Category Activation Model: A Spreading Activation Network Model of Subcategory Positioning When Categorization Uncertainty Is High

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We develop a spreading activation model, which we call the category activation model, to predict where within a category structure consumers are likely to position a subcategory that they have created to accommodate a new hybrid product. Based on this model, we hypothesize that the probability that an individual will position a new category subordinate to a particular category *i* is proportional to the relative number of categories that are already subordinate to *i*. We report the results of two studies that support this hypothesis and provide evidence that accessibility is an underlying mechanism.

In this era of digital convergence, consumers often encounter new hybrid products that do not fit unambiguously into their existing mental categories (Gregan-Paxton, Hoeffler, and Zhao 2005). For example, when consumers encountered the Motorola Envoy, which would later be acknowledged as the first personal digital assistant (PDA), they had difficulty categorizing it since it shared features with portable computers and personal organizers yet was distinctly different from products in both of these categories (Keller, Sternthal, and Tybout 2002).

When consumers encounter a new product, such as the Envoy, which has features that differ significantly from existing categories, they may respond by creating a new subcategory (e.g., the PDA subcategory) within their existing category structure for products (Sujan and Bettman 1989). If the new product could conceivably be placed into more than one existing category due to similarities (e.g., shared features) with several existing categories (i.e., categorization uncertainty is high; Gregan-Paxton et al. 2005; Moreau, Markman, and Lehmann 2001), consumers must determine where to position the new subcategory. For example, upon encountering the Motorola Envoy, which shared features with both portable computers and personal organizers, consumers had to decide under which of these two categories to position the new PDA subcategory. Extant consumer research has not examined how this decision is made.

Understanding how consumers decide where to position a new subcategory when categorization uncertainty is high is important since new products, including really new products, are often derived from existing product categories (Goldenberg, Mazursky, and Solomon 1999; Moreau, Lehmann, and Markman 2001; Ward 1995). Recent examples include LG's 5-megapixel camera phone, which also functions as an organizer; Sony Ericsson's Walkman phone, which also functions as an MP3 player, camera, pedometer,

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and organizer; and Apple's iPhone, which combines features from a wide range of different categories.

Furthermore, consumers' categorization decisions can have striking implications for firms. Research in psychology has shown that individuals use categories as bases for inductive inference and prediction (Yamauchi and Markman 2000). In the marketing domain, consumers use information contained in existing product categories to make inferences about the features, functions, and performance of new products and to predict the retail store departments in which they will be stocked (Gregan-Paxton et al. 2005; Gregan-Paxton and Moreau 2003). Furthermore, the manner in which consumers categorize products affects their thoughts about, attitudes toward, and overall evaluations of these products (Moreau, Markman, and Lehmann 2001; Sujan 1985; Sujan and Bettman 1989), their memory for product features (Gregan-Paxton and Moreau 2003; Sujan and Bettman 1989), and their likelihood of recalling and subsequently choosing the products in memory-based choice (Nedungadi 1990; Nedungadi, Chattopadhyay, and Muthukrishnan 2001).

Since consumers' categorization decisions can have such profound effects, it follows that firms might benefit by influencing the manner in which consumers position subcategories for new products. If Motorola had made a concerted effort to influence the positioning of the PDA subcategory, perhaps the Envoy would have been more successful (Keller et al. 2002). In order to exert such influence, firms need to understand how consumers are naturally inclined to position the new subcategory. Such understanding could help the firm estimate the level of marketing effort needed to reinforce or alter the positioning of the subcategory to its advantage.

In this article, we address the academically and managerially important question of how consumers position subcategories for new products when categorization uncertainty is high. We develop and test an analytical model of the process of subcategory construction under high categorization uncertainty. Our research provides insight into the process of subcategory creation in general and the categorization of new products in particular.

CONSUMER CATEGORIZATION OF PRODUCTS

Consumer research on the categorization of products is grounded in a long literature within psychology, which shows that the use of category structures to differentiate objects is a fundamental cognitive activity (Barsalou 1992). According to this research, individuals create and maintain taxonomic representations of objects that they encounter. The goal of categorization is to create a categorical structure that maximizes the similarity of objects within each category while simultaneously minimizing the similarity of objects in different categories (Rosch 1978). These categorical structures enable individuals to efficiently store and recall information learned from experience, make inferences about newly encountered objects (e.g., products), and form evaluations of them (Cohen and Basu 1987; Sujan and Dekleva 1987). Individuals can also form categorical organizations in response to goals (e.g., "things to take out of your house in case of a fire"; Barsalou 1983, 1991). These goal-derived, or ad hoc, categories exist in harmony with taxonomic category structures (Ross and Murphy 1999).

Subtyping

Given that the goal of categorization is to classify objects within category structures that maximize within-category similarity while simultaneously minimizing between-category similarity, the following question arises: How might consumers respond to product information that suggests both significant similarities and differences with the most closely related product category? To answer this question, consumer researchers have used Taylor's (1981) subtyping model, which suggests that individuals respond to discrepant information about an object by creating subcategories within more general categories when inconsistencies are large and cannot be filtered out. Consumer research has observed that consumers who are experts within a particular product category are more likely than novices to partition that product category using subcategories (Alba and Chattopadhyay 1985; Sujan 1985). Moreover, consumers' category structures for products can have several levels of categories and subcategories, with each deeper level containing a narrower, more well-defined group of products (Sujan and Dekleva 1987).

Sujan and Bettman (1989) have conducted the most detailed investigation of consumer subcategory creation to date. In studies involving fictitious new brands of cameras, they observed that, when participants perceived a brand as being strongly discrepant from the camera category, they created a niche subcategory for the brand, whereas when they perceived a brand as being only moderately discrepant, they placed it directly into the camera category. Importantly, Sujan and Bettman (1989) showed that consumers create a new subcategory in response to even just one highly discrepant brand.

Multiple Category Inferences

Although research on subtyping has generally assumed that the category into which an object will be placed is known (e.g., the camera category in Sujan and Bettman's 1989 studies), some objects are congruent with more than one category (Murphy and Ross 1994). Only relatively recently has consumer research examined the mental processes of individuals when they encounter objects that could potentially belong to multiple categories. This research has focused on how the multiple categories to which the object could potentially belong each contribute to individuals' expectations and inferences about the object and their evaluations of it. For example, Gregan-Paxton et al. (2005) examined the nature of consumers' inferences when faced with a product that could belong to multiple categories (e.g., a PDA phone), and Moreau, Markman, and Lehmann (2001) examined the formation of expectations and preferences for such products.

Goals of the Present Research

Although categorization research has established that subtyping is an important phenomenon and more recently has begun to explore the mental processes underlying multiple category inferences, extant research has not yet connected these two important topics in a coherent way. The goal of the present research is to fill this gap by developing an analytical model of how subtyping occurs when the target object is similar to, yet substantially different from, more than one potential parent category (i.e., when categorization uncertainty is high).

Upon encountering a product that shares features with multiple categories but that is also highly discrepant from each of them, Sujan and Bettman's (1989) research, discussed above, suggests that consumers will create a new subcategory, due to the significantly discrepant features. Extant research relies on similarity to predict where within a category structure people are likely to position an object, in this case a new subcategory (Barsalou 1992). However, in the context of our research, similarity is not diagnostic (i.e., it does not yield a unique result) since the object being categorized shares similarities with multiple categories. Thus, going back to the example of the Motorola Envoy, which shared features with both portable computers and personal organizers, similarity would not be diagnostic for predicting under which of these categories consumers would position the new PDA subcategory.

In this article, we develop and test an analytical process model, the category activation model (CAM), to predict where within a taxonomic category structure consumers will position a subcategory for a new product when categorization uncertainty is high. In doing so, we bring together research on subtyping and multiple category inferences, advance theory within both of these domains, and demonstrate the usefulness of this new understanding in a consumer context that is highly relevant to managers who are grappling with digital convergence. Our work is particularly significant since new products are often derived from existing product categories (Goldenberg et al. 1999; Ward 1995), and yet to date there has been no research to address the issue that we discuss.

A MODEL OF SUBCATEGORY POSITIONING

Models of Categorization

Models of categorization focus on how individuals organize and represent knowledge and the implications of these representations for inductive inferences (Medin and Schaffer 1978). They seek to explain how individuals categorize a newly encountered object and then how they use their knowledge of this category to make inferences about the object. These models draw on research on the learning and memory of classifications (Shepard 1964; Shepard and Chang 1963; Shepard, Hovland, and Jenkins 1961) and are based on the notion of selective attention, which proposes that in the process of classification individuals tend to narrow their attention to only those dimensions that are relevant for the given classification. Most major categorization models, including exemplar models (Nosofsky 1986; Nosofsky and Palmeri 1997), prototype models (Minda and Smith 2000; Smith and Minda 1998), and rule-based models (Smith, Patalano, and Jonides 1998), include selective attention as a key mechanism.

Category Activation Model

The CAM differs from extant models of categorization in two important ways. First, whereas extant models primarily seek to describe how category knowledge is represented and to predict into which categories objects will be placed, the goal of the CAM is to predict where entire new subcategories will be positioned when categorization uncertainty is high (i.e., when the new subcategory is created to classify an object that shares significant similarities with multiple categories but also differs significantly from each of them). Second, whereas extant models are largely based on the notion of selective attention, the CAM relies on category accessibility, a point that we elaborate on next.

According to models of classification and comprehension (Wyer and Srull 1989), when an individual encounters an object, he or she first interprets it in terms of stored knowledge, without regard to any specific processing goal. The specific representation that the individual retrieves from "permanent storage" at this early processing stage is a function of "the frequency and recency with which it has been used in the past and the degree to which its contents match" the encountered object (Wyer and Radvansky 1999, 92). Thus, if the encountered object (or subcategory in the present case) is ambiguous (i.e., possesses features that are congruent with several alternative categories), the individual will be more likely to position it under those categories that have been more frequently and recently used (i.e., those that are more accessible). Research on the classification of ambiguous entities strongly supports this contention (Wyer 2007).

In this article, we examine the classification of a new subcategory for an ambiguous object that shares both similarities and differences with multiple categories. When a new subcategory could potentially be positioned under more than one category (because the encountered object possesses features that are congruent with more than one category), the accessibility of the competing categories becomes crucial. Thus, the CAM focuses on a context in which accessibility plays a critical role in determining the category to which the new subcategory is assigned. It is important to note that we do not suggest that similarity per se is unimportant in subcategory positioning but rather that, given the context that we study, accessibility becomes the key arbiter of subcategory positioning. Drawing on recent mathematical research on the growth of networks (Barabasi and Albert

1999, 2002), we next develop a model of where within an existing taxonomic category structure individuals are likely to position a new subcategory when category uncertainty is high.

Spreading Activation

We build on previous research that shows that priming a category increases its accessibility and subsequent use (Herr 1986, 1989). We assume that when a category is accessed (e.g., by thinking about a product in the category), some of the resulting activation remains with the category, and the rest spreads through the entire network. Furthermore, we assume that the increase in activation that results when a category is accessed increases the probability that a new subcategory will be positioned under it. Combining these two assumptions, it follows that if we accurately describe the process by which activation spreads through the network, we should be able to predict the probability that a new subcategory will be positioned at any relevant location within the category structure. We expect that these probabilities will depend on the existing link structure since these links determine how activation spreads through the network.

We describe the spreading activation process as follows. Let 1, 2, . . . , n denote the nodes (i.e., categories) within the existing network (i.e., category structure). A link connects two nodes if a subordinate relationship exists between them (i.e., one is a subcategory of the other). We assume that the access of nodes initiates activation, which then spreads through the network. We model each time period during which no new nodes are created. For such a time period, we derive the limit activation level (i.e., the activation level at the end of the time period) of each node as the result of a discrete iterative process. In this process, node i starts with an arbitrary activation level, $a_i^{(0)}$, and $A^{(0)} = \sum_{i=1}^{n} a_i^{(0)}$ denotes the total activation in the network. At the beginning of each step in the iterative process, we assume that the activation level of each node increases by β_1 due to external activation that is uniformly distributed across the network. This assumption is equivalent to saying that, during a given time period, each existing category is accessed the same number of times on average. We use this assumption to simplify the exposition of the model, and we control for it in study 1. However, we show in appendix A, available in the online version of the *Journal of Consumer Research*, that relaxing this assumption by allowing each node to receive an independent amount of external activation leads to a qualitatively identical result (i.e., the same hypothesis).

We assume that β_2 units of this activation remain at node i, and $a_i^{(t)} + \beta_1 - \beta_2$ units of activation spread to node i's neighbors (i.e., its subcategories and the parent category to which it is connected). To again ease exposition, we assume that these units of spreading activation are distributed equally among node i's neighbors. However, in the generalized model that we develop in online appendix A, we show that the results are qualitatively the same when this assumption is relaxed. Finally, at the end of the iterative step, we assume that the activation level of each node decreases by β_1 such that the overall activation level of the entire network remains constant until a new subcategory is created. This uniform decrease of activation means that "forgetting" of the categories in the existing network is, on average, identical for each category. We relax this uniformity assumption in the generalized model (see online app. A). The iterative process is represented by the following equation:

$$a_i^{(t+1)} = \beta + \frac{a_{i1}^{(t)} - \beta}{d_{i1}} + \frac{a_{i2}^{(t)} - \beta}{d_{i2}} + \ldots + \frac{a_{ik}^{(t)} - \beta}{d_{ik}}, \qquad \textbf{(1)}$$

where $\beta = \beta_2 - \beta_1$; $i1$, $i2$, . . . , ik are the neighbors of node i; and d_{ij} is the degree (number of neighbors) of neighboring node j. In online appendix B, we show that the series $a_i^{(t)}$ converges as $t \to \infty$ for arbitrary starting values. Furthermore, we show that convergence occurs quickly if, instead of arbitrary starting values, we use the final activation levels of all existing nodes as new starting values after a new node is created.

To complete the description of the category positioning process, we must define a new starting activation for every newly created node. If we arbitrarily assume that the total activation of the network is constant over time, then we define this starting activation level to be zero. However, this assumption is not necessary since the proof in online appendix B shows that the process converges from any starting values. Thus, we may instead assume that the activation level of the network increases or decreases as it grows. To model increasing total activation, we define the starting activation level of the new node to be positive, and all of the results still follow. We may also assume that the total activation level of the entire network decreases over time, and again the results remain unchanged.

Knowing that the iterative process in equation 1 converges, it follows that the limit activation level of any node i, denoted by a_i, must satisfy equation 2.

$$a_i = \beta + \frac{a_{i1} - \beta}{d_{i1}} + \frac{a_{i2} - \beta}{d_{i2}} + \ldots + \frac{a_{ik} - \beta}{d_{ik}}. \qquad \textbf{(2)}$$

In online appendix B, we show that normalizing $A^{(0)}/(2n - 2 + n\beta)$ to one and solving equation 2 for each node in the network yields the following limit activation level just before a new node is created:

$$a_i = d_i + \beta. \qquad \textbf{(3)}$$

Thus, we propose that before a new node is created, the activation level of each node in the existing network is a linear function of its degree (i.e., the number of other nodes to which it is directly linked). Since, in a taxonomic category structure, the degree of each category is equal to the number of subcategories that are connected to it plus one (for its parent category), the CAM predicts that the activation level of each category is proportional to the number of subcategories that are connected to it.

Following a large body of previous categorization research in both marketing and psychology, we have thus far assumed the use of taxonomic category structures. Nevertheless, the model can be generalized to more complex structures in which an object can be placed in multiple subcategories, subcategories can be connected to multiple parent categories, and horizontal and vertical connections can exist between categories. All of our previous results hold for this greatly generalized CAM, as shown in online appendix A.

Hypothesis Development

Combining the prediction that the activation level of each category is proportional to the number of subcategories that are connected to it with our assumption that the probability that a new subcategory will be positioned under an existing category is directly related to the existing category's activation level (when the new subcategory contains an ambiguous object that shares similarities with several potential parent categories) leads to our hypothesis:

H1: The probability that an individual will position a new category subordinate to a particular category i is proportional to the relative number of categories that are already subordinate to i.

What link structures should result from the process of subcategory positioning that we have proposed? As the process progresses, we are likely to observe a network in which the vast majority of subcategories are connected to a relatively small number of parent categories. The tendency for links to form between new nodes and those existing nodes that have high degrees is called preferential attachment by network theorists and is a common property of many naturally occurring networks. Popular examples include the human nervous system, the World Wide Web, terrorist networks, and the network of reactions in protein synthesis (Barabasi and Albert 1999).

We next report the results of two studies. In study 1, we experimentally test our hypothesis in a new product context and provide evidence in support of our assumption that accessibility is an underlying mechanism. In study 2, we differentiate between the impact of subcategory numerosity and perceived category breadth in order to rule out an alternative explanation.

STUDY 1: CATEGORIZATION OF A NEW HYBRID PRODUCT

The purpose of study 1 was to test our hypothesis in the context of a new hybrid product. Furthermore, we sought to test our proposition that accessibility underlies the effect. We employed a 3 (priming: entertainment vs. health vs. neutral) × 2 (subcategory numerosity: entertainment vs. health) fractional factorial design. Participants in the neutral priming condition were divided equally between the two subcategory numerosity conditions, whereas all participants in the entertainment priming condition were assigned to the health subcategory numerosity condition, and all participants in the health priming condition were assigned to the entertainment subcategory numerosity condition.

Method

Participants. Ninety-six students at Eötvös Loránd University in Budapest, Hungary, participated in the study in exchange for one or two candy bars. Participants were recruited to ostensibly participate in two separate studies and were randomly assigned to the experimental conditions described below.

Independent Variables. We manipulated the number of subcategories belonging to two broad product categories (entertainment electronics and health electronics) and controlled the frequency with which these subcategories were accessed. The stimuli included a three-level taxonomic category structure with consumer electronics at the top level, entertainment and health at the middle level, and a set of seven subcategories at the bottom level.

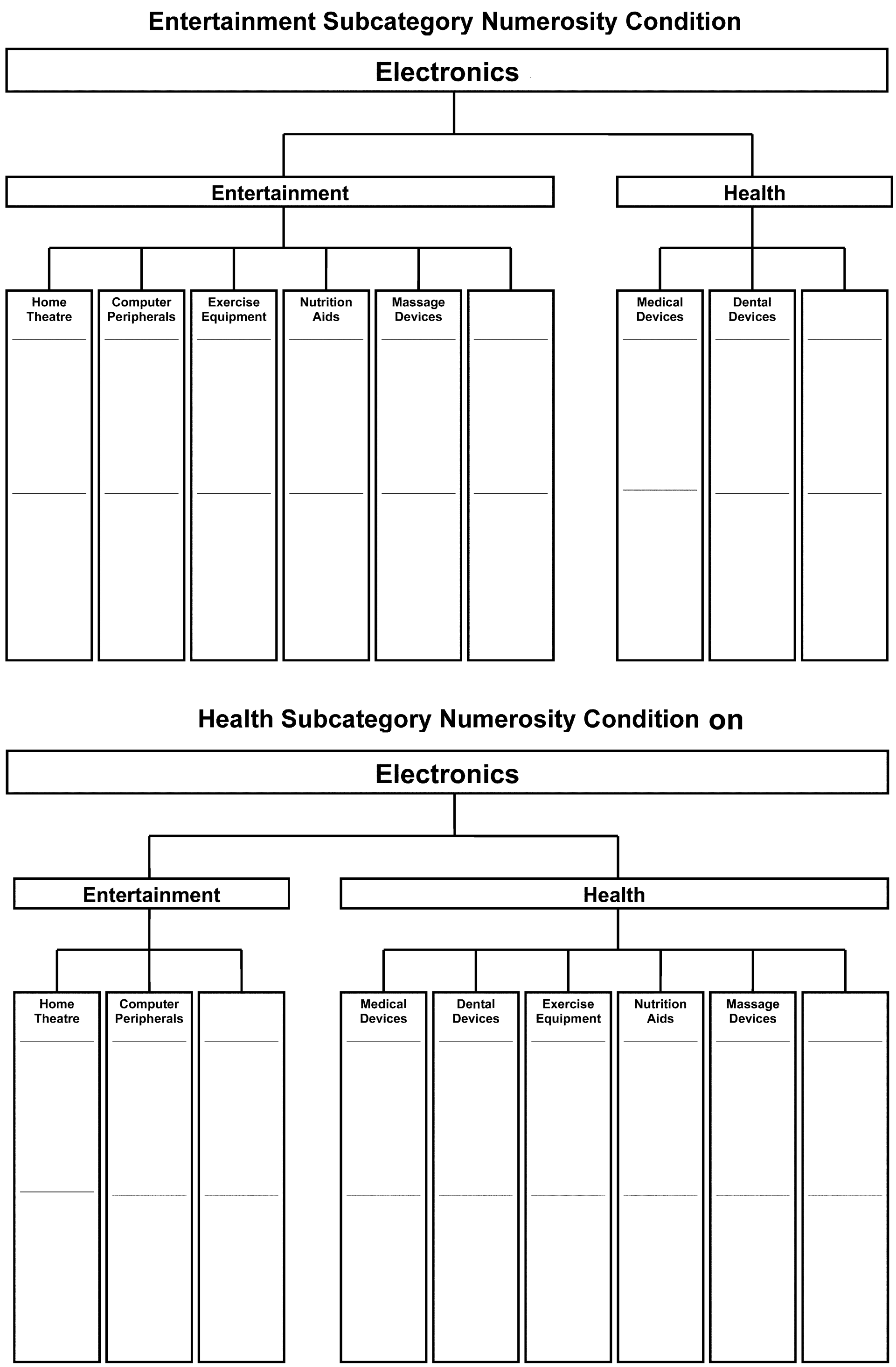
We selected the seven bottom-level subcategories—home theater, computer peripherals, medical devices, dental devices, exercise equipment, nutrition aids, and massage devices—on the basis of pretest results. Specifically, we selected these particular subcategories because pretest participants were significantly more likely to categorize them as belonging to the entertainment or health categories than to a list of several other broad categories (e.g., home, office, communication). Furthermore, pretest participants were significantly more likely to categorize home theater and computer peripherals as entertainment electronics rather than as health electronics (home theater: $t = 21.86$, $p < .001$; computer peripherals: $t = 26.98$, $p < .001$), were significantly more likely to categorize medical devices and dental devices as health electronics rather than as entertainment electronics (medical devices: $t = 50.84$, $p < .001$; dental devices: $t = 19.47$, $p < .001$), and were statistically equally likely to categorize exercise equipment, nutrition aids, and massage devices as either entertainment electronics or health electronics (exercise equipment: $t = .47$, $p > .6$; nutrition aids: $t = .32$, $p > .7$; massage devices: $t = .22$, $p > .8$). These results allowed us to create the two subcategory numerosity conditions by manipulating the position of the three subcategories that were equally likely to be categorized as entertainment electronics or as health electronics.

In the entertainment subcategory numerosity condition, five subcategories were positioned under the entertainment category, and two subcategories were positioned under the health category, whereas in the health subcategory numerosity condition, five subcategories were positioned under the health category, and two subcategories were positioned under the entertainment category (see fig. 1). The titles of the seven bottom-level subcategories were held constant across the two subcategory numerosity conditions. Based on the pretest results, both of these structures were equally congruent with participants' category beliefs.

We also manipulated the accessibility of the health and

FIGURE 1

STUDY 1: CATEGORY STRUCTURES BY CONDITION



entertainment categories through priming. We implemented the priming manipulation, which had three levels (entertainment, health, and neutral), through a proofreading task that was described to participants as a separate study. The experimenter instructed participants to read a 750-word news story with the goal of identifying 20 misspelled words to ostensibly assess the importance of grammatical correctness in newspapers. In the entertainment prime condition, the story was titled "Survey: E-Entertainment," whereas in the health prime condition the story was titled "America's Health Care Crisis," and in the neutral prime condition the story was titled "Canadian-American Relations." Furthermore, in the entertainment prime condition, the story contained 20 instances of the word "entertainment" and no instances of the word "health," whereas in the health prime condition it contained 20 instances of the word "health" and no instances of the word "entertainment," and in the neutral prime condition it did not contain any instances of the words "entertainment" or "health."

Procedure. The experimenter greeted passersby in a student union building and asked them whether they would be interested in participating in two short studies in exchange for one or two candy bars, depending on their performance on a proofreading task in the first study. Those who agreed read and signed a consent form and then took part in the experiment individually.

In the first part of the experiment, participants completed the proofreading (i.e., priming) task. To ensure that they read their assigned stories carefully, the experimenter promised them a second candy bar if they succeeded in identifying all the misspelled words in the story.

After participants completed the priming task, they were asked to participate in the supposed second study. In this part of the experiment, participants first familiarized themselves with their assigned category structure, which was presented on large format paper, by placing small pieces of paper with the names of 14 familiar electronics products (see table 1) under the seven bottom-level subcategories. We chose these products on the basis of a pretest that showed that participants reliably placed two of them into each of the seven bottom-level categories. Thus, by asking participants to categorize these 14 products, we led them to access each of the seven bottom-level subcategories twice. It follows that the number of times that they accessed the middle-level entertainment and health categories differed between the two subcategory numerosity conditions. In the entertainment subcategory numerosity condition—in which five subcategories were connected to the entertainment category and two subcategories were connected to the health category—each participant accessed the entertainment category 10 times and the health category four times. In the health subcategory numerosity condition—in which two subcategories were connected to the entertainment category and five subcategories were connected to the health category—each participant accessed the entertainment category four times and the health category 10 times.

Next, the experimenter presented participants with a description of a fictitious new product called the Exercise Buddy (see fig. 2). The Exercise Buddy was a hybrid product that shared characteristics with both familiar entertainment electronics (e.g., stores up to 1 gigabyte of MP3s) and familiar health electronics (e.g., monitors number of calories burned). The results of a pretest indicated that participants were statistically equally likely to categorize the Exercise Buddy as an entertainment electronics or a health electronics product ($t = .27$, $p > .7$) when given a list of five general categories of electronics from which to choose (communications, entertainment, health, home, and office). In the experiment, participants could categorize the Exercise Buddy either by placing a small piece of paper containing its name under one of the seven bottom-level subcategories in their assigned category structure or by creating a new bottom-level subcategory, connected either to the entertainment category or to the health category. To create a new subcategory, participants wrote the name of the new subcategory directly onto their assigned category structure in one of two blank spaces—one with a subordinate relationship to the entertainment category and one with a subordinate relationship to the health category (see fig. 1)—and then placed the piece of paper that represented the Exercise Buddy under it. The dependent measure of primary interest was whether participants positioned a new subcategory beneath the entertainment category or beneath the health category. Finally, participants completed a questionnaire that contained questions about individual factors (e.g., gender, age, academic major)

TABLE 1

STUDY 1: CATEGORY FAMILIARIZATION PRODUCTS

Category	Product
Home theater	Kenwood stereo system with Dolby Digital 5.1
	Sony high definition television with ultra flat screen
Computer peripherals	Thrustmaster cockpit simulator with joystick and floor pedals
	Logitech Webcam with face-tracking software
Medical devices	Welch Allyn blood pressure monitor with digital display
	Minimed insulin pump with backlit display
Dental devices	Oral-B electric toothbrush, with floss action brush head
	Phillips ultrasonic plaque remover with adjustable intensity
Exercise equipment	Pacific Fitness treadmill with 25% maximum incline
	ProForm stationary bicycle with 30 preprogrammed courses
Nutrition aids	Juiceman smoothie maker with 20 speed settings
	Omega electric wheatgrass juicer with twin gear technology
Massage devices	Human Touch robotic massage recliner with heat
	Sonic Skin ultrasonic face massager with antiwrinkle cream

FIGURE 2

STUDIES 1 AND 2: NEW HYBRID PRODUCT

NEW: Exercise Buddy

Exercise Buddy makes working-out fun and safe:
- Stores up to 1 Gb of MP3s -Jam out to your favorite music!
- Built-in AM, FM, and XM radio -Tune in to your favorite programs!
- Continuously monitors your heart rate, blood pressure, body temperature, and hydration levels –Keep your work-out safe!
- Monitors the number of calories you have burned –Take the guesswork out of weight loss!
- Connects to your computer or high definition TV via Bluetooth -Continuously monitor your vital levels!
- Uploads exercise data to your computer -Track your progress!
- Slim, shock resistant case –Tougher than your opponent in full-contact sports!

and an open-ended suspicion probe. Upon completion of the questionnaire, participants were debriefed and given the reward of one or two candy bars.

Results and Discussion

Based on an independent coder's judgments of responses to the suspicion probe, we excluded five participants who might have been hypothesis aware. Four of these participants guessed that the first and second studies were related, and one suggested that the number of subcategories connected to the entertainment and health categories may have influenced her positioning of a new subcategory for the Exercise Buddy. After these exclusions, the study had 91 valid participants.

All 91 of these participants categorized the 14 familiar products by placing them into the subcategories that we expected based on pretest results (see table 1). Thus, each participant accessed each of the seven bottom-level subcategories twice (by placing two products into it) before categorizing the Exercise Buddy.

Subcategory Numerosity. Our hypothesis states that the probability that an individual will position a new category subordinate to a particular category i is proportional to the relative number of categories that are already subordinate to i. In this experiment, we varied the relative number of subcategories that were subordinate to two categories—entertainment and health. In the entertainment subcategory numerosity condition, five subcategories were subordinate to the entertainment category and two subcategories were subordinate to the health category, whereas in the health subcategory numerosity condition two subcategories were subordinate to the entertainment category and five subcategories were subordinate to the health category (see fig. 1). Thus, based on our hypothesis, we predicted that among those participants who received a neutral prime and subsequently chose to create a new subcategory for the Exercise Buddy, five out of seven, or approximately 71%, would position this new subcategory under the category that already possessed five, rather than two, subcategories.

To test our hypothesis, we first examined the subcategories that were created by participants in the entertainment subcategory numerosity condition who had received a neutral prime. Twenty-one of the 22 valid participants in this condition chose to create a new subcategory for the Exercise Buddy. Consistent with our prediction, significantly more of these participants positioned this new subcategory under the entertainment category ($N = 16$) than under the health category ($N = 5$; $\chi^2(1) = 5.76$, $p < .05$). Furthermore, the percentage of participants who positioned the new subcategory under the entertainment category rather than under the health category (76%) was statistically equal to 71% ($\chi^2(1) = .27$, $p > .50$), as we predicted.

We next examined the subcategories that were created by participants in the health subcategory numerosity condition who had received a neutral prime. All 23 valid participants in this condition chose to create a new subcategory for the Exercise Buddy. Consistent with our prediction, significantly more of these participants positioned this new subcategory under the health category ($N = 17$) than under the entertainment category ($N = 6$; $\chi^2(1) = 5.26$, $p < .05$). Furthermore, the percentage of participants who positioned the new subcategory under the health category rather than under the entertainment category (74%) was statistically equal to 71% ($\chi^2(1) = .09$, $p > .75$), as we predicted. Together, the results in both the entertainment and the health subcategory numerosity conditions support our hypothesis that the probability that an individual will position a new category subordinate to a particular category i is proportional to the relative number of categories that are already subordinate to i.

Priming. In the model setup, we proposed that differences in accessibility underlie the effect of subcategory numerosity on the positioning of a new subcategory. Thus, we expected that the effect of the subcategory numerosity manipulation on new subcategory positioning that we observed in the first part of this experiment was due to the relatively greater accessibility of the entertainment category in the entertainment subcategory numerosity condition and to the relatively greater accessibility of the health category in the health subcategory numerosity condition.

To test this, we used a priming manipulation to increase the accessibility of the category that we predicted to be less accessible in each condition. Specifically, we primed a group of participants in the entertainment subcategory numerosity condition with a health theme and primed a group of participants in the health subcategory numerosity condition with an entertainment theme. We predicted that this priming manipulation would diminish the effect of the subcategory numerosity manipulation on the positioning of the new subcategory.

We first examined the subcategories that were created by participants in the entertainment subcategory numerosity condition who received a health prime. All 22 valid participants in this condition created a new subcategory for the Exercise Buddy. Consistent with our prediction, the number of these participants who positioned this subcategory under the entertainment category ($N = 13$) was statistically equal to the number who positioned it under the health category ($N = 9$; $\chi^2(1) = .73$, $p > .25$). Furthermore, the percentage of participants in this condition who positioned the new subcategory under the entertainment category rather than under the health category (59%) was marginally significantly different from the 76% that we observed among those participants in the entertainment subcategory numerosity condition who received a neutral prime ($\chi^2(1) = 3.45$, $p < .06$).

Next, we examined the subcategories that were created by participants in the health subcategory numerosity condition who received an entertainment prime. Twenty-two of the 24 valid participants in this condition chose to create a new subcategory for the Exercise Buddy. Consistent with our prediction, the number of these participants who positioned this subcategory under the health category ($N = 12$) was statistically equal to the number who positioned it under the entertainment category ($N = 10$; $\chi^2(1) = .18$, $p > .50$). Furthermore, the percentage of participants in this condition who positioned the new subcategory under the health category rather than under the entertainment category (55%) was significantly different from the 74% that we observed among those participants in the health subcategory numerosity condition who received a neutral prime ($\chi^2(1) = 4.33$, $p < .05$).

In summary, the results show that nearly all participants in all conditions created a new subcategory for the new hybrid product. Furthermore, participants who received a neutral prime were more likely to position the new subcategory under the category (entertainment or health) to which relatively more subcategories were already connected. Finally, our priming manipulation, which increased the accessibility of the category to which fewer subcategories were connected, wiped out this preferential positioning effect. Taken together, the results support our hypothesis that individuals are more likely to position a new subcategory under a category to which relatively more subcategories are already connected and our proposition that this effect occurs because categories with more connected subcategories are more accessible.

STUDY 2: DIFFERENTIATING THE IMPACT OF NUMEROSITY AND BREADTH

Although the results of study 1 support our hypothesis and provide support for accessibility as an explanatory mechanism, one could argue that the results were instead driven by differences in perceived category breadth or abstraction across the subcategory numerosity conditions. Specifically, one could argue that the category (entertainment or health) to which relatively more subcategories were connected was not more accessible than the category with relatively fewer subcategories but rather that participants perceived it as being broader or more abstract. If this were the case, then it is possible that participants were more likely to position a new subcategory under the category with relatively more subcategories due to this greater perceived breadth rather than to higher accessibility. Although the results of the priming manipulation in study 1 suggest that accessibility matters, it is possible that, by increasing the accessibility of the less broad category, this manipulation simply countered an opposing effect of perceived breadth. The purpose of study 2 was to rule out perceived breadth as an alternative explanation by manipulating subcategory numerosity and the breadth of each category independently. The study had a 2 (subcategory numerosity: entertainment vs. health) × 2 (entertainment category breadth: high vs. low) × 2 (health category breadth: high vs. low) between-subjects design.

Method

Participants. Three hundred and seventy-one students at the Université Paris-Sorbonne (Paris IV) in Paris, France, participated in the study in exchange for a voucher for a sandwich and a drink that was redeemable at a nearby café.

Independent Variables. As in study 1, we manipulated the number of subcategories that were connected to two broad product categories (entertainment electronics and health electronics) and controlled the frequency with which these subcategories were accessed. Furthermore, in this study we also manipulated the perceived breadth of each of these two categories. As in study 1, the stimuli included a three-level taxonomic category structure with consumer electronics at the top level, entertainment and health at the middle level, and a set of seven subcategories at the bottom level. In the present experiment, the identities of the bottom-level subcategories varied across the entertainment and health category breadth conditions.

We selected the bottom-level subcategories on the basis of three pretests. The purpose of pretest 1 was to identify three broad groups of product subcategories—one group consisting of subcategories that participants strongly associated with entertainment rather than health, one group consisting of subcategories that participants strongly associated with health rather than entertainment, and one group consisting of subcategories that participants strongly and equally associated with both entertainment and health. To accomplish this goal, we asked participants to rate the degree to which they associated each of 38 different subcategories with entertainment and with health on 9-point scales, ranging from 1 (not at all associated with entertainment/health) to 9 (very associated with entertainment/health). We presented the subcategories in four random orders and counterbalanced the order of the entertainment and health scales between surveys.

Pretest 1 revealed that participants were significantly more likely to categorize digital video disc (DVD) players, ice cream makers, global positioning systems (GPSs), and two-way radios as entertainment electronics rather than as health electronics (DVD players: $t = 16.66$, $p < .001$; ice cream makers: $t = 2.80$, $p < .01$; GPSs: $t = 6.26$, $p < .001$; two-way radios: $t = 6.39$, $p < .001$), were significantly more likely to categorize humidifiers, juicers, electronic food scales, and electronic body scales as health electronics rather than as entertainment electronics (humidifiers: $t = 4.84$, $p < .001$; juicers: $t = 5.89$, $p < .001$; electronic food scales: $t = 4.99$, $p < .001$; electronic body scales: $t = 6.98$, $p < .001$), and were statistically equally likely to categorize bicycle computers, handheld electric massagers, and dive computers as either entertainment electronics or health electronics (bicycle computers: $t = 1.17$, $p > .2$; handheld electric massagers: $t = 1.12$, $p > .2$; dive computers: $t = 1.03$, $p > .3$).

The purpose of pretest 2 was to identify groups of five subcategories that together are perceived as either very broad or very narrow. Additionally, we wanted each group of five subcategories to consist of three subcategories that participants strongly and equally associated with both entertainment and health plus either two subcategories that they strongly associated with entertainment rather than health or two subcategories that they strongly associated with health rather than entertainment. In the instructions, we defined a broad group of subcategories as being relatively unrelated or dissimilar to each other (the more unrelated or dissimilar, the broader), and we defined a narrow group of subcategories as being relatively related or similar to each other (the more related or similar, the narrower). We then asked participants to rate the breadth of 40 groups of five subcategories, which we presented in four random orders, on scales ranging from −4 (very broad) to +4 (very narrow).

Pretest 2 revealed that participants considered a group of five entertainment subcategories composed of DVD players, ice cream makers, bicycle computers, handheld electric massagers, and dive computers to be significantly broader than a group of five entertainment subcategories composed of GPSs, two-way radios, bicycle computers, handheld electric massagers, and dive computers ($t = 5.86$, $p < .001$). Pretest 2 also revealed that participants considered a group of five health subcategories composed of humidifiers, juicers, bicycle computers, handheld electric massagers, and dive computers to be significantly broader than a group of five health subcategories composed of electronic food scales, electronic body scales, bicycle computers, handheld electric massagers, and dive computers ($t = 3.13$, $p < .005$).

The purpose of pretest 3 was to identify groups of two subcategories—which were either both strongly associated with entertainment rather than health or both strongly associated with health rather than entertainment—that together are perceived as either very broad or very narrow. Additionally, we wanted each group of two subcategories to correspond with a group of five subcategories (minus the three subcategories that were strongly associated with both entertainment and health) from pretest 2. We presented the same instructions as in pretest 2 and then asked participants to rate the breadth of 40 groups of two subcategories, which we presented in four random orders, on scales ranging from −4 (very broad) to +4 (very narrow).

Pretest 3 revealed that participants considered a group of two entertainment subcategories composed of DVD players and ice cream makers to be significantly broader than a group of two entertainment subcategories composed of GPSs and two-way radios ($t = 7.44$, $p < .001$). Furthermore, pretest 3 revealed that participants considered a group of two health subcategories composed of humidifiers and juicers to be significantly broader than a group of two health subcategories composed of electronic food scales and electronic body scales ($t = 9.75$, $p < .001$).

The results of these three pretests allowed us to manipulate subcategory numerosity and category breadth independently. Table 2 lists the subcategories that were connected to the entertainment and health categories in each of the experiment's eight cells. In the experiment, we also counterbalanced which category (entertainment or health) appeared on the left side of the category structure.

Procedure. A recruiter greeted passersby in the streets outside a behavioral laboratory and asked them whether they would be interested in participating in a study in exchange for a voucher for a sandwich and a drink. Those who agreed read and signed a consent form and then took part in the experiment individually.

Participants engaged in the study using a computer program that we wrote. The program divided the screen into upper and lower halves. The upper half of the screen displayed product descriptions, and the lower half of the screen displayed the participant's assigned category structure.

As in study 1, participants first familiarized themselves with their assigned category structure by categorizing 14 familiar electronics products (see table 3) under the seven bottom-level subcategories in the condition to which they were assigned. We chose these products on the basis of a pretest that showed that participants reliably placed two of the products into each of the 22 bottom-level categories included in the experiment across the category breadth conditions. However, whereas in study 1 we only showed par-

TABLE 2

STUDY 2: SUBCATEGORIES BY CONDITION

Condition	Subcategories connected to the entertainment category	Subcategories connected to the health category
High entertainment subcategory numerosity:		
High entertainment category breadth:		
High health category breadth	DVD players	Humidifiers
	Ice cream makers	Juicers
	Bicycle computers	
	Handheld electric massagers	
	Dive computers	
Low health category breadth	DVD players	Electronic food scales
	Ice cream makers	Electronic body scales
	Bicycle computers	
	Handheld electric massagers	
	Dive computers	
Low entertainment category breadth:		
High health category breadth	Global positioning systems	Humidifiers
	Two-way radios	Juicers
	Bicycle computers	
	Handheld electric massagers	
	Dive computers	
Low health category breadth	Global positioning systems	Electronic food scales
	Two-way radios	Electronic body scales
	Bicycle computers	
	Handheld electric massagers	
	Dive computers	
High health subcategory numerosity:		
High entertainment category breadth:		
High health category breadth	DVD players	Humidifiers
	Ice cream makers	Juicers
		Bicycle computers
		Handheld electric massagers
		Dive computers
Low health category breadth	DVD players	Electronic food scales
	Ice cream makers	Electronic body scales
		Bicycle computers
		Handheld electric massagers
		Dive computers
Low entertainment category breadth:		
High health category breadth	Global positioning systems	Humidifiers
	Two-way radios	Juicers
		Bicycle computers
		Handheld electric massagers
		Dive computers
Low health category breadth	Global positioning systems	Electronic food scales
	Two-way radios	Electronic body scales
		Bicycle computers
		Handheld electric massagers
		Dive computers

ticipants the name of each product, in this study we showed them each product's name and a brief description of its key functions and features. In the experiment, we only included those 14 products that corresponded with the seven bottom-level subcategories in the participant's assigned condition. Participants categorized each product by clicking the subcategory into which they wanted to place it and then confirming their selection in a pop-up box. At the conclusion of this task, participants were given the opportunity to rearrange the products in any manner that they wanted by freely dragging and dropping the products between categories.

Next, the experimenter presented participants with a description of the same fictitious new hybrid product that we used in study 1—the Exercise Buddy (see fig. 2). Participants could categorize the Exercise Buddy either by clicking the name of one of the seven bottom-level subcategories in their assigned category structure to place it there or by creating a new bottom-level subcategory, connected either to the entertainment category or to the health category. To create a new subcategory, participants could click one of two blank spaces—one with a subordinate relationship to the entertainment category and one with a subordinate relationship to the health category—and could then confirm their selection and provide a name for the subcategory in a

TABLE 3

STUDY 2: CATEGORY FAMILIARIZATION PRODUCTS

Category	Product
Bicycle computers	Filzer bicycle computer VDO wireless bicycle computer
Dive computers	Suunto Vyper dive computer Aladin Cobra dive computer
DVD players	Peekton DVD player DivX Multizones H&B DVD player
Electronic body scales	Tefal Electronic body scale EKS white metal electronic body scale
Electronic food scales	Terraillon Inox electronic food scale WIK electronic food scale
Global positioning systems	TomTom GPS Europe ViaMichelin GPS France
Handheld electric massagers	Bestron infrared electric massager OXO Design Kwaq electric massager
Humidifiers	White and Brown humidifier Tigex humidifier
Ice cream makers	Bestron ice cream maker Elta ice cream maker
Juicers	Riviera & Bar juicer Bestron juicer
Two-way radios	Motorola two-way radio family pack Kenwood 6 km portable two-way radios

pop-up box. As in study 1, the dependent measure of primary interest was whether participants positioned a new bottom-level subcategory beneath the entertainment category or beneath the health category. Finally, participants completed a computer-based questionnaire that contained questions about individual factors (e.g., gender, age, academic major) and an open-ended suspicion probe. Once participants had completed these tasks, the experimenter debriefed them and gave them each a voucher for a sandwich and a drink.

Results and Discussion

All 371 participants categorized the 14 familiar products that were presented by placing them into the bottom-level subcategories that we expected based on pretest results (see table 3). Thus, as in study 1, each participant accessed each of the seven bottom-level subcategories in his or her assigned category structure twice before categorizing the Exercise Buddy.

Forty of the study's 371 participants placed the Exercise Buddy into one of the existing subcategories. The other 331 participants created a new subcategory for the Exercise Buddy. In order to determine whether any of our manipulations influenced the propensity of participants to create a new subcategory, we regressed a dummy variable—which took the value of zero if a participant placed the Exercise Buddy into one of the old subcategories and one if the participant created a new subcategory for the Exercise Buddy—on dummy variables for subcategory numerosity (entertainment = 0; health = 1), entertainment category breadth (low = 0; high = 1), health category breadth (low = 0; high = 1), category on left side of screen (entertainment = 0; health = 1), and a constant using binary logistic regression. The analysis revealed that the effects of all four of our manipulations were not significant (see table 4). Thus, in the remainder of the analyses, we focus only on the responses of those participants who created a new subcategory for the Exercise Buddy.

Our hypothesis states that the probability that an individual will position a new category subordinate to a particular category i is proportional to the relative number of categories that are already subordinate to i. Furthermore, we propose that categories with more subordinates are relatively more accessible than those with fewer subordinates and that it is this difference in accessibility, rather than a difference in perceived category breadth, that underlies the influence of subcategory numerosity on the positioning of a new subcategory that we observed in study 1. In the present study, we again varied the relative number of subcategories that were connected to the two categories of interest (entertainment and health) and also independently varied the breadth of the entertainment category and the breadth of the health category. We predicted that the subcategory numerosity manipulation would influence participants' positioning of a new subcategory for the Exercise Buddy above and beyond any effects of the breadth manipulations.

As a preliminary test of this prediction, we first examined the subcategories that were created by participants in the entertainment subcategory numerosity condition, pooled across the breath conditions. Consistent with our prediction, more of these participants positioned the new subcategory under the entertainment category ($N = 87$) than under the health category ($N = 79$), although this effect was not statistically significant ($\chi^2(1) = .19$, NS).

We next examined the subcategories that were created by participants in the health subcategory numerosity condition, pooled across the breadth conditions. Consistent with our prediction, significantly more of these participants positioned the new subcategory under the health category ($N = 103$)

TABLE 4

STUDY 2: LOGISTIC REGRESSION RESULTS WITH DEPENDENT VARIABLE = CREATED NEW SUBCATEGORY VERSUS NOT

Variable	β	Wald	p	exp(β)
Subcategory numerosity	−.094	.079	.778	.910
Entertainment breadth	.094	.079	.778	1.099
Health breadth	−.005	.000	.988	.995
Category on left	.132	.155	.694	1.141
Constant	−2.180	32.965	.000	.113

NOTE.—$N = 371$; dependent variable = 1 if a participant created a new subcategory for the Exercise Buddy, 0 if he or she placed the Exercise Buddy into an existing subcategory; subcategory numerosity = 1 if the health category had more subcategories, 0 if the entertainment category had more subcategories; entertainment breadth = 1 if breadth of the entertainment category was high, 0 otherwise; health breadth = 1 if breadth of the health category was high, 0 otherwise; category on left = 1 if the health category was on left side of screen, 0 otherwise.

than under the entertainment category ($N = 62$; $\chi^2(1) = 4.93$, $p < .05$).

As a more complete test of our predictions, using only those 331 observations of participants who created a new subcategory, we regressed a dummy variable—which took the value of zero if a participant positioned the new subcategory under the entertainment category and one if the participant positioned the new subcategory under the health category—on dummy variables for subcategory numerosity (entertainment = 0; health = 1), entertainment category breadth (low = 0; high = 1), health category breadth (low = 0; high = 1), category on left side of screen (entertainment = 0; health = 1), and a constant using binary logistic regression. Consistent with our prediction, this analysis revealed that the effect of subcategory numerosity was significant ($\chi^2(1) = 7.2$, $p < .01$; see table 5). The positive sign on the parameter estimate indicates that participants were more likely to position a new subcategory under the category (entertainment or health) to which more subcategories were already connected, in support of our hypothesis. Additionally, the effect of entertainment category breadth was marginally significant ($\chi^2(1) = 3.13$, $p = .07$), and the effect of health category breadth was not significant ($\chi^2(1) = .32$, NS). These results suggest that breadth mattered to some degree. However, the key finding is that the effect of subcategory numerosity was above and beyond any effect of breadth since both numerosity and breadth were included in the regression model.

Together, these results indicate that whereas subcategory numerosity did not influence the propensity of participants to create (vs. not create) a new subcategory for the Exercise Buddy, subcategory numerosity did influence the propensity of participants to position a new subcategory under the entertainment category or under the health category, in a manner congruent with the results of study 1. Furthermore, by manipulating subcategory numerosity and the breadth of the entertainment and health categories independently, we showed in this study that subcategory numerosity has an effect on the positioning of a new subcategory that is above and beyond any effect that is attributable to differences in perceived category breadth. Together, the results of the priming manipulation in study 1 and the results of the present study provide strong support for our proposition that the effect of subcategory numerosity on the positioning of a new subcategory is due to differences in accessibility between categories to which more or fewer subcategories are connected.

TABLE 5

STUDY 2: LOGISTIC REGRESSION RESULTS WITH DEPENDENT VARIABLE = POSITIONED NEW SUBCATEGORY UNDER ENTERTAINMENT VERSUS UNDER HEALTH

Variable	β	Wald	p	exp (β)
Subcategory numerosity	.604	7.211	.007	1.829
Entertainment breadth	−.398	3.131	.077	.672
Health breadth	.128	.323	.570	1.136
Category on left	−.047	.044	.833	.954
Constant	.065	.066	.797	1.067

NOTE.—$N = 331$; dependent variable = 1 if a participant positioned a new subcategory for the Exercise Buddy under the health category, 0 if he or she positioned it under the entertainment category; subcategory numerosity = 1 if the health category had more subcategories, 0 if the entertainment category had more subcategories; entertainment breadth = 1 if breadth of the entertainment category was high, 0 otherwise; health breadth = 1 if breadth of the health category was high, 0 otherwise; category on left = 1 if the health category was on left side of screen, 0 otherwise.

GENERAL DISCUSSION

The tendency to classify or categorize a new object within one's existing knowledge structure is a basic and ubiquitous phenomenon. Previous consumer research has demonstrated that the ways in which consumers categorize products can have striking implications for firms. In particular, Sujan and Bettman (1989) demonstrated that when consumers encounter a new product that shares significant similarities with an existing category yet differs significantly from it in other ways, they deal with the incongruity by subtyping, or creating a new subcategory. However, whereas Sujan and Bettman assumed that the general category into which a new product will be placed is known (the camera category in their studies), other research has demonstrated that objects may be congruent with more than one category, a phenomenon referred to as categorization uncertainty (Gregan-Paxton et al. 2005; Moreau, Markman, and Lehmann 2001). In such situations, it is not enough to predict whether consumers will create a subcategory for a new product. One must also predict under which relevant category they will position this subcategory. This was the focus of our research.

In this article, we developed the CAM to predict where within a category structure consumers will position a subcategory for a new product when categorization uncertainty is high (i.e., when the new subcategory could fit within multiple potential parent categories, due to shared similarities). Building on previous research that shows that priming a category increases its accessibility and subsequent use (Herr 1986, 1989), we assumed that when a category is accessed (e.g., by thinking about a product in the category), some of the resulting activation remains with the category, and the rest spreads through the entire network. Furthermore, we assumed that when the activation level of a category is increased due to the category being accessed, the probability that a new subcategory will be positioned under it is increased. Combining these two assumptions, we proposed that if we were to accurately describe the process by which activation spreads through the category structure, we would be able to predict the probability that a new subcategory would be positioned at any relevant location in the structure. We then described this spreading activation process and showed that these probabilities depend on the existing subordinate relationships in the structure. Specifically, based on our model we hypothesized that the probability that an individual will position a new category subordinate to a particular category i is proportional to the relative number of categories that are already subordinate to i, consistent with previous research that has shown that such preferential attachment is a common property of many naturally occurring networks (Barabasi and Albert 1999).

We tested the CAM's predictive ability in two studies. In study 1, we experimentally tested the CAM in the context of a new hybrid product. Furthermore, we included a priming manipulation to test our proposition that accessibility is an underlying mechanism. Consistent with our hypothesis, we found that the relative number of subcategories connected to two parent categories significantly influenced participants' positioning of a subcategory for a new hybrid product within these categories. Furthermore, consistent with our proposition regarding accessibility, we showed that the priming manipulation attenuated this effect. In study 2, we ruled out an alternative explanation of our study 1 results by employing a similar procedure but manipulating subcategory numerosity and category breadth independently. The results of this study showed that subcategory numerosity affects the positioning of new subcategories above and beyond any effect that can be attributed to breadth.

This article makes a significant contribution to categorization research in both marketing and psychology by providing a framework to describe and predict how individuals position subcategories for discrepant objects when categorization uncertainty is high, thereby bringing together research on subtyping and multiple category inferences. Furthermore, by conceptualizing category structures as spreading activation networks and providing a rigorous mathematical account of the spreading activation process, this article contributes to research on the modeling of categorization phenomena.

In addition to the theoretical contributions that we have discussed, the finding that the probability that individuals will position a new category subordinate to a particular relevant category is proportional to the relative number of categories that are already subordinate to that category has significant managerial applications. For example, the CAM provides a means for firms to assess how consumers are likely to position a subcategory for a new product. A firm could then use this prediction to estimate the level of marketing effort that would be needed to alter or support the manner in which consumers position the subcategory to the firm's advantage.

Furthermore, the CAM suggests one means by which such influence might be exerted. Since, based on our findings, consumers will be more likely to position a new subcategory within a category that already has many subcategories, it follows that advertising that prompts consumers to think about several subcategories within a particular domain should increase the likelihood that they will position the new subcategory within that domain.

Returning again to the example of the Motorola Envoy, Keller et al. (2002) explain that consumers had difficulty categorizing the world's first PDA since it shared features with portable computers and personal organizers yet was distinctly different from products in both of these categories. Keller et al. argue that consumers' indecisiveness regarding the categorization of the Envoy was a key factor leading to its ultimate failure. That is, if Motorola had made a concerted effort to influence consumers to create a new subcategory for the Envoy under either the portable computer or personal organizer category, the product may have been more successful. Motorola could have used the CAM in its marketing effort in two ways. First, if Motorola had a general notion that consumers would be likely to associate the Envoy with multiple existing categories (e.g., portable computers, personal organizers, pagers), it could have used the CAM to quickly assess the relative strength of each connection by asking consumers to list the subcategories that they associated with each of these parent categories. Furthermore, once Motorola had determined which connection was likely to be strongest and by what margin, it could have reinforced this connection, not only through traditional advertising but also through ads and interactive activities that increased the accessibility of the target category (e.g., portable computers) by leading consumers to recall and elaborate on several of its subcategories. Future research should explore such ways in which the CAM might be used not only to predict but also to influence the manner in which consumers categorize new hybrid products.

It should be noted, however, that consumers' individual category structures for products are likely to differ based on a variety of factors such as expertise, the individual's culture, and variations in independence from or interdependence with others. Future research should explore the effects of these and other potential moderators.

Future research should also more fully investigate the role of accessibility in this process. In study 1, we provided evidence from a priming manipulation that suggests that the influence of subcategory numerosity on the positioning of a new subcategory is due to differences in accessibility between categories to which differing numbers of subcategories are connected. Furthermore, in study 2 we ruled out differences in perceived breadth or abstraction as an alternative explanation. However, it is possible that our results in both studies were driven by differences in visual salience rather than by differences in accessibility.

Future research could potentially test whether the effects of subcategory numerosity are driven by accessibility or by visual salience by examining whether the effect is robust over long periods of time. Differences in the relative accessibility of categories should decay over time if neither of the categories is reaccessed. Thus, if accessibility drives the effect of subcategory numerosity, the magnitude of the effect should diminish over time following exposure to the category structure. In contrast, if visual salience drives the effect of subcategory numerosity, we would not expect the effect to diminish over time.

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