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The Nature and Methodological Implications of the Cognitive Representation of Products

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Abstract

A general relationship is proposed wherein more abstract attributes are likely to resemble continuous dimensions while more concrete attributes are likely to resemble dichotomous features. While some methodologies assume dimensional representations, others assume feature-based representations. This suggests that dimensional methods may better capture abstract product representations while feature-based methods may better capture concrete representations. The results of two studies that support both the general relationship and its methodological implications are reported.

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The Nature and Methodological Implications of the Cognitive Representation of Products

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A general relationship is proposed wherein more abstract attributes are likely to resemble continuous dimensions while more concrete attributes are likely to resemble dichotomous features. While some methodologies assume dimensional representations, others assume feature-based representations. This suggests that dimensional methods may better capture abstract product representations while feature-based methods may better capture concrete representations. The results of two studies that support both the general relationship and its methodological implications are reported.

Consumer research often focuses on individuals' cognitive representations of products. To gain insight into these representations, a variety of research methods have been used, including similarity scaling (Green and Rao 1972), discriminant analysis (Johnson 1971), and factor analysis (Hauser and Urban 1977). Two important and separate distinctions are often drawn to describe the product attributes within these representations: concreteness–abstractness (Hirschman 1983; Howard 1977; Johnson 1984), and continuous dimensions vs. dichotomous features (Cooper 1973; Green, Wind, and Claycamp 1975; Johnson 1981). Previous research has not, however, considered the possible relationship between these distinctions.

The purpose of this research is to examine the general relationship between these two important distinctions and its implications. Two considerations are central to this relationship. First, dimensions capture or contain many features just as abstract attributes capture or contain much concrete information. Second, given human information processing limitations, a large number of concrete attributes may be represented using simple features while fewer, more abstract attributes may be represented in a more complex, dimensional fashion. As a result, abstract attributes may be more likely to resemble dimensions while more concrete attributes may be more akin to features.

This theoretical relationship has important meth-

odological implications. The feature–dimension distinction is implicit in the use of different methods, particularly similarity scaling procedures (Carroll 1976; Pruzansky, Tversky, and Carroll 1982). If, in fact, concrete attributes resemble features while abstract attributes resemble dimensions, procedures that implicitly assume features may better capture proximity judgments based on more concrete representations. Likewise, procedures that assume dimensions may better capture judgments based on more abstract product representations. As a result, the relative usefulness of methods may vary depending on whether the analysis is aimed at a more concrete brand level or at a more abstract product market boundary level. In order to understand better the very nature of competition and market boundaries, it is essential to know how consumers represent and compare products at these different levels of abstraction (Johnson 1986).

After discussing each distinction in more detail, the relationship between concreteness–abstractness and the feature–dimension distinction is described. Experiments are then presented that test the relationship both in a direct, theoretical fashion and a more applied, methodological fashion.

CONCRETENESS–ABSTRACTNESS

Although various definitions of concreteness–abstractness exist, following Paivio (1971), we view abstractness as the inverse of how directly an attribute denotes particular objects or events, and we equate concreteness–abstractness with the specificity–generality of terms and the subordination–superordination of categories. In the context of product attributes, Johnson (1984) argues in a similar vein that abstract

attributes are more general and imply a summarizing or concentration of information. For example, a television's value on one abstract attribute, such as entertainment, summarizes or captures several concrete attribute values, such as screen size, number of speakers, and color quality. Consistent with this, Rosch et al. (1976) define more abstract categories as being more inclusive or superordinate. Rosch et al. (see also Mervis and Rosch 1981) use levels of abstraction to indicate points at which basic category distinctions are made. The importance of abstraction is reflected by its role in a variety of psychological research domains, including that of verbal learning (Paivio 1971) and categorization (Murphy and Smith 1982; Rosch 1975, 1977; Rosch et al. 1976; Tversky and Hemenway 1984). Rokeach (1973; see also Howard 1977) also uses concreteness–abstractness to distinguish among instrumental and terminal human values. Instrumental values are considered to be more concrete values of "doing," while terminal values are more abstract values of "being."

Traditionally, consideration of the concreteness–abstractness of products and product attributes in marketing has been concentrated in discussions of the domains of marketing and consumer research, market segmentation, and consumer judgment and choice. In discussing the limited domain of consumer research, Holbrook and Hirschman (1982) recently argued that tangible product attributes, such as calories in a soft drink or miles per gallon in an automobile, have been studied to the exclusion of important experiential aspects of consumption, such as cheerfulness and sociability. Although abstractness as defined here and tangibility are conceptually distinct, their argument and examples do suggest that consumer researchers have focused on concrete attributes while often ignoring important abstract attributes. (For a similar discussion see Hirschman 1983.)

A similar view emerges from discussions of market segmentation. In his seminal article, Haley (1968) urged managers to concentrate more on abstract product benefits than on concrete, descriptive product factors when segmenting consumer markets. This view of segmentation is also consistent with existing economic views of consumer and human behavior (Becker 1976; Lancaster 1971). Both Becker and Lancaster theorize that individuals derive utility from the "characteristics" that goods possess rather than from the goods themselves. One does not, for example, obtain utility directly from either an automobile or from gasoline, but rather from the "transportation" that they together provide. As utility is derived directly from these relatively abstract benefits or characteristics, it is logical that segmentation occur at this level for many products.

Beginning with Bettman's (1974), Boote's (1975), and Howard's (1977) work on hierarchical choice, and more recently evidenced in Johnson's (1984) study of noncomparable choice, concreteness–abstractness has pre-

figured in the study of consumer choice. Howard, for example, views consumer choice as a more or less hierarchical process where different levels of choice in a hierarchy are considered to be at different levels of abstraction. Higher level choices occur among more abstract alternatives, such as product categories, while lower level choices occur among more concrete alternatives such as brands within a category. This view is consistent with the definition of abstraction as being equivalent to the subordination–superordination of categories.

Howard goes beyond the simple notion of a choice hierarchy to posit that there exists a corresponding evaluative hierarchy of choice criteria; consumers choose criteria in the evaluative hierarchy at a level of abstraction that corresponds to the level of the choice. Thus, a direct relationship is hypothesized between the abstractness of choice alternatives and the abstractness of choice criteria. Boote (1975) found indirect support for this hypothesis. In Boote's study, subjects rated the relative importance of Rokeach's instrumental and terminal values to both product category and brand-level choices. Consistent with Howard's hypothesis, the more concrete instrumental values were judged as more important to brand-level choices while the more abstract terminal values were judged as more important to product category level choices.

Howard's hypothesis can be generalized beyond choice and choice criteria. In general, the abstractness of descriptive attributes within a product representation should increase directly with the abstractness of the product. This hypothesis is consistent with other theoretical arguments, including those in human memory (Collins and Loftus 1975), and specifically the notion of cognitive economy. Cognitive economy implies that concept or category nodes in memory are at the same level of abstraction or generality as their immediately associated attributes. The economy is realized by representing category-wide knowledge at the category nodes rather than at each of the subordinate nodes.

Recently, Johnson (1984), noting that choice is not always hierarchical, studied choices involving specific alternatives from different product categories, or "noncomparable" alternatives. Johnson hypothesized a continuum of attributes from the concrete to the abstract in which increasingly abstract attributes describe an increasing number of products. Specific alternatives from different categories, initially noncomparable or described on different concrete nonprice attributes, may be made comparable by representing the alternatives at a higher level of abstraction. The more noncomparable the alternatives are on nonprice attributes, the higher the level of abstraction required to make comparisons. While two stereos might be compared on speaker size, and a stereo and a television might be compared on entertainment value, a stereo and a refrigerator may only be comparable on necessity or practicality. John-

son found support for subjects abstracting product representations to a level where comparability exists in order to make within-attribute comparisons. As the comparability of alternatives decreased, there were corresponding increases in the abstractness of choice attributes.

An important implication of abstraction is that as representations become more abstract, and individual attributes contain more and more information, it should follow that the number of attributes in a representation decrease (Johnson 1984). Although some information may be lost in the abstraction process, roughly the same amount of information is contained in a few abstract attributes as in many more concrete attributes. The studies conducted by Boote (1975) involving brand-level (concrete) versus category-level (abstract) choices, and by Johnson (1984) involving choice alternatives varying in comparability, support this decrease in relevant aspects with attribute abstraction.

FEATURES AND DIMENSIONS

We may better understand representations that vary in concreteness–abstractness by simultaneously considering the distinction between features and dimensions. While dimensions are continuous attributes on which objects differ as a matter of degree, features are dichotomous attributes that objects either have or do not have (Garner 1978; Restle 1959; Tversky 1977). Tversky (1977; see also Gati and Tversky 1982, 1984; Tversky and Gati 1982) argues that many stimuli (such as countries) are naturally described using features while others are naturally described by dimensions (such as colors). Generally, he suggests that conceptual stimuli may be more feature-based in their representations while perceptual stimuli may be more dimensionally based (an issue we shall return to shortly).

The use of features or dimensions is also, however, often a matter of choice. For example, one may either represent soft-drinks as having varying degrees of cola flavor, indicating the use of a dimension, or simply represent some soft drinks as colas, indicating the use of a feature. Thus, inherently dimensional attributes may be mapped into simpler, feature-based representations (Gati and Tversky 1982). A recent study by Johnson and Tversky (1984) illustrates how subjects' representations may depend on the judgment tasks they are required to perform. Subjects in the study made similarity judgments, conditional predictions, and dimensional evaluations among a set of risky alternatives. While both the similarity judgments and conditional predictions were better explained by additive tree models, indicating feature-based representations, the dimensional evaluations were better explained by multidimensional scaling and factor analysis, indicating the use of dimensional representations. The authors suggest that subjects

are more likely to use feature-based representations the more holistic the required judgment.

CONCRETENESS–ABSTRACTNESS AND THE FEATURE–DIMENSION DISTINCTION

While more abstract or noncomparable products may be represented using more abstract attributes, there is also reason to believe that a general relationship exists between the concreteness–abstractness of attributes and the use of features or dimensions. Central to this relationship is the property of inclusion that underlies both distinctions. Consider that one dimension may capture or contain information about several features. The opposite is less likely to be true. Therefore, just as one abstract attribute captures or includes several more concrete attributes, so does a single dimension capture several features. This is consistent with Gati and Tversky's (1982) notion that a dimension can be represented as a set of nested features (while they do not argue that a feature may be represented as a set of nested dimensions) and Green et al.'s (1975) suggestion that groups of features are captured by or map into more basic (and presumably abstract) dimensions. The inherent similarity between these two important distinctions suggests that more abstract attributes are more likely represented as dimensions, while more concrete attributes are more likely represented as features.

A separate yet convergent argument can be made by considering that, first, features are relatively simple compared to dimensions (Garner 1978), and second, we face a limited information processing capacity. Because features have but two levels (Garner 1978; Restle 1959), their representation may require less processing capacity than the representation of continuous dimensions. Feature-based representations may, therefore, be more likely as the number of attributes in a representation increases. Because a concrete representation requires more aspects or attributes than an abstract representation to capture approximately the same amount of information (Johnson 1984), consumers may be more likely to use feature-based representations as a means of staying within a limited information processing capacity. In other words, values on concrete dimensions, such as level of gas mileage or price, may be mapped into dichotomous features, such as whether or not a vehicle is "fuel efficient" or "expensive," for the sake of simplicity.

Thus, for reasons inherent to both the distinctions and our processing ability, a direct relationship is hypothesized between the concreteness–abstractness of the attributes in a representation and the use of features or dimensions. This hypothesis is only expected to hold, however, in a general sense. It does not exclude the possibility of concrete dimensions or abstract features.

Certain stimuli may be more naturally described by features or dimensions irrespective of their concreteness–abstractness. Representations may also be modified as required by the task at hand.

The experiments described below test the general relationships among the abstractness of products, their attributes, and the use of features or dimensions. Johnson (1984) previously showed that product attributes become increasingly abstract as products become more noncomparable (dissimilar). The relationship between product abstractness (category level) and attribute abstraction has not, however, been directly tested. While Boote's (1975) study provides indirect support for this hypothesis using Rokeach's instrumental and terminal values, a more direct test of the hypothesis involves using actual consumer product attributes. Therefore, the experiments below involve the use of actual product attributes to test the following hypothesis:

H1: The level of abstraction of product representations (descriptive attributes) should increase as products become more abstract.

Our second hypothesis concerns the abstractness of the attribute representation and the related use of features or dimensions.

H2: The use of continuous dimensions as opposed to dichotomous features should increase as product representations become more abstract.

On the surface, this hypothesis seems contradictory to recent findings in psychology concerning the representation of conceptual versus perceptual stimuli. The results of both Pruzansky, Tversky, and Carroll (1982) and Tversky and Hutchinson (1986) suggest that dimensional space representations are more appropriate for perceptual stimuli (e.g., colors, tones), while feature tree representations are more appropriate for conceptual stimuli (e.g., occupations). If we view conceptual stimuli as more abstract than perceptual stimuli, then these results seem contradictory to those predicted by our second hypothesis.

There are at least two important differences, however, between the representation of concrete versus abstract products and the representation of perceptual versus conceptual stimuli as reported by Pruzansky et al. and Tversky and Hutchinson. First is the inherent qualitative difference between the two distinctions. Our discussion and definition of concreteness–abstractness focus on variations in abstraction within the domain of product concepts, ranging from concrete brands to more abstract product categories. It is problematic, therefore, to equate perceptual stimuli, such as colors or tones, with brand-level concepts. In fact, consistent with the results of Pruzansky et al. and Tversky and Hutchinson, feature tree representations may, on average, provide better representations of product concepts. At the same

time, our hypothesis predicts that spatial representations will become more appropriate, in a relative fashion, as these products become more abstract.[1]

A second problem with equating concrete product concepts and perceptual stimuli centers on the number of aspects within a representation. Recall that one reason why abstract product representations are hypothesized as more dimensional is because fewer aspects are involved. As a result, they may be represented in a more complex, dimensional fashion, given our information-processing limitations. This argument is consistent with one explanation of the findings in Pruzansky et al. and Tversky and Hutchinson. The representation of conceptual stimuli, such as occupations, generally requires the use of more underlying aspects than does the representation of perceptual stimuli, such as a series of tones or colors. In addition, representations based on more aspects may be better captured or approximated by a large number of features, and hence a feature-based tree representation, than by a small number of continuous dimensions, as in a dimensional space (Tversky and Hutchinson 1986). Thus one reason why feature trees may be superior to dimensional spaces for conceptual as opposed to perceptual stimuli might be the same reason why trees may be superior to spaces for concrete as opposed to abstract product representations.[2]

Three levels of product abstraction are used to test the hypotheses. These include superordinate level (abstract), category level (intermediate), and brand level (concrete) stimuli. This is consistent with Kotler's (1984) generic, form, and brand competition distinctions. Stimuli were chosen from three separate superordinate category types—home entertainment, domestic appliance, and mode of transportation. The stimuli included, from the abstract to the concrete, home entertainment device, television, and Sony television for the home entertainment category; domestic appliance, refrigerator, and General Electric refrigerator for the domestic appliance category; and mode of transportation, bicycle, and Schwinn bicycle for the mode of transportation category. (The specific brands used in

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[1] It is possible, albeit speculative, to place both distinctions on one more general concreteness-abstractness continuum. This continuum may range from the extremely concrete (perceptual stimuli) to some intermediate level (concrete concepts) to the extremely abstract (abstract concepts). The result may then be a nonmonotonic relationship between abstractness and the use of dimensional representations. Extremely concrete and extremely abstract stimuli may be more dimensional while stimuli at an intermediate level may be more feature-based.

[2] Tversky and Hutchinson provide two additional explanations of their findings. First, the inherent hierarchical nature of conceptual, as opposed to perceptual, stimuli may be more consistent with hierarchical, feature tree representations. Feature trees may also be better at representing common features while, at the same time, such common features are weighted more heavily in representations of conceptual than perceptual stimuli (Gati and Tversky 1984).

the study were chosen on the basis of frequency of mention after asking a random sample of 50 University of Michigan students for the brands in each category with which they were most familiar.)

These three levels of product abstractness correspond roughly to the superordinate, basic, and subordinate level stimuli used in many studies of categorization in psychology (Murphy and Smith 1982; Rosch et al. 1976; Tversky and Hemenway 1984). An important finding in these studies is the central importance of basic-level categories. In their seminal article, Rosch et al. argue that basic-level categories are at a level of abstraction that carries the most information and that, as a result, most differentiates objects from one another. Category distinctions below this basic level (e.g., subordinate categories) add relatively little information. In support of their argument, these authors report on a series of experiments that find relatively large differences in abstraction (inclusiveness) between superordinate- and basic-level categories and relatively small differences between basic-level and subordinate-level categories. Specifically, they found that many new descriptive attributes are added in going from a superordinate to a basic level, but few are added in going from a basic to a subordinate level. Both Murphy and Smith (1982) and Tversky and Hemenway (1984) obtained similar results.

This suggests that if Hypothesis 1 is supported, larger differences may be observed between superordinates and categories than between categories and brands. Unfortunately, although our superordinate and category levels are equivalent to Rosch et al.'s superordinate and basic levels, respectively, we can not equate our brand-level stimuli with Rosch et al.'s subordinate-level stimuli. Therefore, although larger differences might be expected between our superordinate category and category levels than between our category and brand levels (given the "basic category" nature of our categories), we do not make any explicit prediction regarding the difference in abstractness of product attributes from level to level.

Two studies were conducted to test our hypotheses. In the first, subjects were asked to freely elicit attributes associated with products at each of the three levels of abstraction. A separate group of judges was then asked to classify these attributes according to whether they constitute features or dimensions. Basically, this experiment examines the relationship between abstract products and abstract attributes and whether abstract attributes resemble dimensions rather than features.

As suggested, the results of the first experiment may have important methodological implications for the study of cognitive representations via perceptual mapping. Two of the most frequently used approaches— multidimensional scaling and clustering procedures— implicitly make different assumptions about underlying cognitive representations (Carroll 1976; Pruzansky et

al. 1982). Multidimensional scaling techniques look upon attributes as dimensions; clustering techniques, including hierarchical clustering and additive tree procedures, view them as features. Consequently, our second hypothesis implies that multidimensional scaling should be more suitable for abstract attributes, and cluster analysis, for concrete attributes. This notion will be investigated in a second study where proximity data are fitted using both feature-based (additive tree) and space-based (multidimensional scaling) techniques. First, however, two pilot studies are described.

PILOT STUDIES

Two pilot studies conducted by Johnson and Kisielius (1985) provide initial support for our hypotheses. The first pilot study tested Hypothesis 1, and the second tested Hypothesis 2. The method and results of both studies are summarized briefly here.

Johnson and Kisielius' pilot study 1 tested Hypothesis 1 by determining the level of abstraction of attributes for products at different levels of abstraction. Product abstraction was operationalized by using products (described earlier) at three distinctly different category levels—superordinate (abstract), category (intermediate), and brand (concrete)—taken from three different category types: home entertainment, domestic appliance, and mode of transportation. Subjects were asked to indicate the five attributes that most easily came to mind, from first to fifth, in response to the different products. A list of 25 possible attributes ranging from the concrete to the abstract accompanied each product. These attributes were taken from a larger list of 248 attributes obtained from protocols in a separate study (Johnson 1984) involving stimuli from the same product categories. The original 248 attributes had been rated on a scale of zero (very concrete) to 10 (very abstract) by eight judges, and the attribute ratings were obtained by averaging across the judges (average interjudge correlation = 0.70). Attributes were chosen to equally represent the entire range of concrete to abstract attributes. The five attributes mentioned most frequently by Johnson's subjects were selected in each category in each of five ranges of concreteness–abstractness (0.0 to 2.00, 2.01 to 4.00, etc.). This resulted in three lists of 25 attributes, one for each of the three superordinate product categories. Attributes in each list were presented in random order. Subjects were instructed to indicate the five attributes among the 25 attributes on a particular product's list that most easily came to mind when they thought about the product. A Latin-square design (see Experiment 1 below) was used ($n = 128$), and the results were tested using an analysis of variance model with level of abstraction of the chosen attributes as the dependent variable.

The results of Johnson and Kisielius provide initial support for our Hypothesis 1. Overall, representations became more abstract the more abstract the product. Consistent with the results of Rosch et al. (1976), a comparison of the factor-level means showed superordinate categories having significantly ($p < 0.05$) more abstract

representations than either categories or brands, and showed no significant difference between categories and brands (mean level of abstractness of 5.2, 4.1, and 4.2, respectively, for superordinate categories, categories, and brands).

A second pilot study conducted by Johnson and Kisielius tests our second hypothesis (i.e., that more abstract attributes are more likely to be represented as dimensions while more concrete attributes are more likely to be represented as features). The stimuli in this study included all 248 attributes from the Johnson (1984) study, rated from very concrete (0) to very abstract (10). Subjects were asked to classify the attributes on the basis of how they are "typically" used. Subjects classified an attribute as a feature if it was something a product typically either had or did not have. If the attribute was something on which products typically differed as a matter of degree, it was classified as a dimension. If subjects could not classify an attribute in one of the two categories, they were instructed to classify it as being used equally often as both. This intermediate classification was necessary, given the nature of the task. As subjects were instructed to classify on the basis of typical use (as opposed to use in describing a particular product), a strict feature or dimension classification was considered too restrictive. A total of 36 subjects completed the task.

The level of abstraction of the classified attributes was used to test Hypothesis 2. As predicted, the mean level of abstraction was 3.0, 4.8, and 5.3, respectively, for the Feature, Both, and Dimension classifications. A discriminant analysis reveals that these means are all significantly different ($F = 7.61$; $p < 0.0005$).

Together, these studies provide initial support for the hypotheses. Both studies are, however, very limited. A more ideal and direct test of the hypotheses would involve simultaneously testing the theoretical links between the concreteness–abstractness of products, their attributes, and the use of features or dimensions. We do not, for example, know whether the representations of subjects in pilot study 1 of Johnson and Kisielius did, in fact, involve feature-based or dimensional representations. The pilot studies also unnecessarily constrained the product representations. Subjects in pilot study 1 were not allowed to elicit representations naturally. The set of possible attributes was constrained to those obtained in a very different experimental context. The pilot studies rely heavily on the attributes taken from the choice protocols of Johnson (1984) and their associated concreteness–abstractness ratings. Experiment 1, which we will now discuss, corrects for these problems. The hypotheses are tested simultaneously using the same unconstrained product representations.

EXPERIMENT 1: PRODUCT REPRESENTATIONS

Method

In Experiment 1, subjects were asked to freely recall and list the attributes that most easily came to mind when they thought about the products in question. Again, three levels of product abstraction were used

(superordinate category, category, and brand) within the three different superordinate category types (home entertainment, domestic appliance, transportation device). Using paper and pencil, products were presented to subjects followed by a blank list numbered from one to five. Subjects were instructed to write down the product attribute that most easily came to mind in blank number one, the second attribute that came to mind in blank number two, and so on. Subjects were instructed to recall attributes one product at a time (each blank product attribute list was presented on a separate sheet of paper) and to spend no more than two minutes on any one product (to avoid the construction as opposed to the recall of associated attributes; Ericsson and Simon 1980). Attributes were not forced; if subjects could not think of five attributes they simply moved on to the next product.

Judges rated the different attributes listed by subjects on concreteness–abstractness to test Hypothesis 1. To test Hypothesis 2, separate judges classified the listed attributes according to whether they resembled features or dimensions. An attribute was classified as a feature if it was something the product in question either had or did not have, and as a dimension if it was something the product varied on as a matter of degree. Unlike Johnson and Kisielius's pilot study 2 in which judges classified attributes according to typical or general use, the judges in Experiment 1 classified attributes as stated by the test subjects.

Design and Procedure

Using a Latin-square design, each subject recalled attributes for three different products, each at a different level of abstraction, and each from a different category type. This design avoids any interference in recall that might occur by having the same subjects receive products either at the same level of abstraction or products from the same category type. Each of the three stimulus conditions were also counterbalanced for order (one third of the subjects received the superordinate category first, one third received the category first, and one third received the brand first) resulting in nine experimental conditions overall. Subjects were 46 University of Michigan students who were paid for their participation. Responses from three subjects were dropped after they failed to perform the task as instructed. Using the data from the remaining 43 subjects, one group of judges rated the elicited attributes on concreteness–abstractness, while a second group of judges classified the attributes according to whether they constituted features or dimensions.

Analysis

Following Johnson (1984), concreteness–abstractness ratings were obtained by asking judges to rate the con-

creteness–abstractness of the 191 different attributes the subjects elicited on a scale from 0 (very concrete) to 10 (very abstract). A convenience sample of 29 judges was recruited to rate the attributes. Consistent with our definition of attribute abstractness, the judges were instructed to rate an attribute as very concrete if the attribute described some specific, particular aspect of a product and to rate an attribute as very abstract if the attribute was a more general description or overall evaluation of a product. A paper and pencil format was used. Six attributes were presented first as a warm-up, followed by the test attributes presented in random order. Judges were paid for their participation.

Concreteness–abstractness ratings were operationalized by averaging across the ratings of judges who were generally consistent in their judgments. Of the 29 judges, one was thrown out because he failed to complete the task. Two judges were also dropped because of interjudge rating correlations well below the rest of the judges ($r = 0.26$ and 0.42). The remaining 26 judges had an average interjudge correlation of $r = 0.62$. As a manipulation check, the concreteness–abstractness ratings obtained by Johnson (1984) and used in the pilot studies were compared with those obtained here. The concreteness–abstractness ratings of identical attributes taken from the two studies were, in fact, very highly correlated ($r = 0.94$, $n = 72$). Therefore, although there is some inconsistency from judge to judge, averaging concreteness–abstractness ratings across even a small group of judges (only eight in the Johnson (1984) study and 26 here) produces a very reliable measure.

Hypothesis 1 was tested using an analysis of variance (ANOVA) model with main effects and one interaction term. The model tested for significant differences in the dependent variable—the level of abstraction of attributes recalled—with changes in the independent variables. The independent variables included in the model were the level of product abstraction (three levels), category type (three levels), degree of association (five levels), a subjects factor (43 levels), stimulus order (three levels), and a level of abstraction by degree of association interaction term. The five levels of association reflect the order of elicitation of the attributes (i.e., whether the attribute was placed in blank one, two, three, four, or five). Naturally, the attributes subjects most easily associated with the products may be the most important and, therefore, deserve more attention. If the results are affected by the degree of association of the attributes, the outcome will either be a significant main effect for attribute association or a significant interaction between product abstraction and attribute association.

For the purpose of testing Hypothesis 2, three separate and naive judges were asked to classify the attributes listed as features or dimensions. Those attributes on which all three judges were in complete agreement were used to test the hypothesis. The three judges agreed in classifying 483 of the 591 attributes (81.7 percent). The

TABLE 1

EXPERIMENT 1: ANALYSIS OF VARIANCE RESULTS

	df	MS	F (sign.)
Abstraction	2	2,359.00	4.46 (.0120)
Category type	2	1,647.85	3.12 (.0451)
Subjects	42	1,284.91	2.43 (.0001)
Stimulus order	2	779.49	1.47 (.2298)
Association	4	185.75	0.35 (.8431)
Abstraction			
× Association	8	497.19	0.94 (.4824)

reliabilities among the judges (the probability that an attribute classification by one judge agrees with that of a second judge), were 0.87, 0.88, and 0.87, respectively, for judges 1 and 2, judges 1 and 3, and judges 2 and 3. The corresponding measure of agreement among all three pairs of judges, using Cohen's Kappa (see Bishop, Fienberg, and Holland 1975, p. 395), was 0.71 (significant at $p < 0.0001$). To specifically test the hypothesis, Bartholomew's test for ordered proportions (see Fleiss 1973, pp. 100–102) was used to determine whether the proportion of dimensions to total attributes increased from brands to categories to superordinate categories.

Results

The ANOVA results, presented in Table 1, support Hypothesis 1. Level of abstraction, subjects, and category type all had significant main effects ($p < 0.05$), with level of abstraction and subjects having the most significant overall effects. Consistent with the first pilot study of Johnson and Kisielius (1985), a Student-Newman-Keuls test for means shows superordinate categories as significantly more abstract ($p < 0.05$) than either categories or brands with no difference between the latter pair (mean level of abstractness of 4.9, 4.4, and 4.2, respectively, for superordinate categories, categories, and brands). Adding attributes of decreasing association has little systematic effect on the results, as indicated by the lack of a main effect for attribute association or significant interaction between level of abstraction and association.

The results of Bartholomew's test for order, reported in Table 2, support Hypothesis 2. Overall, the use of dimensions increased significantly from brands to categories to superordinate categories. Consistent with all previous results, the proportion of dimensions to features increases much more from categories to superordinate categories than from brands to categories. There was a significant increase in the use of dimensions for stimuli in two individual categories—domestic appliance and mode of transportation, but not for home entertainment. (In hindsight, the brand-level home entertainment stimulus, Sony television, was more ab-

TABLE 2

EXPERIMENT 1: PROPORTION OF DIMENSIONAL ATTRIBUTES
ACROSS PRODUCT LEVELS AND CATEGORIES

	Level of product abstraction			
Product type	Brand	Category	Super-ordinate category	Chi-square[a]
Home entertainment	.21	.15	.28	2.181
	(38)	(71)	(45)	
Domestic appliance	.15	.23	.87	90.344[b]
	(58)	(47)	(66)	
Mode of	.15	.28	.43	10.526[b]
transportation	(61)	(50)	(44)	
Overall	.17	.22	.47	39.828[b]
	(157)	(168)	(155)	

[a] = Chi-square using Bartholomew's test for ordered proportions.
[b] = Significant at $p < 0.005$.
NOTE: Absolute number of dimensions given in parentheses.

stract than the other brand-level stimuli due to a more frequent association of "quality" with Sony.)

To summarize, Experiment 1 determined both the concreteness–abstractness and the feature–dimension classification of freely elicited product attributes. Subjects associated more abstract attributes to more abstract products, and these abstract attributes were more likely to resemble dimensions. Although superordinate categories were much more likely to be abstract and dimensional than either categories or brands, the differences between categories and brands were much smaller. Considering the basic level of abstraction of our category-level stimuli, this result is very consistent with the finding that large changes in abstraction or inclusiveness do not exist below basic-level categories (Rosch et al. 1976). In other words, the difference in abstractness of the attributes elicited by our subjects, and their associated use of features or dimensions, simply reflects the difference in the abstractness of the stimuli.

EXPERIMENT 2: TREES VERSUS SPACES

Perhaps one of the most important implications of these results is for methodology. The appropriateness of methodologies, particularly similarity scaling procedures, should depend on the consumer's use of feature-based or dimensional representations. As noted earlier (Carroll 1976; Pruzansky et al. 1982), while dimensions are implicit in multidimensional scaling procedures and resulting product spaces (Shocker and Srinivasan 1979), feature-based representations underlie many recent similarity scaling procedures, including hierarchical clustering, additive trees, and additive clustering (Tversky 1977). A very straightforward implication of the relationship between attribute abstrac-

tion and the feature–dimension distinction is that dimensional procedures such as multidimensional scaling (MDS) may be more appropriate for more abstract or noncomparable stimuli (which are represented using more abstract attributes), while feature-based, additive tree procedures such as ADDTREE (Sattath and Tversky 1977), may better fit more concrete, comparable stimuli (which are represented using more concrete attributes).

We do not suggest relying on only one technique. Remember that the observed relationship does not exclude the possibility of important abstract features or concrete dimensions. Consumers are likely to use both features and dimensions when representing and evaluating many products. Therefore, both types of procedures, trees and spaces, should continue to reveal important psychological aspects of any particular stimuli (Carroll 1976; Shepard 1980), including products that are relatively concrete or relatively abstract. In fact, researchers have long found it useful to embed representations obtained via clustering within multidimensional scaling solutions (Shepard and Arabie 1979). The use of one technique or the other may also depend on reasonable presumptions regarding consumers' use of particular judgment or choice strategies. A strategy such as elimination by aspects (Tversky 1972), for example, is very consistent with hierarchical trees (Tversky and Sattath 1979; Urban, Johnson, and Hauser 1984), while product spaces may be more consistent with more compensatory strategies (i.e., by representing a product as a point in a multidimensional space, more than one attribute is simultaneously considered). Finally, the representations may have very different strategic uses. Spaces may better reveal a product's position in a market, while trees may better reveal a market's competitive structure (see, for example, O'Shaughnessy 1984, Chapter 5).

Nevertheless, attribute abstraction and the resulting use of features or dimensions has two important implications regarding the ability of similarity scaling procedures to "fit" proximity data. First, as fewer product attributes or aspects are probably used by consumers when judging more abstract or noncomparable alternatives (Boote 1975; Johnson 1984), the fit of both feature-based and dimensional procedures should improve. Second, as more abstract attributes also tend to be more dimensional, the improvement in fit with attribute abstraction should be greater for dimensional techniques (MDS) than for feature-based techniques (ADDTREE). An important consideration here is that a switching over from features to dimensions in and of itself should not "hurt" the feature-based techniques as much as it "helps" those that assume dimensions. Dimensions may be approximated using a relatively small number of binary features (Tversky and Hutchinson 1986). Having to use whole dimensions in a spatial configuration to capture particular features, however, should signifi-

cantly hurt the ability of multidimensional scaling to capture feature-based judgments.

Method

To test these implications, proximity judgments among various sets of stimuli whose descriptive attributes were likely to vary with respect to level of abstraction were collected. Following the procedure of Sattath and Tversky (1977) and Pruzansky et al. (1982), each data set was analyzed using two scaling techniques: a multidimensional scaling technique (SSA; Smallest Space Analysis) assuming both two and three dimensions, and a feature-based additive tree procedure (ADDTREE). (Other forms of tree fitting mentioned earlier, including hierarchical clustering and additive clustering, could also be used. Sattath and Tversky (1977) describe the differences among these techniques.) For more equal comparison, the data were restricted to direct, overall similarity or dissimilarity judgments (i.e., no preference data, substitutabilities, etc.). A total of 31 data sets were gathered and used in the experiment. Many of these (a total of 24) were collected by student teams as part of a consumer behavior course conducted by one of the authors. (The number of subjects ranged from a minimum of 25 to a maximum of 60, and judgments were averaged across subjects.) The remaining seven data sets were obtained from existing research articles, a research text, and a dissertation (Green and Rao 1972; Horne and Johnson 1986; Levine 1977; Lindquist 1972). As mentioned above, the criteria for selection was that the data involved overall judgments of similarity or dissimilarity. (Notice that these data sets are not systematically nested from superordinate categories to brands as was the case in Experiment 1. The sets do, however, include some nested categories whose operationalizations of abstractness (described later) generally go in the predicted direction.)

Given the data sets, four variables require operationalization: (1) the abstraction of the attributes on which the judgments are based, (2) the fit of the ADDTREE solutions, (3) the fit of the two-dimensional SSA solutions, and (4) the fit of the three-dimensional SSA solutions. Previous studies (Pruzansky et al. 1982; Sattath and Tversky 1977) have only compared the fit of additive tree solutions to two- and three-dimensional space solutions in order to keep the number of free parameters as comparable as possible in the two cases. A free tree procedure with a path length metric such as ADDTREE has approximately the same number of independent parameters as does a two-dimensional spatial configuration (see Carroll 1976 for a discussion). Although the number of free parameters is not equal for any two cases, of importance here is the independent relative improvement in the ability of trees and spaces to capture judgments involving increasingly abstract representations. (We do not directly compare the fit of particular

space-based and tree-based solutions that may differ in their degrees of freedom.) Again, the prediction is that attribute abstraction will positively affect the fit of both the ADDTREE and SSA solutions (due to a reduction in the number of attributes), but will have a greater positive impact on the SSA solutions (because abstract attributes are more dimensional).

Attribute abstraction was operationalized by determining the amount of variance explained in the similarity judgments by latent roots via principal components analysis. (Average similarities were normalized to a 0 to 1 scale for analysis.) Using the explanatory power of latent roots as a measure of abstractness follows directly from Howard's notion of an attribute hierarchy. According to this notion, more abstract representations capture the same information using fewer aspects or attributes than do concrete representations (Howard 1977; Johnson 1984). More abstract representations should, therefore, be characterized by fewer, more explanatory roots. A more concrete representation should, on average, require more latent variables to achieve the same explanatory power. Therefore, the more variance explained by a small number of roots for a given stimulus set, the more abstract the representations used to produce the similarity judgments.

In order to avoid making an arbitrary decision about how many latent roots to use, a multiple indicators approach was chosen. Drawing from a procedure reported in Fornell and Robinson (1983), and discussed in Fornell (1986), a total of five indicators were employed where the first indicator was the variance explained by the first latent root, the second indicator was the variance explained by the first two latent roots, and so on up to five roots (after extracting the fifth root, only a very small amount of variance was typically left). The basic idea is that when a latent variable (such as "abstractness") is to be used empirically, but when it cannot be considered synonymous with a corresponding set of measurement operations, and there are measures that bear some, albeit perhaps weak, relationship to the latent variable, a weighted index can be formed from these measures as long as they contain some relevant variance. Such is the case with concentration indices measuring monopoly power in economics. Most analysts agree that concentration ratios are not good measures, but that they do contain some information about monopoly power (Fornell 1986). The task, then, is to isolate this information in the estimation procedure. In this study, we consider each latent root indicator to contain some information about "abstractness," and we form an index by a linear combination of the indicators, weighted in such a way that the error variances of our analysis model (to be discussed next) will be minimized.

The fit variables for the ADDTREE and SSA solutions were operationalized using two common measures, Kruskal's stress (indicating "badness of fit"), and the linear R^2 (indicating "goodness of fit"). Table 3 lists

TABLE 3

DATA SETS AND ASSOCIATED MEASURES OF FIT AND ATTRIBUTE ABSTRACTION

Data set	Tree stress	2-D space stress	3-D space stress	Tree R^2	2-D space R^2	3-D space R^2	Variance explained by latent roots				
							1	1-2	1-3	1-4	1-5
Airlines	.060	.096	.047	.949	.890	.937	.583	.731	.781	.824	.863
Beverages	.049	.061	.026	.930	.875	.902	.515	.689	.767	.833	.878
Breakfast foods	.091	.079	.050	.787	.925	.956	.507	.707	.814	.862	.903
Cereals	.061	.091	.001	.915	.829	.803	.503	.597	.675	.741	.800
Chevrolets	.060	.065	.025	.930	.871	.925	.402	.562	.655	.737	.799
Cola soft drinks	.052	.070	.047	.930	.880	.941	.433	.559	.623	.677	.729
Dining out #1	.039	.051	.026	.954	.885	.910	.487	.658	.759	.821	.875
Dining out #2	.047	.051	.009	.948	.803	.946	.443	.641	.740	.816	.882
Drinking places	.059	.031	.001	.886	.865	.890	.420	.563	.684	.767	.827
Entertainment #1	.085	.191	.123	.719	.577	.737	.379	.496	.591	.679	.759
Entertainment #2	.076	.184	.102	.735	.616	.724	.478	.611	.703	.786	.852
Exercise alts.	.065	.138	.090	.856	.730	.819	.460	.612	.714	.781	.833
Fast foods places	.065	.087	.049	.908	.812	.894	.520	.590	.657	.722	.780
Female apparel #1	.043	.014	.005	.970	.975	.989	.567	.778	.841	.896	.926
Female apparel #2	.047	.046	.029	.939	.897	.899	.539	.676	.760	.826	.873
Gums	.065	.102	.051	.921	.825	.857	.390	.544	.617	.680	.742
Ice cream places	.075	.053	.014	.914	.902	.958	.419	.594	.681	.744	.799
Luxury autos	.064	.069	.036	.917	.916	.897	.559	.767	.846	.892	.928
Magazines	.061	.128	.066	.823	.647	.786	.382	.518	.617	.701	.769
Male apparel	.038	.067	.031	.947	.919	.929	.593	.709	.781	.826	.868
MBA programs	.087	.121	.061	.805	.820	.907	.543	.631	.699	.750	.794
Meeting places	.068	.079	.017	.909	.899	.941	.531	.687	.800	.860	.902
News sources	.074	.083	.036	.922	.859	.900	.496	.592	.671	.740	.798
Rent-a-cars #1	.054	.078	.044	.933	.871	.910	.536	.649	.713	.769	.815
Rent-a-cars #2	.064	.111	.057	.886	.779	.824	.615	.755	.818	.870	.914
Shampoo	.056	.088	.050	.917	.879	.928	.516	.616	.689	.753	.799
Snacks #1	.071	.150	.073	.557	.670	.760	.488	.648	.768	.881	.943
Snacks #2	.040	.034	.006	.976	.952	.961	.430	.648	.723	.786	.839
Soft drinks	.052	.096	.062	.889	.832	.843	.449	.628	.743	.810	.870
Sports alts.	.080	.085	.043	.900	.921	.958	.675	.743	.780	.813	.843
Toothpastes	.091	.167	.112	.825	.791	.850	.478	.598	.689	.761	.814

all 31 data sets (in alphabetical order) and the measures used to operationalize attribute abstraction and fit. Column 1 lists the data sets; columns 2, 3, and 4 list measures of Kruskal's stress for the ADDTREE, two-dimensional SSA, and three-dimensional SSA, respectively; and columns 5, 6, and 7 list corresponding measures of R^2. Finally, columns 8 through 12 give the five measures of attribute abstraction as measured by the explanatory power of latent roots obtained by principal components analysis. The correlation matrix for the measures in Table 3 is presented in Table 4.

Analysis

To facilitate an understanding of the analysis, the model just outlined is stated here in equation form. As mentioned, if attribute representations are very abstract, a small number of principal components should account for much of the variance in the similarity judgments. We operationalize abstractness as a construct that is formed by five indicators: the variance explained by the first latent root (x_1); the variance explained by roots one and two (x_2); the variance explained by roots one through three (x_3); the variance explained by roots one through four (x_4); and the variance explained by roots one through five (x_5). Thus, we can express our notion of abstractness (ξ) as:

$$\xi = [\pi_{x1}, \pi_{x2}, \pi_{x3}, \pi_{x4}, \pi_{x5}] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$$

where π_{x1} to π_{x5} are parameters to be estimated.

Thus, our latent variable, abstractness, is operationalized as a weighted index of the explanatory power of the five latent root measures from principal components. These indicators are, by definition, correlated. It is the increment in variance explained that constitutes the difference between the measures. With respect to the latent variable, "abstractness," we would expect a closer correspondence between the measured and the latent when few latent roots account for a large portion

TABLE 4

CORRELATION MATRIX FOR MEASURES OF FIT AND ATTRIBUTE ABSTRACTION

	Tree stress	2-D space stress	3-D space stress	Tree R^2	2-D space R^2	3-D space R^2	Variance explained by latent roots				
							1	1–2	1–3	1–4	1–5
Tree stress	1.000										
2-D space stress	0.646	1.000									
3-D space stress	0.581	0.922	1.000								
Tree R^2	−0.616	−0.756	−0.673	1.000							
2-D space R^2	−0.394	−0.853	−0.748	0.742	1.000						
3-D space R^2	−0.322	−0.815	−0.682	0.702	0.911	1.000					
Root 1	−0.021	−0.160	−0.145	0.187	0.414	0.319	1.000				
Roots 1–2	−0.211	−0.372	−0.312	0.254	0.547	0.445	0.842	1.000			
Roots 1–3	−0.199	−0.349	−0.300	0.136	0.476	0.365	0.725	0.960	1.000		
Roots 1–4	−0.194	−0.280	−0.255	−0.006	0.344	0.236	0.621	0.889	0.974	1.000	
Roots 1–5	−0.192	−0.221	−0.215	−0.088	0.234	0.131	0.523	0.815	0.930	0.987	1.000

of the variance. In other words, we eventually expect the loadings[3] to become smaller as more roots are added to explain variance. The endogenous variables are operationalized as:

$$
\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} = \begin{bmatrix} \lambda_{y1} & 0 & 0 \\ \lambda_{y2} & 0 & 0 \\ 0 & \lambda_{y3} & 0 \\ 0 & \lambda_{y4} & 0 \\ 0 & 0 & \lambda_{y5} \\ 0 & 0 & \lambda_{y6} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \end{bmatrix}
$$

where

y_1 = Fit of tree according to Kruskal's stress.

y_2 = Fit of tree according to R^2.

y_3 = Fit of two-dimensional MDS solution according to Kruskal's stress.

y_4 = Fit of two-dimensional MDS solution according to R^2.

y_5 = Fit of three-dimensional MDS solution according to Kruskal's stress.

y_6 = Fit of three-dimensional MDS solution according to R^2.

λ_{y1} to λ_{y6} are parameters to be estimated.

η_1 to η_3 are composites of tree fit, two-dimensional MDS fit, and three-dimensional MDS fit, respectively.

ϵ_1 to ϵ_6 are residuals.

As abstractness increases we expect the improvement in fit to be greater for the space models (multidimensional scaling) than for the tree model. To test this, we estimate the relationships between the unobservable

construct, "abstractness," ξ, and the composite fit indices, η_1, η_2, and η_3. We can write this as:

$$
\begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} \xi + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix}
$$

where γ_1 to γ_3 are parameters to be estimated, and ζ_1 to ζ_3 are residuals.

We standardize such that $E(\mathbf{x}) = E(\mathbf{y}) = E(\eta) = E(\xi) = 0$ and $Var(\eta_i) = Var(\xi_j) = Var(x_k) = Var(y_r) = 1$, all i, j, k, r. With respect to the residual structure, we assume that $E(\eta\zeta') = E(\zeta) = E(\zeta\zeta') = E(\zeta\epsilon') = 0$.

Because of the nature of the sample (31 product groups) and the data, estimation was done via partial least squares (Fornell and Bookstein 1982; Wold 1982). The results, along with a graphical presentation of these equations, are provided in the Figure.
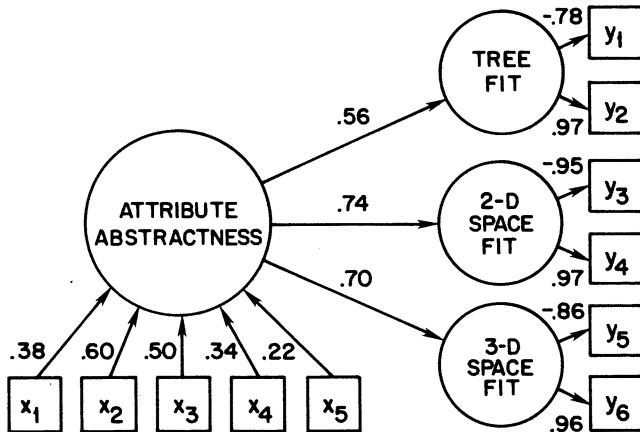
Results

Overall, the results show that fit improves with increasing levels of abstractness, and as hypothesized, that "space fitting" benefits more than "tree fitting." The relationships between abstractness and the two composites of "space fit" are substantively stronger (0.74 and 0.70) than that between abstractness and "tree fit" (0.56). Further, the construct of "abstractness" alone accounts for a substantial amount of the variation in the various fit measures. As shown in Table 5, abstractness explains about 50 percent of the total variance in the space fits. As expected, this is very different from the tree fit, whose variance is not accounted for nearly as well (0.32 for the composite, 0.20 for stress, and 0.30 for R^2). Thus, there appears to be a considerably stronger relationship between abstractness and fitting via multidimensional scaling than between abstractness and fitting via tree clustering.

By questioning the main assumption underlying the model, we offer an alternative explanation of these re-

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[3] The loadings are $\Lambda_x = \mathbf{R}_{xx}\pi$.

FIGURE

GRAPHICAL REPRESENTATION OF PLS MODEL AND RESULTS

TABLE 5

SUMMARY STATISTICS OF PLS MODEL

Model fit	Statistics
R^2	
Tree fit	.32
2-D Space fit	.55
3-D Space fit	.49
Operational variance (redundancy)	
Tree fit	
Stress	.20
R^2	.30
2-D Space fit	
Stress	.50
R^2	.52
3-D Space fit	
Stress	.36
R^2	.45
Fornell-Larcker measurement index	
Abstractness	.18
Tree fit	.78
2-D Space fit	.92
3-D Space fit	.83

sults. Although the model assumes that a small number of large latent roots indicates an abstract representation, it may be the number of aspects alone and not abstractness per se that is driving the results. Inherently, a feature-based tree will capture more aspects than a two- or three-dimensional space. Therefore, if our abstractness construct actually reflects the number of aspects in a representation independent of abstractness, one would expect the same results. However, two important observations support an interpretation based on abstractness rather than number of aspects only. First, abstractness was measured by the explanatory power of a small number of latent roots rather than by the number of significant roots. Although very similar, the former follows more directly from the notion of an attribute hierarchy in which very few abstract attributes are required to describe any particular product. Second, and most importantly, an interpretation that relies only on "number of aspects" is inconsistent with the results of both Experiment 1 and the pilot studies.

With respect to the measurement properties of the model, we note that all endogenous measures have high loadings. For the exogenous construct, the Fornell-Larcker index (Fornell and Larcker 1981) is well below 0.5. Part of this is due to the fact that the incremental information in each indicator following the third root is small. Nevertheless, since abstractness is an exogenous variable that is expressed as a deterministic function of its indicators, the large residual variance does not have drastic implications (Fornell and Bookstein 1982). Recall that the purpose here is to construct a linear combination of x variables in such a way that the error variances of the endogenous variables are minimized.[4]

To summarize, the results of Experiment 2 are consistent with those of Experiment 1 and the pilot studies. Taken together, the experiments strongly support the relationship between attribute concreteness–abstractness and the use of features or dimensions. In addition, the results of Experiment 2 show the significance of the research hypotheses. The ability of similarity scaling procedures to fit similarity judgments depends on the nature of the underlying product representations. The more abstract or noncomparable the alternatives, the better multidimensional scaling analyses capture or fit consumer judgments relative to feature-based additive trees.

DISCUSSION

The experiments reported here support a general relationship between the abstractness of products, the abstractness of their attributes, and whether these attributes resemble features or dimensions. Abstract products tend to have more abstract attribute representations. In addition, more abstract representations generally contain more dimensions, while concrete representations contain more features. The relationship between attribute abstraction and the use of features or dimensions was supported using qualitatively different research methods.

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[4] We acknowledge the possibility that our latent root measures of abstractness might be considered as reflective rather than formative. As a result, the model was tested treating the x variables as both formative and reflective. The resulting relationships were quite robust and only marginally affected by the formative or reflective specification.

The experimental results are very consistent with findings in the psychological literature concerning both the nature of basic-level categories and the representation of perceptual versus conceptual stimuli. Both the pilot studies of Johnson and Kisielius (1985) and Experiment 1 reveal larger differences between superordinate and more basic, category-level stimuli than between category and brand-level stimuli. As noted in Experiment 1, this is consistent with the studies of Rosch et al. (1976) that find relatively small differences in abstraction below basic-level categories. (Recall that very few additional attributes are required to describe categories below this level.) We also suggested that although dimensional spaces become more appropriate the more abstract the product representation, feature-based trees may, on average, provide better representations of product concepts (consistent with the findings of Tversky and Hutchinson 1986 and Pruzansky et al. 1982). The data in Table 3 support this contention. Although ADDTREE uses slightly fewer parameters than does a two-dimensional SSA solution (Sattath and Tversky 1977), the fit of the ADDTREEs in Table 3 was, on average, superior to the fit of the two-dimensional spaces (the average ADDTREE stress and linear R^2 measures equaled 0.063 and 0.884, respectively, while the corresponding averages for the two-dimensional spaces were 0.089 and 0.836).

A potential problem of the research reported here, specifically Experiment 1, is the reliability of subjects' ability to both distinguish between features and dimensions and rate attribute concreteness–abstractness. While the psychological difference between features and dimensions is often assumed, the judges in Experiment 1 were actually asked to classify specific product attributes according to their use as features or dimensions. That the three judges agreed in classifying over 80 percent of the attributes supports the psychological validity of the feature–dimension distinction. In addition, only the attributes on which the judges were in agreement were used to test Hypothesis 2. Subjects also appear to be able to produce reliable estimates of attribute concreteness–abstractness. The concreteness–abstractness ratings obtained by Johnson (1984), and used in the Johnson and Kisielius (1985) pilot studies, were very consistent with those obtained and used in Experiment 1 reported here. Thus the experimental results do not appear to be artifacts of the ratings required to operationalize both attribute concreteness–abstractness and feature–dimensionality.

These findings should help focus the use of both theory and methodology in consumer research. Theoretically, as different choice models presume different representations, knowing what representation to expect may help predict strategy use. A lexicographic strategy (Coombs 1964), for example, assumes a dimensional representation (Garner 1978). Consumers using this strategy choose the alternative that ranks highest on their most important dimension. In contrast, feature-based representations are implicit in models such as elimination by aspects (Tversky 1972; Tversky and Sattath 1979). The results here suggest that, because concrete alternatives tend to be represented using features, strategies such as elimination by aspects may be more likely to be used than dimensional strategies such as the lexicographic rule. Conversely, because abstract or noncomparable alternatives may be thought of more dimensionally, dimensional strategies may be more likely to be used. Methodologically, as demonstrated in Experiment 2, the use of similarity scaling procedures may depend on the nature of consumers' underlying representations. The more abstract the representations, the more insight dimensionally based scaling procedures may provide, while feature-based procedures may be more useful in analyzing more concrete representations. As cautioned earlier, however, either technique may be useful for analyzing both concrete and abstract representations depending on the objectives of the analysis.

IMPLICATIONS FOR FUTURE RESEARCH

Several factors that were not studied here may directly affect the relationship between the abstractness of a representation and the use of features or dimensions. One such factor is the risk or error at stake in making a judgment or choice. Consider that dimensions may be more precise and, hence, more informative than features. If so, concrete attributes may be represented as dimensionally as possible when the choice is an important one. While consumers may only care to represent two thermos bottles as being able to keep food "hot," the same consumers may think more precisely about just "how hot" two prospective homes may be in the winter. A product's complexity at a given level of abstraction should also have some effect on representation. Faced with a product that must be described on a disproportionately large number of attributes, consumers may use more features. Alternatively, or in addition, consumers may have an incentive to represent the same information using fewer, more abstract attributes (Johnson 1986). Still other factors, including consumer knowledge and product type, should also be considered. Further exploration of these factors should continue to provide insights into the nature and methodological implications of the cognitive representation of products.

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