Asymmetries in the Sequential Learning of Brand Associations: Implications for the Early Entrant Advantage

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The highlighting effect occurs when the order in which consumers learn about brands determines the strength of association between these brands and their attributes. In four experiments, we find that consumers more strongly associate common attributes with early learned brands and unique attributes with late-learned brands. These findings imply an advantage for late entrants when unique attributes offer a higher value than attributes that are common to late and early entrants. We extend an attention-based model of associative learning to accommodate sequential learning of brand associations and predict when late versus early entrants will be able to sustain an advantage.

When Microsoft introduced its Zune MP3 player to compete with Apple's iPod, it offered attributes that were common to iPod (e.g., high resolution display) while emphasizing attributes that were unique (e.g., wireless communication between two Zune players). Microsoft's strategy to create a product of common plus unique attributes is frequently used for overcoming an early entrant's advantage. This strategy has been more successful in some cases (e.g., PlayStation vs. Nintendo) than in others (e.g., R. J. Reynolds's Eclipse smokeless cigarette).

Consumer researchers have identified possible causes of an early entrant advantage and attempted to uncover its boundary conditions. First, when consumers are uncertain about attribute levels, they use the attribute levels of an early entrant as a standard (i.e., ideal) by which they judge the attribute levels of late entrants (Carpenter and Nakamoto 1989). Second, consumers more intensively process the attributes of early entrants, which results in increased memory for these attributes and preference for the early entrant over late entrants (Kardes and Kalyanaram 1992). Third, consumers process alignable differences (i.e., common attributes with different values) more intensively than nonalignable differences (i.e., attributes that are unique to each brand) when comparing brands (Zhang and Markman 1998). This results in an advantage for the early entrant when it offers higher value on alignable attributes. However, it also implies that late entrants may overcome the early entrant advantage when they offer higher value on such attributes (Zhang and Markman 1998). These findings highlight the importance of both common and unique attributes in understanding the limits of the early entrant advantage.

The early entrant advantage is intrinsically related to how consumers learn associations between brands and attributes. Therefore, it is surprising that an associative-learning perspective, which has been used to study how consumers learn relationships between product attributes and product benefits (Janiszewski and Van Osselaer 2000; Van Osselaer and Alba 2000; Van Osselaer and Janiszewski 2001), has not been used to study the early entrant advantage. Consider a situation in which a consumer initially learns that a brand of pain reliever (the early entrant) has a rapid release property and is gentle to the stomach. Later, the consumer learns that another brand of pain reliever (the late entrant) has the same rapid release property but also has anti-inflammatory properties. Recent research in associative learning, namely, research on the highlighting effect (Kruschke 2001a, 2001b; Kruschke, Kappenman, and Hetrick 2005; Medin and Edelson 1988), suggests that the consumer should develop a

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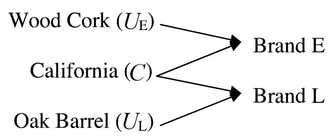
FIGURE 1

HIGHLIGHTING TERMINOLOGY AND PROCEDURE

Panel A: Associations Learned



Panel B: Learning Procedure

Cue Code	Attributes	Brand
CU_E	California, Wood Cork	Brand E
CU_L	California, Oak Barrel	Brand L

Panel C: Test Procedure

Cue Code	Attributes	Possible Responses	Observed Response
C	California	Brand E, Brand L	Brand E
$U_E\,U_L$	Wood Cork, Oak Barrel	Brand E, Brand L	Brand L

stronger association between the common attribute (rapid release property) and the early entrant than between the common attribute and the late entrant. In addition, the consumer should develop a stronger association between the late entrant and its unique attribute (anti-inflammatory properties) than between the early entrant and its unique attribute (gentle to the stomach). The implication of these asymmetric associations is that the early entrant advantage may be contingent on the value of common attributes compared to the value of unique attributes.

This article is organized as follows. We initially describe the highlighting effect and attentional learning theory (ALT), the theory currently used to account for the highlighting effect. We then discuss ALT's limitations in explaining how consumers establish associations when learning about brands and their attributes and propose an extended model that accommodates market entry order effects. Next, we test this extended model in a series of experiments. A preliminary experiment tests the predictions of the extended model and lays out the basis for how brand-attribute associations may influence brand evaluation. Experiment 1 shows that these associations affect the evaluation of brands with equally valued attributes. Experiment 2 rules out an accessibility-based explanation for the results of experiment 1 and presents moderators of the attention allocation process. Experiments 3 and 4 provide evidence that brand-attribute associations drive the brand preference results and show additional evidence for the attention allocation process. We conclude with a discussion of the theoretical and practical implications of our results and avenues for future research.

CONCEPTUAL BACKGROUND

The Highlighting Effect

The highlighting effect is an intriguing associative-learning phenomenon. Medin and Edelson (1988) first demonstrated this effect (originally named the inverse base-rate effect) in a medical-learning task in which respondents learned to use multiple symptoms to predict the occurrence of a disease. The highlighting effect predicts that the learning order of two stimuli, each featuring cues that are imperfect (i.e., common to the two stimuli) and perfect (unique to each of the stimuli) predictors of an outcome, produces an asymmetric pattern of association strengths from cues to outcomes. This effect can be illustrated in a consumer-learning setting. Suppose that a consumer who is shopping for wines first learns that a wine from California, sealed with wood cork, is produced by brand E (i.e., an early learned brand). She then learns that a wine from California, aged in oak barrels, is produced by brand L (i.e., a late-learned brand; see fig. 1, panel A). In this learning structure, both brands of wine present a common attribute (C; California) and unique attributes: U_E (wood cork), which is unique to brand E, and U_L (oak barrel), which is unique to brand L. The consumer learns about these brands sequentially (i.e., $CU_E \rightarrow$ E is followed by the learning that $CU_L \rightarrow$ L; see fig. 1, panel B).

The test phase of a highlighting design assesses the learned associations. It involves presenting the consumer with the common attribute by itself (C; California) and with a combination of the unique attributes (U_EU_L; wood cork and oak barrel). The diagnosticities of the single attributes C, U_E, and U_L for brands E and L are given by $\Pr(\mathrm{E}|C) = \Pr(\mathrm{L}|C) =$

50% and $\Pr(\mathrm{E}|U_{\mathrm{E}}) = \Pr(\mathrm{L}|U_{\mathrm{L}}) = 100\%$. However, previous findings indicate that consumers may respond as follows: $\Pr(\mathrm{E}|C) > \Pr(\mathrm{L}|C)$ and $\Pr(\mathrm{E}|U_{\mathrm{E}}U_{\mathrm{L}}) < \Pr(\mathrm{L}|U_{\mathrm{E}}U_{\mathrm{L}})$. These results are puzzling because the main difference between each wine brand is the order in which they are learned (i.e., both stimuli have one common and one unique cue; see fig. 1, panel C). This effect has been replicated in contexts such as the learning of random words (Dennis and Kruschke 1998) and geometric stimuli (Fagot et al. 1998).

One of the most successful explanations for the findings discussed above posits that learners strategically allocate attention across cues to preserve prior knowledge and accelerate learning through error reduction (ALT; Kruschke 2001b). Protection of learning is activated when the learning of a new association conflicts with previously learned associations. Take the wine context discussed above as an example. When learning the early associations $CU_{\mathrm{E}} \rightarrow \mathrm{E}$ (i.e., California and wood cork → brand E), people are likely to learn that both attributes are associated with brand E because neither attribute has been previously associated with another brand. Thus, both attributes should acquire moderate association with brand E. However, when learning the late associations $CU_{\mathrm{L}} \rightarrow \mathrm{L}$ (i.e., California and oak barrel → brand L), there is conflict stemming from the established association between the common attribute C and brand E. Given that attribute U_{L} does not conflict with prior learning, ALT predicts that people will shift attention away from C toward U_{L}. As a consequence, attribute U_{L} (C) becomes strongly (weakly) associated with brand L. When attribute C is presented by itself, it more strongly elicits brand E than brand L, thus the result $\Pr(\mathrm{E}|C) > \Pr(\mathrm{L}|C)$. When attributes U_{E} and U_{L} are presented jointly, attribute U_{L} more strongly elicits brand L than attribute U_{E} elicits brand E, thus the result $\Pr(\mathrm{E}|U_{\mathrm{E}}U_{\mathrm{L}}) < \Pr(\mathrm{L}|U_{\mathrm{E}}U_{\mathrm{L}})$.

One important assumption of ALT is that learning occurs from multiple cues to a single outcome (e.g., attributes C and U_{E} signal brand E, and attributes C and U_{L} signal brand L). Thus, ALT assumes that learners strategically allocate attention across cues. However, many consumer settings may challenge this assumption. For instance, a consumer may become aware of a brand and later learn about the multiple benefits this brand delivers (e.g., Volvo → safety and reliability). Based on the assumption that cues temporally precede outcomes (Waldmann 2000), this characteristic of consumer contexts implies learning that a single cue (brand) predicts multiple outcomes (attributes).

It is unknown whether the pattern of associations predicted by the highlighting effect can be observed in consumer contexts. We are especially interested in, but not limited to, contexts in which a single cue (i.e., brand) predicts multiple outcomes (i.e., attributes). This investigation will allow us to demonstrate that (1) outcomes may also compete for attention, (2) people may learn to allocate attention strategically across outcomes, and (3) the simple presentation of a brand name may elicit competition between attributes to be predicted by that brand name. The idiosyncrasies of the sequential learning of brand associations pose a challenge for ALT's explanation for the highlighting effect and require a reexamination of the theory.

An Extended Model of Associative Learning

ALT has its roots on Mackintosh's (1975) associative-learning model of selective attention and relies on the assumption that cues compete for limited attentional resources. Our first step is to modify Mackintosh's model to account for learning when a single cue (brand) predicts multiple outcomes (attributes). Let α_i ($\alpha_i \in [0,1]$) be the learning-rate parameter of cue i, β_j ($\beta_j \in [0,1]$) be the learning-rate parameter of outcome j, λ_j ($\lambda_j \in [0,1]$) be the magnitude of learning supported by outcome j (i.e., the asymptote of conditioning), and n be the trial number. The change in the strength of association from cue i to outcome j is given by

$$\Delta V_{ij}^{n} = \alpha_i \beta_j^{n} (\lambda_j - V_{ij}^{n-1}). \quad \textbf{(1)}$$

The strength of an association between a cue and an outcome (V_{ij}^{n}) after a given learning trial can be expressed as

$$V_{ij}^{n} = V_{ij}^{n-1} + \Delta V_{ij}^{n}. \quad \textbf{(2)}$$

Mackintosh's original model assumes that the amount of attention allocated to cues, which affects the α parameter, drives the updating of the strength of association between a cue and an outcome. We extend this assumption to situations in which attention is allocated to outcomes, which affects the β parameter. Given that the extended model focuses on situations in which consumers learn from a single cue to multiple outcomes, α is assumed to be constant. The starting values of the learning-rate parameters in the first learning trial are assumed to be positively correlated with the salience of their respective stimuli.

The mechanism of strategic allocation of attention uses history of learning to decide how much attention to allocate to each stimulus. This mechanism has two important properties: (1) attention allocated to outcomes affects the updating of associations, and (2) people tend to protect previously learned associations. The first property posits that as more (less) attention is allocated to a given outcome, an association from a cue to an outcome will increase faster (slower). Given that the β parameter captures the amount of attention allocated to an outcome, it is important to describe a rule that captures the updating of β's. Let C and U be the indexes for the common and unique outcome, respectively, and $\Delta\beta_C$ be the change in the learning-rate parameter of the common outcome. The updating of the parameter following the first learning trial can be described as

$$\Delta\beta_C^{n} = f(|\lambda_U - V_{iU}^{n-1}| - |\lambda_C - V_{iC}^{n-1}|), \quad \textbf{(3)}$$

where $f(\cdot)$ is a monotonically increasing function that vanishes at zero. Equation 3 indicates that the updating of β's is a function of how well a cue predicts each outcome, which will ultimately determine the amount of attention an outcome receives. Given the assumption that attention is a limited resource, if outcome C receives less attention, then outcome U receives more attention and vice versa. Thus, as β_C decreases (increases), β_U increases (decreases). To illustrate the updating process, assume that both outcomes support equivalent amounts of learning (i.e., $\lambda_C = \lambda_U$) and are equally salient at the beginning of the learning process; thus, they draw equivalent amounts of attention (i.e., $\beta_C = \beta_U$). In this situation, V_{iC} and V_{iU} increase at equivalent rates (see eqq. 1 and 2), and $|\lambda_U - V_{iU}| = |\lambda_C - V_{iC}|$ in every trial. As a consequence, the values of β_C and β_U remain unchanged after each trial, and the cue becomes equally associated with each outcome. However, if outcome C receives less attention than outcome U, then $\beta_C < \beta_U$, and V_{iC} increases at a slower rate than V_{iU} (see eqq. 1 and 2). As a consequence, $|\lambda_U - V_{iU}| < |\lambda_C - V_{iC}|$ and β_C decreases, while β_U increases, after each learning trial (see eq. 3). In this case, the cue becomes more strongly associated with the unique than with the common outcome. Alternatively, if outcome C receives more attention than outcome U, then $\beta_C > \beta_U$, and V_{iC} increases at a faster rate than V_{iU}. As a consequence, $|\lambda_U - V_{iU}| > |\lambda_C - V_{iC}|$ and β_C increases, while β_U decreases, after each learning trial. In this case, the cue becomes more strongly associated with the common than with the unique outcome.

The second property posits that when an outcome has been previously predicted by a different cue, people will detect conflict and protect prior learning by shifting attention away from that outcome and toward a novel outcome. This strategy, used when consumers learn that an attribute that was predicted by a brand is also predicted by a different brand, reduces error and accelerates new learning. For instance, when people learn that brand E predicts both California and wood cork (CU_E), there is no conflict with prior learning for either of the outcomes. Thus, prior learning does not need to be protected. As a result, brand E acquires similar strength of association with both C and U_E (as in the example in which $\beta_C = \beta_U$). However, when people first learn that brand L predicts California and oak barrel (CU_L), there is conflict with prior learning about outcome C, which is already predicted by brand E. This conflict directs attention away from outcome C toward outcome U_L, which does not signal conflict and can help accelerate the learning about which outcome cue L predicts. As a result, brand L becomes more strongly associated with outcome U_L than with outcome C (as in the example in which $\beta_C < \beta_U$). One might ask what happens when a consumer is exposed to the brand-attributes pairing $E \rightarrow CU_E$ again after having seen $L \rightarrow CU_L$. The extended model assumes that conflict only arises when a learner attempts to create a new association for a stimulus for which an association has already been created in the absence of conflict. Because a consumer learned to shift attention away from attribute C when brand L is present, the association between brand L and attribute C does not need to be protected when a consumer encounters $E \rightarrow CU_E$ again. Thus, attribute C should receive the same amount of attention it received prior to learning that $L \rightarrow CU_L$. This is consistent with recent findings that people come to "learn" the shifts of attention and know which stimuli should receive more or less attention (e.g., Kruschke and Johansen 1999).

The extended model has important theoretical implications for associative learning. First, it proposes that outcomes may compete for attention. This possibility has been largely overlooked by the associative-learning literature. Second, it is possible that the representation of the learned associations can be elicited by the mere presentation of brand names (i.e., single cues). In other words, when a brand name is presented, two attributes (i.e., outcomes) may be elicited based on their strengths of association with the brand and be jointly used to generate a brand evaluation. In the standard highlighting effect, the pattern of associations is tested by presenting a pair of cues that will elicit a single outcome as a response.

We start the empirical investigation with a preliminary study. This study tests whether the learning order (i.e., early vs. late) of two brands can influence the strengths of association between these brands and their attributes as predicted by the extended model. This study also tests whether competition between attributes can be elicited by presentation of a single brand name. Next, we test whether the strengths of associations between brands and attributes resulting from this competition can affect brand evaluations and determine market entry order effects. We then present moderators of the effects and provide process evidence for the role of associations and learning protection in brand evaluation.

PRELIMINARY STUDY

We conducted a preliminary study to test whether the order in which consumers learn about brands affects the strengths of associations between these brands and their attributes as predicted by the extended model. Respondents were initially exposed (i.e., early learning) to one brand name (e.g., Valpizzol—brand E), followed by a delay and presentation of the brand's two attributes (e.g., wine region: California and type of cork: plastic). Respondents (N = 61) were then exposed (i.e., late learning) to a second brand name (e.g., Dalduga—brand L), followed by a delay and presentation of the brand's two attributes (e.g., wine region: California and type of aging: stainless steel). Note that one attribute was common to both brands and that the other two were unique to each brand. The unique attributes were randomly assigned to be paired with brand names. In the test phase, respondents were shown two wine types and were asked to indicate which brand they expected each wine to be. When respondents were shown a wine featuring the common attribute only (i.e., wine region: California), they were more likely to choose brand E ($\hat{\pi}_E = 85.20\%$) than brand L ($\hat{\pi}_L = 14.80\%$). When respondents were shown a wine featuring the two unique attributes (i.e., type of cork: plastic and type of aging: stainless steel), they were more likely to choose brand L ($\hat{\pi}_L = 65.60\%$) than brand E ($\hat{\pi}_E = 34.40\%$). In both cases the choice proportions were significantly different from 50% (both p's < .05). These results are evidence that common attributes become more strongly associated with early learned brands, while unique attributes become more strongly associated with late-learned brands. Experiment 1 investigates whether this pattern of associations can influence the evaluations of equally valued brands and moderate the early entrant advantage.

EXPERIMENT 1

The results of the preliminary study suggest an asymmetry in the sequential learning of brand associations. If strengths of associations from brands to attributes influence the brand evaluation process (i.e., attributes with stronger associations with the brand are more heavily weighted), then an early versus a late entrant advantage could be moderated by the value of common attributes relative to the value of unique attributes. The following account provides the basis for this prediction.

First, an estimate of attribute importance based on strengths of associations can be generated by dividing the strength of association from a brand to an attribute by the sum of all brand-attribute associations. For instance, the relative weight of the common attribute when one evaluates brand E could be estimated as $V_{EC}/(V_{EC}+V_{EU_E})$. Given the pattern of associations found in the preliminary study, the common attribute C should receive a larger weight when one evaluates brand E than when one evaluates brand L. Alternatively, the unique attribute should receive a larger weight when one evaluates brand L than when one evaluates brand E. Now, let S_C, S_{U_E}, and S_{U_L} be the values (i.e., how desirable an attribute is) of C (i.e., common attribute), U_E (i.e., unique attribute of brand E), and U_L (i.e., unique attribute of brand L), respectively. Assume that the valuation of a brand is a function of the sum of the cross product of the value of each attribute and its relative weight. Because the common attribute should receive a larger weight in the evaluation of brand E than in the evaluation of brand L, brand E should have a higher evaluation than brand L for any $S_C > S_{U_E} = S_{U_L}$. Because the unique attribute should receive a larger weight in the evaluation of brand L than in the evaluation of brand E, brand L should have a higher evaluation than brand E for any $S_C < S_{U_E} = S_{U_L}$. In sum, an early entrant advantage should be observed when the common attribute has a greater value than the unique attributes of two competing brands, while a late entrant advantage should be observed when the unique attributes have a greater value than the common attribute of two competing brands.

Design, Stimuli, and Procedure

In total, 141 undergraduate students at the University of Florida and the University of Washington received extra credit to participate in the experiment. The design was a value of the common attribute (larger = Brazil vs. smaller = Sudan) by learning order (early vs. late) mixed design. The value factor was manipulated between subjects, and the learning-order factor was manipulated within subjects.

Respondents were instructed to learn about different types of wines. After initial instructions about the task, the computer screen showed target and filler attributes. The target attributes, which later would be used in the learning phase, were wine region: Brazil, assigned to attribute C in the larger value condition ($S_C > S_{U_E} = S_{U_L}$); wine region: Sudan, assigned to attribute C in the smaller-value condition ($S_C < S_{U_E} = S_{U_L}$); and type of cork: plastic and type of aging: stainless steel, randomly assigned to attributes U_E and U_L. The filler attributes were type of cork: wood and type of aging: oak barrel. The filler and target attributes were presented at the beginning of the task to give respondents an idea of possible wine attributes. To test our predictions regarding brand evaluations, we assigned values to each attribute in the form of star ratings. Respondents were told that the star ratings represented experts' assessment of the value of each attribute. To generate the perception of attribute values necessary for this test, the target stimuli Brazil, Sudan, plastic cork, and stainless steel barrel received experts' ratings of 3, 1, 2, and 2 stars, respectively. The remaining contextual stimuli (California, wood cork, and oak barrel) received 5-star ratings. Respondents saw the same expert ratings across conditions. The ratings of the contextual stimuli were used to provide respondents with comparison standards that would decrease noise in the perceptions of value of the target stimuli. The brand names were fictitious (Valpizzol and Dalduga) and were randomly assigned to the early and late-learned brands (brands E and L).

After seeing the experts' ratings for the stimuli on the computer screen, respondents rated the desirability of each attribute, one per screen, on a 9-point scale (-4 = very undesirable; +4 = very desirable). In addition, respondents were asked to rate the desirability of the two fictitious brand names (Valpizzol and Dalduga). These ratings were used as checks for the manipulation of the values of attributes S_C, S_{U_E}, and S_{U_L} and as an assessment of whether there was any preference for one of the fictitious brand names.

Learning Phase. Respondents were asked to learn about wines described by combinations of the target attributes listed above. In the early learning phase, there were two $E \rightarrow CU_E$ trials. In the late-learning phase, there was one $E \rightarrow CU_E$ trial and one $L \rightarrow CU_L$ trial. Respondents were not aware of the early versus late brand-learning manipulation and only saw a single learning block with three brand E and one brand L trials. Each trial started with the brand name appearing on the screen for 2 seconds. Then, information about the attributes was added: wine region: Brazil or wine region: Sudan, depending on the value condition, and type of cork: plastic or type of aging: stainless steel, depending on the random assignment of these attributes to U_E and U_L. The common and the unique attributes appeared simultaneously and were centered on the screen, separated by two lines. Their order on the screen (top vs. bottom) was randomized per respondent. After a 2-second delay, a Continue button appeared, and a new trial was initiated once respondents had clicked on this button. Respondents were allowed to look at the information on the screen for as long as they wished. After the first block of trials, respondents were told that the information would be repeated once again to improve their learning about the wines. This procedure was repeated a third time for a total of three blocks of three brand E and one brand L trials.

Test Phase. In order to investigate whether a brand name can elicit competition between attributes based on the strengths of associations, we presented respondents with brand names in the test phase. Respondents were shown one of the brand names and asked to estimate, on a 9-point scale (1 = very unlikely; 9 = very likely), the likelihood that they would buy a bottle of wine from that brand. This procedure was then repeated for the second brand. The order of presentation of the brands was randomized.

Results

Attribute Values. An examination of the desirability ratings revealed that the attribute Brazil was rated as significantly more desirable ($M_{Br} = 0.79$) than both plastic cork ($M_{pl} = -0.98$; $t(140) = 9.20$, $p < .001$) and stainless steel barrel ($M_{st} = -0.78$; $t(140) = 8.23$, $p < .001$). The attribute Sudan, however, was rated as significantly less desirable ($M_{Sud} = -1.87$) than both plastic cork ($t(140) = 5.63$, $p < .001$) and stainless steel barrel ($t(140) = 7.03$, $p < .001$). The attributes plastic cork and stainless steel barrel did not significantly differ from each other ($t(140) = 1.11$, $p > .25$), and Brazil was rated as significantly more desirable than Sudan ($t(140) = 16.22$, $p < .001$). In addition, no differences were observed in the desirability ratings of the brand names ($M_{Val} = 0.38$, $M_{Dal} = 0.30$; $t(140) = 1.24$, $p > .20$). These results show that the values of attributes C, U_E, and U_L had the proper characteristics for the testing of our predictions (i.e., $S_C > S_{U_E} = S_{U_L}$ in the larger-value condition, and $S_C < S_{U_E} = S_{U_L}$ in the smaller-value condition).

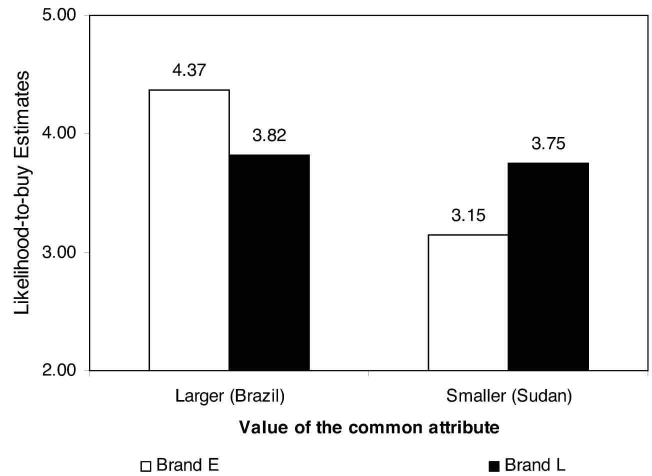
Likelihood-to-Buy Estimates. A repeated-measures ANOVA on the likelihood-to-buy estimates showed a significant interaction between the value and learning-order factors (see fig. 2; $F(1, 139) = 9.87$, $p = .002$). In the larger-value condition, respondents were more likely to buy brand E than brand L ($M_E = 4.37$, $M_L = 3.82$; $F(1, 139) = 5.36$, $p = .02$). In the smaller-value condition, however, respondents were more likely to buy brand L than brand E ($M_L = 3.75$, $M_E = 3.15$; $F(1, 139) = 4.63$, $p = .03$).

Discussion

Experiment 1 tested whether consumers' evaluations of brands featuring equally valued attributes vary as a function of the order in which they learn about brands. We found preference for the early learned brand over the late-learned brand when the value of common attribute C was larger than the value of the unique attributes U_E and U_L. In addition, we found preference for the late-learned brand over the early learned brand when the value of attribute C was smaller

FIGURE 2

EXPERIMENT 1 RESULTS



than the value of attributes U_E and U_L. This result implies that when people learn associations from brands to attributes, exposure to a brand name in the test phase and subsequent evaluation of the brand may trigger a very interesting process. Attributes that acquired different levels of association with a brand, resulting from the order in which this brand was learned in a sequence (i.e., early vs. late), are combined to generate the evaluative output. The fact that the valuation of the brands varied as a function of the strength of associations between a brand and two attributes is additional evidence that outcomes may compete for association with a single cue.

The results of experiment 1 suggest another way in which late entrants may be able to overcome the early entrant advantage. If late entrants deliver unique attributes with a higher value than common attributes, they may establish an advantage. Alternatively, early entrants will sustain advantage when they are able to deliver a higher value for a common attribute relative to the value of unique attributes of a late entrant. This result is counterintuitive given that past research (e.g., Tversky 1977) indicates that people tend to ignore common attributes.

There is, however, a potential alternative explanation for the results of experiment 1. Research suggests that the value of the unique attribute may be the main driver of the brand evaluation process when brands are learned sequentially (Mantel and Kardes 1999). Specifically, because the unique attribute of the late-learned brand might be the most accessible attribute, this attribute may have driven the brand evaluation process. This finding has been labeled the direction-of-comparison effect (Mantel and Kardes 1999; Tversky 1977). We test this alternative explanation next.

EXPERIMENT 2

Experiment 2 was designed to investigate whether the direction-of-comparison effect can account for the results in experiment 1. Hypothesis 1a of Mantel and Kardes (1999, 338) predicts that the discrepancy in the evaluation of the early and late-learned brand should be a monotonically increasing function of an individual's need for cognition (NFC). Because the unique attribute of the late-learned brand should be more accessible for high-NFC individuals, differences in the ratings of the brands should be magnified for high- (vs. low-) NFC individuals. Alternatively, we predict that people strategically allocate attention away from the common attribute C and toward the unique attribute U_L in the late-learning phase. This process results in decreased processing of the common attribute when people learn about the late brand. The decreased processing of attribute C conflicts with the processing goals of high-NFC individuals who are more likely to fully process information about all attributes. As a result, the expected differences in the ratings of the brands should be attenuated for high- (vs. low-) NFC individuals.

In addition, the direction-of-comparison effect predicts that information about the unique attribute of the late-learned brand is more accessible and that recall should be enhanced for high-NFC individuals. Our predictions are based on the strength of association between brands and attributes rather than on accessibility; thus, the recall of attributes should not vary. Finally, in order to alleviate any potential concerns based on the number of exposures to each brand (i.e., the 3 : 1 presentation ratio within each learning block), we added a condition in which the frequency did not vary.

Design, Stimuli, and Procedure

In this experiment we manipulated the frequency of presentation of the brands so that in one condition it was 3 : 1, replicating experiment 1, but in a second condition it was 2 : 2. We also measured respondents' NFC using the 18-item scale proposed by Cacioppo, Petty, and Kao (1984). The design was a frequency of presentation (3 : 1 vs. 2 : 2) by NFC (low vs. high) by learning order (early vs. late) mixed design. The frequency and the NFC factors were between-subjects factors, and the learning-order factor was a within-subjects factor. In total, 67 undergraduate students at the University of Florida and University of Washington received extra credit to participate in the experiment and were randomly assigned to frequency conditions.

The wine region California was used as attribute C (5-star rating), and stainless steel and plastic cork were randomly assigned to attributes U_E and U_L (both with a 3-star rating). Except for the frequency-of-exposure manipulation, the learning procedure and test phase replicated those of experiment 1. After the test phase, we asked respondents to rate their level of agreement with several statements (the 18-item NFC scale). Following these ratings, respondents were presented with one of the brands and asked to type in a text box which attributes described the brand. This procedure was repeated for the second brand (order of presentation was randomized). This information was used to check the recall of the attributes for the two brands.

Results

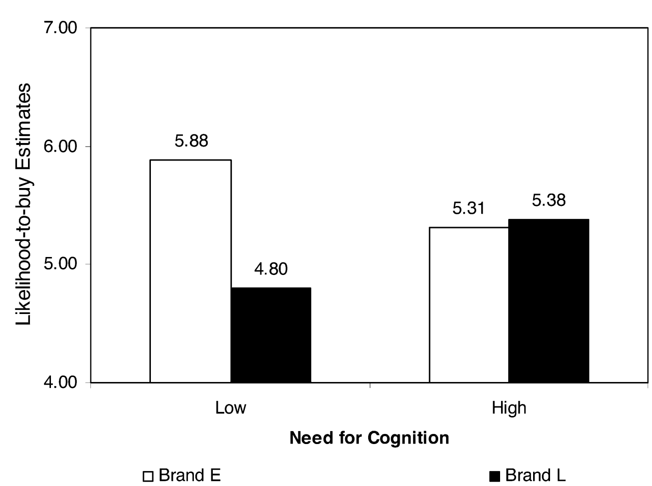
Attribute Values and Need for Cognition. An examination of the desirability ratings revealed that the attribute California was rated as significantly more desirable ($M_{Cal} = 3.22$) than both plastic cork ($M_{pl} = -.61$; $t(66) = 18.07$, $p < .001$) and stainless steel barrel ($M_{st} = -.46$; $t(66) = 19.12$, $p < .001$), which did not significantly differ from each other ($t(66) = 0.76$, $p > .40$). There was no statistically significant preference for either of the brand names ($M_{Val} = 0.73$, $M_{Dal} = 0.66$; $t(66) = 0.60$, $p > .50$).

Following Mantel and Kardes's (1999) procedure, we did a median split of the mean composite of the 18 items of the NFC scale (Cronbach's alpha = .86). The new coded factor indicated a large difference between the low- ($M_{lo} = 4.13$) and high-NFC ($M_{hi} = 5.46$; $p < .001$) groups. The number of low- versus high-NFC individuals did not vary systematically within levels of the frequency factor ($\chi^2(1) = 0.14$, $p > .70$), as expected given random assignment.

Likelihood-to-Buy Estimates. A repeated-measures ANOVA on the likelihood-to-buy estimates showed a nonsignificant three-way interaction ($F(1, 63) < 1$) and a nonsignificant interaction between the frequency of presentation and the learning-order factors ($F(1, 63) = 2.82$, $p > .10$). Thus, we collapsed the data across levels of the frequency factor. There was, however, a significant interaction between the NFC and the learning-order factors (see fig. 3; $F(1, 63) = 6.20$, $p = .02$). An examination of simple effects within levels of the NFC factor revealed that, in the low-NFC condition, respondents were significantly more likely to buy brand E than brand L ($M_E = 5.88$, $M_L = 4.80$; $F(1, 63) = 11.50$, $p = .001$). In the high-NFC condition, however, respondents were indifferent to buying brand E or brand L ($M_E = 5.31$, $M_L = 5.38$; $F(1, 63) < 1$). These results are consistent with our predictions but inconsistent with the direction-of-comparison effect.

FIGURE 3

EXPERIMENT 2 RESULTS



Recall Measures. Two judges, who were unaware of the study hypotheses, coded the recalled attributes and reached a high level of agreement (98%). Each answer was coded as 1 if California was recalled, 0 if California was not recalled, and -1 if a different region was recalled as the common attribute. The same coding system was applied to the unique attributes. Thus, we created two recall variables per brand, one capturing recall of the common attribute and one capturing recall of the unique attribute. Two repeated-measures ANOVAs on the attribute recall measures showed no main effect of recall across brands for attribute C ($M_{\mathrm{E}} = 0.94$, $M_{\mathrm{L}} = 0.97$; $F(1, 65) < 1$) or for attributes U_{E} and U_{L} ($M_{\mathrm{E}} = 0.88$, $M_{\mathrm{L}} = 0.94$; $F(1, 65) < 1$). In addition, there was no interaction with the NFC factor in either of the analyses (both p's $> .10$).

Discussion

Experiment 2 shows that the results of experiment 1 cannot be explained by the process predicted by the direction-of-comparison effect or by the frequency of exposure to each brand. The results also uncover an individual characteristic (NFC) that may influence the strategic allocation of attention during learning. People who are high in NFC may not be as affected by market entry order effects as are people who are low in NFC. The magnitude of learning protection seems to be small for high-NFC individuals, indicating that such individuals may be better able to fully process the attributes of late entrants and establish appropriate associations.

To explore factors other than NFC that may affect the magnitude of learning protection, we ran an experiment that had an additional condition in which respondents were told, prior to the learning phase, that "experts suggest that all attributes are important when consumers evaluate wines." Presenting this piece of information should motivate allocation of attention to all attributes and decrease the magnitude of the difference in brand evaluation relative to the condition in which this piece of information was not added. A repeated-measures ANOVA on the likelihood-to-buy estimates revealed a significant interaction ($F(1, 55) = 7.08$, $p = .01$). When no additional information was presented, respondents were more likely to buy brand E than brand L ($M_{\mathrm{E}} = 6.67$, $M_{\mathrm{L}} = 5.30$; $F(1, 55) = 25.06$, $p < .001$). When additional information regarding the experts' opinion was presented, however, respondents were indifferent to buying brand E or brand L ($M_{\mathrm{E}} = 6.00$, $M_{\mathrm{L}} = 5.63$; $F(1, 55) = 1.99$, $p > .10$).

EXPERIMENT 3

Experiment 3 was designed to provide further evidence for the process driving the results of experiments 1 and 2. Specifically, we tested whether the likelihood-to-buy estimates are indeed the result of differences in the strength of association between attributes and brands. We also conducted the recall task from experiment 2 as a way to check whether differences in strength of association could be explained by accessibility of attribute information. In addition, we collected reaction times during the learning phase as a proxy measure for the strategic allocation of attention.

Design, Stimuli, and Procedure

In total, 52 undergraduate students at the University of Florida and the University of Washington received extra credit to participate in the experiment. The design was a learning order (early vs. late) within-subjects design. The procedure and stimuli followed that of experiment 2 for the condition in which the frequency of presentation of each brand was held constant (2 : 2 condition). We made one change in the learning phase: there was no delay between the presentation of the brand name and the attributes and no delay prior to the appearance of a Continue button. This change was introduced because we wanted to collect reaction times during the learning phase to capture the amount of processing of all the information available on the screen.

The other change to the design was introduced after the test phase. We showed respondents each brand (in random order) and asked them to choose, from the list of three attributes (C, U_{E}, and U_{L}), which attribute best characterized that brand. This was a forced-choice task in which respondents could choose only a single attribute. The brands were presented one at a time on the top of the screen with the three attributes on the bottom. This task was used to measure the association between the attributes and the brands. After the association task, respondents performed a recall task.

Results

Attribute Values and Likelihood-to-Buy Estimates. An examination of the desirability ratings revealed that the attribute California was rated as significantly more desirable ($M_{\mathrm{Cal}} = 3.06$) than both plastic cork ($M_{\mathrm{pl}} = -1.56$; $t(51) = 16.01$, $p < .001$) and stainless steel barrel ($M_{\mathrm{st}} = -1.62$; $t(51) = 16.32$, $p < .001$), which did not significantly differ from each other ($t(51) = 0.42$, $p > .70$). There was no statistically significant preference for either of the brand names ($M_{\mathrm{Val}} = -.06$, $M_{\mathrm{Dal}} = .04$; $t(51) = 0.42$, $p > .65$). The likelihood-to-buy estimates replicated the predicted pattern. Respondents indicated to be significantly more likely to buy brand E than brand L ($M_{\mathrm{E}} = 5.31$, $M_{\mathrm{L}} = 4.77$; $t(51) = 2.13$, $p = .04$).

Reaction Times. We used the reaction times (measured as the time that passed from the presentation of information on each screen until respondents hit the Continue button) as a proxy measure for the amount of information processing in a given trial. As people spread attention more evenly across two attributes rather than paying attention to one attribute more than the other, processing of information should slow down. Therefore, it should take longer to process the information for brand E than for brand L (i.e., attention is more focused on the unique attribute of brand L). This is supported by the reaction time data. Respondents spent significantly more time (in seconds) looking at the information regarding brand E than the information regarding brand L ($M_E = 3.01$, $M_L = 2.00$; $F(1, 51) = 125.57$, $p < .001$).

In addition, respondents should learn how to more efficiently allocate attention across attributes as they go through the learning phases. Thus, the processing of information should also become more efficient, and reaction times should decrease with learning. This is supported by the significant decrease in the amount of time across blocks of training ($M_{bl1} = 3.99$, $M_{bl2} = 2.18$, $M_{bl3} = 1.54$; $F(1, 51) = 125.57$, $p < .001$). The decrease in reaction times, however, should not be equivalent for both brands. In our experiments, training should be more beneficial to brand E because attention is more spread across its attributes, implying slower reaction times. Thus, repetition of information should provide larger returns in efficiency for the processing of brand E. To test this prediction, we computed, for each individual, the slope indicating the decreases in reaction times across trials, calculated as the difference in reaction times between trial 2 and trial 1 of each brand within a learning block divided by the reaction time in trial 1 for that brand. The first learning block was treated as a training block and was not used in the analysis, given that respondents were still getting used to the procedure and stimuli at that point. A two block (learning block 2 vs. learning block 3) by two brand (E vs. L) within-subjects ANOVA on these slope measures showed a significant main effect of the brand factor with a larger negative slope for brand E than for brand L ($M_E = -.524$, $M_L = -.429$; $F(1, 51) = 5.08$, $p = .03$), indicating that repetition of information benefits brand E more than it benefits brand L. There was a nonsignificant main effect of the block factor ($M_{bl2} = -.522$, $M_{bl3} = -.431$; $F(1, 51) = 3.49$, $p = .07$). These results did not vary across blocks (i.e., nonsignificant block-by-brand interaction; $F < 1$).

Measures of Association and Recall. To test whether the brand preferences were indeed driven by brand associations, we assessed which attribute respondents were more likely to select as the one that best characterized each brand. We predict a smaller discrepancy in the strength of associations between common and unique attributes for brand E than for brand L. Thus, respondents should be indifferent to selecting the common or the unique attribute as the one that better characterizes brand E and more likely to select the unique than the common attribute as the one that better characterizes brand L. The analysis of choice proportions showed that when brand E was presented, 50.0% of the respondents selected the common attribute C, and 46.2% selected the unique attribute U_E (3.8% were mistakes in which respondents selected U_L). These choice proportions are not significantly different from 50% (both p's $> .30$). When brand L was presented, 28.8% of the respondents selected the common attribute C, and 63.5% selected the unique attribute U_L (7.7% were mistakes in which respondents selected U_E). These choice proportions are significantly different from 50% (both p's $< .05$). These results are consistent with the pattern of strength of associations predicted to drive the likelihood-to-buy estimates.

We further tested the extent to which these measures of association were independent of respondents' ability to recall attributes. We repeated the recall task procedures, coding, and analyses conducted in experiment 2. Again, there was no main effect of recall of attribute C for each brand ($M_E = 0.94$, $M_L = 0.89$; $t(51) = 1.65$, $p > .10$) or for attributes U_E and U_L ($M_E = 0.79$, $M_L = 0.77$; $t(51) = 0.23$, $p > .80$).

Supplemental Analyses. We coded respondents' choices as a function of whether they were consistent or inconsistent with the predicted process influencing the strengths of associations. Participants who chose attribute U_L as the attribute that better characterizes brand L were coded as consistent with the predicted process. Participants who chose attribute C as the attribute that better characterizes brand L were coded as inconsistent with the predicted process. For this analysis, we removed the four participants who made mistakes as reported above, which did not affect the results. Accordingly, the differences in the likelihood-to-buy estimates observed in the analysis of the dependent measure should be larger for participants who were consistent with the predicted process than for participants who were inconsistent with the predicted process. Participants with a choice pattern that was inconsistent with the predicted process were not significantly more likely to buy brand E than brand L ($M_E = 5.27$, $M_L = 5.40$; $t(14) = -.32$, $p > .70$). Of course, this result has to be considered with caution because of the sample size ($n = 15$). Participants with a choice pattern that was consistent with the predicted process were significantly more likely to buy brand E than brand L ($M_E = 5.39$, $M_L = 4.61$; $t(32) = 2.54$, $p = .02$). It is encouraging that the magnitude of the effect size increased for consistent participants (Cohens's $d = 0.90$) relative to the analysis with both consistent and inconsistent participants (Cohens's $d = 0.57$).

Discussion

Experiment 3 focused on whether the brand preference results of previous experiments were driven by strengths of associations. A forced-choice task showed the predicted pattern of brand-attribute associations. In addition, we provided exploratory reaction time evidence that supports the proposed process.

EXPERIMENT 4

In experiment 4 we sought to provide evidence that (1) the predicted pattern of brand-attribute associations mediate brand evaluations and (2) strategic allocation of attention affects brand evaluations both when cues and when outcomes compete for attention. If consumers allocate attention strategically across cues as they do across outcomes, a pattern of brand evaluations similar to that of the previous experiments should emerge when consumers learn associations from multiple cues to a single outcome (i.e., multiple attributes are used to predict a brand name).

Experiment 4 also provides stronger evidence of outcome competition. Our evidence so far depends on whether respondents learned associations according to the order that brands and attributes were presented on the screen. However, it is plausible that respondents waited for all information to be displayed on the screen prior to establishing associations and learned from multiple cues (i.e., attributes) to a single outcome (i.e., brand). Experiment 4 used a standard supervised-learning procedure to exert stronger control over the direction of learning.

Design, Stimuli, and Procedure

In total, 85 undergraduate students at the University of Florida and the University of Washington received extra credit to participate in the experiment. The design was a number of outcomes (single vs. multiple) by learning order (early vs. late) mixed design. The number-of-outcomes factor was manipulated between subjects, while learning order was manipulated within subjects.

Learning Phase. In the single (multiple) outcome condition, participants saw a brand (two attributes) on the screen followed by a 2-second delay and information about the attributes (brand). Different from the previous experiments, participants were asked to choose the outcome (pair of attributes or brand name, depending on the number-of-outcomes condition) that they expected the cue or cues to predict. In the multiple-outcome condition, respondents saw brand E followed by a delay and information about both pairs of attributes (CU_E and CU_L, randomly assigned to the left or right position on the screen). After choosing which pair of attributes they expected that brand to predict, they received feedback (i.e., correct/incorrect) on a different screen and started a new trial. The procedure was repeated for brand L for a total of three blocks of two early and two late-learning trials. The same procedure was followed in the single-outcome condition with the critical difference that a pair of attributes was presented first and respondents had to choose which of two brands (brand E or brand L, randomly assigned to the left or right position on the screen) they expected that pair of attributes to predict.

Test Phase. After completing the learning phase, participants provided likelihood-to-buy estimates for each of the brands. Finally, to provide evidence for the role of associations in determining the likelihood-to-buy estimates, we showed participants each brand name (on separate screens and in random order) and asked them to indicate, on a 9-point scale, which attribute best characterized that brand. The common attribute was anchored at 1, and the unique attribute, at 9. This measure of association allowed us to conduct a within-subject mediation analysis (Judd, Kenny, and McClelland 2001).

Results

As in the previous experiments, all the attribute values and brand ratings (i.e., control measures) presented the appropriate pattern for the testing of our predictions. Respondents indicated that they were significantly more likely to buy brand E than brand L ($M_E = 5.24$, $M_L = 4.38$; $F(1,83) = 12.64$, $p = .001$). Importantly, this pattern did not vary depending on whether a brand (multiple-outcome condition) or a pair of attributes (single-outcome condition) was presented first ($F(1,83) < 1$). Simple-effect tests showed that the differences in brand preferences were significant both when a brand was presented first ($M_E = 5.08$, $M_L = 4.30$; $F(1,83) = 4.91$, $p = .03$) and when attributes were presented first ($M_E = 5.40$, $M_L = 4.47$; $F(1,83) = 8.02$, $p = .006$).

Mediation Analysis. In order to provide further process evidence, we conducted a within-subject design mediation analysis following the guidelines of Judd et al. (2001). We first regressed each brand's likelihood-to-buy estimate on its respective measure of association and, as expected, found that they were both significant (both p's $= .01$). According to Judd et al.'s (2001) guidelines, associations can be said to mediate the likelihood-to-buy estimates if two conditions are met. First, the difference in the association measures should be significant and in the predicted direction. We found that participants rated the unique attribute as the one that best characterized brand L relative to brand E ($M_E = 4.91$, $M_L = 5.80$; $t(84) = 2.91$, $p = .005$). Second, regressing the difference in the likelihood-to-buy estimates on the difference in the association measures for brands E and L and on the centered sum of these association measures (i.e., the sum of measures minus the average of the sum) should render a statistically significant parameter estimate for the difference in associations and a nonsignificant parameter estimate for the centered sum of the associations. Accordingly, the beta for the difference measure was significant ($\beta = .272$, $t = 2.54$, $p = .01$), while the beta for the centered sum was not ($\beta = .001$, $t = 0.15$, $p > .90$). By Judd et al.'s (2001) criteria, this pattern of results indicates full mediation.

Discussion

Experiment 4 used a supervised-learning task to provide further support for the hypothesis that consumers may learn from a single cue to multiple outcomes and that outcome competition may occur. Using a procedure that forced respondents to look at a brand (i.e., cue) and predict which attributes (i.e., outcomes) were associated with this brand, we showed the same pattern of results as when respondents looked at two attributes (i.e., cues) and predicted which brand (i.e., outcome) was associated with these attributes. These findings imply that when consumers learn about brands and the attributes associated with these brands, multiple outcomes may compete for attention to be predicted by a cue. Previous associative-learning research on the highlighting effect has only looked at how multiple cues compete for attention to predict a single outcome. Moreover, a mediation analysis supported the claim that strengths of association drive the brands' likelihood-to-buy estimates.

GENERAL DISCUSSION

Drawing on the highlighting effect (Medin and Edelson 1988), we presented an extended model of attentional learning to accommodate sequential learning of brand associations. Our findings show that consumers more strongly associate an attribute possessed by two brands with the brand they learned of earlier and more strongly associate a unique attribute with the brand they learned of later (preliminary experiment). As a result, when an attribute common to two brands has a better value than the unique attributes of each brand, participants prefer the early learned brand. When the common attribute is inferior to the unique attributes, participants prefer the late-learned brand (experiment 1). This effect is a result of the strengths of associations between attributes and brands (experiments 3 and 4) and is not driven by accessibility (experiments 2 and 3). Finally, the effect occurs among individuals who are low in NFC but is attenuated among individuals who are high in NFC (experiment 2).

The current research has conceptual implications for associative-learning research. First, current models used to explain the highlighting effect (Kruschke 2001a, 2001b) assume that people strategically allocate attention across cues when learning relationships between cues and outcomes. Current models make no predictions regarding the strategic allocation of attention when learning occurs from a single cue to multiple outcomes. Our results indicate that people may allocate attention strategically across outcomes, ultimately implying outcome competition (Arcediano et al. 2005; Miller and Matute 1998). Second, the current research shows that such competition affects brand evaluations. Two brands with equivalent attribute values were perceived as having different utility, with their overall utility varying according to predictions of the process of strategic allocation of attention. Third, human causal learning theories postulate that stimulus competition should be a function of causal relationships between cues and outcomes (causes and effects) and of the learning tasks (predictive vs. diagnostic; Waldmann 2000; Waldmann and Holyoak 1992). In a consumer brand-learning situation, it is unlikely that consumers assume that a brand name "causes" attributes or that attributes "cause" a brand name. Thus, our findings are congruent with an associative-learning framework that predicts that associations are simply established as a function of the temporal contiguity of the stimuli independent of causality assumptions (but see the backward-conditioning literature, e.g., Chang, Blaisdell, and Miller [2003], for the role of order of learning in eliciting responses at test). Fourth, our research adds to a growing body of literature in consumer research focusing on the impact of strategic allocation of attention on the learning of associations between cues and outcomes within a single context (Cunha, Janiszewski, and Laran 2008b) and across contexts (Cunha, Janiszewski, and Laran 2008a). Finally, the model we propose handles situations in which a single cue predicts multiple outcomes. The implication is that a more general theory of attention in consumer learning is still to be developed (Van Osselaer 2008). Future modeling efforts should be able to handle learning from both a single cue to multiple outcomes and multiple cues to a single outcome.

Our research also contributes to the literature on the early entrant advantage. Kardes and Kalyanaram (1992) demonstrated that an early entrant's advantage may be a function of the larger amount of processing devoted to the early entrant's features. Thus, people better recall the common and unique features of the early entrant. In this research, we found that a stronger association between the unique attribute and the late-learned brand may result in a late entrant's advantage when the unique attributes are more valued than the common attributes. This reversal is not predicted by a memory-based process through which people remember more information about an early entrant independent of whether the attributes are common or unique. In addition, previous research has shown that the early entrant's advantage may result from the increased value people derive from an early entrant's attribute levels. In other words, when consumers are unsure about the optimal levels of attributes, they shift their ideal point toward the early entrant's attribute levels (Carpenter and Nakamoto 1989). Our procedure suggests that an early entrant advantage may also be the result of a highly valued common attribute. When a common attribute is more valued than unique attributes, the early entrant will have an advantage because its brand name will be more strongly associated with the common attribute. This result is counterintuitive in light of the fact that companies strive to offer unique, differentiating attributes.

An interesting research question concerns the role of attribute alignability in determining early versus late entrant advantages. Zhang and Markman (1998) use a reminding-based learning process to predict conditions under which late entrants could offset the early entrant's advantage. According to this process, consumers (1) compare new brands to existing ones and (2) elaborate more on alignable differences (i.e., differences across the same attributes) than on nonalignable differences. As a consequence of this increased elaboration, Zhang and Markman suggest that people overweight alignable differences and tend to favor whichever brand provides more value on these attributes. Since nonalignable differences are underweighted, people do not process them intensively for late entrants when late entrants are compared to the early entrant. As a consequence, nonalignable attributes are recalled more easily for the early entrant (Zhang and Markman 1998). Assuming that the unique attributes in our experiments parallel nonalignable differences, our findings contradict the latter prediction. We show that people develop a strong association between the unique attribute and the late-learned brand. The fact that our experiments featured a smaller number of attributes and there were no alignable differences that could draw respondents' attention may have driven the allocation of attention to the nonalignable difference. Moreover, the attribute values we used made the brands equivalent, which may have inhibited explicit comparison processes between the brands. Future research is needed to understand when and why the attentional process proposed in our extended model overrides the role of alignability.

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