_{1,L}|\{H_1 < H_2,\ L_1 < L_2\}\right) = 0$, $P\left(m = m_{2,H}|\{H_1 < H_2,\ L_1 < L_2\}\right) = 0$, and $P\left(m = m_{2,L}|\{H_1 < H_2,\ L_1 < L_2\}\right) = 0$.

Given the above conditional probabilities, the overall probabilities (for all states of the world) that the recommender will speak about an attribute are: $P\left(m = m_{1,H}\right) = \frac{1-X_2+X_3}{4}$, $P\left(m = m_{1,L}\right) = \frac{X_2+X_4}{4}$, $P\left(m = m_{2,H}\right) = 0$, and $P\left(m = m_{2,L}\right) = 0$.

Furthermore, the probability of receiving a message about one attribute, given the state of the other attribute, are: $P(m = m_{1,H}|L_1 > L_2) = \frac{1-X_2}{2}$, $P(m = m_{1,H}|L_1 < L_2) = \frac{X_3}{2}$, $P(m = m_{1,L}|H_1 > H_2) = \frac{X_2}{2}$, and $P(m = m_{1,L}|H_1 > H_2) = \frac{X_4}{2}$.

By plugging these probabilities into Expressions (3) and (4) in Lemma 1, we obtain:

$$P\left(U_1 > U_2|m = m_{1,H}\right) = \rho + (1-\rho)\frac{1-X_2}{1-X_2+X_3},\ P\left(U_1 > U_2|m = m_{1,L}\right) = \rho\frac{X_2}{X_2+X_4} + (1-\rho).$$

Now that we know $P^N(U_1 > U_2|m)$ and $P(U_1 > U_2|m)$, we can use Expression (A5) to write the conditional profit expression for all states of the world ($E[\pi|w]$ for all $w \in W$):

$$E[\pi|\{H_1 > H_2,\ L_1 > L_2\}] = U_0 + (1-X_2)V\left\{\lambda\left(\frac{1}{2}+\frac{\rho}{2}\right) + (1-\lambda)\left[\rho + (1-\rho)\frac{1-X_2}{1-X_2+X_3}\right]\right\}$$
$$+X_2V\left\{\lambda\left(1-\frac{\rho}{2}\right) + (1-\lambda)\left[\rho\frac{X_2}{X_2+X_4} + (1-\rho)\right]\right\},$$

$$E[\pi|\{H_1 < H_2,\ L_1 > L_2\}] = U_0 + X_4V\left\{\lambda\left(1-\frac{\rho}{2}\right) + (1-\lambda)\left[\rho\frac{X_2}{X_2+X_4} + (1-\rho)\right]\right\} + (1-X_4)V\frac{1}{2},$$

$$E[\pi|\{H_1 > H_2,\ L_1 < L_2\}] = U_0 + X_3V\left\{\lambda\left(\frac{1}{2}+\frac{\rho}{2}\right) + (1-\lambda)\left[\rho + (1-\rho)\frac{1-X_2}{1-X_2+X_3}\right]\right\} + (1-X_3)V\frac{1}{2},$$

$$E[\pi|\{H_1 < H_2,\ L_1 > L_2\}] = U_0 + \frac{1}{2}V.$$

The derivative $\frac{\partial E[\pi]}{\partial X_2} = -\frac{(2\rho-1)\lambda}{8}V$ is negative; thus $X_2^* = 0$ and $X_1^* = 1 - X_2^* = 1$. The derivative $\frac{\partial E[\pi]}{\partial X_3} = \frac{\rho\lambda+(2\rho-1)(1-\lambda)}{8}V$ is positive; thus $X_3^* = 1$. Lastly, the derivative $\frac{\partial E[\pi]}{\partial X_4} = \frac{(1-\rho)\lambda+(1-2\rho)(1-\lambda)}{8}V$ 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
$\{H_1 > H_2,\ L_1 > L_2\}$	$m = m_{1,H}$
$\{H_1 > H_2,\ L_1 < L_2\}$	$m = m_{1,H}$
$\{H_1 < H_2,\ L_1 > L_2\}$	$m = \varnothing$
$\{H_1 < H_2,\ L_1 < L_2\}$	$m = \varnothing$

Therefore, when the state of the world is $w = \{H_1 < H_2, L_1 > L_2\}$, the equilibrium message is $m^* = \varnothing$ and consumers would select products according to their priors: $P^*(U_1 > U_2|m = \varnothing) = \frac{1}{2}$. Notice that a message about attribute 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 $P\left(m = m_{1,L}|\{H_1 < H_2,\ L_1 > L_2\}\right) \equiv X_4 = 1$, 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: $P\left(U_1 > U_2|m = m_{1,L}\right) = \rho 0 + (1-\rho)1 = (1-\rho)$.

A.6. Proof of Proposition 4

In this scenario, consumers know that $b = \bar{b}$ and $= \bar{e}$; thus, for simplicity, we will drop these indexes. The biased-novice recommender does not know which attribute is more important.

Thus, she perceives the probability consumers will select the product as follows:

$$P(U_i > U_j|m) = \frac{\rho P(H_i > H_j|m) + (1-\rho)P(L_i > L_j|m)}{2} + \frac{(1-\rho)P(H_i > H_j|m) + \rho P(L_i > L_j|m)}{2}$$
$$= \frac{P(H_i > H_j|m) + P(L_i > L_j|m)}{2}. \quad \text{(A6)}$$

By recognizing that the above expression is mathematically identical to the probability assessment made by the Biased Expert Recommender (Expression A1) when $\rho = \frac{1}{2}$, 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 $\frac{\partial E[\pi]}{\partial X_3} = \frac{\lambda}{16}V$ is positive; thus $X_3^* = 1$. Lastly, the derivative $\frac{\partial E[\pi]}{\partial X_4} = \frac{\lambda}{16}V$ 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
$\{H_1 > H_2,\ L_1 > L_2\}$	$m = m_{1,H}$ or $m = m_{1,L}$ with equal probability
$\{H_1 > H_2,\ L_1 < L_2\}$	$m = m_{1,H}$
$\{H_1 < H_2,\ L_1 > L_2\}$	$m = m_{1,L}$
$\{H_1 < H_2,\ L_1 < L_2\}$	$m = \varnothing$

Therefore, when the state of the world is $= \{H_1 < H_2, L_1 > L_2\}$, the equilibrium message is $m^* = m_{1,L}$.

Consumers need to consider the entire space of messages in the table above and compute the probability that the recommended product (product 1) dominates the other product (product 2). By applying Expression (4) in Lemma 1, we compute the likelihood that consumers will select the recommended product given a message about attribute L (*i.e.*, $m^* = m_{1,L}$) to be: $P^*(U_1 > U_2|m = m_{i,L}) = \rho\frac{1}{3} + (1-\rho) = \frac{3-2\rho}{3}$.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2021.11.003.

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