Same or Different? How Distance and Variation Affect Similarity Judgments

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ABSTRACT

The effects of distance and variation on product-category similarity judgments are examined in two studies. Distance between product categories is characterized as the mean difference in the average scores of all brands in one category with all brands in another on a comparison attribute. Variation is characterized as a degree of spread of brands along that comparison attribute. Study 1 finds that both distance and variation influence the perceived similarity of two product categories. An interaction between distance and variation is also observed. Study 2 is designed to replicate and extend these results, determining if distance and variation also affect similarity judgments when brands in the two product categories are not described by the same attribute—but instead where a comparison attribute must be abstracted. The results confirm the main effects of distance and variation. However, the interaction effects between distance and variation disappear, suggesting that subjects lose some information about distribution knowledge in the abstraction process. Both studies support consumers' use of distribution knowledge about brands (distance and variation) in product-category similarly judgment tasks. © 2004 Wiley Periodicals, Inc.

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Considerable research has supported the effect of similarity between brands and product categories on consumers' brand judgments (Johnson & Horne, 1992). Similarity among brands within a product category, for example, has been found to affect the perceived positioning of products (Aaker & Shansby, 1982; Arabie, Carroll, DeSarbo & Wind, 1981; Dube & Schmitt, 1999; Viswanathan & Childers, 1999) and the extent to which brands are perceived as close to or far from a prototypical brand (Loken & Ward, 1990). Similarity of brands across categories has been found to affect cross-category competition (Ratneshwar & Shocker, 1991), the extent to which brands are regarded as "comparable" (Bettman & Sujan, 1987; Johnson, 1984, 1988, 1989; Park & Smith, 1989), and the extent to which brand extensions are judged as favorable (e.g., Aaker & Keller, 1990; Boush, 1993; Boush & Loken, 1991; Dacin & Smith, 1993; Keller & Aaker, 1992; Park, Milberg, & Lawson, 1991).

Distance and Variation under Product-Category Similarity Judgment Task

Despite the importance of similarity judgments to marketing and consumer behavior, theoretical models about the factors that drive similarity judgments are scarce. A common assumption of research in this area has been that the closer two brands are in terms of a common attribute or a set of common attributes, the more similar they are perceived to be. As such, the distance between two brands drives similarity judgments. Although distance might be conceptualized as interpoint distance between two brands on a similar attribute, similarity judgments could also be affected by *context* (Tversky, 1977). A different conceptualization of distance could be conceived when consumers compare two different product categories. In this situation, context could be conceptualized as the value of brands in each product category on a common attribute. Here, distance is conceptualized as the *average* distance between all brands in product category A and all brands in product category B. The existence of other brands and variation among these brands on a given attribute suggests a second factor affecting context and hence the perceived similarity between two product categories: *variation*. Variation reflects the distributional overlap of the product categories on one or more comparison attributes. One objective of this article is to examine (1) whether consumers encode distance and variation information of brands in two product categories, and (2) whether and to what extent perceived distance and variation affect judgments of the similarity between two product categories.

Abstraction Process under Product Category Judgment Tasks

Distance and variation judgments may be most readily encoded when brands are described along a common and directly comparable attribute. For example, brands of running shoes and dress shoes, though in different product categories, may be described in terms of a common attribute such as arch support, with each brand having a given value on arch support. However, the product categories included in a consideration set do not always have directly comparable attributes. In such cases, products can only be compared through an abstraction process in which higher-order attributes or common benefits are identified (Graeff, 1997; Johnson, 1984; Park & Smith, 1989). For example, running shoes and running shorts are not directly comparable in terms of physical features; however, a consumer may compare them in terms of a more abstract attribute or benefit such as comfort. Comfort is a likely basis for comparison as it serves as a criterion for choosing athletic-wear products (Bagozzi & Dholakia, 1999). A second objective of this article is to ask whether distance and variation also affect perceived similarity between two product categories when the attributes are not directly comparable and an abstraction process must be engaged.

Hypotheses regarding the effects of distance and variation on similarity judgments were formulated based on models of similarity judgments developed in psychology and mathematics. Two experiments were then designed to test the hypotheses. Study 1 examined the impact of distance and variation when attributes in the two product categories were directly comparable. Study 2 extended these results to product categories where the attributes were not directly comparable but could only be compared through an abstraction process.

HYPOTHESES

Based on various similarity models (described below), the similarity between two product categories is described as $s(A,B) = \alpha D + \beta_1 V_A + \beta_2 V_B$, where $s(A, B)$ is the perceived similarity between product category A and B, D is the distance between product category means on a comparison attribute, and V_A and V_B reflect variation among brands within product category A and B on a comparison attribute. To clarify, consider two product categories: TVs and stereos, with each product category comprised of nine brands: A1, A2, A3, A4, . . . , A9 and B1, B2, B3, B4, . . . , B9, respectively. Each product category has brands described by a set of attributes. Moreover, each brand has a value on each attribute. For simplicity's sake, consider a case where brands are directly comparable in terms of only one common attribute (e.g., sound quality). Based on prior models of similarity, the impact of distance and variation on similarity judgments is considered.

The Effect of Distance on Similarity Judgments

Theoretical analysis of similarity relations has been dominated by geometric models, which are contained within a larger class of multidimensional scaling (MDS). Geometric models have represented objects as points in some coordinate space such that the observed dissimilarities between objects correspond to the metric *distances* between the respective points. That is, the smaller the distance between the corresponding points in the metric space, the more similar the objects are perceived to be.

Many algorithms for similarity have been developed, including nonmetric models based on ordinal properties (Shepard, 1962a, 1962b) and a method that has used individual differences to generate multidimensional space (Carroll & Wish, 1974). Horan (1969) and Carroll and Chang (1970) introduced the weighted Euclidean model as a generalization of the above equation. The weighted Euclidean model has been further generalized to allow for perceptual dependencies (Tucker, 1977).

The question raised in this study has less to do with the similarity between *brands* on a given attribute, than with the similarity between *product categories based on that attribute.* The basic idea investigated here is that in order to compare two product categories, consumers must derive some overall representation of the average distance of brands in product category A to brands in product category B. As such, consumers must be able to intuitively compute an average mean value of product category A on the comparison attribute and compare its distance to the average value of product category B on the same attribute. It is expected that the shorter the distance between product category A and product category B on the comparison attribute, the more similar the product categories appear to be. Although the idea that distance affects similarity judgments is not new, what is new is the idea that consumers may intuit average distances between product categories on the comparison attribute and that these intuited distances may affect the perceived similarity of two product categories. The presence of such intuitive computations should result in consumers' being sensitive to the average distance between the product categories on the comparison brand. Thus, it is proposed that

H1: The shorter the distance between the means of two product categories on a given attribute, the greater the perceived similarity between the two product categories.

The Effect of Variation on Similarity Judgments

Although simple distance models have gained acceptance in the assessment of similarity judgments, Tversky (1977) showed that these models violate metric axioms. Krumhansl (1978) suggested that a geometric approach can account for violations of metric axioms if the traditional MDS scaling model is augmented by the assumption that *spatial density* in the configuration (in addition to distance) has an effect on similarity judgments. Spatial density is a measure of how much a stimulus differs from other members of the stimulus set. As the distance between a stimulus and its neighbors decreases the spatial density increases. As a result, the perception of similarity between stimuli decreases. This model was based on Parducci and colleagues' range-frequency theory (Birnbaum, 1974; Parducci, 1965; Parducci & Perrett, 1971). Empirical tests of that theory have shown that spatial density accounts for a number of effects that pose difficulties for the traditional geometric approach. For example, Appelman and Mayzner (1982) have shown that letters that are in less spatially dense regions are more easily recognized than letters that are in more spatially dense regions and that asymmetric confusion errors result when one member of letter pair is in a denser region than the other letter.

Spatial density can be reflected by the *variation* among brands in a product category on a comparison attribute. The general recognition theory of Ashby and colleagues (Ashby & Gott, 1988; Ashby & Townsend, 1986) has suggested that variation affects the possible confusion between two stimuli and thus the probability of correct recognition. Specifically, the perceptual effects of a stimulus could be described by region, not by a point. This idea is illustrated in Figure 1(a), which shows the distribution of the perceptual effects when two stimuli are presented, and in Figure 1(b), which is a view of plane in Figure 1(a) from above. According to general recognition theory, the perceived similarity of stimulus A to B is defined as the proportion of the A perceptual distribution falling in the response region assigned to B in an unbiased two-choice task. Ashby and colleagues have shown that general recognition theory is not constrained by distance axioms. By varying distributional overlap while holding the distance between prototypes constant, Ashby and Perrin (1988) have shown that similarity judgments increase with overlap.

The category density model described by Fried and Holyoak (1984) has also focused on the impact of distribution of category exemplars over a feature space. The density model has treated the learning process as the acquisition of knowledge about the distribution of category exemplars over a feature space. Unique to the density model is that the category exemplars one encounters are used as samples to form a density function over the feature space. Once the density function has been formed, one can use a decision rule based on relative likelihood to classify novel instances on the basis of distributional knowledge. The relative likelihood rule in this model is analogous to the distributional overlap idea from general recognition theory. Flannagan, Fried, and Holyoak (1986) found that the form of the category distribution affects cognitive learning, especially the speed of learning.

In summary, these new geometric models have suggested that category distributions influence category classification, category learning, and similarity judgment. In those models, category distribution has been characterized not only by distance but also by variation on certain dimensions.

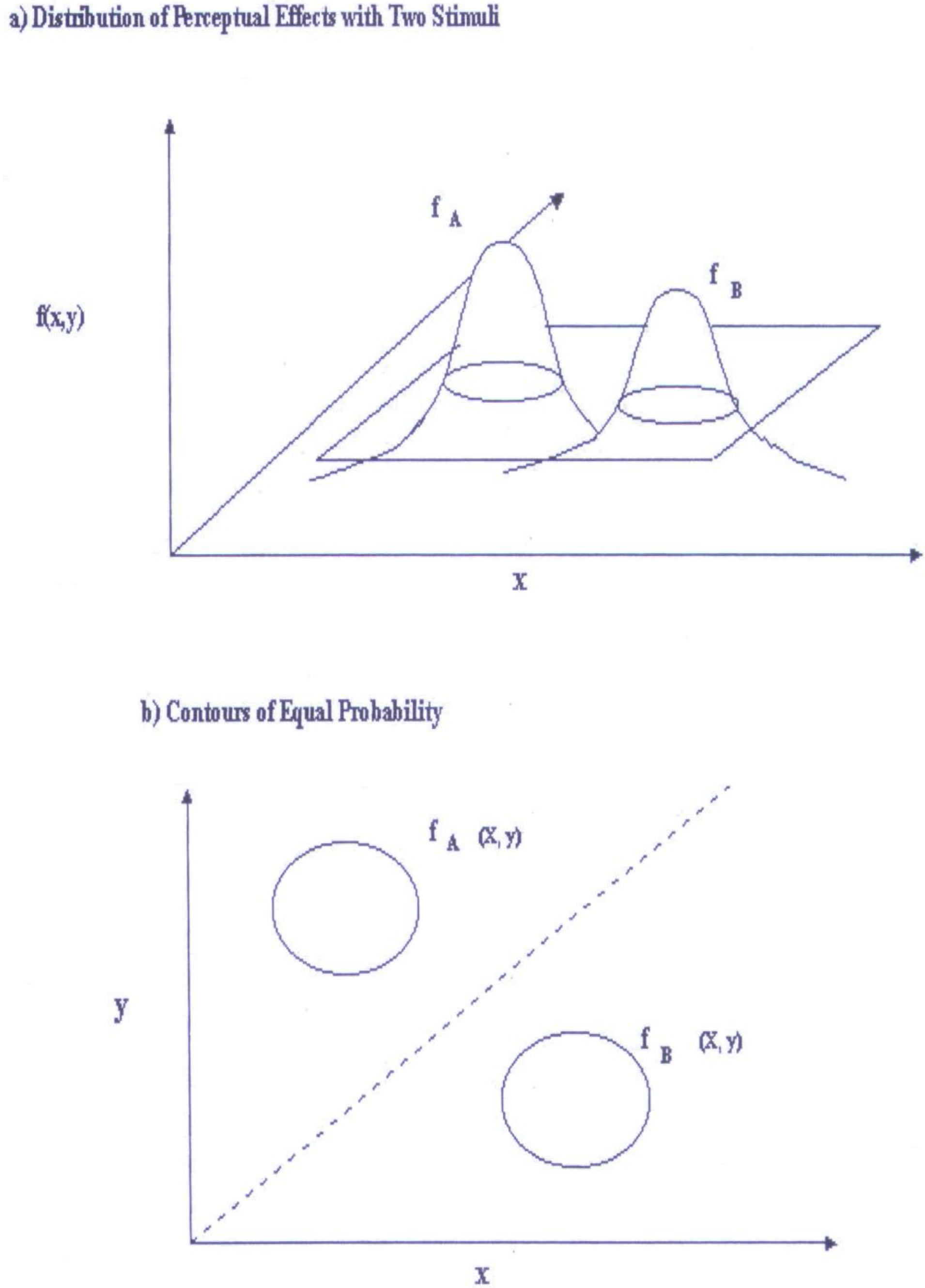

Figure 1. Distribution of perceptual effects.

Distributional overlap is viewed as a predictor of product category similarity judgments in this study. In a marketing context, brands are the members (or components) of a product category. As such, the product category can be summarized and characterized by how each brand is distributed in a dimensional space. If distributional overlap does affect the perceived similarity of two product categories, one would expect that:

H2: The greater the variation among brands in the two product categories, the more similar the two product categories are perceived to be.

The Interaction between Distance and Variation on Similarity Judgments

The effects of variation on similarity judgments might also depend on the distance between product-category means, yielding an interaction between distance and variation. Figure 2 illustrates these ideas. The figure plots distributional overlap for six conditions marked by small versus large variation in the distribution of brands within two product categories and short versus moderate versus long distance between the means of two product categories.

In the short-distance condition (the extreme case being zero distance), considerable overlap exists in terms of the two product categories on the

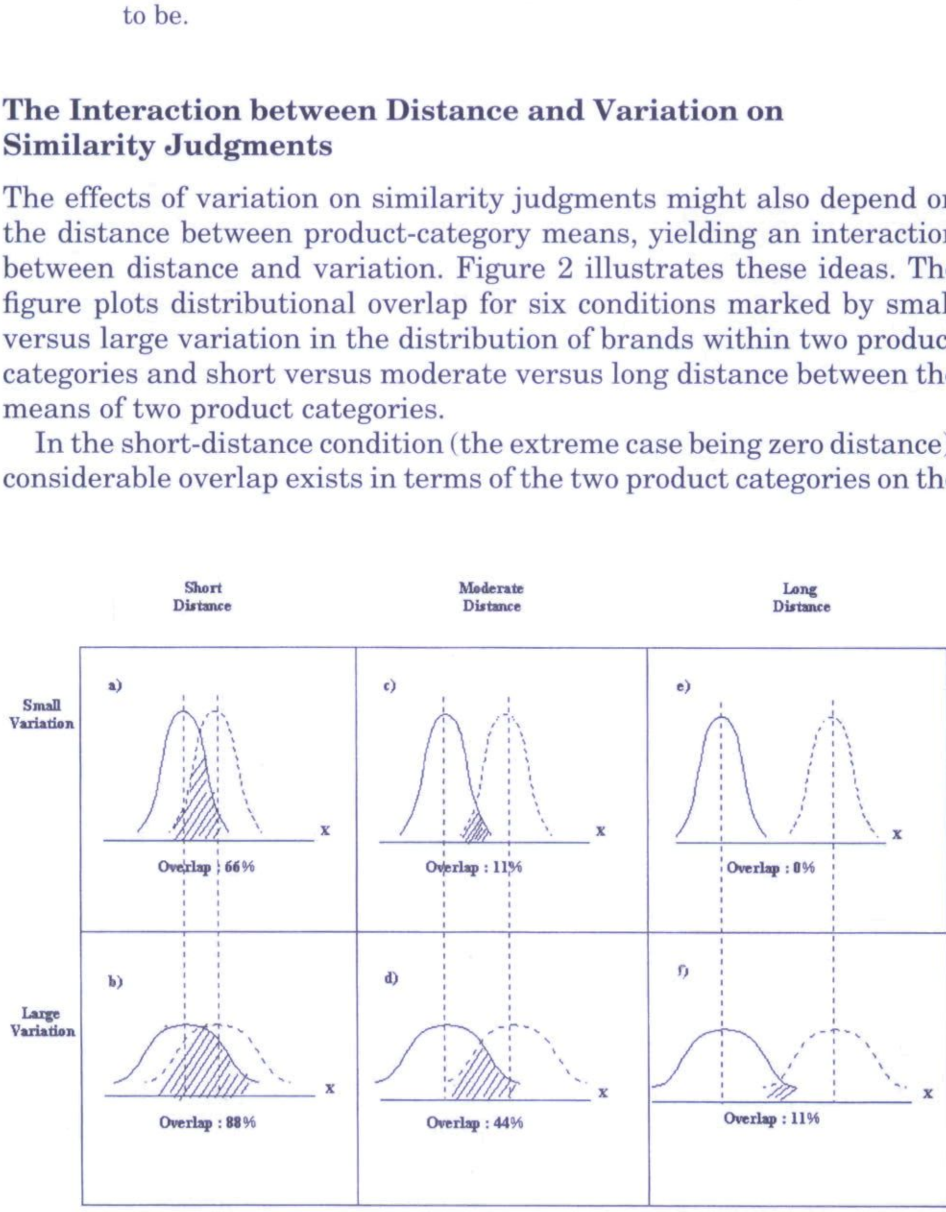

Figure 2. Change of overlap proportion by distance and variation.

comparison attribute. Although variation can increase the overlap between the two categories, the impact of the overlap is only modest, going from 66% to 88% in Figures 2(a) and 2(b). Similarly, in the long-distance condition, Figures 2(e) and 2(f) show that changing variation from small to large increases overlap between the categories from 0% to 11%. Figures 2(c) and 2(d), however, show proportionally greater change in overlap between the small and large variation conditions, with overlap changing from 11% to 44%. Consequently, it was anticipated that the impact of variation on perceived similarity would be greatest when distance was moderate versus short or long. Thus it was expected that:

H3: The effects of variation on similarity judgments will be greatest when distance is moderate vs. short or long.

It was assumed in this study that brands in each product category are symmetrically distributed over the comparable attributes. This is not a strict assumption, since basic-level natural categories seem to consist of a dense central region of typical instances, surrounded by sparser regions of atypical instances (Rosch, 1978; Rosch & Mervis, 1975). Each product category forms a distribution, and each distribution is characterized by means and variations on a comparison attribute such as enjoyment level.

STUDY 1: EFFECTS OF DISTANCE AND VARIATION

Study 1 examined the impact of distance and variation when consumers formed distributional knowledge along common attributes in the two product categories.

Design and Subjects

The above hypotheses were examined in a 3 × 2 × 2 mixed design with distance between categories (short, moderate, and long), variation among brands in each category (small vs. large) and product-category pair (first vs. second pair) as the independent variables. Ninety-five undergraduate students enrolled in introductory marketing classes participated in this study for partial fulfillment of course requirements.

Stimuli

Two product-category pairs described along a comparable attribute were selected as stimuli in the study. To be eligible for selection, product categories had to be unfamiliar to subjects. For this purpose, products from Korea were selected. The first product-category pair was "Lameon" and "Beongae-Guk," Korean flavored noodles and soup mix, respectively. Because both product categories represent instant foods readily made through the addition of hot water, *convenience* was chosen as the comparison attribute. The second product category pair was "Yon-Tan" and "Gas-Bul", Korean coal-burning stoves and miniature gas ranges, respectively. Because both products are somewhat dangerous to use, *safety* was chosen as the comparison attribute for this product category pair.

Korean product categories were used to ensure that distance and variation could be manipulated independently from prior product category knowledge. Use of unfamiliar categories implies that the effects of distance and variation on similarity judgments is driven by the manipulated variables as opposed to other, confounded variables that are part of prior product-category knowledge. Nine hypothetical brands were presented to subjects in each product category. The number of brands was chosen arbitrarily. Alphanumeric brand names (e.g., A1, A2) were used to make the learning task easier.

Experimental Manipulations

Distance, which reflects the difference between the means of the two product categories on the comparison attribute, was manipulated as a between-subjects factor, with subjects randomly assigned to one of the three distance conditions (i.e., short, moderate, long). Distance was manipulated by changing the mean ratings of the two product categories. Variation, which reflects the degree of spread of brands along a comparison attribute, was manipulated by changing the differences between brands on each product category. For example, each brand in product category A has one of five values (i.e., 38, 42, 46, 50, 54) in the short-distance/*large-variation* condition and one of five values (42, 44, 46, 48, 50) in the short-distance/*small-variation* condition. Note that the average scores of product category A (i.e., 46) are the same in both variation conditions, but variation among brands in product category A is the only factor varied. As such, variation is manipulated, and distance is controlled. Similarly, distance was manipulated, and variation was controlled. Information on attribute values in each condition is provided in Table 1.

Fictitious rather than known attribute values (i.e., only hot water is needed to make food or 5 minutes to make food) were presented so that distance and variation could be manipulated more precisely.

A graphical presentation of this manipulation is shown in Figure 2. For example, the overlap percentage in the small-distance/small-variation condition is 66% (six of the nine brands in product category A fall within the range of attribute values in product category B). Similarly,

Table 1. Attribute Values in the Six Distance and Variation Conditions.

	Small Variation				Large Variation			
	Brand	Value	Brand	Value	Brand	Value	Brand	Value
Short distance	A_1	44	B_1	48	A_1	40	B_1	44
	A_2, A_3	46	B_2, B_3	50	A_2, A_3	44	B_2, B_3	48
	A_4, A_5, A_6	48	B_4, B_5, B_6	52	A_4, A_5, A_6	48	B_4, B_5, B_6	52
	A_7, A_8	50	B_7, B_8	54	A_7, A_8	52	B_7, B_8	56
	A_9	52	B_9	56	A_9	56	B_9	60
Mean		48		52		48		52
Range		8		8		16		16
Medium distance	A_1	42	B_1	50	A_1	38	B_1	46
	A_2, A_3	44	B_2, B_3	52	A_2, A_3	42	B_2, B_3	50
	A_4, A_5, A_6	46	B_4, B_5, B_6	54	A_4, A_5, A_6	46	B_4, B_5, B_6	54
	A_7, A_8	48	B_7, B_8	56	A_7, A_8	50	B_7, B_8	58
	A_9	50	B_9	58	A_9	54	B_9	62
Mean		46		54		46		54
Range		8		8		16		16
Long distance	A_1	40	B_1	52	A_1	36	B_1	52
	A_2, A_3	42	B_2, B_3	54	A_2, A_3	40	B_2, B_3	50
	A_4, A_5, A_6	44	B_4, B_5, B_6	56	A_4, A_5, A_6	44	B_4, B_5, B_6	56
	A_7, A_8	46	B_7, B_8	58	A_7, A_8	48	B_7, B_8	60
	A_9	48	B_9	60	A_9	52	B_9	64
Mean		44		56		44		56
Range		8		8		16		16

the overlap percentage in a short-distance/large-variation condition is 88% (eight out of nine brands in product category A fall within the range of attribute values in product category B).

Variation was manipulated as a within-subjects factor. Subjects were exposed to one of the product category pairs with small (or large) variation in Part 1; subsequently in Part 2, they were exposed to the other product-category pair with a large (or small) variation on the relevant attribute. Order of variation was counterbalanced to reduce order effects. The order of product category pair might cause carryover problems, because subjects were completely aware of the procedures. However, the presence of carryover effects could be detected by interactions between order and variation. If significant interaction effects were found, then only data from Part 1 would be retained. The experimental design is summarized in Table 2.

Experimental Procedures

The experiment consisted of two parts—exposure to the high- (or low-) variation condition for product-category pair 1 and then exposure to the

Table 2. Summary of Design.

	Part I	Part II
Small distance	A&B Small variation A&B Large variation	C&D Large variation C&D Small variation
Moderate distance	A&B Small variation A&B Large variation	C&D Large variation C&D Small variation
Long distance	A&B Small variation A&B Large variation	C&D Large variation C&D Small variation

low- (or high-) variation condition for product-category pair 2. Each part had the same structure and proceeded in three phases: an instruction phase, a learning phase, and a test phase. During the instruction phase, the task was introduced to subjects. During the learning phase subjects were told they would see information about several brands in certain product categories and that they were expected to learn this information. In the test phase, they were told they would be asked to identify the attribute values of some of the brands that they had learned earlier. The learning and test phases are described in greater detail below.

In the *learning phase,* subjects were exposed to the attribute values for each brand in the two product categories. Because it was expected that these product categories would be unfamiliar, characteristics of both product categories were described, as were characterizations of why both product categories were popular in Korea (i.e., cooking speed or convenience). Subsequently, information about the comparison attribute for the two product categories was provided. An information sheet stated that consumer research and testing revealed that convenience (or safety) was the most important factor used by consumers to compare the product category pairs. Each product category included nine brands (with hypothetical brand names e.g., A1–A9). Each attribute value of every brand was represented numerically, with theoretical values ranging from a low of 0 (extremely bad) to a high of 100 (extremely good). To facilitate learning brand values along the comparison attribute, values were presented in ascending order.

Subjects were given 5 minutes to learn as much of the brand information they were given as possible. To further foster attribute value learning, subjects were subsequently asked to list values of some brands on the comparison attribute provided earlier. Pairs of brands from each product category were also provided and subjects were asked to circle the brand that they thought had the better attribute rating. Subjects were then asked to check the accuracy of their answers so as to ensure the learning of attributes was accurate. Subjects were allowed to refer back to the previous information to compare their answers with the represented values. They were then allowed to review the original information for 2 additional minutes.

In the *test phase,* subjects were asked to make two similarity judgments. Similarity between the two product categories was first measured, followed by measures of similarity judgments between brands in the same product category. Similarity judgments were measured on a 9-point scale (*not all similar–very similar*). Finally, tests were given to check subjects' learning performance.

After completing the test phase for the first product category pair, subjects took a 3-minute break. They then repeated the three phases for the second product category pair.

Because the efficacy of the learning manipulation described above has not been reported in the literature, a pretest was conducted to assess subjects' retention of information during the learning phase. Twenty-two students enrolled in an introductory marketing class participated in this pretest. Subjects learned attribute values in the same manner as that described above. The results of pretests confirmed that subjects did learn attribute values through the above-mentioned learning procedures.

Results

Preliminary Analyses. Learning tests were also administered in Study 1 to assess the accuracy of the learning task. The same questions used in the pretest were used in the learning check. As expected, the overall proportion of correct responses was quite high (92%) and the proportion of correct responses was higher when the differences in values between pairs of brands were larger.

Judgments of similarity between brands in the *same* product category were also analyzed to check how successfully subjects gained distributional knowledge. Each subject was asked to make similarity judgments for five combinations of brands (A1 and A5, A5 and A9, B3 and B7, A1 and A9, and B1 and B9). All comparisons were for brands in the same product category. If distributional knowledge has been gained, the following relationships should hold for ratings on the comparison attribute: $d(\text{A1, A9}) = d(\text{B1, B9}) > d(\text{A1, A5}) = D(\text{A5, A9}) = d(\text{B3, B7})$. The results are summarized in Table 3. As expected, there were no significant differences among s(A1, A5), s(A5, A9), and s(B3, B7); and s(A1, A9) [or s(B1, B9)] was significantly lower than s(A1, A5), s(A5, A9), or s(A3, A7). The effects of variation on similarity judgments between the various combinations of brands were also expected, because distances between brands in ratings differ by variation condition. However, the

Table 3. **Learning Check: Study 1.**

	Between-Subjects Factor		Within-Subjects Factors			
	Distance		Variation		D × V	
	F	*p*	*F*	*p*	*F*	*p*
s(A1, A5)	1.46	.239	4.41	.039	1.60	.207
s(A1, A9)	2.05	.136	2.96	.089	2.14	.148
s(A5, A9)	2.54	.086	10.86	.001	0.87	.421
s(B3, B7)	3.79	.027	8.59	.004	2.60	.081
s(B1, B9)	2.80	.108	3.58	.033	1.12	.331

effects of distance on similarity judgments are not expected. As predicted, most pairs were significantly influenced by variation and were not influenced by distance (see Table 3).

These results confirmed that attribute values were learned correctly and that distances between brands and variation among brands in ratings of the comparison attribute were correctly perceived. No significant carryover effects from the product-category pairs in Sequence 1 to Sequence 2 were observed. Hence data from Part 1 and Part 2 were retained to test the hypotheses.

Tests of Hypotheses. Planned ANOVA tests with repeated measures were conducted to test H1 and H2. A significant main effect for distance ($F = 3.58$, $p < .05$), supported H1. The two product categories were perceived as being the most similar in the short distance ($X = 5.5$) compared to the moderate and long distance conditions (X's $= 4.90$, and 5.086, respectively). The latter two means were not significantly different from one another. These results are generally consistent with traditional MDS models, which assume a monotonic decreasing relationship between measures of similarity and inter-point distance.

As suggested by the geometric models (distance–density model and general recognition theory), variation significantly influenced similarity judgments ($F = 5.47, p < .05$), supporting H2. The greater the variation among brands in the product categories, the more similar the two product categories were perceived to be (X's $=$ 5.26 and 4.88 in the large vs. small variation conditions, respectively).

A significant interaction between distance and variation ($F = 3.63$, $p < .05$) was also observed, supporting H3. As anticipated, the effect of variation was greatest when distance was moderate ($X = 4.07$ vs. 5.64 for small and large variation, respectively) than when distance was short ($X = 4.92$ vs. 4.87 for small and large variation) or large ($X =$ 5.50 vs. 5.52 for small and large variation, respectively).

STUDY 2: EVIDENCE FOR AN ABSTRACTION PROCESS

Study 1 showed that distance and variation on a comparison attribute influence similarity judgments between two product categories and that the effects of distance interacts with the effects of variation. However, because brands in the two different product categories were described on the same attribute in Study 1, respondents did not need to engage in an abstraction process to make similarity judgments. Study 2 tests whether distance and variation also affect the perceived similarity judgments between two categories when the comparison attribute is not provided, but rather, must be derived or inferred.

Design and Subjects

Experiment 2 followed the same design as Experiment 1. Ninety-eight undergraduate students enrolled in an introductory marketing class participated in exchange for partial course requirements.

Experimental Manipulations

The experimental manipulations were identical to those of Study 1, with the exception of the product descriptions (provided below). Similar to Study 1, the first product category pair was Lameon and Beongae-Guk. The Lameon product was described in terms of *ease of preparation* while the Beongae-Guk product was described in terms of *cooking speed*. Both could be compared on a derived comparison attribute—convenience. The second product category pair was again Yon-Tan and Gas-Bul, the former described in terms of *possible side effects* and the latter described in terms of *danger from incorrect usage*. Both could be compared on a derived comparison attribute of *safety*.

Experimental Procedures

As with Study 1, the experiment proceeded in two parts, each part having the same structure. Subjects were exposed to Lameon and Beong-Guk in Part 1 and to Yon-Tan and Gas-Bul in Part 2. Each part consisted of three phases: an instruction phase, a learning phase, and a test phase.

Results

Preliminary Analyses. Results of the learning tests were generally consistent with the results of Study 1, though the overall proportion of correct responses was lower (77% vs. 91%) in Study 1. One possible reason is that the brands in each category were described by different attributes, making the learning task more difficult. The 77% learning result is still substantial, and supportive of attribute learning.

Table 4. Learning Check: Study 2.

	Between-Subjects Factor		Within-Subjects Factors			
	Distance		Variation		D × V	
	F	p	F	p	F	p
s(A1, A5)	2.12	.130	1.16	.285	5.24	.008
s(A1, A9)	0.85	.432	6.37	.014	1.21	.306
s(A5, A9)	1.22	.303	5.05	.028	0.34	.707
s(B3, B7)	1.16	.321	9.96	.006	0.73	.483
s(B1, B9)	0.22	.805	3.00	.088	4.87	.011

As with Study 1, there were no significant differences among s(A1, A5), s(A5, A9) and s(B3, B7) in terms of perceived similarity. Additionally, s(A1, A9) and s(B1, B9) were significantly larger than s(A1, A5), s(A5, A9), and s(B3, B7). Variation exerted significant effects on the above similarity judgments (see Table 4), suggesting that subjects correctly perceived the variation among brands on the relevant attributes.

Test of the Hypotheses. A repeated-measures ANOVA was used to test the three hypotheses. Significant main effects were shown for distance and variation ($F = 6.06$, $p < .05$). As predicted by H1, the shorter the distance between product category means, the more similar the two product categories were perceived to be (average similarity scores in the short-, moderate-, and long-distance conditions were 5.6, 5.3, and 4.1, respectively). Also consistent with H2, the main effect of variation was significant ($F = 5.08$, $p < .05$), with similarity judgments being higher when variation was high (average similarity scores in the small and large variation conditions were 4.6 and 5.3, respectively). Unlike the results of Study 1, the interaction between distance and variation was not significant ($F = 0.22$, $p = .80$).

The fact that distance and variation both influenced similarity judgments between two product categories even when the attributes were not directly comparable supports the abstraction process. Subjects must have abstracted a common comparison attribute in order to compare the two product categories as both distance and variation affected judgments of similarity.

DISCUSSION

Summary

Combined, the two studies showed that the similarity between two product categories is affected by both the average distance between the product categories on a comparison attribute and the variation within the categories along that comparison attribute. Study 2 confirmed that these effects were observed even when a comparison attribute was not explicitly provided but had to be derived through an abstraction process.

In Study 1, a significant interaction between distance and variation was also observed, with variation affecting similarity judgments most when distributional overlap was moderate. This effect was not, however, observed in Study 2. The reason might be tied to the presence of the comparison attribute. The 5-minute time constraint involved in the learning phase might not have provided sufficient time for subjects to accurately translate the values of brands on the distinct attributes into values on the comparison attribute. Thus, subjects might have missed some information, and been unable to accurately detect the differential change in distributional overlap.

Managerial and Theoretical Implications

Given the important role of similarity in consumers' evaluations of brands and categories and assessments of their substitutability, these findings identify category-level factors that drive similarity judgments. The effects for distance confirm to commonly held beliefs that a brand can be more easily extended to closely related product categories than to distant product categories. The effects of variation are novel and suggest it would be better for managers to extend the original brand to the product category in which variation among brands on a comparison attribute is large vs. small.

The results also provided meaningful implications for the abstraction process underlying product category judgment tasks (Johnson, 1984). According to Johnson (1984) comparability can be conceptualized as the degree to which alternatives are described by the same attribute. When faced with a comparison of two product categories described by different concrete attributes, consumers engage in an abstraction process designed to identify less concrete and more abstract attributes along which these otherwise non-comparable products can be compared. Importantly, direct evidence for that kind of abstraction process has not been provided in the literature. The results here suggest that subjects did look for a comparison attribute and used it in making similarity judgments.

Limitations

Conclusions from these studies must be tempered by the following limitations. First, unfamiliar product categories were used to reduce possible confounding effects. Because subjects had no visual images of the products, they had to depend on the information presented during the learning phase for their similarity judgments. Demand characteristics might operate in this case. Moreover, making similarity judgments between extremely unfamiliar products might have been a novel and unusual task for subjects. Although use of unfamiliar product categories as stimuli has certain limitations, it did allow us to control for extraneous factors driven by familiarity.

Second, student subjects may differ from the average consumer in their use of memory and their abilities to imagine distributional overlap, as their status as intelligent consumers used to learning novel information might make them more adept at assessing distance and variation than average consumers. The effects of perceptual distribution of brands on similarity judgments might be magnified by ability.

Fourth, multiple items were not used to measure similarity. As a result, the single-item measure likely contains measurement error and may not be a reliable indicator of similarity.

Future Research

Future research might extend the present research by examining the moderating role of distributional form on similarity judgments. In the current studies, distributions among brands in each product category were symmetric. In real life, however, attributes of a given product category may be nonsymmetric (left skewed or right skewed). The nature of distributional overlap should moderate the impact of variation on similarity judgments, with greater impact when distributions are right skewed and less when they are left skewed.

Second, this study examined the impact of these variables for only one attribute. In real life, products are collections of attributes, with each attribute having its own distance and variation parameters. Distributional overlap may be more difficult for consumers to assess in multiattribute cases. Moreover, the effect of dependency between attributes needs to be studied. The basic idea is that the degree of perceptual dependence will be related to the angle between dimensions. Hence, the dependency of the attributes may influence the overlap in perceptual distributions and thereby, similarity judgments.

Third, it was assumed that V_A is equal to V_B. To test the asymmetric axiom one should relax this assumption and instead fix the distance. Then, the model could be modified as follows: $s(\mathrm{A}, \mathrm{B}) = \beta_1 V_A + \beta_2 V_B + \beta_3 V_{A*} V_B$, where V_A and V_B are variations among category members.

Finally, the model should be tested with highly noncomparable products. The product categories chosen in this study were only moderately noncomparable in Johnson's classification scheme). If the product category pair becomes more noncomparable, the comparison attribute will be more abstract (Johnson, 1984). One might speculate that the degree of abstractness moderates the relationship between distance and variation on similarity judgments, since it will be more difficult for consumers to imagine the perceptual distribution.

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