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Consumers use brand names and product features to predict the performance of products. Various learning models offer hypotheses about the source of these predictive associations. Spreading-activation models hypothesize that cues acquire predictive value as a consequence of being present during the acquisition of product performance information. Least mean squares connectionist models hypothesize that any one cue acquires predictive value only to the extent that it can predict differences in performance that are not already predicted by other available cues. Five studies in the context of portfolio-branding strategies provide evidence supporting a least mean squares connectionist model. As predicted by this model, results show that subbranding and ingredient-branding strategies can protect brands from dilution in some situations but can promote dilution in other situations.

A Connectionist Model of Brand–Quality Associations

Over the past decade, a considerable amount of research has shown that brand names can help consumers recall important product information. For example, the association from a brand name to a product benefit helps a person understand a product's positioning, and the association from a brand name to a product category helps a person recognize potential usage situations. This conceptualization of a brand name as a recall prompt has been used to hypothesize how people create consideration sets, evaluate alternatives, and make decisions about the appropriateness of brand extensions (e.g., Keller 1998).

Brand names can function as more than associative cues for information retrieval. Brand names can also serve as predictive cues about product performance (Erdem and Swait 1998; Keller 1993, 1998; Smith and Park 1992). The predictive value of brand names is one of the primary reasons the brand extension strategy is so pervasive. Using a successful family brand name to identify a new product enhances customer expectations about the performance of the new product, which in turn leads to increased trial and/or reduced promotional costs (Smith and Park 1992; Sullivan 1992).

Viewing brand names as predictive cues as opposed to simple associative prompts creates some interesting issues for brand managers. Managers increasingly opt for more-complex branding strategies, in which products are identified by more than one brand name. One important issue is whether the multiple brand names used to describe existing products independently acquire predictive value. For example, many products are marketed under a joint-branding strategy, in which a product carries two brand names (e.g., Kellogg's Pop Tarts with Smucker's jelly, Betty Crocker brownies with Hershey's Kisses). If it is assumed that each brand name acquires predictive value independently of the others, positive experiences with high-quality, cobranded products should make each brand name a better predictor of a high-quality experience. However, if it is assumed that brand names compete to predict product performance, cobrand alliances may be detrimental to one or both brands, even when the cobranded product experiences are positive.

Our goal in this article is to test three competing explanations of how people learn to associate brand names, subbrand names, and ingredient brand names with product performance and how these associations can be used to predict the performance of new products that bear these names. Two of these explanations depend on spreading-activation models, which assume that cues independently acquire their predictive value. The third explanation relies on a connectionist model, which assumes that cues compete to acquire predictive value. We begin with a review of the models and then perform a series of studies that investigate situations in which the predictions of the models are expected to diverge. The first three studies investigate situations in which multiple brand names (e.g., a family brand name and subbrand

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name) are used to describe products with varying levels of performance. These studies place a strong emphasis on internal validity in an attempt to differentiate among the three models. The final two studies investigate the case of ingredient cobranding and demonstrate the implications of connectionist models in a more externally valid context. The data from the studies are most consistent with the connectionist model.

MODELS OF BRAND ASSOCIATIONS

Direct Association Model of Brand Associations

Over the past 25 years, spreading-activation models have been used to predict and explain many phenomena of human memory for objects, facts, concepts, and episodes (Raaijmakers and Shiffrin 1981). According to these models, declarative knowledge is represented as a network of concept nodes connected by links. Activation of a node in long-term memory depends on information that is being processed in working memory and the strength of the association between the node activated in working memory and the target node. For example, activation and recall of the concept “butter” in long-term memory should increase when the concept “bread” is activated in working memory, because there is a strong associative link between “bread” and “butter” that enables a large amount of the activation of “bread” to spread to “butter.”

Keller (1993, 1998) and Aaker (1991) have presented comprehensive applications of spreading-activation models to the domain of brand associations. In Keller’s model, brand knowledge is conceptualized in terms of nodes that are connected by links that vary in association strength. Keller’s conceptualization assumes that (1) associative links from a brand name to an outcome are updated through a process of concurrent activation and (2) the degree of updating depends on the quality of processing. These assumptions can be combined into the following Hebbian learning rule, which reflects the change in the association strength (Δsij) between a cue i (e.g., a brand name) and an outcome j (e.g., high quality) in one learning trial:

\[
\Delta s_{ij} = \beta(q_j)a_i,
\]

where \(q_j\) is the experienced level of outcome j (e.g., the overall quality level), \(a_i\) (\(a_i = 0, 1\)) is the activation level of cue i (e.g., absence/presence of cue i), and \(\beta (0 \leq \beta \leq 1)\) is a learning rate parameter reflecting the quality of processing: Higher-quality processing leads to greater increases in association strength.

The activation of an outcome can be expressed as \(o_j\). The activation that outcome j receives from cue i is equal to the activation level of the cue multiplied by its association strength. When multiple predictive cues are connected to the same outcome, the total activation of the outcome, \(o_j\), is equal to the summed activation from the available predictive cues (for similar assumptions, see Anderson 1993; Raaijmakers and Shiffrin 1981):

\[
o_j = \sum_{i=1}^{n} (s_{ij} \times a_i).
\]

This model makes no assumptions about the nature of the relationship between total outcome activation and the intensity of a consumer’s response to the activation, except that the intensity of the response is a monotonic positive function of overall activation. The direct association (DA) model is attractive because (1) it allows for any salient cue (e.g., brand names, product features) to gain predictive value and (2) each cue is independent and additive. Both of these assumptions are consistent with multiattribute utility models, conjoint utility models, and expectancy-value models (for an empirical application, see Park, Jun, and Shocker 1996).

Least Mean Squares Connectionist Model

Over the past decade, a new set of models has been developed to explain how people learn, remember, and react to stimuli. These adaptive learning models—commonly referred to as parallel distributed processing (PDP) models (Rumelhart, McClelland, and the PDP Research Group 1986), neural or adaptive network models (Gluck and Bower 1988), and connectionist models (Smith 1996)—differ from spreading-activation models in at least three fundamental ways (see Smith 1996). First, consistent with the literature on brand associations (Farquhar and Herr 1993), associations in adaptive learning models are usually asymmetric (Smith 1996). That is, the strength of the link from one node to another is not necessarily equal to the strength of the link in the reverse direction. Second, adaptive learning models assume that people use feedback to update the association strength between cues and outcomes. Third, many adaptive learning models assume that cues compete to predict outcomes.

One popular type of adaptive learning model is a feedforward, single-layer network with the least mean squares (LMS) learning rule (Gluck and Bower 1988). In this model, the activation of a set of sensory cues is passed on directly to a layer of output units, which in turn map onto a response. After each response, feedback is received regarding the experienced outcome (e.g., what really happened) for that set of cues. The system then adjusts the connection weights between the sensory cues and the output units so that the discrepancy between the expected outcome and experienced outcome for each set of sensory cues is reduced. After a sufficient number of trials, the sensory unit–output unit connection weights adjust to provide the smallest possible discrepancies between the expected and experienced outcomes. The adjustments of the weights occur according to an updating algorithm, or “learning rule.” The LMS rule is also referred to as the delta rule (Rumelhart, McClelland, and the PDP Research Group 1986) or Widrow–Hoff rule (Widrow and Hoff 1960) and is similar to the Rescorla–Wagner model (Rescorla and Wagner 1972) of classical conditioning in animals (Sutton and Barto 1981). According to the LMS rule, the change in the connection weight \(s_{ij}\) from input node i to output node j is given by the following function:

\[
\Delta s_{ij} = \beta(q_j - o_j)a_i,
\]

where \(q_j\) is the experienced outcome (e.g., experienced quality), \(o_j\) is the output of the learning system (e.g., expected quality), \(a_i\) (\(a_i = 0, 1\)) is the activation on input node i (absence/presence of cue i), and \(\beta (0 \leq \beta \leq 1)\) is a learning rate parameter. Note that the system output, \(o_j\), is equal to the sum of the activation it receives from each of the input nodes (\(s_{ij}\)), or

\[
o_j = \sum_{i=1}^{n} (s_{ij} \times a_i).
\]

The fundamental difference between the DA and the LMS connectionist models is the assumption that change in the
strength of association between cue i and outcome j is a function of the discrepancy between the experienced outcome (q_j) and the outcome predicted by all cues (o_j). Thus, one determinant of the change in the strength of association between cue i and outcome j—the predicted outcome (o_j)—depends not only on the existing association strength between cue i and outcome j but also on the existing association strengths between other activated cues and outcome j. In contrast, learning the association between a cue i and an outcome j in the DA model depends only on the frequency of cue i being followed by outcome j versus other outcomes, regardless of the concurrent activation of other cues. In summary, whereas the DA model predicts that associations between multiple cues and an outcome are formed independently, the LMS model predicts that the association strengths between each cue and an outcome depend on the association strengths between other cues and the same outcome.

**ACT-R Model**

Whereas the DA model most closely reflects findings and assumptions found in the literature on brand associations, it is not the only spreading-activation–type model that might explain how brand associations are learned. Anderson’s (1993) adaptive character of thought–rational (ACT-R) theory of human cognition includes an explicit model of learning in a spreading-activation framework. The ACT-R model hypothesizes that the total activation of outcome node o_j is a function of the outcome node’s base level of activation in the learning session, b_j, and of incoming activation (s_ij) of the outcome node from cuing nodes i weighted for their activation level (a_i):

\[ o_j = b_j + \sum_{i=1}^{n} (s_{ij} \times a_i) \]

The base level of activation of outcome node o_j, b_j, is a function of the proportion, P(j), of total experiences in which outcome j is present. Incoming activation of outcome node o_j from cuing nodes i (s_{ij}) is the summed association strength between cuing nodes i (e.g., brand names, product features) and the outcome node j (e.g., quality) weighted by the activation level (a_i) of the cuing nodes. The association strength from any cuing node to an outcome node, s_{ij}, can be expressed as a function of the ratio, e_{ij}, of the conditional probability of j’s presence given i’s presence divided by the base rate of j, or

\[ s_{ij} = f(e_{ij}) = f(P(j|i)/P(j)). \]

Thus, overall activation can be expressed as (1) a monotonic positive function of the base rate of j and (2) the sum of incoming association strengths that are a monotonic positive function of the ratio of their conditional probability to the base rate of j, or

\[ o_j = f(P(j)) + \sum_{i=1}^{n} (f(P(j|i)/P(j)) \times a_i). \]

In this equation, a_i is the activation level of cue i (0 ≤ a_i ≤ 1). Similar to the other two models, the ACT-R model assumes that a person’s response with regard to outcome j is a monotonic positive function of overall activation o_j. The main difference between the two spreading-activation models and the LMS connectionist model is that the association between one cue and an outcome is not directly dependent on associations of other cues with the same outcome. The main difference between the ACT-R model and the DA model is its double dependence on the outcome’s base rate probability—as a determinant of baseline activation and as a determinant of association strength.

**Summary**

The DA, LMS connectionist, and ACT-R models provide competing accounts of how people develop associations between cues and a single product benefit. One area in which the differences in these models are likely to be exhibited is in branded portfolios. For example, the liquor, accommodations, and transportation industries frequently use a combination of family and subbrand names to describe their product lines. Consumers use these brand names to anticipate the performance of particular products in the manufacturers’ lines. The three models make different predictions about the impact of different portfolio-branding strategies on the strength of the associations between the brand names used to identify a portfolio of products and product performance. Depending on which theory is supported and the specific combination of branding strategy and quality of products in the portfolio, subbranding (Studies 1–3) and ingredient-branding (Studies 4 and 5) strategies can protect brands from dilution, promote dilution, or have no effect on dilution.

**STUDY 1**

We designed Study 1 to demonstrate that brand names can function as predictive cues and to create a branding scenario in which the models make competing predictions. In Study 1, we investigated three product lines that ranged from 100% high quality to 33% high quality under two different

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1. Anderson (1993) argues that the base level of activation, b_j, is a function of (1) the number of times node j has been in working memory, (2) the time passed since each occurrence of node j in working memory, and (3) a constant that reflects the rate of decay. In this article, we compare the base level of activation across experimental conditions. If the number of times node j has been in working memory can be assumed to be equal to the frequency of exposure to concept j, then the number of times node j has been in working memory is a direct function of the proportion, P(j), of total exposures in which j is present. Any influence of the time passed since the last exposure can be negated by presenting exposures in an order that equalizes the average time passed since exposure, which allows us to ignore this parameter. Similarly, the decay rate constant should not differ across similar contexts (e.g., conditions in an experiment) and can be ignored. Thus, the value of b_j is a monotonic function of its base rate, P(j).

2. The incoming activation from a cuing node (s_{ij}) also depends on the pre-existing association strength and the number of times each cuing node i is presented. In an experimental context, these factors are controlled by keeping activating nodes constant between conditions (e.g., using the same brand name) or by using novel activating nodes (e.g., novel brand names). Thus, the value s_{ij} is a positive monotonic function of the probability ratio, P(j|i)/P(j).

3. The LMS connectionist model can incorporate base-level activation/priming effects similar to the ACT-R model by putting in a background/context parameter (e.g., Rescorla and Wagner 1972; Wasserman et al. 1993). Modeling base-level activation as context allows the model to predict case-based results. Thus, the LMS model does not need to rely on ACT-R frequency and recency rules but can change the base rate to represent changes in expected outputs by situation, location, and so forth.

4. To simplify our discussion, we focus on one anticipated outcome, overall quality. Quality is closely related to overall brand attitude and is one of the most influential factors in purchase behavior (Krishnan and Chakravarti 1993; Nakamoto, MacInnis, and Jung 1993; Smith and Park 1992). We also assume that a product experience can be a vicarious (Studies 1, 2, and 3) or an actual (Studies 4 and 5) consumption experience. Each type of experience has been shown to influence brand quality associations (Krishnan and Chakravarti 1993; Nakamoto, MacInnis, and Jung 1993).
branding strategies (for design, see Table 1). In all conditions of this study (and Studies 2 and 3), subjects received written brand and quality information about unfamiliar product lines in a single experimental session. In the family-branded product line, all products were identified by just a family brand name (henceforth abbreviated F). The products in the line were all high quality (F+ 100%), two-thirds high quality (F+ 67%, F− 33%), or one-third high quality (F+ 33%, F− 67%). In the combination family brand (abbreviated F_S) and subbrand (abbreviated S) product line, one-third of the products were high quality and were identified by a family brand name plus a subbrand name. The remaining two-thirds of the products in the line were identified by the family brand name only. Depending on the quality of the products that had only the family brand name, the product line was again all high quality (F_S+ 67%, F_S− 33%), two-thirds high quality (F_S+ 33%, F_S− 33%, F_SS+ 33%), or one-third high quality (F_S− 67%, F_S+ 33%). Examples of the last two types of product lines are commonly found when companies vertically extend to premium products, such as Gallo Varietals wines, Hoegaarden Grand Cru beer, Campbell’s Chunky soup, Starkist Gourmet’s Choice tuna, Holiday Inn Select hotels, Swatch Irony watches, and Whirlpool Gold appliances.

The design also included a low-quality baseline/control brand (abbreviated B) that was always low quality (not shown in Table 1). Product line quality was manipulated between subjects, whereas the two branding strategies were manipulated within subjects.

Stimuli and Procedure

Ninety-five subjects from an introductory marketing class viewed quality ratings for three branded product lines (two experimental, one control) of Russian motorcycles: (1) a family brand (e.g., Gorodin), (2) a family brand (e.g., Velki) with subbrand (e.g., Wolf), (3) and a low-quality baseline brand (e.g., Kacmirski). A stimulus booklet presented four years of historical performance data using a five-star rating system, in which one star meant “poor” and five stars meant “excellent.” The experimentally manipulated brands offered 3 products in Year 1, 6 products in Year 2, 9 products in Year 3, and 12 products in Year 4. In each year, the percentage of low-quality products was equivalent to the percentage of low-quality products in the four years combined. Each product in the line was a different size motorcycle, as expressed by the cubic centimeters of the engine (e.g., 65 cc–1000 cc). Engine size was uncorrelated with quality. The low-quality baseline brand (i.e., rated one or two stars) offered 1 product in Year 1, 2 products in Year 2, 3 products in Year 3, and 4 products in Year 4.

Subjects were told that all three brands were produced in the former Soviet Union and that all three manufacturers were considering exporting motorcycles to the United States. Subjects were told they would be playing the role of a U.S. importer and that they needed to learn about the breadth and quality of the product line of each manufacturer. After viewing the performance data, subjects were asked to make judgments about how much, as an importer, they would be willing to pay for each brand of motorcycle. Subjects were asked to prepare bid prices on four products labeled with (1) the family brand name (e.g., Gorodin), (2) the family brand name that had appeared with the subbrand name (e.g., Velki), (3) the family and subbrand names (e.g., Velki Wolf), and (4) the baseline brand name (e.g., Kacmirski). To reduce the variance in bid prices, subjects were told that all bids were made on a base engine size of 50 cc and that a Japanese motorcycle with an average quality rating had been bid at $522 in the previous year. Subjects then indicated the degree to which each brand name signified quality, durability, and reliability.

Predictions About Family-Branded Portfolios

The three models make similar predictions about the influence of a drop in portfolio quality on brand–quality associations when the product line is family branded (see “Predicted Value of F” in Figure 1). The DA model predicts that association strength should be a function of the concurrent activation of the brand name and high-quality performance; therefore, the brand–quality association should become weaker as the number of high-quality products declines (see Equation 1). The LMS connectionist model makes similar predictions to those of the DA model for product lines with a single brand cue (see Equation 3). When the portfolio is high quality, the connection weight should increase to a positive asymptote with increased experience, whereas a portfolio that is only one-third high quality should result in a more negative connection weight. The ACT-R model predicts that total activation of the high-quality node in a family-branding situation should depend on the base level of activation of the quality node (b_q) and the incoming activation from the family brand node (s_q) (see Equation 5). The base rate, P(j), of quality should drop as the quality of the product line drops, whereas the incoming activation from the family brand node should remain constant. Thus, total activation of the high-quality node should decrease with decreasing quality.

H1: When a family brand name is used to identify a portfolio of products, a decrease in the quality of some of the products in the portfolio will lead to a decrease in total activation of the high-quality node when the family brand name is presented.

The incoming activation from the family brand name node j is the ratio of the conditional probability to the base rate, P(j)/P(j). In this branding scenario, all the products in the portfolio carry the family brand name i. Therefore, a drop in portfolio quality should yield a proportional reduction in the conditional probability, P(j), and the base rate, P(j). Thus, incoming activation from the family brand name node should remain constant.
Figure 1
STUDY 1 PREDICTIONS AND RESULTS

The ACT-R prediction is for the $s_j$ component of the model only.

Notes: $F =$ family brand names, $F_S =$ family brand names that appear with subbrand names, $S =$ subbrand names.
Predictions About Family-Branded Portfolios with a Subbrand

The three models make competing predictions about the influence of a drop in portfolio quality on brand–quality associations when the product line is branded with both a family brand name and a subbrand name. These differences can be illustrated by comparing the scenario in which a subbrand name is used to identify one-third of the products in a consistently high-quality portfolio (e.g., F,S+ 67%, F,S+ 33%) with the scenario in which a subbrand name is used to identify only the high-quality products in a variable-quality portfolio (e.g., F,S– 67%, F,S+ 33%).

DA model. The DA model predicts that the association strength between a brand name and high quality should depend directly on the quality of all products that carry the name, regardless of whether other names are present. As the proportion of low-quality to high-quality products increases, the family brand name is paired with more low-quality products, and therefore the association between the family brand name and high quality should decrease (see “Predicted Value of FS” in Figure 1). As the proportion of low-quality to high-quality products increases, the subbrand name continues to be exclusively paired with high-quality products, and therefore the association between the subbrand name and high quality should remain strong and stable (see “Predicted Value of S” in Figure 1).

H2: The DA model predicts that when a subbrand name is used to identify the high-quality products in a family-branded portfolio, a decrease in the quality of the products identified solely by the family brand name (a) will decrease the strength of the association between the family brand name and high quality and (b) will not influence the strength of the association between the subbrand name and high quality.

LMS connectionist model. The LMS connectionist model predicts that the association weights assigned to the family brand name and subbrand name are interdependent. When a high-quality portfolio (F,S+ 67%, F,S+ 33%) has products identified by a family brand name and a subbrand name (F,S) and products identified by the family brand name only (F,S), the consumer learns that the family brand name is the best predictor of quality. The family brand name gains predictive value when it is the sole identifier of a product, and it inhibits learning about the subbrand name when the two names jointly identify a product. In contrast, when only 33% of the products in the portfolio are high quality (F,S– 67%, F,S+ 33%), the family brand name can perfectly predict the low-quality outcomes, and the subbrand name can perfectly predict the high-quality outcomes; therefore, the family brand name should have a more negative connection weight, and the subbrand name should have a more positive connection weight. These predictions are shown in Figure 1.

H3: The LMS connectionist model predicts that when a subbrand name is used to identify the high-quality products in a family-branded portfolio, a decrease in the quality of the products identified solely by the family brand name (a) will decrease the strength of the association between the family brand name and high quality and (b) will increase the strength of the association between the subbrand name and high quality.

ACT-R model. According to the ACT-R model, the total activation of the high-quality node in the presence of a brand name cue is a function of the base level of activation of the quality node,  \( b_j = f[P(j)] \), and the incoming activation from the brand connecting node,  \( s_{ij} = f[P(j|i)/P(j)] \). In the case of the family brand name, the ACT-R model makes the same prediction as in the sole family-branding strategy discussed previously: A drop in portfolio quality should reduce the base level of activation of the quality node but have no influence on the association strength between the family brand name and high quality (see “Predicted Value of FS” in Figure 1). In the case of the subbrand name, a drop in portfolio quality should increase the association strength between the subbrand name and high quality. The association strength between the subbrand name and quality increases because the ratio of the conditional probability of quality to the probability of quality, \( P(j|i)/P(j) \), increases as portfolio quality decreases (see “Predicted Value of S” in Figure 1).

H4: The ACT-R model predicts that when a subbrand name is used to identify the high-quality products in a family-branded portfolio, a decrease in the quality of the products identified solely by the family brand name (a) will reduce the base level of activation of the high-quality node, (b) will not influence the strength of the association between the family brand name and high quality, and (c) will increase the strength of the association between the subbrand name and high quality.

Results

Family brand value. The bid price for the family-branded (F) motorcycle was used as a measure of the strength of association between the brand name and quality (DA and LMS models) or the total activation of the quality node (ACT-R model). The price subjects bid for the 50-cc family-branded motorcycle declined as the relative frequency of the negative information about the brand increased (\( \bar{X}_{100\%} = \$683, \bar{X}_{57\%} = \$619, \bar{X}_{33\%} = \$572; F(2,92) = 2.94, p = .05, \sigma^2 = .05 \)). The linear trend test was significant (\( F(1,92) = 8\).

1These predictions can be illustrated algebraically. Correct mapping for outcomes identified solely by the family brand name can be achieved only when the connection weight of the family brand name (\( s_{1j} \)) equals -1, because only in this case will the condition be fulfilled that \( s_{0j} = s_{1j} + s_{2j} \) = 1. For subbranded products, correct mapping is achieved by any pair of connection weights (\( s_{2j} \)) that allows the expected output to sum to 1 (i.e., \( s_{0j} = (s_{1j} + 1 + s_{2j} \times 1 = 1) \). For family brand–only products, correct mapping can only be achieved when the connection weight of the family brand equals 1, because only in that case will the condition be fulfilled that \( s_{1j} = s_{0j} \times 1 = 1 \). The only pair of connection weights that correctly maps both input patterns onto the desired output pattern consists of a weight of 1 for the family brand (\( s_{1j} \)) and a weight of 0 for the subbrand (\( s_{2j} \)).
The three quality ratings (quality, durability, and reliability) that were collected at the end of the questionnaire were summed to create a quality association score ($\alpha = .96$). The rated quality of the family brand decreased with increased numbers of low-quality products ($X_{100\%}^{67\%} = 17.31, X_{67\%}^{67\%} = 15.90, X_{33\%}^{67\%} = 14.28; F(2,92) = 10.68, p < .001, \omega^2 = .15$), a finding consistent with all three models.

**Family brand and subbrand value.** The bid price for the family-branded ($F_S$) motorcycle was used as a measure of the strength of association between the family brand name and quality (DA and LMS models) or the total activation of the quality node (ACT-R model). The bid price for the 50-cc family-branded motorcycle declined as the relative frequency of negative information about the family brand increased ($X_{100\%}^{67\%} = \$693, X_{67\%}^{67\%} = \$604, X_{33\%}^{67\%} = \$581; F(2,92) = 3.37, p < .05, \omega^2 = .05$). The linear trend test was significant ($F(192) = 6.10, p < .05, \omega^2 = .05$). These data are consistent with the DA model ($H_2a$), the LMS connectionist model ($H_{3a}$), and the ACT-R model ($H_{4a}$ and $H_{4b}$). The rated quality of the family brand decreased with increasing numbers of low-quality products ($X_{100\%}^{67\%} = 17.58, X_{67\%}^{67\%} = 16.08, X_{33\%}^{67\%} = 14.84; F(2,92) = 6.40, p < .01, \omega^2 = .10$), which paralleled the bid results.

The strength of association between the subbrand name (S) and high quality was measured as the premium/discount subjects were willing to bid for the family-branded/sub-branded 50-cc motorcycle ($F_{S-S}$) relative to the family-branded 50-cc motorcycle ($F_S$). This difference score measured isolated the association strength between the subbrand name and high quality. Subbrand value ($F_{S-S} - F_S$) rose as the relative frequency of negative information about the family brand increased ($X_{100\%}^{67\%} = \$47, X_{67\%}^{67\%} = \$138, X_{33\%}^{67\%} = \$198; F(2,92) = 7.25, p < .01, \omega^2 = .13$). As predicted, the linear trend test was significant ($F(192) = 14.37, p < .001, \omega^2 = .12$). These data are consistent with the LMS connectionist model ($H_{3b}$) and the ACT-R model ($H_{4b}$), but not the DA model ($H_{2b}$). The rated quality of the subbrand increased with increased numbers of low-quality products ($X_{100\%}^{67\%} = 14.07, X_{67\%}^{67\%} = 16.38, X_{33\%}^{67\%} = \$17.74; F(2,92) = 13.39, p < .01, \omega^2 = .19$).

**Discussion**

The data from the first study show that a decrease in the quality of products in a family-branded portfolio decreases the value of the family brand name as a predictive cue, whether the portfolio is family branded or family and subbranded. These data are consistent with all three models of association formation. The data from the first study also show that a decrease in the quality of products in a family-branded portfolio increases the value of the subbrand name as a predictive cue, provided that the subbrand name identifies only the high-quality products. These data are consistent with the LMS connectionist model ($H_{3b}$) and the ACT-R model ($H_{4b}$), but not the DA model ($H_{2b}$). The DA model predicted no difference in the associative strength between the subbrand name and quality across conditions.

Study 1 does not enable us to differentiate between the LMS connectionist model and the ACT-R model. The inability to differentiate between the two models can be traced to the influence of a between-subjects manipulation of product line quality on the predictions of the ACT-R model. Recall that the ACT-R model predicts that the association strength between any brand name and quality is $|P(j|S)P(j)|$. In Study 1, the subbrand always described a high-quality product; therefore, the conditional probability of a high-quality product given the subbrand name, $P(j|S)$, was 1.0. In contrast, the base rate of high quality, $P(j)$, declined as quality declined. The result was an increase in the association strength between the subbrand name and high quality. A within-subjects manipulation of the quality of the competing product lines would allow the base rate of high quality, $P(j)$, to remain constant across product lines. Thus, if people were exposed to a high-quality product line with some subbranding (e.g., Line 1 is $F_1S^+$ 67%, $F_1S_1^+ 33\%$) and a variable-quality product line with a high-quality subbrand (e.g., Line 2 is $F_2S^-$ 67%, $F_2S_2^+ 33\%$), the total number of high-quality experiences and therefore the base rate of quality, $P(j)$, would be constant for both lines. As a consequence, the association between the subbrand name and quality should not differ between these product lines.

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10 For a test of the DA and LMS connectionist models, the analysis could have been performed by taking a difference score between the prices subjects were willing to bid for products that carried the family brand name and prices bid for products that carried the baseline brand name as a means of controlling for error variance. In this alternative analysis, both the grand mean test ($X_{100\%}^{67\%} = \$299, X_{67\%}^{67\%} = \$224, X_{33\%}^{67\%} = \$128; F(2,92) = 7.03, p < .01, \omega^2 = .12$) and the linear trend test ($F(192) = 13.92, p < .001, \omega^2 = .12$) were significant.

11 Again, if the difference between the bid price for the family brand and the bid price for the baseline brand is computed, both the grand mean test ($X_{100\%}^{67\%} = 310, X_{67\%}^{67\%} = 209, X_{33\%}^{67\%} = \$137; F(2,92) = 6.64, p < .01, \omega^2 = .11$) and the linear trend test ($F(192) = 13.22, p < .001, \omega^2 = .11$) were significant.

12 The ACT-R model predicts that activation in the presence of the family brand name is $|P[Quality]| + |P[Quality][family brand name]|P[Quality]|$ and activation in the presence of the family and subbrand name is $|P[Quality]| + |P[Quality][family brand name]|P[Quality]| + |P[Quality][subbrand name]|P[Quality]|$. The difference between these two equations is the association strength between the subbrand name and quality $|P[Quality][subbrand name]|P[Quality]|$.

Likewise, the LMS connectionist model states that the family brand name predicts quality using the equation $o_i = s_j \times 1 + s_k \times 0$ and family and subbrand can be used to predict quality using the equation $o_j = s_j \times 1 + s_k \times 1$. The difference between the two equations is the association strength between the subbrand name and quality ($\omega_k$).
H₅: The ACT-R model predicts that when subbrand names are used to identify high-quality products in competing family-branded portfolios, a decrease in the quality of family-branded products in one of the portfolios will not influence the strength of the association between each subbrand name and high quality.

**STUDY 2**

In Study 2, we investigated two family brand/subbrand portfolios using a within-subject experimental design to compare two lines of motorcycles (for design, see Table 2). In a consistently high-quality portfolio of 12 products, the family brand name (e.g., Gorodin) identified all products, and the subbrand name (e.g., Wolf) identified one-third of the products (F₁+ 67%, F₁S₁+ 33%). In a variable-quality portfolio of 12 products, a second family brand name (e.g., Velki) identified all products, and a second subbrand name (e.g., Spider) appeared on the one-third of the products that were high quality (F₂– 67%, F₂S₂+ 33%). Thus, the family brand/subbrand product lines used here were similar to the family brand/subbrand product lines used in Study 1. Subjects also saw 8 low-quality products from a baseline brand (e.g., Kacmirski; not shown in Table 2).

The background information provided to subjects was changed slightly from Study 1. In an effort to separate the subbrand identity from the family brand identity (in this case the manufacturer), subjects were informed that each subbrand was associated with a style of motorcycle (e.g., performance motorcycle, touring motorcycle). Motorcycle styles were counterbalanced with product line to remove any bias owing to people’s preference for performance or touring motorcycles.

After viewing the performance data, subjects were asked to prepare bid prices on 50-cc motorcycles bearing the family brand name from Product Line 1 (e.g., Gorodin), the family brand name from Product Line 2 (e.g., Velki), the baseline brand name with the subbrand name from Product Line 1 (e.g., Kacmirski Wolf), and the baseline brand name with the subbrand name from Product Line 2 (e.g., Kacmirski Spider). To anchor their bids, subjects were told a 50-cc Japanese motorcycle with an average-quality subbrand was associated with a style of motorcycle (e.g., Spider) appeared on the one-third of the products that were high quality (F₂– 67%, F₂S₂+ 33%). Thus, the family brand/subbrand product lines used here were similar to the family brand/subbrand product lines used in Study 1. Subjects also saw 8 low-quality products from a baseline brand (e.g., Kacmirski; not shown in Table 2).

The background information provided to subjects was changed slightly from Study 1. In an effort to separate the subbrand identity from the family brand identity (in this case the manufacturer), subjects were informed that each subbrand was associated with a style of motorcycle (e.g., performance motorcycle, touring motorcycle). Motorcycle styles were counterbalanced with product line to remove any bias owing to people’s preference for performance or touring motorcycles.

After viewing the performance data, subjects were asked to prepare bid prices on 50-cc motorcycles bearing the family brand name from Product Line 1 (e.g., Gorodin), the family brand name from Product Line 2 (e.g., Velki), the baseline brand name with the subbrand name from Product Line 1 (e.g., Kacmirski Wolf), and the baseline brand name with the subbrand name from Product Line 2 (e.g., Kacmirski Spider). To anchor their bids, subjects were told that a 50-cc Japanese motorcycle with an average-quality rating had been bid at $522 in the previous year. Subjects finished by indicating the degree to which each brand or subbrand name signified quality, durability, and reliability.

**Predictions**

All three models predict that the family brand name identifying the high-quality portfolio of products (Fₛ₁) should have a stronger association with high quality than the family brand name identifying the variable-quality portfolio of products (Fₛ₂). Predictions regarding the association between the two subbrand names and quality vary by model. The DA model predicts that the subbrand name association with quality will not differ between the two product lines, because the subbrand name is always associated with a high-quality outcome (H₂b). The LMS connectionist model predicts that the subbrand that identifies the high-quality products in the variable-quality product line (Fₛ₂– 67%, Fₛ₂S₂+ 33%) will become more associated with high quality than the subbrand that identifies high-quality products in the high-quality product line (Fₛ₁+ 67%, Fₛ₁S₁+ 33%) (H₃b). The ACT-R model predicts that the subbrand name association with quality will not differ between the two product lines, because the base rate of activation of the high-quality node in a within-subject design is constant for the two subbrands (i.e., .50) and the association strength between each subbrand and quality is the same |f(P[ji]/P[j]) = [f(1/0/50)] (H₃).

**Results**

Twenty-eight subjects from an introductory marketing class received extra credit for their participation in the study. There was no influence of the counterbalancing manipulation in any of the tests.

**Comparing the value of family brands.** The strength of association between the family brand name and high quality was measured as the price subjects were willing to bid for the family brand. The average bid price for the 50-cc motorcycle identified with the family brand name from the consistently high-quality portfolio (Fₛ₁+ 67%, Fₛ₁S₁+ 33%) was higher than the bid price of the motorcycle identified by the family brand name from the variable-quality portfolio (Fₛ₂– 67%, Fₛ₂S₂+ 33%) (X₁₅₀% = $836, X₃₃% = $588; F(1,26) = 8.20, p < .01, 0² = .19). The rated quality of the family brands paralleled the value estimates (X₁₅₀% = 19.1, X₃₃% = 8.0; F(1,26) = 248.55, p < .01, 0² = .47). These data are consistent with the predictions of all three models (H₂a, H₃a, and H₄a).

**Comparing the value of subbrands.** The strength of association between the subbrand and high quality was measured as the price subjects bid for a product identified by the baseline brand and subbrand name. The average bid price for the baseline-branded (e.g., Kacmirski) 50-cc motorcycle carrying the subbrand name from the variable-quality portfolio (Fₛ₂– 67%, Fₛ₂S₂+ 33%) was higher than it was for a baseline-branded motorcycle bearing the subbrand name from the high-quality portfolio (Fₛ₁+ 67%, Fₛ₁S₁+ 33%) (X₁₅₀% = $705, X₃₃% = $695; F(1,26) = 5.21, p < .05, 0² = .15). The rated quality of the subbrands paralleled the bid estimates (X₃₃% = 18.8, X₁₅₀% = 16.6; F(1,26) = 10.64, p < .01, 0² = .26).

**Discussion**

The DA model (H₂b) and ACT-R model (H₃) predicted that reducing the quality of the products that carry the family brand name in a partially subbranded product line would not influence the association between the subbrand name and quality when the subbrand name was used to identify...
high-quality products. The data from Study 2 show that the association between the subbrand name and quality increased as the quality of the portfolio decreased, a result predicted only by the LMS connectionist model ($H_{3b}$).

**STUDY 3**

If the LMS connectionist model describes how people form predictive brand associations, there should also be portfolio-branding situations in which the family brand name behaves in a manner inconsistent with the spreading-activation models. One such situation is when the family brand identifies high-quality products and the family brand name and subbrand name jointly identify low-quality products. Examples of lower quality subbrands include Fairfield Inn by Marriott, Courtyard by Marriott hotels, Fetzer Sundial wines, Beaulieu Vineyards Coastal wines, and MetroJet by US Airways airline.

In Study 3, we used a 2 × 2 between-subjects design (see Table 3). The manipulated factors were whether the portfolio was family branded or family branded and subbranded and whether the portfolio was 100% high quality or 60% high quality. In the first condition, subjects received information about a product line that included only high-quality products that carried only a family brand name (F+ 100%). In the second condition, only 60% of the products in a family-branded line were high quality (F+ 60%, F– 40%). In the third condition, all products in the line were high quality, but only 60% carried the family brand name, whereas the remaining 40% carried both the family brand name and a subbrand name (F+ 60%, F3S+ 40%). In the fourth condition, 60% of the products were high-quality products that carried the family brand name, whereas the remaining 40% were low-quality products that carried both the family brand name and a subbrand name (F3+ 60%, F3S– 40%). Each condition also included a low-quality baseline brand (not shown in Table 3).

<table>
<thead>
<tr>
<th>Condition</th>
<th>Family Brand and Subbrand</th>
</tr>
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<tr>
<td>1</td>
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</tr>
<tr>
<td>2</td>
<td>F+ 60% F– 40%</td>
</tr>
<tr>
<td>3</td>
<td>F3+ 60% F3S+ 40%</td>
</tr>
<tr>
<td>4</td>
<td>F3+ 60% F3S– 40%</td>
</tr>
</tbody>
</table>

Notes: Subjects judge F, F3, and S.

Sixty-eight subjects from an introductory marketing class viewed quality ratings for two motorcycle lines—one treatment and one baseline. A stimulus booklet presented three years of historical performance data using a five-star rating system. The treatment brand (e.g., Velki) offered three products in Year 1, six products in Year 2, and eight products in Year 3. In the subbrand conditions, seven of the products were also described using the subbrand name Wolf. Engine size was uncorrelated with subbranding. The low-quality baseline brand (e.g., Kacmirski) offered one product in Year 1, two products in Year 2, and three products in Year 3.

The procedure was similar to Study 1. After viewing the data, subjects were asked to prepare a bid on a 500-cc Japanese motorcycle, a size they had not seen before. Subjects in the family brand conditions were informed that a 500-cc Japanese motorcycle cost $2100 and were asked to prepare bids on a product labeled with the family brand name (Velki) and the baseline brand name (Kacmirski). Subjects in the family brand/subbrand conditions also bid on a family and subbrand name (Velki Wolf) motorcycle. All subjects finished by indicating the degree to which each brand or subbrand name signified quality, durability, and reliability.

**Predictions**

All predictions are shown in Figure 2. The family brand–only conditions are similar to those investigated in Study 1 and are included for comparative purposes. Therefore, the discussion of the predictions will be restricted to the family brand/subbrand strategy conditions.

**DA model.** The DA model predicts that association strength is a function of the concurrent activation of brand names and outcomes. As the number of low-quality products identified by a family brand and subbrand name increases, each of these cues should become more associated with low quality.

$H_{3c}$: The DA model predicts that when a subbrand name is used to identify the low-quality products in a family-branded portfolio, an increase in the proportion of low-quality products in the portfolio (a) will decrease the strength of the association between the family brand name and high quality and (b) will decrease the strength of the association between the subbrand name and high quality.

**LMS connectionist model.** The LMS connectionist model predicts that the connection weights assigned to family brand and subbrand names are interdependent. When the product portfolio is high quality (F3+ 60%, F3S+ 40%), the family brand name can perfectly predict the high-quality outcomes, whereas the subbrand name is redundant information that has no predictive value. When the quality of the product portfolio is only 60% high quality (F3+ 60%, F3S– 40%), the family brand name can perfectly predict the high-quality outcomes, and the subbrand name can perfectly predict the low-quality outcomes.

Note that a configurational version of the DA model would predict the same as the elemental DA and the ACT-R models. A configurual DA model predicts that subjects will base their quality judgments on the products to which the product to be judged is most similar. In this experiment, the evaluated baseline brand/subbrand combinations are most similar to the baseline-branded (e.g., Kacmirski) and the family-branded/subbranded products. The historic quality of the baseline and subbranded products did not differ by condition. Thus, the configurual DA model predicts no difference in the strength of association between the subbrands and quality.

15Note that a configurational version of the DA model would predict the same as the elemental DA and the ACT-R models. A configurual DA model predicts that subjects will base their quality judgments on the products to which the product to be judged is most similar. In this experiment, the evaluated baseline brand/subbrand combinations are most similar to the baseline-branded (e.g., Kacmirski) and the family-branded/subbranded products. The historic quality of the baseline and subbranded products did not differ by condition. Thus, the configurual DA model predicts no difference in the strength of association between the subbrands and quality.

16These predictions can be illustrated algebraically. Correct mapping for outcomes identified solely by the family brand name can be achieved only when the connection weight of the family brand name ($s_{ij}$) equals 1, because only in this case will the condition be fulfilled that $o_{ij} = s_{ij} \times 1 + s_{j} \times 1 = 1$. Both constraints are satisfied only when a strong, negative connection weight is formed for the subbrand ($s_{j} = -2$).
The ACT-R prediction is for the $s_{ij}$ component of the model only.

Notes: $F =$ family brand names, $F_S =$ family brand names that appear with subbrand names, $S =$ subbrand names.
H7: The LMS connectionist model predicts that when a subbrand name is used to identify the low-quality products in a family-branded portfolio, an increase in the proportion of low-quality products in the portfolio (a) will not influence the strength of association between the family brand name and high quality and (b) will decrease the strength of association between the subbrand name and high quality.

**ACT-R model.** The total activation of the high-quality node in the presence of a brand name cue is a function of the base level of activation of the quality node, \( b = f[P(j)] \), and the incoming activation from the brand connecting node, \( s_{ij} = f[P(j')/P(j)] \). When the quality of the portfolio drops from 100% to 60%, the base-level activation of the quality node should drop, because the person is experiencing a lower proportion of high-quality outcomes. The association strength between the family brand name and high quality should remain constant, because the decrease in the conditional probability \( P(j')/P(j) \) is compensated for by a proportional decrease in the base rate, \( P(j) \). The association strength between the subbrand name and quality should decline as portfolio quality drops, because the subbrand identifies low-quality products in the variable-quality portfolio. Thus, the family brand name and the subbrand name should predict low-quality outcomes in low-quality portfolios.

H8: The ACT-R model predicts that when a subbrand name is used to identify the low-quality products in a family-branded portfolio, an increase in the proportion of low-quality products in the portfolio (a) will reduce the base level of activation of the high-quality node, (b) will not influence the strength of association between the family brand name and high quality, and (c) will decrease the strength of association between the subbrand name and high quality.

**Results**

**Family brand conditions.** The bid price for a family-branded (F) motorcycle was used as a measure of the strength of association between the family brand name and quality (DA and LMS models) or the total activation of the quality node (ACT-R model). The bid price of the family-branded 500-cc motorcycle declined as the quality of the portfolio decreased \( (X_{100\%} = \$3015, X_{60\%} = \$2188; F(1,64) = 6.22, p < .05, \omega^2 = .07) \). The rated quality of the family brand also declined as the quality of the portfolio decreased \( (X_{100\%} = 18.2, X_{60\%} = 13.1; F(1,64) = 29.91, p < .01, \omega^2 = .22) \). These data are consistent with all three models (H1).

**Family brand and subbrand conditions.** The bid price for a motorcycle labeled with the family brand name (F3) that appeared with the subbrand name was used as a measure of the strength of association between the brand name and quality (DA and LMS models) or the total activation of the quality node (ACT-R model). The bid price of the family-branded 500-cc motorcycle (F3) remained constant as the quality of the portfolio decreased \( (X_{100\%} = \$2705, X_{60\%} = \$2561; F(1,64) = .20, p > .10) \). The rated quality of the family brand also remained constant as the quality of the portfolio declined \( (X_{100\%} = 18.1, X_{60\%} = 17.0; F(1,64) = 1.50, p > .05) \). These data are consistent with the LMS connectionist model (H2), but not the DA (H3) and ACT-R models (H8a and H8b). The strength of association between the subbrand name (S) and high quality was measured as the premium/discount subjects were willing to bid for the family-branded/subbranded 500-cc motorcycle relative to the family-branded 500-cc motorcycle. This difference score measure isolated the association strength between the subbrand name and high quality. Subbrand value \( (F_S – F_S) \) fell as the quality of the portfolio decreased \( (X_{100\%} = \$51, X_{60\%} = –\$1283; F(1,33) = 33.22, p < .001, \omega^2 = .33) \). The rated quality of the subbrand decreased as the quality of the portfolio decreased \( (X_{100\%} = 18.4, X_{60\%} = 6.2; F(1,33) = 102.23, p < .001, \omega^2 = .43) \). These data are consistent with all three models (H6b, H7b, and H8c).

**Discussion**

The data from Study 3 show that a decrease in the quality of products in a family-branded portfolio does not lead to a decrease in the association strength between the family brand name and quality, provided that the low-quality products are also identified with a subbrand name (F+S 60%, F+S 40%) (for a similar demonstration, see Milberg, Park, and McCarthy 1997). The data are consistent with the LMS connectionist model (H7a), but not the DA (H7b) or the ACT-R (H8a and H8b) models. According to the LMS connectionist model, identifying low-quality products with a subbrand name enables the subbrand name uniquely to predict the low-quality products, which thus protects the association between the family brand name and high quality. As is the case with any null effect, it is possible that the insensitivity of the predictive value of the family brand name to the declining quality of the portfolio could be attributed to a lack of power, but this is not likely. When product portfolios were described solely by a family brand name (F+ 100%; F+ 60%, F– 40%), a decline in portfolio quality had a large impact on the association between the family brand name and quality. Power should have been equivalent for the test of the influence of declining portfolio quality on the family brand name that uniquely identified the portfolio in conjunction with a subbrand name.

Given the support for the LMS connectionist model, it would be interesting to explore the generalizability of the model. In Studies 1 through 3, we investigated situations in which consumers learned vicariously instead of through direct consumption experiences. Although vicarious learning about brands—for example, through advertisements, observation, or word of mouth—is common, consumers also learn from direct experience. It is possible that learning from experience only increases the salience of each learning episode and therefore increases the learning rate parameter in an LMS model. However, it is also possible that learning from experience is fundamentally different from vicarious learning and cannot be described by the LMS model. Studies 4 and 5 test the appropriateness of the LMS connectionist model in experiential learning situations.

**STUDY 4**

It has been found that adding a high-quality branded ingredient (e.g., Hershey’s Kisses) to a high-quality branded product (e.g., Betty Crocker brownies) will create an additive effect in which the joint-branded product (e.g., Betty Crocker brownies with Hershey’s Kisses) will be perceived as superior in quality to the host brand without the branded ingredient (Park, Jun, and Shocker 1996; Simonin and Ruth 1998). This prediction is consistent with the additive prop-
property of the DA, LMS connectionist, and ACT-R models. Yet it is important to note that the predictions and evidence in support of joint-branded product superiority are expectation based, not experience based. Park, Jun, and Shocker (1996) and Simonin and Ruth (1998) test predictions about the expected performance of a joint-branded product, in effect investigating how joint branding influences product trial. The three models discussed in this article are more concerned with the iterative learning of the predictive value of brand cues; therefore, they also make predictions about the association strength between the brand names and quality subsequent to the consumption of the joint-branded product.

**Design, Procedure, and Predictions**

The investigation of the effects of joint branding had two objectives. The first objective was to show that joint branding is beneficial with respect to anticipating the value of the joint-branded product, as has been demonstrated by Park, Jun, and Shocker (1996) and Simonin and Ruth (1998). To investigate this issue, we had subjects participate in a taste test of branded brownies and branded chocolate chips and then anticipate the quality of a branded brownie containing the branded chocolate chips (for the design, see Table 4, Condition 1). Subjects began by tasting three brands of plain brownies (labeled “low quality,” “Delight,” and “Buon Chocolat”) and two brands of chocolate chips (labeled “low quality” and “Silk’n Morsels”). Subjects rated the two brand name brownies (F1 and F2) on three ten-point scales with endpoints labeled “dry”/“extra-moist,” “poor flavor”/“excellent flavor,” and “low quality”/“very high quality.” Subjects rated the brand name chocolate chips (I1) on four ten-point scales with endpoints labeled “waxy”/“extra-creamy,” “gritty”/“extra-smooth,” “poor flavor”/“excellent flavor,” and “low quality”/“very high quality.”

At Time 2, subjects were asked to estimate the expected quality of three brownies with chocolate chips. Subjects estimated the quality of a Delight brownie with Silk’n Morsels (joint-branded F1I1), a Buon Chocolat brownie with chocolate chips (monobranded F2 with nonbranded ingredient), and a Silk’n Morsel brownie with chocolate chips (ingredient extension I1) using the three ten-point brownie rating scales. It was expected that there would be no change in the evaluation of the monobranded product (F2) from Time 1 to Time 2, because no additional information had been gathered subsequent to the taste test at Time 1. It was also expected that there would be no change in the evaluation of the ingredient brand (I1) from Time 1 to Time 2, because no additional information had been gathered subsequent to the taste test at Time 1. Finally, it was expected that the product that went from monobranded product at Time 1 (F2) to a joint-branded product at Time 2 (F1I1) would be rated more positively at Time 2 (see Figure 3, Condition 1 Predictions). The DA (see Equation 2), LMS connectionist (see Equation 4), and ACT-R (see Equation 7) models all predict cue additivity.

The second objective of Study 4 was to investigate the impact of positive experiences with the joint-branded product on the association between the ingredient brand name and quality. To do this, we added two conditions in which subjects participated in a taste test of branded brownies, branded chocolate chips, branded chocolate chip brownies, and branded muffins and then anticipated the quality of a branded muffin containing the branded chocolate chips (for the design, see Table 4, Conditions 2 and 3). As in Condition 1, subjects began by tasting and rating three brands of plain brownies (labeled “low quality,” “Delight,” and “Buon Chocolat”) and two brands of chocolate chips (labeled “low quality” and “Silk’n Morsels”). Next, they were asked to taste three brownies with chocolate chips. The first was the low-quality brownie from Time 1 baked with the low-quality chocolate chips from Time 1. Subjects were told to use this brownie to anchor the lower endpoint of their evaluation scale. Next, subjects tasted and rated the Delight brownie from Time 1 baked with the high-quality Silk’n Morsels chocolate chips. This brownie was labeled “Delight with Silk’n Morsels” (F1I1) in Condition 2 and “Silk’n Morsels” (I1) in Condition 3. Third, subjects tasted and rated a Buon Chocolat brownie from Time 1 baked with the Silk’n Morsels chocolate chips. The brownie was labeled “Buon Chocolat with chocolate chips” (F2) for both groups. Thus, the only difference between Conditions 2 and 3 was the label on the second brownie tasted—subjects in the former condition tasted a joint-branded chocolate chip brownie, whereas subjects in the latter condition tasted an ingredient-branded chocolate chip brownie.

The final phase of the experiment was intended to measure the impact of joint branding versus ingredient branding the chocolate chip brownie on subsequent quality associations to the ingredient brand. Subjects in Conditions 2 and 3 tasted a low-quality muffin (labeled “low quality”) and a high-quality muffin (labeled “Muffin Man”; F3) and rated the high-quality muffin on the same three scales used to rate the brownies. Next, subjects were asked to estimate the expected quality of a Muffin Man muffin with Silk’n Morsels (F2I1) using the same three scales. By taking the difference between the rating of the muffin and the expected rating of the muffin with chocolate chips, we could determine the influence of the previous joint branding on the value of the ingredient brand name.

The predictions of the three models are best explained by condition (see Figure 3, Condition 2 Predictions). In Condition 2, subjects experienced the joint-branded chocolate chip brownie (F1I1) and the monobranded muffin (F3) and then estimated the quality of the joint-branded chocolate chip muffin (F2I1). The DA model predicts that the ingredient brand name should maintain its value after the chocolate chip brownie taste test, provided that the chocolate chip brownie is a high-quality brownie. Joint branding the chocolate chip muffins at Time 4 should result in an expectation of a better-quality muffin (Park, Jun, and Shocker 1996; Simonin and Ruth 1998). The ACT-R model also predicts that the ingredient brand name should maintain its value after participants consume the joint-branded chocolate chip brownie. If the quality of the joint-branded chocolate chip brownie (F1I1) is adequate, the base-level activation of the quality node should remain constant. The conditional probability of quality given the ingredient should also remain constant.

In contrast to the DA and ACT-R models, the LMS model predicts that the association between the ingredient brand...
### Table 4

**STUDY 4: PROCEDURE AND RESULTS**

<table>
<thead>
<tr>
<th>Time</th>
<th>Activity</th>
<th>Product</th>
<th>Brand</th>
<th>Mean</th>
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<th>Product</th>
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<td>Taste/rate</td>
<td>Brownie 2</td>
<td>F2</td>
<td>8.11</td>
<td>Taste/rate</td>
<td>Brownie 2</td>
<td>F2</td>
<td>7.22</td>
<td>Taste/rate</td>
<td>Brownie 2</td>
<td>F2</td>
<td>7.37</td>
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<td>1d</td>
<td>Taste</td>
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<td>L</td>
<td>6.87</td>
<td>Taste</td>
<td>Chocolate chips L</td>
<td>L</td>
<td>7.42</td>
<td>Taste</td>
<td>Chocolate chips L</td>
<td>L</td>
<td>7.84</td>
</tr>
<tr>
<td>1e</td>
<td>Taste/rate</td>
<td>Chocolate chips 1</td>
<td>I1</td>
<td>7.37</td>
<td>Taste/rate</td>
<td>Chocolate chips 1</td>
<td>I1</td>
<td>7.07</td>
<td>Taste/rate</td>
<td>Chocolate chips 1</td>
<td>I1</td>
<td>7.07</td>
</tr>
<tr>
<td>2a</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F1</td>
<td>7.42</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F1</td>
<td>7.84</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F1</td>
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<tr>
<td>2b</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F2</td>
<td>8.02</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F2</td>
<td>7.87</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F2</td>
<td>7.87</td>
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<tr>
<td>2c</td>
<td>Rate</td>
<td>Brownie with chips</td>
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<td>7.22</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F2</td>
<td>7.84</td>
<td>Rate</td>
<td>Brownie with chips</td>
<td>F2</td>
<td>7.84</td>
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<tr>
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<td>L</td>
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<td>Taste</td>
<td>Muffin L</td>
<td>L</td>
<td>7.84</td>
<td>Taste</td>
<td>Muffin L</td>
<td>L</td>
<td>7.84</td>
</tr>
<tr>
<td>3b</td>
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<td>F1</td>
<td>7.07</td>
<td>Taste/rate</td>
<td>Muffin 1</td>
<td>F1</td>
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<td>Taste/rate</td>
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<td>Rate</td>
<td>Muffin 1 with chips</td>
<td>F1</td>
<td>7.07</td>
</tr>
</tbody>
</table>

**Notes:** L = low-quality brands used as scale anchors, F = product brand names (e.g., Delight, Buon Chocolat), I = ingredient brand name (e.g., Silk'n Morsels).
Figure 3
STUDY 4 PREDICTIONS AND RESULTS

Notes: F = family brand names, I = ingredient brand names.
name and quality should weaken after participants taste the joint-branded chocolate chip brownie. The additivity property of the LMS model leads consumers to expect the joint-branded product to be of higher quality than the mono-branded products experienced previously (e.g., the plain brownie $F_1$ and chocolate chips $I_1$). If the joint-branded product is of good quality, but not as high quality as expected, subjects will overpredict, and the connection weights will need to adjust downward to reduce the discrepancy between the predicted and actual quality levels. Thus, when the ingredient brand name is later paired with the muffin brand name, the ingredient brand name will have much less predictive value than it had previously. The ingredient brand name will have lost its value as a consequence of the consumption of the first joint-branded product.

In Condition 3, subjects had the exact same experiences as subjects in Condition 2, except that their chocolate chip brownie was not joint branded. Instead, their chocolate chip brownie was ingredient branded. The DA and ACT-R models both predict exactly the same increase in the strength of association between the ingredient brand and quality as in Condition 2. Joint branding the chocolate chip muffins at Time 4 should result in an expectation of a better-quality muffin (see Figure 4, Condition 3 Predictions). The LMS connectionist model also predicts a positive benefit of joint branding the muffin. Provided that the chocolate chip brownie is of adequate quality, the ingredient brand name should maintain its predictive value, and the consumer should expect the chocolate chip muffin to be a better-quality muffin.

In all three conditions, subjects ate an unsalted soda cracker and had a drink of water in between each of the eight product taste tests. Each product sample was large enough to taste multiple times, and many subjects did so. When ratings were requested, subjects always rated a sample before tasting the next sample. The high-quality brownie brand names were counterbalanced.

**Results**

Forty-five subjects from an introductory marketing class were awarded extra credit to participate in the study. The three items used to rate the brownies and muffins ($\alpha = .90$) and the four items used to rate the chocolate chips ($\alpha = .84$) were averaged and used to measure the strength of association between the brand name and quality. There was no influence of the brownie brand name counterbalancing factor. The results are shown in Figure 3.

**Value of joint branding.** In the first test, we used the data from Condition 1 to investigate the impact of joint branding on product performance expectations. The goal of the test was to assess if the expected performance of a joint brand was superior to the expected performance of a monobrand. The most appropriate test was to compare the increase in the rating for the family-branded brownie ($F_1$) made with the ingredient brand of chocolate chips ($I_1$) with a control brand of brownie ($F_2$) made with nonbranded chocolate chips ($F_2$). In this way, any influence of changing the product from browies to browines with chocolate chips would be captured in the ratings of the control brand. The value of the joint branding was calculated as the difference between the monobrand brownie ($X_{F_1} = 7.07$) and the expected performance of the joint-branded chocolate chip brownie ($X_{F_1I_1} = 7.73$) relative to the difference between the control-branded brownie ($X_{F_2} = 8.11$) and the control-branded chocolate chip brownie ($X_{F_2} = 8.02$). As expected, the increase in the rating of the joint brand was superior to the increase in the rating of the monobrand ($X_{F_1I_1} - F_1 = .66$, $X_{F_2} - F_2 = -.09$; $F(1,14) = 4.91, p < .05, \omega^2 = .18$). Also, the increase in the rating of the joint brand was significant ($X_{F_1I_1} - F_1 = .66$, $F(1,14) = 4.56, p < .05, \omega^2 = .18$), but the
increase in the rating of the monobrand was not ($X_{2F2} - F2 = -.09, F(1,14) = -.24, p > .10$).

**Influence of a joint-branded consumption experience on the value of the ingredient brand.** We used experimental Conditions 2 and 3 to investigate how a positive consumption experience with the joint-branded product influenced the subsequent value of the ingredient brand name. The most appropriate test was to compare the increase in the rating for the family-branded muffin ($F_3$) made with the ingredient brand of chocolate chips ($F_3I_1$) across the two conditions. In this way, we could determine if the prior joint branding of the chocolate chip brownie ($F_3I_1$ in Condition 2) had any influence relative to the ingredient branding of the chocolate chip brownie ($I_1$ in Condition 3). The joint-branded chocolate chip muffin was rated lower when the chocolate chips had been experienced in a joint-branding alliance with brownies ($X_{Condition2A} = .16, X_{Condition3A} = .77$; $F(1,28) = 4.04, p < .05, \omega^2 = .09$). When there was prior joint branding of the ingredient brand name, the rating of the muffin ($X_{F3} = 7.47$) did not significantly increase when the muffin was paired with ingredient-branded chocolate chips ($X_{F3I1} = 7.62, X_{F3I2} - F3 = .16; F(1,14) = .47, p > .10$). When there was no prior joint branding of the ingredient brand name, the rating of the muffin ($X_{F3} = 7.07$) increased when the muffin was paired with ingredient-branded chocolate chips ($X_{F3I1} = 7.84, X_{F3I2} - F3 = .77; F(1,14) = 13.85, p < .05, \omega^2 = .45$). This result is consistent with the predictions of the LMS connectionist model but not the DA or the ACT-R model. As expected, none of the other product ratings significantly differed between Conditions 2 and 3.

**Discussion**

Study 4 provides evidence that joint branding can have both a positive and a negative impact on the participating brands. The data confirmed the finding that a joint-branded product is expected to be higher quality than a monobranded product (Park, Jun, and Shocker 1996; Simonin and Ruth 1998). Subjects expected that a chocolate chip brownie with a name brand chocolate chip would be superior to a chocolate chip brownie with an unbranded chocolate chip. Thus, quality expectations and trial should benefit from a joint-branding strategy. Conversely, consumers who experienced the joint-branded product placed much less value on the ingredient brand in subsequent brand alliances, even though the joint-branded product was high quality. Subjects who tasted the joint-branded chocolate chip brownie put little value on the branded ingredient when it was subsequently added to muffins, whereas subjects who tasted an ingredient-branded chocolate chip brownie believed the ingredient brand had value when it was subsequently added to muffins. Thus, even a positive experience with the joint-branded product can hurt the constituent brand’s associations.

Together, the pre- and postexperience findings in Study 4 suggest that benefits from brand alliances between two strong brands may be situated primarily at trial and that those benefits may come at a price to the constituent brands’ associations.

In Study 4, we investigated a scenario in which two brand names with established outcome associations enter a branding alliance. In Study 5, we investigate two scenarios in which the ingredient brand is a new brand that has not established associations before it enters a branding alliance. In the first scenario, a new ingredient brand (e.g., Nutrasweet) joins an established family brand (e.g., Diet Pepsi). This type of alliance results in a learning sequence of $F_1$ (Diet Pepsi) experiences followed by an $F_1I_1$ (Diet Pepsi with Nutrasweet) experience. In a second scenario, the ingredient manufacturer enters into an agreement with a manufacturer that is planning to use a new brand name in conjunction with the product introduction (e.g., Wow potato chips with Olean). This type of alliance results in a learning sequence of an $F_1I_1$ (Wow potato chips with Olean) followed by $F_1$ experiences in the event the brand name was subsequently used on other products (e.g., Wow tortilla chips). Thus, the two scenarios vary the order in which subjects encounter the ingredient brand—before versus after experiencing a family brand–only product.

**STUDY 5**

In Study 5, we used a two-cell, between-subject design to investigate the influence the order of product experiences had on learning the association between a branded ingredient and quality (for the design, see Table 5). In the first condition, people experienced an $F_1I_1+$, $F_2+$, $F_1+$, $F_2I_2+$ sequence of taste experiences, in which the $F_2$+$I_2+$ sequence was equivalent to the Wow potato chips with Olean example discussed previously and the $F_2+$, $F_2I_2+$ sequence was equivalent to the Diet Pepsi with Nutrasweet example discussed previously. In a second condition, the ingredient pairings were reversed so that people had an $F_1I_2+$, $F_2+$, $F_1+$, $F_2I_1+$ sequence of taste experiences. After experiencing the products, people predicted whether the quality of a new product would be higher if it contained $I_1$ or $I_2$.

**Procedure**

The experiment was run in the context of a taste test for low-fat brownies, muffins, and croissants. Subjects were told that low-fat products are created by substituting ingredients (e.g., oil substitutes) to lower calories or by lowering cooking temperatures to allow for a reduction in the amount of oil that is needed to prevent drying. Subjects were asked to taste and rate samples of baked goods, some with oil substitutes. At Time 1, subjects tasted and rated four brownies using seven-point “dry”/“moist,” “poor flavor”/“good flavor,” “low quality”/“high quality” rating scales. The first two products were filler products; one was described as a non–low-fat product (selected to be high quality), and the other as a low-fat product (selected to be low quality). The first two products were filler products; one was described as a non–low-fat product (selected to be high quality), and the other as a low-fat product (selected to be low quality). The

<table>
<thead>
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<th>Family Brand</th>
<th>Ingredient Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition 1</td>
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</tr>
<tr>
<td></td>
<td>$F_2+$ 100%</td>
</tr>
<tr>
<td></td>
<td>$F_1+$ 100%</td>
</tr>
<tr>
<td></td>
<td>$F_2I_2+$ 100%</td>
</tr>
<tr>
<td>Condition 2</td>
<td>$F_1I_2+$ 100%</td>
</tr>
<tr>
<td></td>
<td>$F_2+$ 100%</td>
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<tr>
<td></td>
<td>$F_1+$ 100%</td>
</tr>
<tr>
<td></td>
<td>$F_2I_1+$ 100%</td>
</tr>
</tbody>
</table>

Notes: Subjects express preference between $I_1$ and $I_2$. 

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third product was a branded, low-fat product with an oil substitute (e.g., a brownie labeled “Treats with Nu-Oil”) and represented the F1I1+ trial. The fourth product was a branded, low-fat competitor without an oil substitute (e.g., a brownie labeled “Goodies”) and represented the F2+ trial. At Time 2, subjects tasted and rated four additional products (e.g., muffins). Again, the first two products were filler products that were selected and labeled as previously. The third product was labeled with the same name as the third product tasted earlier, but without the oil substitute brand name (e.g., muffin labeled “Treats”) and represented the F1+ trial. The fourth product was labeled with the same brand name as the fourth product tasted earlier plus an oil substitute (e.g., muffin labeled “Goodies with Oilean”) and represented the F2I2+ trial. As in Study 4, subjects ate an unsalted soda cracker and had a drink of water in between each of the eight product trials.

After tasting the eight samples, subjects rated the expected consequence of using the oil substitutes in a yet-to-be-produced low-fat croissant. Subjects were told that a manufacturer (Regency) was planning to use Nu-oil or Oilean in its low-fat croissant and was interested in their perceptions of which product would be better. Subjects used three eight-point scales with endpoints labeled “Regency with Nu-Oil” and “Regency with Oilean” to indicate which product would be moister, be higher quality, and have better flavor.

The experimental manipulation was whether the I1 (e.g., Nu-Oil) or I2 (e.g., Oilean) appeared at Time 1 (e.g., the third brownie at Time 1) or at Time 2 (e.g., the fourth muffin at Time 2). Counterbalancing brand names (e.g., Treats versus Goodies), ingredient brand names (Nu-Oil versus Oilean), and product order (e.g., brownies versus muffins tasted at Time 1) resulted in 16 test cells.

Predictions

The DA model predicts that there should be no difference in preferences for the branded ingredients among the conditions, because there is an equal number of pairings between each ingredient and high-quality outcomes (see Figure 4). The LMS connectionist model predicts that people should have a greater preference for I1 than I2 when they experience an F1I1+, F2+, F1+, F2I1+ sequence of experiences (Chapman 1991). Here, I1 gains association strength in the first taste test (F1I1+), and I2 is inhibited from gaining association strength in the last taste test (F2I1+) because of the prior exposure to F2. People should have a greater preference for I2 than I1 when they experience an F1I2+, F2+, F1+, F2I1+ sequence of product trials, because I2 gains association strength in the first taste test (F1I2+) and I1 is inhibited from gaining association strength in the last taste test (F2I1+) because of the prior exposure to F2. The standard ACT-R model predicts no difference in preferences for the branded ingredients, because the number and timing of high-quality experiences is identical in both conditions. If the ACT-R model is modified to allow for the decay of brand associations and not just decay of baseline activation, it would predict a recency effect. Under this relaxed assumption, ACT-R would predict that I2 should be preferred to I1 when people experience an F1I1+, F2+, F1+, F2I1+ sequence of taste experiences and I1 should be preferred to I2 when people experience an F1I2+, F2+, F1+, F2I1+ sequence of taste experiences.

Results

Forty-eight subjects from an introductory marketing class were awarded extra credit to participate in the study. The three dependent-measure scales were combined to create a composite measure of the value of the oil substitute brand names (α = .92). There were no significant influences of the counterbalancing factors.

The between-subjects design was used to test if the first oil substitute to be introduced was equivalent (DA or ACT-R model), disliked (modified ACT-R model), or liked (LMS model) relative to the second oil substitute to be introduced. Subjects expected that the Regency croissant with the I1 ingredient would be a better product when they experienced the F1I1+, F2+, F1+, F2I1+ sequence of products (X11 = 13.75) and that the Regency croissant with the I2 ingredient would be a better product when they experienced the F1I2+, F2+, F1+, F2I1+ sequence of products (X12 = 17.25). The difference in the preference for I1 relative to I2 varied by condition (F(1,46) = 4.71, p < .05, ω2 = .07) in a direction consistent with the LMS connectionist model. Note that this preference for the oil substitute that was introduced first could not be attributed to differences in product quality, preferences for ingredient names, or preferences for brownies or muffins, because these factors were counterbalanced.

Discussion

Study 5 provides evidence that the order of exposure to product cues can influence the association strength between the cues and an outcome. A learning sequence of F1I1+, F1+ created more predictive value for the ingredient I1 than the sequence F2+, F1I1+ created for the ingredient I2. The LMS connectionist model predicts that a person is more likely to form an association between an ingredient (I) and a positive outcome when the ingredient appears early in the sequence of experiences (F1I1+, F1+) than when it appears later in the sequence of experiences (F2+, F2I1+), because the discrepancy between the predicted and the experienced outcome is larger during early trials, which allows for more learning. Note that these results are inconsistent with the DA and ACT-R models. In addition, the results in Study 5 raise the possibility that the negative effect of a joint-branding strategy on ingredient brand associations found in Study 4 might be attenuated when consumers experience the joint-branded product before experiencing the ingredient brand in isolation.19

18These predictions follow from the amount of updating in the LMS connectionist models depending on (1) the amount of discrepancy between the experienced outcome, qj, and the expected outcome, oj, and (2) the fact that output activation is an additive function of incoming activation. Exposure to F2 before exposure to F2I2 creates a strong, positive association between F2 and high quality, so the high-quality node is already activated by the F2 stimulus when I2 is encountered during the F2I2 trial. Thus, the discrepancy between the expected outcome, based on the F2 association, and the experienced outcome is already quite small, which leaves little room for the updating of the I2–quality association.

19We thank one of the reviewers for suggesting this qualification of the effect found in Study 4.
GENERAL DISCUSSION

Across five studies, a simple LMS connectionist model provided the best explanation of how people learn to use brand name information to predict product performance. The data are not consistent with the two spreading-activation models of memory, the DA and the ACT-R models. That the findings contradict these models is significant, because spreading-activation models of human associative memory form the basis for the most influential conceptualizations of brand equity (Aaker 1991; Keller 1993, 1998).

The finding that spreading-activation models cannot account for predictive brand associations in common portfolio-branding scenarios raises the question whether customer-based brand equity can be conceptualized fully in terms of spreading-activation models, which were originally proposed as models of recall, not of prediction or evaluation. Applied to the branding context, they may account very well for brand awareness, that is, the likelihood and ease with which brand names come to mind. Spreading-activation models may explain how characteristics of a brand come to mind when a consumer encounters a brand name. A brand name, then, acts as a peg or library locator for information about a product’s attributes. However, to the extent that brand equity is defined in terms of the favorableness of consumers’ reactions to the marketing of a brand (e.g., Keller 1993), a conceptualization of brand equity in terms of spreading-activation memory models appears to be incomplete. For evaluation to take place, the recalled characteristics of a product (including the brand name) must be valenced. That is, for positive evaluation to take place, a consumer must have learned the value of brand names, product features, and other diagnostic cues. In our opinion, learning to value may be different from learning to recall. It is the diagnostic value of recalled characteristics that drives the most important consumer responses—evaluation and choice. Thus, learning to recall and learning to value are both necessary components of brand equity. Our experiments suggest that learning to value depends on a different kind of learning process. Whereas the learning process that drives recall may be best described by spreading-activation models, the learning process that gives valence to recalled product characteristics seems to be described better by simple connectionist models, such as the LMS model.

Managerial Implications

The findings in the studies reported here represent several common branding scenarios. Our results in these common scenarios suggest several managerial implications. For example, Study 3 suggests that the potential negative impact of the low-quality products in a product line could be mitigated by the use of a subbrand name. This finding is consistent with a similar conclusion by Milberg, Park, and McCarthy (1997) but appears to be based on a different process. Studies 4 and 5 suggest that joint branding is often useful to enhance trial but decreases or limits the value of one or both brands. These negative effects of joint branding are particularly serious when novel brands join established brands (Study 5) or when two established brands enter a joint-branding alliance (Study 4) and the joint-branded product is not significantly better than the value the joining brand names would predict separately (Study 4). On a more general level, the experimental support for the LMS connectionist model encourages the use of the LMS model to generate hypotheses about the impact of alternative branding strategies and scenarios on brand equity.

Limitations of the LMS Connectionist Model and Further Research

The LMS model presented here is only one of several feed-forward connectionist models, most of which are much more complex (e.g., Kruschke 1996; Pearce 1994; Schmajuk, Lamoureux, and Holland 1998). In our test of connectionist versus spreading-activation models, we chose to use the simple model for three reasons: (1) It provides a conservative test because it has fewer free parameters and is more tractable and falsifiable (Stone 1986), (2) it provides a parsimonious explanation of many findings in the classical conditioning and causal learning literature (see, e.g., Miller, Barnet, and Grahame 1995; Young 1995), and (3) most of the more complex models would depend on exactly the same fundamental properties that explain the effects reported here—error-driven learning and additive output activation that combine to produce cue competition effects.

The use of a simple LMS model has some limitations. First, the prediction of association strengths at full learning may appear to be the result of a puzzle in which consumers consciously try to solve two simultaneous constraints—basically a linear programming exercise. Second, the predicted association strengths oscillate infinitely in some variable-quality learning environments (e.g., the straight family-branding scenario in Study 1). Third, it is difficult to anticipate the magnitude of the learning parameter, which should depend on the relevance or salience of brands and outcomes. Yet in defense of the model, there is evidence that the LMS model has been effective at correctly capturing trial-by-trial learning paths that cannot be accounted for by a more analytic process (e.g., Shanks 1987). It has also been assumed that the updating of connection weights will decrease with the number of trials, which allows the connection weights to converge instead of oscillating infinitely (Sutton and Barto 1981). Finally, recent studies have started to investigate determinants of learning rates. For example, Kruschke’s (1996) ADIT model adds an attentional mechanism to the simple LMS model that changes learning rates when unexpected outcomes are encountered.

Further research should investigate potential boundary conditions of the phenomena described by the LMS model. Although the studies reported in this article test learning models (1) in several portfolio-branding scenarios, (2) in vicarious and experiential situations, (3) with abstract and concrete brand names, and (4) with several types of brand names, our studies do not, for example, address situations in which information is received about more than one benefit. In such situations (i.e., in multicue/multioutcome environments), the LMS connectionist model predicts that the same patterns of cue competition effects should occur. Yet this prediction might not always hold true. In our studies, consumers were always confronted with one clear outcome about which they were motivated to learn. However, when consumers receive information about multiple benefits, they might not be able or motivated to try actively to learn to value each brand cue for each outcome. Thus, it is possible that consumers are less likely to try actively and intention-
ally to learn to value brand cues with respect to all benefits. For those benefits, people might need to rely on a more general and basic learning process: They may simply try to store memories of episodes or instances that can be recalled later. That is, in multilocus situations, people might only learn to recall.

We expect people to rely on the best information available when they make predictions. If predictive associations have been formed through a process of learning to value, available cues activate predictive associations to outcomes, as described by the LMS connectionist model. However, when the outcome to be predicted is not the focus of prediction during learning, people will first try to recall the outcomes in the individual instances they have experienced and then try to compute something like a simple correlation between each cue and the outcome. We expect that the learning of associations involved in such recall of stimulus characteristics (outcomes) would be more consistent with the DA model or the ACT-R model than the LMS model. Thus, it may be that people store instances/episodes that can be recalled to construct the predictive value of cues for outcomes but that people do not use instances when they have predictive associations available (Price and Yates 1995). It is this interplay of retrospective processes based on episodic memory and online processes based on predictive associations that represents the next opportunity for understanding the formation and evolution of brand associations and brand equity.

Conclusion

In five studies, we investigated the impact on brand equity of several specific portfolio-branding strategies. In addition to documenting the impact of specific strategies on the value of family brands, subbrands, and ingredient brands, our studies illustrate the merit of viewing brands as predictive cues. According to this view, the impact of a brand name on consumer evaluations and choice depends to a large extent on the strength of predictive associations between brand names and performance (or any other benefit). Our data suggest that the learning of these predictive associations cannot be described by models in the spreading-activation tradition but can be described by a simple connectionist model with an LMS learning rule. According to this connectionist model, a brand name acquires predictive value only to the extent that it can account for differences in performance that are not already predicted by other available cues. On the basis of these findings, we speculate that there is a difference between learning to recall, which may be best described by models presented in the spreading-activation literature, and learning to value, which may be best described by LMS-type models. At a more general level, our findings attest to the theoretical and practical importance of studying the fundamental learning processes that underlie the formation and evolution of customer-based brand equity.

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In five studies, we investigated the impact on brand equity of several specific portfolio-branding strategies. In addition to documenting the impact of specific strategies on the value of family brands, subbrands, and ingredient brands, our studies illustrate the merit of viewing brands as predictive cues. According to this view, the impact of a brand name on consumer evaluations and choice depends to a large extent on the strength of predictive associations between brand names and performance (or any other benefit). Our data suggest that the learning of these predictive associations cannot be described by models in the spreading-activation tradition but can be described by a simple connectionist model with an LMS learning rule. According to this connectionist model, a brand name acquires predictive value only to the extent that it can account for differences in performance that are not already predicted by other available cues. On the basis of these findings, we speculate that there is a difference between learning to recall, which may be best described by models presented in the spreading-activation literature, and learning to value, which may be best described by LMS-type models. At a more general level, our findings attest to the theoretical and practical importance of studying the fundamental learning processes that underlie the formation and evolution of customer-based brand equity.

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