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Brand-Contingent Attribute-Weighting Process: How Brands Impact Attribute Importance

Weights

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Abstract

Most past studies modeling consumer decision processes treated the brand of a product as an attribute parallel to the price, color, or size of a product; and as a result, such studies assigned an equal (i.e., non-contingent) importance weight across brands for each attribute. In contrast, the current research presents a multi-level choice model that incorporates a *brand-contingent* attribute-weighting process, in which brand is a higher-order construct that influences attribute importance. The empirical results using real purchase decision data and survey data from an airline industry show that attribute importance weights are contingent upon two aspects of a brand—the perceived relative position of the brand and consumers' brand usage experiences. When consumers perceive a brand to be inferior to its competitors in a given attribute, consumers generally place greater weight on that attribute for that brand (i.e., *brand-contingent negativity effect*). In contrast, when consumers perceive a brand to be superior to its competitors in a given attribute, only consumers with an extensive brand usage experience place greater weight on that attribute for that brand (i.e., *brand-contingent positivity effect*). By modeling consumer decision processes based on the consumer behavior literature, this research provides managerial insights on brand positioning and segmentation strategies based on consumers' brand usage experiences.

Keywords: brand, importance weight, modeling consumer behavior, positioning, brand experience, negativity effect

Brands constitute one of the most powerful forces shaping consumers' lives (Fitzsimons 2015; Keller and Lehmann 2006). Brands act as relationship partners for consumers, providing a sense of belongingness and helping them construct, express, and affirm their desired identities (Aaker 1999; Cutright et al. 2014; Escalas and Bettman 2003, 2005; Fournier 1998). Indeed, past research has documented many positive impacts that brands can generate to firms by influencing consumer decisions, such as increased repeat purchases, product recommendations, willingness to forgive product failures, and willingness to pay price premium (Aaker 1996; Aaker, Fournier, and Brasel 2004; Carroll and Ahuvia 2006; Heinrich, Albrecht, and Bauer 2012; Thomson, MacInnis, and Park 2005).

Despite the prominent power that brands exert on consumer decisions, many prior studies modeling consumer decision processes have treated brands as a mere product attribute, parallel to price, color, or size (e.g., Ding et al. 2011; Gilbride, Allenby, and Brazell 2006). Specifically, these past studies examined whether consumers placed more or less weight on brand information compared to other attribute information during their decision-making process, while assuming that the weight of each attribute was constant across brands. However, should brands be treated as equivalent to other product attributes? Can brands influence consumer decision processes—in particular, the importance weights placed on other product attributes—at a level different from those other attributes? It could be possible, for instance, for a consumer trying to purchase a flight ticket to weigh the importance of safety differently depending on the airline brand.

Because consumers draw the meaning of a brand from various sources associated with the brand, such as the brand's product attribute information, related marketing activities, and

consumers' experiences with the brand (Aaker 1991; Keller 1993), a brand reflects cumulative marketing strategies and investments over time (Klein and Leffler 1981). Highlighting this "enriched" nature of brands (Nowlis and Simonson 1997), several marketing gurus have referred to a brand as "the intangible sum of a product's attributes" (Ogilvy 1985) or "a container for a customer's complete experience with the product" (Zyman 2000). These insights converge to suggest that a brand is a higher-order construct that should be distinguished from other product attributes. This conceptual distinction between a brand and other product attributes is important, because past research suggests that brands have the power to function as "tinted eyeglasses through which consumers view products" (Keinan and Avery 2008, 2), impacting how consumers value different product information (Ahluwalia 2000, 2002; Erdem, Swait, and Louviere 2002).

Building on these insights, we propose that brands, as a higher-order construct, can influence how consumers weigh the importance of various product attributes in their decision-making process. As a result, the importance weight of an attribute would differ across brands, resulting in a brand-contingent attribute-weighting process. To investigate *when* and *how* brands impact the importance weight of product attributes, we introduce a multi-level choice model in which brands can influence the importance weights at a level different from product attributes. In particular, we examine whether attribute weights are contingent upon the following two aspects of a brand: (1) the position of a brand relative to its competitors and (2) consumers' past brand usage experiences.

Using both real purchase decision data and survey data from an airline industry, we

demonstrate that attribute importance weights are indeed contingent upon the relative position of brands and consumers' past brand usage experiences. We find that, in general, a brand's inferior position increases attribute importance, but a superior position does not. Specifically, when a brand is perceived to be inferior to its competition in a given attribute, the weight assigned to that attribute is increased for that brand. For instance, if a consumer perceives the safety of airline brand A to be worse than that of competing brands, the consumer would place a greater weight on the safety for brand A compared to other brands. In contrast, we do not observe the impact of a brand's superior position on attribute weights. Extending the findings from consumer behavior and psychology literatures, which advocate the dominance of negative information (i.e. inferior position) over positive information (i.e., superior position), we name this effect the *brand-contingent negativity effect* (Baumeister et al. 2001; Rozin and Royzman 2001). However, when consumers have an extensive usage experience with a brand, we do observe the *brand-contingent positivity effect*. Specifically, consumers with an extensive brand usage experience place greater weights on attributes that are superior to those of competitors only for that brand. On the other hand, past brand usage experiences do not affect the brand-contingent negativity effect—that is, regardless of whether consumers have limited or extensive usage experiences with a brand, they place greater weights on attributes that are inferior to those of its competitors.

The current research contributes to both theory and practice in several important ways. First, we contribute to the limited body of research modeling consumer decision processes based on consumer behavior theories while estimating the model using real market data (Kopalle 2015).

Second, we advance the literature on consumer decision processes by modeling the attribute-weighting process that is contingent upon brands. Specifically, our model specifies *when* and *how* brands influence the importance weights—that is, depending on the perceived relative position of a brand and consumers’ past brand usage experiences. Third, our findings provide managerial insights on whether marketers should prioritize highlighting the perceived superiority of their brand or improving the perceived inferiority compared to competing brands. Finally, our results validate the managerial importance of segmenting customers based on the level of their brand usage experience.

In the following section, we review prior research that studied how consumers weigh the importance of various product attributes in their choice process. We then propose our predictions on the brand-contingent attribute-weighting process based on past findings from the psychology, consumer behavior, and modeling literatures. Next, we fully specify our model and present the estimation results that corroborate our proposition. Finally, theoretical contributions and limitations of our research, possible areas for future research, and managerial implications on brand positioning and segmentation strategies are discussed.

Conceptual Development and Hypotheses

Past Research on Attribute Importance Weights

Although many experimental studies have investigated the conditions under which attribute importance weights change, none has specifically focused on the impact of brands on these changes (e.g., Evangelidis and Levav 2013; Irwin and Naylor 2009; Kahn and Meyer 1991; Kivetz and Simonson 2000; Shapiro and Spence 2002). Furthermore, in some of these studies,

brand information was treated similar to other product attribute information (e.g., Kivetz and Simonson 2000). As an exception, Nowlis and Simonson (1997) distinguished brand from other attributes at the conceptual level as an enriched attribute compared to other attributes such as price. They revealed that brand [price] becomes more [less] important when evaluated separately than when evaluated jointly with other options—i.e., weights are contingent upon the decision mode. However, they did not explore the possibility that brand as a higher-order construct can impact the importance of other product attributes, which would result in different weights for one attribute (e.g., price) across brands even under a given decision mode. Ahluwalia (2000, 2002) uniquely investigated this possibility and found that weights assigned to product attribute information changes depending on brand related factors, such as consumers' commitment to a brand and their familiarity with a brand. Building on this initial evidence for the brand-contingent attribute-weighting process, we explore whether managerially important brand related factors, such as brand positioning and consumer's brand usage experience that marketers are keen to manage in practice, influence attribute weights differently across brands.

Past research modeling consumers' decision strategies (e.g., weighted average, lexicographic, elimination by aspects, etc.) often examined importance weights of product attributes in consumers' choice processes. However, the focus of these past works was not on exploring whether brands can change attribute importance weights. For instance, Gilbride and Allenby (2004, 2006) aimed at modeling screening rules that consumers adopted to eliminate alternatives based on specific attribute-level thresholds, and consequently, their models adopted an equal (i.e., non-contingent) importance weight across brands for each attribute, instead of

brand-contingent attribute weights. In fact, most studies in this stream did not include brand as part of the information that decision-makers considered as their studies were not conducted in product or brand choice contexts (e.g., Tversky 1972). Even when the studies included brand information, they treated brand as equivalent to other product attributes such as product size and color. For example, Gilbride et al. (2006) treated brand as one of sixteen attributes in their conjoint study to estimate their decision process model. Ding et al. (2011) also included brand as one of the product features when investigating which model of decision rules better predict how consumers formulate consideration sets. As such, this stream of research did not examine whether and how brands influence attribute importance weights.

A limited number of studies modeling consumer decision processes have introduced the concept of “contingent weights.” However, such weights were contingent upon decision contexts—for instance, type of response mode (choice vs. value matching; Tversky, Sattath, and Slovic 1988) and background information learned from previous choices (Tversky and Simonson 1993)—rather than brands. Furthermore, which attribute received a greater weight under a given response mode or choice context was “either assumed or assessed by a pretest” (Willemsen and Keren 2002, 646) rather than estimated using real market-place data. Dzyabura and Hauser (2018) used synthetic data to estimate a model for product recommendation in which consumers update product attribute weights during their product search. However, since the research focus was on consumers’ learning of attribute weights over time (i.e., the weights were contingent upon consumers’ search), the possibility of brand-contingent attribute-weighting process was left unexplored.

In the empirical modeling literature, brand choice models based on panel data typically specify importance weights of product attributes (e.g., price or promotion sensitivity) parameters to be common across brands at the product category level (e.g., Guadagni and Little 1983; Fader and Hardie 1996; Mela, Gupta, and Lehmann 1997; Villas-Boas and Winer 1999). Although these models also include brand-specific intercepts separately to capture intrinsic values of brands, only few models have incorporated brand-specific attribute importance weights—which implies that attribute importance can be contingent upon (vs. fixed across) brands—and have focused on the “process” via which a brand can influence attribute importance in a consumer’s choice process. Among the few works, Erdem et al. (2002) show that brand credibility can change the sensitivity (i.e., importance weight) of price in consumers’ product choice processes. However, the effect of brand was limited to a single attribute (i.e., price) and was explored only from the brand credibility perspective. Therefore, how different aspects of a brand other than its credibility influence attribute weights in a multi-attribute and multi-brand context has yet to be explored.

Our research adds to these few attempts that modeled consumers’ decision processes to investigate *when* and *how* brands influence attribute importance weights in a multi-attribute and multi-brand context. Specifically, based on the contemporary view of brands as an enriched, higher-order construct that can guide how product attribute information is valued in consumer decisions, we introduce a multi-level choice model in which brands can influence product attribute weights at a level that is different from that of those attributes. Furthermore, to understand when and how attribute weights change, we propose an attribute-weighting process

that is contingent upon the two critical aspects of brand management: (1) the perceived relative position of a brand, and (2) consumers' brand usage experiences. Each of these aspects will be explained further in the following sections.

Perceived Relative Position of a Brand

Brand positioning is considered to be the highlight of the marketing process that guides marketing mix plans (Kotler 1997). The goal of positioning strategy is to occupy an attractive and distinctive position in target consumers' minds, thus gaining a competitive advantage over the other brands considered by target consumers (Ries and Trout 1986). Hence, a brand position refers to a *perceived* position in consumers' minds *relative* to competing brands.

To build hypotheses regarding how a brand's superior or inferior position in an attribute influences the importance of that attribute, we introduce past research on how people weigh positive information (relevant to superior position) and negative information (relevant to inferior position) differently. Past research has heavily advocated the greater weighting of negative information compared to similarly positive information. For instance, Baumeister et al. (2001, 323) conducted a review across various streams of the psychology literature, including impression formation, learning, emotions, and stereotypes, and concluded that the impact of "bad is stronger than good." Rozin and Royzman (2001) also reviewed evidence from religious, cultural, and literary sources in addition to evidence from psychology research and found that negative entities are more potent and dominant than positive entities. Indeed, this perspective is well captured in the value function of prospect theory, which illustrates that "losses loom larger than gains" (Kahneman and Tversky 1979, 279).

Such a greater weighing of negative information compared to positive information has also been observed in consumer contexts, particularly in the context of customer reviews and the related word-of-mouth effects (Basuroy, Chatterjee, and Ravid 2003; Chevalier and Mayzlin 2006; Chiou and Cheng 2003; Hennig-Thurau, Wiertz, and Feldhaus 2014; Herr, Kardes, and Kim 1991; Lee, Rodgers, and Kim 2009; Mizerski 1982). For instance, Mizerski (1982) showed that negative reviews of a product from a peer consumer exerted greater impact over positive reviews on product quality judgments. In other studies, negative online reviews had a greater influence than positive online reviews on brand evaluation and product purchase decisions (Basuroy et al. 2003; Chiou and Cheng, 2003; Hennig-Thurau et al. 2014).

Past research offers insights into possible mechanisms underlying the negativity effect. First, negative information tends to be more diagnostic than positive information in forming related judgments. For instance, impression formation research has heavily documented that negative information (e.g., one dishonest behavior) is more useful than positive information (e.g., one honest behavior) in categorizing (or forming an impression about) a person as either bad or good, and thus negative information receives a greater weight (e.g., Fiske 1980; Klein 1991; Skowronski and Carlston 1987, 1989). Likewise, in consumer contexts, product failure information is found to be more diagnostic than positive performance information in making product evaluations (Herr et al. 1991). Second, people encounter negative information less frequently than positive information—the sheer amount of the latter is greater than that of the former (Baumeister et al. 2001; Chevalier and Mayzlin 2006)—and this lower frequency in itself serves as useful information, as it indicates a change from the default of positive experiences

(Fiske 1980; Skowronski and Carlston 1989). Third, consumers tend to attribute the source of positive reviews to reviewers rather than to the positive performance of the product, whereas they tend to attribute negative information to the product or service itself (Chen and Lurie 2013; Mizerski 1982). As such, negative information receives greater weight when making judgements and purchase decisions related to a product or service.

Altogether, these past findings suggest that consumers are likely to focus on and assign greater importance to attributes for which the focal brand is perceived to be inferior (vs. superior) to competing brands. Accordingly, we propose that attribute weights will be contingent upon the perceived relative position of a brand, especially when a brand occupies an inferior position relative to its competitors. That is, an attribute will receive a greater weight if a brand occupies an inferior position for that attribute compared to its competitors. However, we do not expect an attribute for which a brand is in a superior position to receive a greater weight. We therefore formally hypothesize:

H1a: The *inferior* position that a brand occupies in an attribute relative to competing brands will *magnify* the weight assigned to that attribute for that brand (i.e., a significant brand-contingent negativity effect).

H1b: The *superior* position that a brand occupies in an attribute relative to competing brands will *not affect* the weight assigned to that attribute for that brand (i.e., a non-significant brand-contingent positivity effect).

Brand Usage Experience

Despite the prevalence of the negativity effect, several researchers have found an important boundary condition for this effect (Ahluwalia 2002; Block and Keller 1995; Klein and Ahluwalia 2005; Maheswaran and Meyers-Levy 1990). Specifically, they found that consumers focus on negative information only when they are motivated to process information in-depth—for instance, when they are seriously involved in an issue (Maheswaran and Meyers-Levy 1990), when the outcome promised by a message seems uncertain (Block and Keller 1995), or when they are not at all familiar with a brand (Ahluwalia 2002). Under these circumstances, consumers are motivated to make an accurate decision and thus are open to information of both valences (Ahluwalia 2002; Chaiken, Giner-Sorolla, and Chen 1996), which in the end leads to overweighing of negative information due to the mechanisms explained in the previous section, such as greater diagnosticity, lower frequency, and greater product-focused attributional tendency for negative information, compared to for positive information.

In contrast, when consumers are familiar with the target of evaluation, they are no longer uncertain about the outcome and thus are not driven by the accuracy motivation. Instead, their pre-existing evaluation of the target directs how they process information, resulting in selective information processing that reinforces their pre-existing attitude towards the target (Ahluwalia 2000, 2002; Chaiken et al. 1996; Ditto et al. 1998; Petty and Caccioppo 1986; Russo Meloy, and Medvec 1998). That is, when their pre-existing attitude is negative [positive], consumers will place greater weight on negative [positive] information. This leads to a polarization effect—that is, the stronger the pre-existing brand attitude is, the greater the weight assigned to the attributes that are consistent with the pre-existing attitude, because consumers with strong pre-existing

brand attitudes are motivated to defend those attitudes (Ahluwalia 2000, 2002; Chaiken et al. 1996).

In sum, these past findings suggest that consumers who have a limited experience with a brand, and thus are uncertain about the brand, will focus on negative information, whereas consumers who have an extensive experience with a brand will focus on either negative or positive information depending on their pre-existing attitude towards the brand. In other words, negative information will be weighed heavily regardless of the level of consumers' brand experiences, whereas positive information will be weighed heavily only when consumers have an extensive brand experience.

When applied to our context of interest, these findings suggest that the impact of a brand's inferior position on its attribute importance weights (i.e., the brand-contingent negativity effect) will not depend on the level of consumers' past brand usage experiences. Specifically, both consumers with a limited brand usage experience (under the accuracy motivation) and consumers with an extensive experience (under the defense motivation) will increase the weight of attributes perceived to be inferior to those of competitors. In contrast, the impact of a brand's superior position (i.e., the brand-contingent positive effect) will depend on (i.e., be magnified by) consumers' brand usage experiences. Specifically, consumers with an extensive brand usage experience will increase the weight of attributes that they perceive to be superior than those of competitors, whereas consumers with a limited brand usage experience will not increase the weight of superior attributes. Therefore, we formally hypothesize:

H2a: The brand-contingent *negativity* effect will not depend on the level of consumers'

brand usage experience.

H2b: The brand-contingent *positivity* effect will be magnified by consumers' brand usage experience.

Model Specification

To investigate when and how attribute importance weights are contingent upon brands, we present a two-level random coefficients multinomial logit model in which the importance weight of an attribute can vary across brands. Specifically, we model importance weights (i.e., the coefficients of product attributes in consumers' utility function) as a function of, thus to be contingent upon, (1) the perceived relative position of a brand and (2) consumers' brand usage experience. Next, we explain the utility function of our model and the operationalization of our key variables in detail.

Utility Specification of a Brand Choice Model

We assume that consumers have an additive utility function for a brand choice and the utility that consumer i obtains from choosing brand j can be specified as a function of the perceived values of each attribute (X_{ijm}) weighted by their correspondent importance (β_{ijm}) as follows:

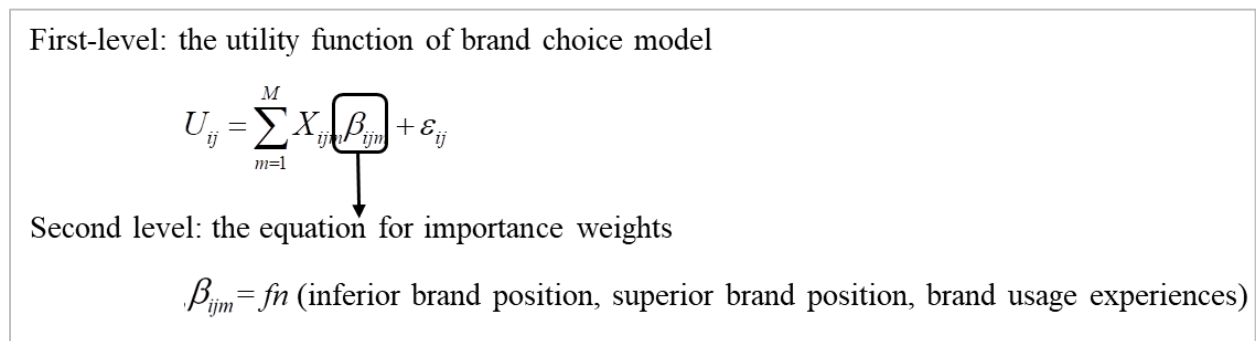
$$U_{ij} = \sum_{m=1}^M X_{ijm} \beta_{ijm} + \varepsilon_{ij}, \quad m = 1, 2, \dots, M \quad (1)$$

where X_{ijm} is consumer i 's evaluation of attribute m of brand j and β_{ijm} is the importance weight of attribute m of brand j for consumer i . M indicates the total number of product attributes. ε_{ijm} is a random error that is iid extreme value. Using this equation, we estimate the corresponding

choice probability for brand j using a typical method of simulated maximum likelihood for random coefficients multinomial logit model (McFadden and Train 2000).

This utility function allows the importance weights (β_{ijm}) to vary not only across attributes and individuals, but also across brands. Next, we specify the brand-specific importance weight for each attribute m (β_{ijm}) as a function of (i.e., contingent upon) (1) the perceived relative position of brands and (2) consumer's brand usage experiences (figure 1).

Figure 1. The equations of the main effects model



Perceived Relative Position of a Brand

We have hypothesized that the importance weight of an attribute can be influenced by the perceived position of a brand relative to its competing brands in consumer i 's consideration set (H1a and H1b). Despite the managerial importance of brand positioning, only few past models have considered the impact of the perceived relative position of a brand (or of a choice option) when examining the impact of different attributes on a consumer's choice. For instance, Shafir, Osherson, and Smith (1989, 1993) included relative advantage between available options as a component in their choice model. However, their model was formulated specifically for binary choices between lotteries with two attributes (i.e., payoff and probability of winning). Thus, its

applicability to multi-attribute products or services was limited. Tversky and Simonson (1993) introduced a model that captured the perceived tradeoff among multi-attribute products and incorporated a contingent weighting process. However, the attribute weights were not contingent upon the relative tradeoffs (i.e., the relative position of the options), but upon consumers' past choices. Furthermore, all of these past models did not examine the effect of relative advantage separately from the effect of relative disadvantage. Unlike these past models, we incorporate an attribute-weighting process that is contingent upon the perceived relative position of a brand. In addition, we separately specify perceived relative advantage and disadvantage of a multi-attribute brand compared to its competitors. Therefore, we model that the importance weight consumer i places on attribute m for brand j (i.e., β_{ijm} in Equation (1)) is a function of the perceived relative disadvantage (inferior position) and advantage (superior position) of brand j in attribute m as follows:

$$\begin{aligned} \beta_{ijm} = & \alpha_{0im} + \alpha_1 | X_{ijm} - \bar{X}_{i(-j)m} | \cdot I[X_{ijm} - \bar{X}_{i(-j)m} < 0] \\ & + \alpha_2 | X_{ijm} - \bar{X}_{i(-j)m} | \cdot I[X_{ijm} - \bar{X}_{i(-j)m} > 0] \end{aligned} \quad (2)$$

While α_{0im} denotes the intrinsic importance of attribute m for consumer i (i.e., general attribute importance in the product category that is not contingent upon brand), all the other components of the equation indicate changes in the attribute weight contingent upon the perceived relative position of the brand. That is, our equation incorporates both the intrinsic importance and the importance contingent upon the context (i.e., brand position), following past research that considered both of these aspects for importance weights (Willemse and Keren 2002). This specification enables us to explore the process underlying the changes in attribute weights,

beyond capturing the “global” changes in weights observed in past research (Tversky and Simonson 1993).

We express the perceived relative position of a brand for each attribute as $|X_{ijm} - \bar{X}_{i(-j)m}|$, which is the absolute difference between the perceived value of attribute m for consumer i for brand j and the mean of the perceived value of attribute m for consumer i across all the other brands (excluding brand j). This specification captures consumers’ cognitive process, in which a consumer perceives a brand’s positioning by comparing the brand’s performance relative to a reference point that summarizes the relationship among all other brands competing in consumers’ minds.¹ Compared to past specifications of relative advantage (e.g., Tversky and Simonson 1993), our specification reflects a process that is cognitively more efficient and thus is more likely.² Indeed, past findings show that consumers adopt relational heuristics to minimize cognitive effort exerted in decision making by encoding the gist of the relationships among choice alternatives (Bettman, Luce, and Payne 1998). In our specification, the gist of the

¹ Although past models (e.g., Shafir et al., 1989, 1993; Tversky and Simonson 1993) did not utilize the term *reference point* when specifying the relative advantage of an option, their specification of relative advantage is mathematically and conceptually similar to our specification that utilizes a reference point. Specifically, past models assumed that consumers perceive the relative advantage of an option by going through multiple rounds of pairwise comparisons among all possible pairs in the choice set. Such pairwise comparisons among three brands, for example, can be specified as $X_{i1m} - X_{i2m}$ and $X_{i1m} - X_{i3m}$ and the sum of these comparisons is $2X_{i1m} - (X_{i2m} + X_{i3m})$, which is equivalent to $(X_{i1m} - \bar{X}_{i(-1)m})$ of our model once divided by 2.

² In Tversky and Simonson (1993)’s choice model, the relative advantage of an option reflected consumers’ cognitive process that first calculated the relative advantages and disadvantages of an option by going through multiple rounds of pairwise comparisons among all possible pairs in the choice set for each attribute, and then re-calculated the proportion of the overall advantages out of the sum of advantages and disadvantages. This reflects a cognitive process that is much more effortful compared to our specification, especially in multi-brand, multi-attribute contexts. Furthermore, the past specification using the proportion format did not allow examining the separate effects of relative advantage and relative disadvantage on a consumer’s choice simultaneously.

relationship among all the other brands is encoded as a reference point against which the focal brand's position is compared (i.e., $|X_{ijm} - \bar{X}_{i(-j)m}|$).³ We take the absolute value in order to distinguish the magnitude effect of this difference from its directional effect as we explain next.

To separately estimate the effects of relative disadvantage (i.e., negativity; H1a) and relative advantage (i.e., positivity; H1b) of a brand, the indicator components $I[X_{ijm} - \bar{X}_{i(-j)m} < 0]$ and $I[X_{ijm} - \bar{X}_{i(-j)m} > 0]$ are multiplied by the perceived relative brand position component. Past models did not distinguish between relative advantage and relative disadvantage, and thus, could not examine their separate effects on consumer choice simultaneously (e.g., Shafir et al. 1989, 1993; Tversky and Simonson 1993). However, prior behavioral studies suggest that an increase in one of these effects might not mean a decrease in the other (Ahluwalia 2002). As such, our model examines the separate effects of both relative advantage (positivity) and disadvantage (negativity) on attribute weights. H1a and H1b can be tested by examining the significance of α_1 and α_2 in Equation (2).

Interaction with Consumers' Brand Usage Experience

To investigate the impact of consumers' brand usage experience on brand-contingent positivity and negativity effects, we add the interactions between the perceived brand position (i.e., each of the positivity and negativity terms) and consumers' brand usage experience to

³ We propose the mean as a reference point because, unlike the median, it takes into account the precise value of each attribute and includes the information about the distribution and/or extreme value of attributes, which is critical in brand choice contexts. Also, the mean is more appropriate than the maximum or minimum (i.e., the best or the worst performing brand in a given attribute), because adopting maximum or minimum values of alternative options as the reference point would hinder us from separately estimating the effects of relative disadvantage and relative advantage.

Equation (2) as follows:

$$\begin{aligned}
\beta_{ijm} = & \alpha_{0im} \\
& + \alpha_1 | X_{ijm} - \bar{X}_{i(-j)m} | \cdot I[X_{ijm} - \bar{X}_{i(-j)m} < 0] \\
& + \alpha_2 | X_{ijm} - \bar{X}_{i(-j)m} | \cdot I[X_{ijm} - \bar{X}_{i(-j)m} > 0] \\
& + \alpha_3 | X_{ijm} - \bar{X}_{i(-j)m} | \cdot I[X_{ijm} - \bar{X}_{i(-j)m} < 0] \cdot BrandExperience_{ij} \\
& + \alpha_4 | X_{ijm} - \bar{X}_{i(-j)m} | \cdot I[X_{ijm} - \bar{X}_{i(-j)m} > 0] \cdot BrandExperience_{ij} \\
& + \alpha_5 BrandExperience_{ij}
\end{aligned} \tag{3}$$

H2a and H2b can thus be tested by checking the significance of α_3 and α_4 in Equation (3).

Empirical Results

Data

For estimation, we used proprietary data collected by an Asian airline company as part of its internal consulting project. The airline provided flight services only for the routes between an island and mainland cities within an East Asian country at the time of data collection. Only two other airlines operated on the same domestic routes connecting the island and mainland then. The data included consumer survey data, which were linked with real flight purchase decision data. Specifically, the consumer survey was conducted in May 2007 at the check-in counter areas of the airport located on the island and the airports of the relevant mainland cities. The survey was distributed across different dates (weekdays and weekends) and times (morning and afternoon). Customers who completed the check-in process and held a boarding pass of one of the three airlines were approached for the survey. Hence, customers of all three airlines were included as the survey participants. As an incentive to complete the survey, customers were offered a gift set consisting of premium skincare products, which was actually sold at the duty-free shops of the airports at that time. When a customer agreed to participate in the survey, we recorded his/her

current flight purchase information (i.e. their airline choice) based on their boarding pass and handed out a questionnaire marked with the airline code that matched the customer's airline choice. A total of 608 customers participated in the survey, of whom 311 completed all the questions necessary for our study. As a result, we used these 311 participants as the final sample for our main estimation.

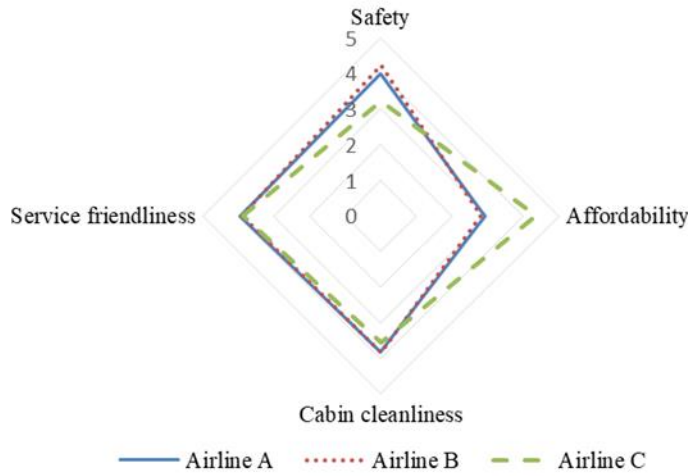
The survey asked participants to rate the importance of various factors that they considered when they purchased their flight ticket on a five-point scale (1= not at all important; 3 = neither important nor unimportant; 5 = very important). The factors included nine dimensions related to brand image (e.g., youthfulness, playfulness) and five attributes related to product quality (i.e., affordability, safety, service friendliness, cabin cleanliness, and seat comfort). These latter five attributes were among the most commonly included criteria in the airline service quality evaluation literature (see Wang et al. 2011 for a review) and were the variables relevant to our interest for the present study. Four of these five quality-related attributes, excluding seat comfort, received an average importance rating of 4.5 or greater out of 5, indicating that these attributes played very important roles in customers' flight ticket purchase decisions. Seat comfort received an importance rating of 4.26, still higher than many of other image-related dimensions which were mostly considered neither important nor unimportant. However, seat comfort was highly correlated with cabin cleanliness (correlation over .65). Considering a potential multi-collinearity problem when including the two variables, we excluded seat comfort whose importance rating was lower than that of cabin cleanliness and used the remaining four attributes in our main analyses.

After rating the general attribute importance, participants were asked to evaluate the three airlines on those product attributes on a five-point scale (1 = not at all, 5 = very good).

Participants were also asked to indicate how many past usage experiences they had with the three airline companies. The survey also included other questions for the consulting project, such as participants' purpose of travel; methods of flight reservation; top of the mind airline brand; exposure to word of mouth related to the airlines; and demographic information such as age, gender, income level, and education level.

Figure 2A illustrates the customers' evaluations of the three airlines on the four attributes (i.e., X_{ijm} of our model averaged across participants), which were rated on a five-point scale (1 = not at all, 5 = very good). Figure 2B more directly depicts the perceived relative differences among the three airlines in the four attributes that we modeled (i.e., $X_{ijm} - \bar{X}_{i(-j)m}$). As the figures indicate, Airline C shows quite different attribute ratings and perceived relative position compared to Airline A and Airline B. Specifically, Airline C occupies a low-fare position, while Airlines A and B occupy a more premium position in customers' minds. This overall customer perception reflects the actual ticket price and services offered by the three airlines. Airline C offered substantially lower ticket prices and operated on smaller aircrafts compared to the two other airlines. It was also the first airline in the country to eliminate free in-flight meals.

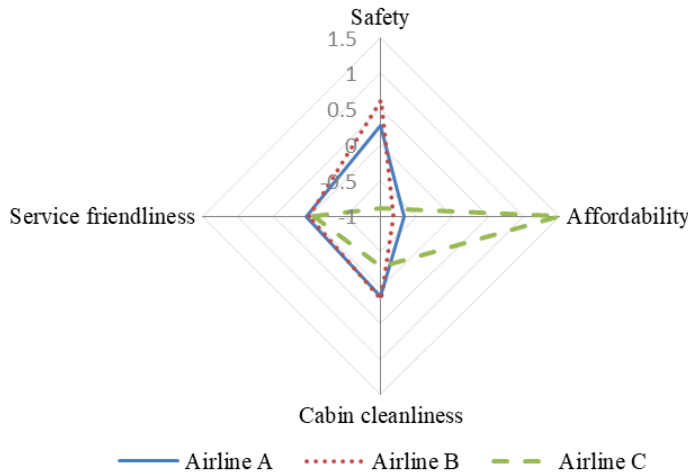
Figure 2A: Evaluation of Three Airline Brands on Four Attributes



Mean (Std.Dev.) of Product Attribute Evaluation

	Safety	Affordability	Cabin cleanliness	Service friendliness
Airline A	3.98 (0.76)	2.91 (0.93)	3.82 (0.83)	3.94 (0.86)
Airline B	4.21 (0.81)	2.81 (1.04)	3.86 (0.81)	3.91 (0.87)
Airline C	3.21 (0.96)	4.36 (0.96)	3.55 (0.97)	3.88 (0.96)

Figure 2B: Perceived Relative Differences Among the Airline Brands



Mean (Std.Dev.) of Perceived Relative Differences

	Safety	Affordability	Cabin cleanliness	Service friendliness
Airline A	0.27 (0.63)	-0.67 (0.78)	0.12 (0.73)	0.05 (0.70)
Airline B	0.62 (0.85)	-0.83 (0.95)	0.17 (0.78)	-0.00 (0.85)
Airline C	-0.89 (1.04)	1.50 (1.35)	-0.29 (1.07)	-0.05 (1.07)

Model Results

Table 1 presents the results of our two models: (1) Model 1 for testing the main effect of inferior position (H1a) and the main effect of superior position (H1b) on attribute importance weights, and (2) Model 2 for testing the interaction effect between consumers' brand usage experience and each of the main effect terms (H2a and H2b). We first compared the goodness of fit of these two models incorporating the brand-contingent weighting process against that of the baseline model that did not incorporate the contingent weighting process (i.e., Equation (1) without incorporating Equation (2)). The AIC of the baseline model (565.148) was higher than the AIC of our two models (559.066 and 557.550), indicating that our models with the brand-contingent weighting process provide a better fit to our dataset than the baseline, non-contingent weighting model.

The parameter estimates in Table 1 offers insights on when and how importance weights vary across brands. First, the Model 1 column shows that the coefficient of the brand-contingent negativity effect was significant and positive ($\alpha_1 = .118, p < .01$). Consistent with H1a, attribute importance weights varied depending on brands—that is, depending on the extent to which the brand position was perceived to be inferior to its competitors. The result indicates that consumers in general place greater weight on an attribute when a brand was in a competitive disadvantage for that attribute. For instance, if a consumer perceived Airline A to be worse in safety and Airline B to be worse in cabin cleanliness compared to competitors, the consumer placed a greater weight on safety when evaluating Airline A and on cabin cleanliness when evaluating brand B. In contrast, supporting H1b, the coefficient for brand-contingent positivity effect was

not significant ($\alpha_2 = -.019, p = .550$). That is, the superior position that a brand occupied for an attribute compared to its competing brands did not impact the importance weight of that attribute for that brand.

Table 1. Parameter Estimates of the Brand Choice Model Incorporating the Brand-Contingent Attribute-Weighting Process

Parameter Estimate	Model 1 <i>Main Effects</i>	Model 2 <i>Model 1 + Interaction Effects</i>
<i>The Main Effect of Brand Position</i>		
Negativity (inferior position)	.118 (.044) ^{***}	.107 (.043) ^{**}
Positivity (superior position)	-.019 (.033)	-.021 (.032)
<i>The Interaction with Brand Usage Experience</i>		
Negativity x Brand usage experience		.015 (.010)
Positivity x Brand usage experience		.010 (.005) ^{**}
Brand usage experience		-.005 (.004)
<i>Intrinsic Attribute Importance</i>		
Mean attribute importance – Safety	.486 (.243) ^{**}	.405 (.200) ^{**}
Mean attribute importance – Affordability	1.640 (.467) ^{***}	1.687 (.486) ^{***}
Mean attribute importance – Service friendliness	.603 (.270) ^{**}	.654 (.266) ^{**}
Mean attribute importance – Cabin cleanliness	-.632 (.220) ^{***}	-.591 (.205) ^{***}
Standard deviation – Safety	.325 (.221)	.467 (.223) ^{**}
Standard deviation – Affordability	1.090 (.387) ^{***}	1.183 (.483) ^{**}
Standard deviation – Service friendliness	.366 (.225)	.408 (.180) ^{***}
Standard deviation – Cabin cleanliness	.626 (.431)	.105 (.198)
Log likelihood	-269.533	-265.775
AIC	559.066	557.550

*** $p < .01$, ** $p < .05$ based on two-tailed tests. Standard errors are shown in parentheses.

Note: The log-likelihood of the baseline model without the brand-contingent weighting process is -274.574 and its AIC is 565.148.

Note that the individual-level intrinsic importance of each attribute (α_{0im}) was estimated as random effects. The standard deviation of the intrinsic importance of only one attribute, affordability, was significant ($SD = 1.090$; $p < .005$). This indicates that there was variability in importance of affordability (i.e., price factor) across consumers, which makes sense considering the wide variation in price sensitivity of consumers in general.

The Model 2 column presents the results of the interaction model that tested the impact of consumers' brand usage experience on brand-contingent negativity and positivity effects. Consistent with H2a, the brand-contingent negativity effect did not interact with brand usage experience ($\alpha_3 = .015$, $p = .116$), indicating that this effect does not depend on consumers' past brand usage experience. In fact, the main effect of the brand-contingent negativity remained significant even when the interaction term was included ($\alpha_1 = .107$, $p < .05$). In contrast, supporting H2b, the brand-contingent positivity effect depended on consumers' past brand usage experience ($\alpha_4 = .010$, $p < .05$).

Following up with the significant interaction, we conducted spotlight analyses at each level of brand usage experience to examine whether the brand-contingent positivity effect changed at different levels of consumers' brand usage experience (Krishna 2016; Spiller et al. 2013). The analyses revealed that only consumers who had fourteen or more brand usage experiences in the past showed a significant brand-contingent positivity effect (all p 's $< .032$; table 2). On the other hand, consumers who had four or fewer usage experiences showed either a marginal or significant reversed brand-contingent positivity effect (all p 's $< .091$; table 2). Altogether, the results indicate that when a consumer perceives a brand to be superior to its

competitors in an attribute, the consumer's repeated brand usage experience magnifies the importance weight s/he places on that attribute for that brand (H2b).

Table 2. The Spotlight Analyses at Different Levels of Brand Usage Experience

Brand Usage Experience	Negativity Effect			Brand Usage Experience	Positivity Effect		
	Parameter				Parameter		
	Estimate	S.E.	P> z		Estimate	S.E.	P> z
1	1.356	.618	.028	1	-.975	.474	.040
2	1.371	.617	.026	2	-.832	.422	.049
3	1.231	.645	.056	3	-.726	.435	.095
4	1.400	.618	.023	4	-.547	.324	.091
5	1.232	.540	.023	5	-.380	.262	.147
6	1.564	.732	.033	6	-.088	.131	.503
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
10	1.679	.796	.035	10	-.183	.340	.590
11	1.574	.686	.022	11	-.559	.632	.377
12	1.906	.917	.038	12	-.536	.425	.207
13	1.734	.830	.037	13	.309	.289	.286
14	1.704	.830	.040	14	.996	.437	.023
15	2.343	1.072	.029	15	.937	.404	.020
16	1.614	.669	.016	16	.810	.325	.013
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
20	1.619	.829	.051	20	.831	.387	.032
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
30	1.981	.954	.038	30	3.602	1.424	.011
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
50	3.389	1.801	.031	50	4.526	1.829	.013

Note: The colored rows indicate that the negativity effect and/or the positivity effect are either significant ($p < .05$) or marginal ($p < .01$) at the corresponding level of consumers' brand usage experience.

Although the interaction between the brand-contingent negativity effect and consumers' brand usage experience was not significant (H2a), we conducted supplementary spotlight analyses at each level of brand usage experience to better understand the brand-contingent

negativity effect across different levels of consumers' brand usage experience. The analyses revealed that the brand-contingent negativity effect was either significant or marginal at all levels of brand usage experience (all p 's < .056; table 2). Thus, regardless of whether consumers had limited or extensive brand experience, consumers placed a greater weight on an attribute of a brand if the brand was perceived to be inferior to its competitors in that attribute.

Robustness Check

So far, we have shown that attribute importance weights are contingent upon the relative position of a brand as well as consumers' brand usage experience. In doing so, we have assumed that the relative position is perceived by comparing a brand against other competing brands on each attribute—an assumption taken from past research (e.g., Tversky and Simonson 1993). However, it could also be possible that attribute importance weights are influenced by the evaluation of a brand conducted *across attributes per brand*, instead of the evaluation conducted *across brands separately per attribute*. According to past research on alternative-based processing, consumers can evaluate whether an alternative (i.e., a brand in our context) is strong or weak in certain attributes even when the alternative is evaluated on its own, prior to comparing it to other alternatives in a choice process (Bettman et al. 1988). Therefore, as a robustness check, we verified whether the relative position of a brand influences attribute importance weights even when our model allows for the weights to be contingent upon the brand's position inferred based on the within-brand, across-attributes evaluation.

Similar to the reference point of our main model to which the focal brand's performance

in an attribute was compared (i.e., $|X_{ijm} - \bar{X}_{i(-j),m}|$), we modeled that consumers would perceive a brand to be particularly strong or weak in a certain attribute by comparing its performance in one attribute against its performances in all other attributes (i.e., $|X_{ijm} - \bar{X}_{ij(-m)}|$). As we did in our main analysis, we then multiplied this component with the two indicator functions that separately estimated the main effect of attribute superiority and inferiority (compared to other attributes, perceived from a within-brand evaluation) on importance weights. We replaced the original variables with these new variables to test the attribute-weighting process that is contingent upon the position of a brand inferred based on the within-brand, across-attribute evaluation, instead of the original within-attribute, across-brand evaluation. Moreover, we also tested another extended model that included both the original variables and the new variables to allow for the attribute-weighting process that is contingent upon both the relative brand position perceived within an attribute (i.e., original variables), and the position of a brand inferred based on the within-brand, across-attribute evaluation (i.e., new variables).

We tested these two extended models and their parameter estimates are reported in the Appendix. We found that the goodness-of-fit (AIC) of the first extended model (including only the new variables) was larger (570.361) than that of our original main effects model (559.066; Model 1 in table 1), which implies that our original model outperforms the first extended model with new variables. Furthermore, none of the new variables were significant in the extended model (all p 's $> .528$), indicating that the attribute importance weights did not vary depending on the brand position perceived from an across-attribute comparison conducted within the brand. Adding the original variables to these new variables (extended model 2) improved the AIC

(561.314), but the original main effects model still fitted the data better. Furthermore, in the second extended model, none of the new variables were significant (all p 's $> .790$), whereas the original variable denoting the inferior relative brand position had a significant impact on attribute importance weights (i.e., the significant brand-contingent negativity effect; $p = .0008$) even when the new variables were included. The results reconfirmed that attribute weights are contingent upon the perceived position of a brand *relative to its competitors*. Although consumers may be able to evaluate a brand's strength or weakness by comparing its own performance across different attributes (instead of comparing against other brands), we did not find this evaluation to influence weights assigned to corresponding attributes.

General Discussion

Although brands are considered to be among the most important intangible assets of many firms (Keller and Lehmann 2006), past research that modeled consumer choice processes treated brands as product attributes similar to price, size, and color (e.g., Ding et al. 2011; Gilbride et al. 2006). In contrast, we distinguished brand from other product attributes as a higher-order construct that can influence the importance consumers place on those other attributes during their choice processes. We model this brand-contingent attribute-weighting process by introducing a two-level choice model, in which two aspects of a brand—the perceived relative position of a brand and consumer's past experiences with the brand—influence attribute importance weights. Using consumers' real flight purchase data linked with their survey data, we estimated our proposed model and demonstrated that the importance weight for an attribute does differ across brands. Specifically, the weight of an attribute was magnified when the brand under

consideration was perceived to be inferior to its competitors in the given attribute (i.e., brand-contingent negativity effect). This effect was observed regardless of the level of past experiences consumers had with the brand. In contrast, the perceived superior position of a brand in a given attribute increased the importance of that attribute for that brand (i.e., brand-contingent positivity effect) only when consumers had extensive past experiences with the brand.

Theoretical Contributions

Our findings contribute to the literature in several important ways. First, we add to the limited body of research modeling consumer decision processes based on the insights from the consumer behavior literature while estimating the model using real market data (Kopalle 2015). Specifically, we built our hypotheses on how the relative position (i.e., relative disadvantage and advantage) of a brand would influence attribute weights by extending the past findings on negativity and positivity effects from the psychology, consumer behavior, and modeling literatures. We also proposed how those effects of relative brand position on attribute weights would change depending on brand usage experiences based on the past behavioral research findings on the effects of experience-related motivation on processing of positive or negative information.

Second, we conceptually distinguished brand from other product attributes and presented a model in which brand can influence product attribute weights, allowing for a brand-contingent attribute-weighting process. Past studies that modeled consumer decision processes incorporating attribute importance weights did not allow for brand-contingent weights in their models (e.g.,

Ding et al., 2011; Gilbride and Allenby 2004, 2006; Tversky and Simonson 1993). Instead, a fixed (i.e., non-contingent) importance weight was assigned to each product attribute across brands. Also, past empirical studies using brand choice models typically did not adopt “brand-specific” coefficients for product attribute variables (i.e., attribute importance weight) and thus it was impossible to examine the process via which brands change importance weights of product attributes. The current research fills this gap by introducing a model that specifies the attribute-weighting process, reflecting when and how attribute importance weights change due to brand. Specifically, we modeled and empirically showed that attribute weights depend on how consumers perceive the position of a brand relative to competing brands and consumers’ past experiences with the brand.

Finally, unlike past research that modeled relative tradeoffs between choice options (Shafir et al. 1989, 1993; Tversky and Simonson 1993), we distinguished relative advantage from relative disadvantage and examined their separate effects on attribute weights. We also explored their separate interaction effects with consumers’ past brand usage experiences. By doing so, our research provided managerial insights on brand positioning and target-marketing strategies based on past brand usage experiences, which we discuss in the next section.

Managerial Implications

Brand positioning involves seeking to occupy a distinctive and attractive position relative to competing brands; thus, it naturally leads practitioners to focus on distinguishing a brand from the competition by highlighting the attributes in which the brand is more attractive than its competitors. As a result, marketing mixes prioritize communicating the superior attributes that

differentiate the brand from competitors. Interestingly, however, our findings suggest that consumers care about inferior aspects of a brand more than the extent that marketers believe consumers do. Therefore, marketers should invest in enhancing consumer perceptions on inferior attributes (e.g., by using communication plans or improving the actual attribute) rather than solely focusing on emphasizing superior attributes. Indeed, our spotlight analysis results suggest that improving perceived inferiority would be effective for consumers with all levels of brand usage experiences, as the results showed that consumers consider inferior attributes important regardless of the level of their brand usage experience.

As customers' brand usage experience increases, our results suggest that they would consider superior aspects of a brand more important compare to when they had less experience with the brand (while they still do care for inferior attributes of the brand). Since customers with extensive experiences would consider information of both valences important (compared to customers with limited experiences who tend to care more for negative information), these customers should be targeted with messages highlighting the perceived superiority of the brand and improving the perceived inferiority of the brand concurrently. For instance, brands with price advantage, such as JetBlue and Walmart, should send targeted messages to frequent customers emphasizing their superior aspects (i.e., price advantage) as well as enhancing inferior aspects (e.g., premium wine selection for JetBlue or organic product offering for Walmart). However, to attract new customers or customers with only few usage experiences, more effort should be placed on enhancing the perceived inferiority of the brand (e.g., product/service quality of JetBlue and Walmart).

Limitations and Directions for Future Research

Future research can extend the current model by exploring different ways that consumers perceive a brand's relative position and incorporating those into the model. For example, we assumed that consumers use the mean attribute value of competing brands as a reference point in perceiving the relative position of the focal brand. This assumption was based on past models that calculated relative advantage of an option against all other alternatives in the choice set (Shafir et al. 1989, 1993; Tversky and Simonson 1993; see footnote 1). Although we explained in our model section the advantages of using the mean of competing brands as a comparison point over other possible reference or comparison points (e.g., the maximum or the minimum, which indicates the best or worst performing brand in the given attribute), it is still possible that consumers may adopt other relational heuristics to identify the comparison point when perceiving the relative position of a brand. Hence, future research can explore different types of reference or comparison points consumers would adopt and conditions under which one type is preferred over another. These insights can be incorporated into the current model to better reflect consumers' actual decision-making processes.

Another possible area for future research is to investigate how the brand-contingent weighting process changes when the choice options in a consumers' consideration set include multiple products of the same brand. The current research focused on brand purchase situations in which each brand represented a choice alternative. However, our model can be extended to situations in which a choice set consists of multiple options under the same brand in addition to options with different brands. In such a case, the change in attribute weight caused by the

perceived relative brand position may be similar for the options under the same brand, especially if the brand positioning is clear in consumers' minds and as a result the perceived differences between options with the same brand are minimal (e.g., color difference between two iPhones). Alternatively, it is also possible that the relative position of the brand is perceived differently between two options with the same brand, thus resulting in different importance weights for the given attribute between the two options. It would be interesting for future research to examine which of these expectations is confirmed when the consideration set includes options with the same brand.

Future research can also examine the boundary conditions of the brand-contingent attribute-weighting process. One possible condition is when the number of brands under consideration is significantly increased. In such a case, consumers may engage in a brand-contingent attribute-weighting process only in the final choice stage, after a majority of brands have been screened out and only a few brands remain in the consideration set. The brand-contingent attribute-weighting process may not be applicable in the preliminary decision stages including an extensive number of brands or choice options, because engaging in the brand-contingent attribute-weighting process could be cognitively burdensome under such circumstances.

Finally, our survey data were collected among consumers who had already made their purchase decision. This situation helped us link the real consumer purchase data with survey data, but it came with a drawback—it is possible that consumers' brand choice had affected self-reported responses of attribute evaluation. Although we believe the effect of this potential

self-report bias on our key findings is minimal, future research can collect the self-report measures of the survey before consumers make their final purchase decision. This alternative order of data collection also accompanies another bias (i.e., responding to self-report measures can bias the purchase decision in a way that is unnatural in most real decision-making contexts), but it would help verify whether the brand-contingent attribute-weighting process is robust beyond the potential self-report bias present in the current data set.

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Appendix

Table A. Parameter Estimates of the Robustness Check Models

Parameter Estimate	Robustness Check Model 1 <i>Includes brand positions perceived only from across-attribute comparisons</i>	Robustness Check Model 2 <i>Includes brand positions perceived from both across-attribute comparisons & across-brand comparisons</i>
<i>The Main Effect of Brand Position</i>		
Negativity (inferior position perceived from <i>across-brand</i> comparison)		.117 (.044)**
Positivity (superior position perceived from <i>across-brand</i> comparison)		.0008 (.028)
Inferior position perceived from an <i>across-attribute</i> comparison	-.074 (.117)	-.015 (.060)
Superior position perceived from an <i>across-attribute</i> comparison	.023 (.049)	-.036 (.137)
<i>Intrinsic Attribute Importance</i>		
Mean attribute importance – Safety	.252 (.147)*	.358 (.176)**
Mean attribute importance – Affordability	1.179 (.201)***	1.444 (.357)***
Mean attribute importance – Service friendliness	.285 (.170)***	.583 (.236)***
Mean attribute importance – Cabin cleanliness	-.612 (.168)*	-.576 (.193)**
Standard deviation – Safety	.311 (.187)	.411 (.194)**
Standard deviation – Affordability	.518 (.226)**	.950 (.374)**
Standard deviation – Service friendliness	.092 (.276)	.381 (.181)**
Standard deviation – Cabin cleanliness	.050 (.336)	.077 (.183)
Log likelihood	-275.180	-268.660
AIC	570.361	561.314

*** $p < .01$, ** $p < .05$, * $p < .1$ based on two-tailed tests. Standard errors are shown in parentheses.