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THINKING ABOUT PRODUCTS:
A MODEL OF CONSUMER COGNITIVE REPRESENTATIONS

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ABSTRACT

The paper develops and tests an integrated model of how consumers cognitively represent product concepts. The model delineates three descriptive aspects of a representation and their interrelationships: attribute abstraction, size, and feature-dimensionality. The model also incorporates the direct and indirect effects of the judgment stimuli and consumer knowledge and experience on cognitive representations. An empirical study that provides initial support for the model as well as some insight into the methodological implications of cognitive representations is reported.

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INTRODUCTION

Understanding consumer judgment and choice processes requires an understanding of the cognitive representations on which these processes are based. Although marketing and consumer researchers have used a variety of techniques to explore cognitive representations (cf. Shocker and Srinivasan 1979), very little attention has been paid to when and why consumers use particular types of representations when making judgments and choices.

Our goal is to develop and test a model of the cognitive representation of brand and product concepts. Central to the model is the notion that consumers represent products using qualitatively different types of attributes, ranging from the concrete to the abstract and from dichotomous features to continuous dimensions. Being able to identify representations that vary on these aspects is important for at least two reasons. First, as suggested, qualitatively different product representations underlie the use of different judgment and choice processes. Second, different representations are implicit in the use of different methodologies for analyzing consumer judgments. A better understanding of cognitive representations should improve both our general understanding of information processing and our choice of research methods.

Our model builds on research in both psychology (Garner 1978; Pruzansky, Tversky, and Carroll 1982; Restle 1959; Tversky 1972, 1977; Tversky and Hutchinson 1986) and consumer behavior (Alba and Hutchinson 1987; Bettman and Sujan 1987; Johnson 1981, 1986b; Johnson and Fornell 1987; Sujan 1985) which describes the cognitive representation of judgment or choice stimuli. Our research goes beyond the existing studies in several respects. First, the model delineates the major descriptive dimensions of a representation. Second, the model incorporates stimulus factors and individual differences in knowledge and experience that may affect representations. Third, the model describes how these factors combine to produce a representation. Finally, an experiment is reported which tests the integrated model.

As the title of the paper suggests, the model describes how consumers "think about" products and services. We focus on the information that consumers extract from memory when they consider products and perform a judgment task. We begin by describing the important descriptive aspects of a cognitive representation and their interrelationships. We then describe how the judgment stimuli and individual differences affect representations and empirically test the model. The paper ends with an exploration and discussion of the model's methodological implications.

THE ASPECTS OF A REPRESENTATION

Previous research has identified three conceptual aspects or dimensions on which product representations vary: the size of a representation, the feature-dimensionality of the information in a representation, and the concreteness-abstractness of that information (Johnson and Fornell 1987).

Size of the Representation

The first aspect, the size of a representation, refers to the number of meaningful units of information recalled and used to describe particular judgment or choice alternatives. One of the underlying assumptions of an information processing approach is that there is a limit to the number of aspects or units of information that can be consciously considered or represented at any one time (Anderson 1983; Newell and Simon 1972; Wyer and Srull 1986). The size of a representation should vary with the amount of information that consumers have stored in memory, the level of abstraction of the information in a representation, and the usefulness or diagnosticity of available information. These relationships are described in detail below.

Attribute Resolution: From Features to Dimensions

A second descriptive aspect of a representation is the feature-dimensionality of the attributes involved. Previous researchers have described attributes as resembling features or dimensions (Restle 1959; Tversky 1977; Garner 1978). Many attributes are inherently continuous or dimensional in nature, such as the sweetness of a soft-drink. Other attributes are more dichotomous or feature like. For example, soft-drinks may or may not contain a particular additive. Even inherently continuous attributes may be represented as features. Consumers may simply describe soft-drinks as sweet or not sweet even though they vary continuously on sweetness.

There is room in between these two extremes for inherently continuous attributes to be represented with greater resolution than a dichotomous feature though less resolution than a continuous dimension. Park (1978) refers to such representations as categorical attributes, where inherently continuous attributes may be categorized into two, three, or more ranges or categories of values. For example, consumers may think of soft-drinks as not sweet, sweet, or very sweet. The important point is that naturally continuous attributes vary in the resolution of their representation from discrete, either-or features to more continuous dimensions.

Different degrees of feature-dimensionality or resolution are implicit in the use of different evaluation and choice strategies. Elimination type strategies, such as the conjunctive and disjunctive models (Einhorn 1970) and elimination by aspects (Tversky 1972), presume that consumers either start with or form relatively feature-based representations (e.g., acceptable and unacceptable value ranges). More additive, compensatory strategies, as well as lexicographic strategies (Coombs 1964), presume more dimensional representations. A better understanding of cognitive representations across consumers, products, and tasks should, therefore, suggest logical strategies for judging consumption alternatives.

The dimensionality of a representation may also be important to consider when choosing a research methodology. Different methods or techniques used to analyze product and service judgments presume more or less dimensional product representations. Techniques that produce spatial representations of perception, such as multidimensional scaling, presume more continuous dimensions. Techniques that produce tree-like structures, such as hierarchical clustering, additive clustering, or additive tree procedures, presume more feature-based representations (Carroll 1976; Johnson and Fornell 1987; Pruzansky, Tversky, and Carroll 1982; Tversky and Hutchinson 1986). The ability of different analytical techniques to capture or explain perceptual judgments may depend on whether the representation presumed by the method corresponds to the consumers' representation. The more dimensional the consumers' representation, the more appropriate dimensional techniques such as multidimensional scaling may become; the more discrete or feature-based the representation, the better may be the fit of clustering techniques (Johnson and Fornell 1987).

Attribute Abstraction

The third important descriptive aspect of cognitive representations modeled here is the concreteness-abstractness of the attributes in a representation. Attribute concreteness-abstractness is defined as the directness with which attributes describe particular products and is equated with the specificity-generality of terms (Paivio 1971). More abstract attributes, such as "worth" or "value" for example, describe products more indirectly and completely; more concrete attributes, such as a television's screen size or remote control, describe products more directly and specifically (Johnson 1984; Johnson and Fornell 1987). The importance of attribute abstraction lies in its effects on the two previously described aspects of a representation, size and dimensionality. These relationships are described below.

Relationships Among the Aspects

An important characteristic of the proposed model is that the three descriptive aspects of a representation (size, dimensionality, and attribute abstraction) combine in determining the representations consumers use when considering and judging products. Figure 1 presents the major components of our model and their interrelationships.

As alluded to above, attribute abstraction should affect both the size and dimensionality of a representation. First, a direct negative relationship is proposed from attribute abstraction to the size of a representation. This is consistent with the definition of abstraction. Abstraction implies a summarizing or concentration of information and, hence, fewer aspects. A product's safety, for example, integrates a good deal of concrete information, such as an automobile's size, weight, and braking system. At an even more abstract level, an auto's worth or utility captures not only its safety, but its necessity, practicality, and fun. Because more abstract representations require fewer attributes to capture approximately the same amount of information, abstraction reduces the necessary size of a representation. Studies by both Boote (1975) and Johnson (1984) support a decrease in the size of a representation with abstraction.

Next, a direct positive relationship is proposed from attribute abstraction to the dimensionality of a representation. Johnson and Fornell (1987) argue that there is an inherent similarity between feature-dimensionality and attribute concreteness-abstractness. Just as a dimension captures or contains a set of nested features, an abstract attribute captures or contains several concrete attributes. It is hard to think of abstract attributes, such as safety, necessity, or value, that are not naturally continuous. Hence abstraction should have a direct, positive effect on feature-dimensionality.

The size of a representation may also affect its dimensionality. When considering a very large number of attributes, simpler, feature-based representations of inherently continuous attributes may be necessary to stay within the limits of one's cognitive capacity (Johnson and Fornell 1987). Put differently, smaller representations allow for more resolution on individual attributes. We thus posit a negative relationship from size to dimensionality. This assumes, however, that processing limitations are reached and impose a constraint on the representation. An alternative hypothesis is that larger representations may actually be more dimensional. Larger representations may allow consumers to "fill in" the levels of some inherent, underlying dimension rather than forcing consumers to adapt to a processing constraint.

Overall the model posits a positive effect of an increase in attribute abstraction on the dimensionality of a representation. Two studies support this general relationship. Johnson and Kisielius (1985) presented subjects with 248 product attributes that varied in their concreteness-abstractness (from Johnson 1984). The subjects were asked to classify the attributes as either features (i.e., something that products typically had or did not have), dimensions (i.e., something that products typically varied on as a matter of degree), or both (i.e., used equally often as a feature and a dimension). As predicted, abstraction increased from the feature to the dimension classified attributes. Johnson and Fornell (1987) presented subjects with products at increasing levels of abstraction and asked them to elicit all the attributes that came to mind in response to the products. Separate judges then rated these attributes for concreteness-abstractness and feature-dimensionality. The results supported more abstract products being associated with more abstract, dimensional attributes.

According to the model in Figure 1, this general effect of attribute abstraction on feature-dimensionality is due to both direct and indirect effects. Directly, more abstract attributes are inherently dimensional. Indirectly, attribute abstraction reduces the size of a representation which, in turn, allows for more dimensional representations. Just which effect or effects are driving the relationship has not been previously studied.

We now describe two general antecedents of cognitive representations that are captured in the model: 1) the nature of the judgment stimuli, and 2) individual differences in knowledge and experience. The next two sections of the paper incorporate these factors and their effects on representations.

TASK ABSTRACTION, SIMILARITY VARIANCE, AND COGNITIVE REPRESENTATIONS

Two particular stimulus factors are included in the model because of their significant impact on the aspects of a representation: task abstraction and similarity variance. Task abstraction captures the basic categorical level or comparability of the stimuli and directly affects attribute abstraction. According to Howard (1977), consumers face a hierarchy of choice alternatives ranging from abstract product categories to concrete brands. Howard proposed an evaluative hierarchy of concrete to abstract choice criteria which corresponds to this hierarchy of choices. The more categorical or abstract the choice, the more abstract the corresponding choice criteria.

A study by Boote (1975) supports this hypothesis, while Johnson and Fornell (1987) report results that support a general relationship between product abstraction and attribute abstraction.

Consumers also face choices involving relatively noncomparable alternatives, or specific alternatives from very different product categories (Johnson 1984, 1986a, 1988). More noncomparable alternatives are described using very different concrete attributes. As a result, consumers often form abstract representations on which to base product comparisons. The more noncomparable the alternatives, the more abstract the required representations and resulting comparisons. In two studies, Johnson (1984, 1988) reports subjects using more abstract attributes to compare more noncomparable alternatives.

As both the category-level and comparability of products have a similar effect on attribute abstraction, for our purposes these two constructs are combined and referred to as Task Abstraction. Notice that task abstraction, resulting either from more abstract, categorical choices or from more noncomparable choice alternatives, results in a direct positive effect on attribute abstraction.

The second stimulus factor in the model, similarity variance, describes the general construction of a stimulus set. It reflects the degree to which the similarity or comparability of products varies within a stimulus set, or the degree to which products are "unequally different" (Johnson 1988). For example, a toaster, a coffee maker, and a mixer are more equally different, or exhibit lower similarity variance, than a two-slice toaster, a four-slice toaster, and a coffee maker. An increase in the similarity variance of products should directly affect perceptions and judgments. The greater the similarity variance of products in any given set, the more transparent and diagnostic the products' natural categorical relationships become (Johnson 1988). In the example above, the two- and four-slice toasters are likely to be categorized and represented simply as toasters when combined with a coffee maker. In support of this relationship, Johnson (1988) recently found that an increase in similarity variance increased the degree to which subjects eliminated choice alternatives as members of a product category.

Lumping "unequally different" products into groups allows consumers to use category or group membership as a feature in their representation. Therefore, we predict that the greater the similarity variance of any given set of stimuli, the more feature-based the representation. Simplifying a representation by categorizing alternatives also implies that similarity variance should decrease the overall size of a representation. Thus a direct negative relationship is proposed from similarity variance to the size of a representation (see Figure 1).

KNOWLEDGE AND EXPERIENCE EFFECTS ON COGNITIVE REPRESENTATIONS

Expertise is a multidimensional, higher-order thinking skill that includes a consumer's ability to recall, understand, and integrate product information (Alba and Hutchinson 1987; Brucks 1985). Consumer expertise is captured in the model not as a single construct, but rather by the interplay between consumer experience and knowledge on the one hand and the aspects of a representation on the other. As Brucks points out, it is important to distinguish between knowledge and experience because knowledge may not always result from experience. Experience constitutes actual interaction with particular products (Fornell, Robinson, and Wernerfelt 1985) while knowledge is the stored or available information which may or may not result from experience. We distinguish knowledge from experience in this regard and simply treat knowledge as the memory-based information available to the consumer.

Experience Effects

Generally, consumers should have more experience with an array of product categories than with an array of brands. It is not necessary to purchase and consume multiple instances or members of a category to have experience with the category. The more abstract or categorical the judgment task, the more experience the consumers should be able to draw upon and use to represent products. Consumers should, for example, have greater experience with an array of snacks foods or beverages than with an array of particular candy bars or soft-drinks. We predict, therefore, a positive relationship from task abstraction to experience.

Consumer experience should, in turn, directly affect knowledge, the size of a representation, and similarity variance. Experience should have a direct, positive effect on knowledge (information available). As experience grows consumers learn more and more about the relevant attributes of products and services (both concrete and abstract) and, as a result, have more knowledge or information available in memory to recognize and evaluate products (Bettman 1979; Bettman and Park 1980; Howard 1977; Johnson and Russo 1984).

Experience should also reduce the size of a representation. Although experienced consumers may have more information available, they may only use a subset of that information. At least two factors allow experienced consumers to limit their information use. First, these consumers may be aware of or expect ecological correlations among attributes (Alloy and Tabachnik 1984; Brunswik 1943; Einhorn and Hogarth 1978; Johnson and Katrichis 1988) and, as a result, rely on limited information (Einhorn, Kleinmuntz, and Kleinmuntz 1979;

Hagerty and Aaker 1984). Second, experts should be more aware of particularly nondiagnostic or irrelevant information (Tversky 1977). The result of factors such as attribute redundancy and diagnosticity should be a direct negative relationship from experience to the size of a consumer's cognitive representation (see Figure 1).

Finally, experience should positively affect the perception of similarity variance. Experience is a necessary condition for perceiving products as relatively equal or unequal. To a consumer with no experience with candy bars, for example, all candy bars will appear equally similar or different. With experience comes the ability to categorize products (Howard 1977) and thus an ability to perceive variance in similarity. We predict, therefore, a positive relationship from experience to similarity variance (see Figure 1).

Notice that the model posits both direct and indirect effects for consumer experience on cognitive representations. Experience has the direct effect of allowing consumers to be selective in their use of information. Experience indirectly affects representations by adding to consumer knowledge and by allowing consumers to group "unequally different" products into product categories.

Knowledge Effects

Knowledge itself, or the memory-based information available to consumers, should affect all three aspects of a cognitive representation captured in Figure 1. Naturally, knowledge should be positively related to the size of a representation. The more product information consumers have stored in memory, the more information that is activated and accessed when they think about the products. This relationship is consistent with an associative network model of human memory (Anderson 1983; Collins and Loftus

1975; Quillian 1968) as well as consumer behavior studies that find more experienced and knowledgeable consumers using a greater amount of memory-based information when evaluating products (Biehal 1983). Knowledge should also increase the dimensionality of a representation. The more information available to a consumer the finer the discriminations that might be made. In other words, knowledge is required to obtain resolution on attributes and make fine discriminations.

Finally, as knowledge grows so should the availability of abstract attribute information. At least two qualitatively different relationships contribute to the proposed positive effect of knowledge on attribute abstraction. First, early in a consumers' experience, category-level or prototype knowledge develops which can be used to represent and evaluate products (Howard 1977; Sujan 1985). Second, abstract attribute information is added to a consumer's knowledge base as experience grows. Specifically, the higher level evaluations or "brand concepts" (Howard 1977) that result from previous, repeated purchase decisions provide consumers with abstract, summary product information. More experienced consumers have these abstract representations stored in memory and simply recall them when needed (Alba and Hutchinson 1987; Bettman and Jacoby 1976; Bettman and Park 1980; Johnson and Russo 1984). These arguments, taken together, suggest the positive effect of knowledge on attribute abstraction in Figure 1.

The model presented in Figure 1 predicts how the amount and type of information in a representation changes with the judgment stimuli, consumer experience, and resulting knowledge. We now present an empirical test of the model. The incorporation of individual differences necessitates that the test use individual level data. After describing the test and results, we explore the model's methodological implications.

EMPIRICAL TEST

The data for the empirical test was collected using a two part questionnaire. In part one, subjects were asked to provide measures of their knowledge and experience regarding a set of stimuli. In part two, subjects provided judgments of product similarity and were then asked to report on the aspects or attributes that they used to produce the judgments. Similarity judgments were chosen because they require consumers to extract information from memory in order to form representations and produce judgments (Tversky 1977). They are also common inputs for perceptual scaling techniques. The model's relationships were tested by varying the exogenous construct, task abstraction, and then measuring the endogenous constructs for each subject using a multiple indicators approach.

Task Abstraction, Similarity Judgments, and Similarity Variance

Five sets of stimuli were operationalized at two different levels of task abstraction (T_1). Two sets, soft-drinks and candy bars, are very concrete and represent brands from basic-level product categories. The three remaining stimulus sets, beverages, snacks, and lunch products, represent more abstract, categorical alternatives. Soft-drinks and candy bars are nested within beverages, snacks and lunch products, supporting our two-level operationalization.[1] The specific stimuli within each of these five stimulus sets are presented in the Table.

Each stimulus set contained twelve consumption alternatives. Holding the number of alternatives constant across stimulus sets allows for a more

1. Three levels of task abstraction were initially operationalized, with lunch products being more abstract than beverages and snacks. However, a manipulation check revealed that these three stimulus sets did not differ significantly in the level of abstraction of their associated attributes, while all three of these sets were more abstract than either soft-drinks or candy bars. This supports a two- rather than three-level operationalization of task abstraction.

controlled test of the model. Each subject provided paired-comparison similarity ratings for one of the five stimulus sets listed in the Table. Each possible pair of the twelve alternatives was rated on an eleven-point scale ranging from 0 (Very Dissimilar) to 10 (Very Similar) for a total of sixty-six judgments. Similarity variance was operationalized for each subject by computing the standard deviation of the subject's similarity judgments (V_1).

Knowledge and Experience Measures

Knowledge and experience measures were collected from each subject for each of the products in the subject's stimulus set. The measures were chosen to be as comparable across stimulus sets as possible. Objective, absolute measures of knowledge and experience were used where possible in order to maximize their comparability.

Knowledge, or the amount of information available to the consumer, was measured reflectively by three indicators. First, a memory probe was used to elicit all of the attributes that came to mind when consumers thought about each individual stimulus in the stimulus set (Johnson 1986b; Rosch and Mervis 1975). Subjects were provided with the names of the twelve products in their stimulus set, each on a separate page. Below the product were fifteen blank lines numbered from 1 to 15. At the top of each page, the subject was instructed to list, beginning at line one, the aspects that came to mind when they thought of the product. The subjects were given one minute per product to list their associations. The average number of attributes listed across the twelve products was used as an objective measure of the subject's knowledge (K_1).

The subjects were also asked to rate their confidence in judging and evaluating each product. The twelve products were rated on a scale from 0 (not at all confident evaluating the product) to 10 (very confident evaluating the product) and the average confidence rating across the twelve products was used as a second reflective indicator of knowledge (K_2). The basic assumption here is that knowledgeable subjects should be more confident when judging or evaluating stimuli (Park and Lessig 1980).

A third measure of knowledge was provided by having the subjects rate their absolute knowledge of each product's attributes and functions. The scale used was a variation on Johnson's (1984) scale for evaluating absolute knowledge when products are from different product categories. The twenty-one point scale ranged from 0 (no knowledge of the product) to 5 (knowing what the product may be used for) to 10 (knowing the basic uses of the product but not all its details and functions) to 15 (knowing the product's uses, details and functions) to 20 (knowing every aspect of the product and its uses). The average knowledge rating for the twelve products provides a third and final reflective indicator of knowledge for each subject (K_3).

Experience was measured using four objective indicators: frequency of consumption (E_1), frequency of purchase (E_2), recency of consumption (E_3), and recency of purchase (E_4). Each subject was asked to rate their frequency (recency) of consumption (purchase) for each of the twelve products on separate five point scales (past day=1, past week=2, past month=3, past year=4, and year or more=5 for the recency of purchase and recency of consumption questions; every day=1, every week=2, every month=3, every year=4, and never=5 for the frequency of purchase and frequency of consumption questions). Each of these four measures constitutes a qualitatively different aspect of a consumer's experience with particular products which, taken together, constitute the subject's experience. They are, therefore, modeled as formative indicators of experience.

Cognitive Representation Measures

Immediately after collecting the similarity judgments, consumers were asked to recall the product aspects or characteristics that they considered when performing the judgment task. They were asked to recall and list as many aspects as they could "which they used to compare the alternatives". The subjects were told that they could refer to their judgments as a guide to aid them in this task. This prompted-retrospective method of eliciting process information was chosen over alternative methods (e.g. concurrent verbal protocols) because it eliminates any interference with the similarity judgment task.

Immediately after listing each aspect considered, subjects were asked to provide additional information regarding the aspect. Subjects rated whether they used the aspect to look for small or large differences on a scale from 0 (very small differences) to 10 (very large differences). Subjects were also asked to rate whether the aspect was something that the products "either had (were) or did not have (were not)" (i.e., a feature) or "varied on as a matter of degree" (i.e., a dimension). The average size of the product differences on the reported aspects (D_1) and the fraction of elicited aspects that were rated as dimensions (D_2) provide reflective indicators of feature-dimensionality for each subject. A third measure of dimensionality was obtained by having a separate judge (one of the authors) similarly classify each of the listed attributes as a feature or dimension and again measuring the fraction that were dimensions for each subject (D_3). The logic underlying the first of the dimensionality measures is that features, often being dichotomized dimensions, would be used to look for or judge large rather than small differences among the products. The second and third measures are straightforward feature-dimension classification measures.

The aspects that each subject reported they considered were then rated by separate judges to provide measures of attribute abstraction. Following Johnson (1984, 1988; Johnson and Fornell 1987), the different aspects listed were assembled and rated independently by four judges, two of the authors and two naive judges. Each attribute was rated on a ten-point scale ranging from 0 (Very Concrete) to 10 (Very Abstract). Given the potential differences between the authors and the naive judges, the ratings of the two authors were combined into one average and the ratings of the two naive judges were combined into a second average. These concreteness-abstractness measures were then used to calculate separately the average abstractness of the aspects considered by each subject (A_1 and A_2).

The last construct requiring measurement is the size of the subject's cognitive representation for judging similarity. The number of aspects considered provides a very straightforward, process measure of the size of a representation (S_1). Individually scaling the subject's similarity judgments provides a second measure. Each subject's judgments were scaled using two- and three-dimensional MDS (Roskam and Lingoes 1970), an additive tree (ADDTREE; Sattath and Tversky 1977), and an extended additive tree (EXTREE; Corter and Tversky 1986). Using both MDS and additive tree scaling is an integral part of the methodological implications studied later in the paper. ADDTREE is a heuristic additive tree procedure with a path length metric. An additive tree has approximately the same number of independent parameters as a two-dimensional spatial configuration (Carroll 1976; Torgerson 1986). EXTREE is an extension of ADDTREE which, in this particular application, overlays n/2 additional features onto an additive tree. It has approximately the same number of parameters as a three-dimensional solution. Thus the four scaling solutions are balanced with respect to their tree v. space orientation and their free parameters.

Two measures of "fit" were obtained for each of the four scaling solutions: Kruskal's stress and linear variance explained. These eight measures were independently standardized across subjects and combined for each subject creating a fit index (S_2). The logic here is that the better the fit of any particular scaling method, the fewer the number of aspects in the subject's representation. This fit index provides a measure of size that is equally weighted with respect to a spatial or tree orientation.

Procedure

The questionnaire was administered in two parts. The knowledge and experience measures were collected in part one. The subjects read and signed a consent form and were administered the memory probe. Subjects then provided the confidence ratings, the four experience ratings (organized by product), and the attribute knowledge ratings. The stimuli in each stimulus set were probed and rated in one random order by half the subjects and the reverse order by the remaining subjects. In part two, a separate questionnaire was administered to these same subjects. The subjects first rated the similarity of each possible pair of products in the set. The sixty-six pairs were rated in one random order for half the subjects and the reverse order for the remaining subjects. The subjects were then asked to list separately the aspects they considered and to rate the size of the considered differences and the dimensionality of the aspects.

An experimenter paced the subjects' through each phase. The instructions were read aloud and the subjects were instructed to stop and wait for further instructions before beginning the next task. After filling out the first questionnaire, the subjects took a short break (five minutes) and were then administered part two. The subjects were recruited from evening MBA classes at a large midwestern university and were run in small groups of approximately 30 (total n=123). The subjects were paid for their participation.

The cognitive representation model, and later its methodological implications, were tested using data from the same subjects. This necessitated the identification and elimination of subjects producing degenerate or otherwise problematic judgments and MDS representations. Degenerate solutions were operationally defined as any two dimensional solution with zero stress or an R^2 of one (estimated to three decimal places) or with a stress (R^2) measure that increased (decreased) from two to three dimensions. This resulted in the elimination of seven subjects from the sample. The actual number of subjects from which we obtained usable data equaled 20, 24, 21, 24, and 27 respectively for the soft-drink, candy bars, beverages, snacks, and lunch products.

Analysis Model and Results

Following the preceding discussion, the model to be tested can be written:

$$\begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \\ \eta_6 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{2,1} & 0 & 0 & 0 & 0 & 0 \\ \beta_{3,1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \beta_{4,2} & 0 & 0 & 0 & 0 \\ \beta_{5,1} & \beta_{5,2} & \beta_{5,3} & \beta_{5,4} & 0 & 0 \\ 0 & \beta_{6,2} & \beta_{6,3} & \beta_{6,4} & \beta_{6,5} & 0 \end{bmatrix} \cdot \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \\ \eta_6 \end{bmatrix} + \begin{bmatrix} \gamma_{1,1} \\ 0 \\ 0 \\ \gamma_{4,1} \\ 0 \\ 0 \end{bmatrix} \xi + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \\ \zeta_4 \\ \zeta_5 \\ \zeta_6 \end{bmatrix}$$

where

η_1 = Experience

η_2 = Knowledge

η_3 = Similarity Variance

η_4 = Attribute Abstraction

η_5 = Size of Representation

η_6 = Feature-Dimensionality

ξ = Task Abstraction

$\beta_{2,1}$-$\beta_{6,5}$ are structural coefficients between the endogenous (latent) variables

$\gamma_{1,1}$-$\gamma_{4,1}$ are structural coefficients relating the exogenous (treatment) variable to the endogenous (latent) variables

ζ_1 - ζ_6 are residuals

and

$$\eta_1 = \begin{bmatrix} \pi_1 & \pi_2 & \pi_3 & \pi_4 \end{bmatrix} \begin{bmatrix} E_1 \\ E_2 \\ E_3 \\ E_4 \end{bmatrix}$$

and

$$
\begin{bmatrix} K_1 \\ K_2 \\ K_3 \\ V_1 \\ A_1 \\ A_2 \\ S_1 \\ S_2 \\ D_1 \\ D_2 \\ D_3 \end{bmatrix}
=
\begin{bmatrix}
\lambda_{1,1} & 0 & 0 & 0 & 0 \\
\lambda_{2,1} & 0 & 0 & 0 & 0 \\
\lambda_{3,1} & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & \lambda_{5,3} & 0 & 0 \\
0 & 0 & \lambda_{6,3} & 0 & 0 \\
0 & 0 & 0 & \lambda_{7,4} & 0 \\
0 & 0 & 0 & \lambda_{8,4} & 0 \\
0 & 0 & 0 & 0 & \lambda_{9,5} \\
0 & 0 & 0 & 0 & \lambda_{10,5} \\
0 & 0 & 0 & 0 & \lambda_{11,5}
\end{bmatrix}
\begin{bmatrix} \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \\ \eta_6 \end{bmatrix}
+
\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ 0 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \\ \varepsilon_9 \\ \varepsilon_{10} \\ \varepsilon_{11} \end{bmatrix}
$$

and

$\xi = T_1$

where

E_1 = Frequency of Consumption

E_2 = Frequency of Purchase

E_3 = Recency of Consumption

E_4 = Recency of Purchase

K_1 = Average Number of Attributes in Memory Probe

K_2 = Average Confidence Rating

K_3 = Average Knowledge Rating

V_1 = Similarity Variance

A_1 = Expert Judgment of Attribute Abstraction

A_2 = Naive Judgment of Attribute Abstraction

S_1 = Number of Aspects Considered

S_2 = Fit Index

D_1 = Average Rated Size of Product Differences

D_2 = Average Rated Feature-Dimensionality

D_3 = Average Expert Judge Feature-Dimensionality

T_1 = Task Abstraction

$\lambda_{1,1}$ - $\lambda_{11,5}$ are measurement loadings

π_1 - π_4 are measurement weights

ε_1 - ε_{11} are measurement residuals

Because of the nature of the sample (116 subjects) and the model, which contains both formative and reflective indicators, estimation was done via partial least squares (Fornell 1987; Fornell and Bookstein 1982; Wold 1982). Negative construct indicators (e.g. the experience scales) were directionally rescaled so that all of the loadings should be positive.

The results, including the structural coefficients and indicator loadings, are presented in Figure 2. First of all, notice that the indicator loadings are all fairly large and positive. The average variance extracted (Fornell and Larcker 1981) is well above 50% for all constructs, suggesting a sizable portion of valid variance in the measurement. The endogenous constructs, experience, knowledge, similarity variance, attribute abstraction, size of representation, and feature-dimensionality, had R^2's of .63, .33, .09, .21, .20, and .19 respectively. The hypothesized causal structure also receives support. The root mean square residual of the structural portion of the model is .05 which represents 16% of the root mean correlation. In other words, 84% of the covariance of the latent variables is accounted for by the structural model. (For the measurement model, the root mean residual is .07, which represents 81% of the covariance accounted for.)

Eleven of the thirteen structural coefficients were in the predicted direction. Moreover, the larger coefficients were all as predicted. Task abstraction had a positive effect on attribute abstraction. This is consistent with the previous results of Johnson (1984; 1988) and Johnson and Fornell (1987). Task abstraction had a positive effect on experience. This is consistent with the notion that more abstract judgment tasks allow consumers to rely on a greater amount of their product experience. Experience, in turn, had a positive effect on similarity variance. This supports the notion that more experienced consumers perceive the "unequally different" nature of many judgment stimuli.

As predicted, similarity variance negatively affected both the size of a representation and feature-dimensionality. The relatively large negative effect of similarity variance on dimensionality is consistent with the notion that stimulus sets perceived as "unequally different" are categorized and represented using category labels as features. This judgment task finding is consistent with the choice task results of Johnson (1988).

The results also show a direct positive effect of attribute abstraction on feature-dimensionality. This supports Johnson and Fornell's claim that there is a relationship between these constructs. As expected, and previously reported (Boote 1975; Johnson 1984), attribute abstraction negatively affected the size of the representations.

There was a large positive effect of experience on knowledge, and subsequent positive effect for knowledge on the size of a representation. That more experienced consumers had more information available is consistent with a number of consumer research studies (cf. Bettman and Park 1980; Biehal 1983; Johnson and Russo 1984). Experience also had a direct negative effect on size. This supports the notion that experienced consumers are more selective in their use of available information. There was a predicted but weak positive relationship from knowledge to attribute abstraction. One possible explanation of this weak effect is that the stimuli used in the study were relatively well known to the consumers. As a result, there may have been insufficient variance in the knowledge construct to produce large differences in the availability of abstract information.

Not supported was a positive effect for knowledge and a negative effect for size on feature-dimensionality. Recall, however, that a positive effect for size on dimensionality was not completely unexpected. At least for the similarity judgments studied here, an increase in the size of a representation may allow consumers to "fill in" the levels of a dimension rather than force them to adapt to an information processing constraint. This may, in turn, explain why the positive effect of knowledge on dimensionality failed to materialize.[2]

<u>Summary</u>

These results generally support the integrated model of cognitive representations presented in Figure 1. The model captures the predictable effects of both task abstraction and similarity variance on consumer cognitive representations. The model also demonstrates the multidimensionality of consumer expertise (Alba and Hutchinson 1987; Brucks 1985). The results suggest that product experience allows consumers to perceive product relationships, increases the availability of product information, and makes consumers more selective in their use of information. Finally, the model delineates the different aspects of a cognitive representation and their interrelationships. The results suggest, for example, that attribute abstraction directly, rather than indirectly, increases the dimensionality of

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2. As a check, the model was also estimated for each stimulus set. Task abstraction was omitted and the model estimated for each set of subjects that received a different set of stimuli. The results were generally consistent with those in Figure 2, especially in those cases where the endogenous constructs were well explained.

a representation. One modification of the model in light of the results might be to eliminate any general negative effect for size on feature-dimensionality.

METHODOLOGICAL IMPLICATIONS

In this section of the paper we explore the potentially important implications that cognitive representations may have on research methodologies, specifically similarity scaling. We expanded our psychological model in Figure 1 to incorporate the effects that cognitive representations may have on two very different similarity scaling solutions described earlier, a two-dimensional multidimensional scaling space and an additive tree.[3] Two constructs were added to the model, space fit and tree fit. Space fit denotes the ability of the inherently spatial two-dimensional MDS solution to capture or explain consumer perceptions. Tree fit denotes the ability of the inherently feature-based ADDTREE solution to capture perceptions.

Johnson and Fornell (1987) predict an increase in the fit of spatial MDS relative to feature-trees as representations become more abstract. Driving this prediction is the relationship between abstraction and feature-dimensionality. More abstract representations tend to be more dimensional. And the more continuous or dimensional a representation, the better should be the fit of a dimensional, spatial technique relative to a feature-tree (see also Carroll 1976; Pruzansky, Tversky, and Carroll 1982; Tversky and Hutchinson 1986). Thus we predict a positive relationship from dimensionality to space fit and a negative relationship from dimensionality to tree fit.

3. We chose to focus on the two-dimensional MDS and ADDTREE solutions because they are more common than three-dimensional MDS and EXTREE, they have approximately the same number of free parameters (Carroll 1976), they use fewer parameters than three-dimensional MDS and EXTREE and thus allow for more variance in fit across individuals, and their use is consistent with past methodological practice.

Any positive effect of abstraction on spaces relative to trees may not, however, be mediated solely by feature-dimensionality. Abstraction may directly affect space and tree fit, whether due to an interaction between size and dimensionality or some other, unspecified property of abstraction. Therefore, following Johnson and Fornell's general prediction, we posit a direct positive effect for attribute abstraction on space fit and corresponding negative effect on tree fit. Note that our positing of absolute positive and negative effects for abstraction and dimensionality on the fit constructs are for convenience. Strictly speaking, our arguments only suggest that abstraction and dimensionality improve space fit **relative** to tree fit.

Finally, we predict that the larger the size of the representation, in terms of aspects considered, the lower should be the fit of both spaces and trees. The smaller or less complex the representation, the better either a tree or a space should capture perceptions.

Overall the extended model predicts that space fit should increase relative to tree fit as representations become more abstract. Johnson and Fornell (1987) recently tested this general prediction. They obtained group similarity judgments for different sets of products and services and used the variance explained by a small number of principle components to operationalize attribute abstraction. The group judgments were then scaled using both MDS and ADDTREE. While both the MDS and ADDTREE solutions improved with abstraction (presumably because of a decrease in aspects considered), the fit of the dimensional, MDS solutions improved more than the fit of the ADDTREE solutions. This study was limited, however, in that the independent effects of abstraction, size, and dimensionality on space and tree fit could not be estimated. Modeling each subject's representation allows us to delineate the various possible direct and indirect effects of a cognitive representation on the scaling solutions.

Space Fit and Tree Fit

As described under the main study, each subject's judgments were scaled using both MDS and ADDTREE. Our methodological constructs, space fit and tree fit, are based on the individual level two-dimensional MDS and ADDTREE solutions. These constructs were operationalized using our two reflective measures of fit, Kruskal's stress and linear R^2 (F_1 through F_4 in Figure 3).

Notice that adding space and tree fit to the initial model introduces a basic confound between the indicators of fit and the fit index (S_2) previously used to measure size. As a result, only one indicator of size was used to estimate the expanded version of the model, namely the number of aspects considered as revealed by the attribute use probe (S_1). As a process measure, this is the more straightforward of the two size indicators. It also had the highest loading in the initial model (see Figure 2).

Results

The loadings and structural coefficients for task abstraction, experience, knowledge, and similarity variance in the expanded model were very similar to those in Figure 2 and, therefore, are not reported. (The R^2's for the endogenous constructs were almost identical.) Instead we focus directly on the methodological implications. That part of the extended model involving the cognitive representation and space and tree fit latent variables is presented in Figure 3. Notice that the indicator loadings for space fit and tree fit are all large and positive.

As predicted, abstraction had a direct positive effect on space fit and a direct negative effect on tree fit (.25 v. -.18). Also as predicted, the size of the representation negatively affected both fit constructs. However, the effect of size was greater on tree fit than on space fit (.22 v. .05). Most startling were the effects for feature-dimensionality. Dimensionality negatively rather than positively affected the spaces and positively rather than negatively affected the trees. The structural coefficients for dimensionality on space fit and tree fit were -.18 and .12 respectively. Thus the indirect effects of abstraction on space and tree fit, as mediated by feature-dimensionality, were not as predicted. Although abstraction increased the dimensionality of the representations, dimensionality did not mediate any improvement in space fit.

The indirect effects of abstraction on fit are, however, quite small compared to the direct effects of abstraction on fit. The effect of abstraction as mediated by dimensionality, for example, is equal to the structural coefficient from abstraction to dimensionality (.23) times the coefficient from dimensionality to the relevant space or tree fit construct (-.18 or .12). Overall, therefore, abstraction has a positive effect on space fit relative to tree fit and the results are consistent with those of Johnson and Fornell (1987).

Finally, it may be important to consider the relatively small R^2's for the space and tree fit constructs, which equaled .09 and .07 respectively. As described in more detail in the discussion, the methodological implications of cognitive representations may be quite different for the individual level data studied here and the group level data of Johnson and Fornell (1987). The level of analysis is very different in the two studies.[4]

4. The expanded model was also estimated for each stimulus set by omitting task abstraction. The results were again generally consistent with the across set results.

DISCUSSION

We set as our goal the task of developing and testing a model of the cognitive representation of products. The resulting model captures the important descriptive aspects of a representation and incorporates the effects of important task and individual difference variables on these aspects. The model integrates a number of previously separate propositions and relationships into a model of cognitive representations.

Our empirical results are encouraging. There were a number of predictable findings. Consistent with the earlier results of Johnson and Fornell, we observed a positive effect for task abstraction on attribute abstraction as well as a positive effect for attribute abstraction on the dimensionality of a representation. Our results support a negative effect for stimulus similarity variance on dimensionality, which is consistent with consumers' natural inclination to hierarchically categorize products when performing a judgment or choice task (Johnson 1988; Sujan 1985). Also our results demonstrate the importance and complexity of consumer expertise. Product experience allows consumers to perceive the variance in the similarity of a set of products. Experience contributes to the size of a representation by increasing the information available to consumers. At the same time, experience allows consumers to be more selective in their use of information. Finally, the results suggest that attribute abstraction directly rather than indirectly increases the dimensionality of a representation. Johnson and Fornell's argument that an abstraction-dimensionality relationship is the result of **both** direct and indirect effects was not supported.

Although the model was expanded to incorporate the methodological implications of cognitive representations, these results were mixed. Attribute abstraction had a generally positive effect on space fit relative to tree fit, which is consistent with earlier findings. However, this result may not be mediated strictly by the dimensionality of a representation as previously thought (Johnson and Fornell 1987).

It is difficult to draw conclusions regarding the methodological implications of the model. It may be a misspecification to incorporate methodological implications into a model of the individual consumer. Johnson and Fornell's earlier examination of the implications of cognitive representations involved group level data, which is more representative of similarity scaling studies. It is interesting to note that the variance explained by space fit and tree fit was much smaller here (.07 and .09 respectively) than for the same constructs in the Johnson and Fornell study (.55 and .32 respectively). This observation suggests that the methodological implications of cognitive representations may be more apparent for aggregate than individual level data.

Consider the possibility that spatial scaling may not benefit completely from a dimensional, as opposed to a feature-based, cognitive representation until dimension-based judgments are aggregated across consumers. While an individual may think in terms of a dimension, the individual may only use a small number of levels of that dimension when judging a set of stimuli. As a result, the individual's judgments may be very well captured by an additive tree. The methodological implications of a dimensional representation may not be fully realized until perceptions are aggregated over a number of individuals. In the aggregate, a dimension may become operationally as well as cognitively continuous. Different consumers may use different levels of the dimension, making their aggregate perceptions more continuous than might be the case for features. Thus "dimensionality" may benefit spaces relative to trees for aggregate level data.

CONCLUSION

The main contribution of the study is the development of and general support for the model of consumer cognitive representations presented in Figure 1. As cognitive representations serve as inputs to judgment and choice processes, a better understanding of these representations improves our theoretical understanding of consumers and, potentially, our ability to predict subsequent information processing. Yet by no means is our task complete. Any conclusions regarding the usefulness of the model will only follow the elimination or change of problematic construct relationships, the incorporation of important constructs that have been overlooked, and continued empirical tests involving other than food product stimuli.

The methodological implications of cognitive representations are not as clear as first expected. At the individual level, attribute abstraction had a more direct effect on space and tree fit than expected. Furthermore, it is not clear just how the implications of a representation change with aggregation. We speculate that the full advantage of spatial scaling when consumers think in terms of dimensions may only materialize when judgments are aggregated over consumers. It is important that future research examine the effects that aggregation may have on cognitive representations and their methodological implications.

TABLE

STIMULUS SETS

BRAND-LEVEL STIMULI

Soft-Drinks	Candy Bars
Sprite	Three Musketeers
Seven-Up	Mars Bar
Diet Sprite	Milky Way
Diet Seven-Up	Snickers
Orange Crush	M&M Plain
Diet Orange Crush	M&M Peanut
Coke Classic	Hershey's Plain
New Coke	Hershey's Almond
Pepsi	Nestle's Crunch
Cherry Coke	Reece's Peanut Butter Cups
Diet Coke	Twix Carmel
Diet Pepsi	Kit Kat

CATEGORY-LEVEL STIMULI

Beverages	Snacks	Lunch Products
Ice Cream Soda	Popcorn	Carrot
Milk Shake	Nacho Chips	Apple
Chocolate Milk	Crackers	Fruit Juice
Milk	Potato Chips	Yogurt
Fruit Juice	Cheese	Milk
Lemonade	Grapes	Ice Cream
Soft-Drink	Apple	Cookie
Diet Soft-Drink	Yogurt	Candy Bar
Club Soda	Ice Cream	Soft-Drink
Iced Tea	Cookie	Pizza
Bottled Water	Candy Bar	Chicken Sandwich
Iced Coffee	Brownie	Hamburger

FIGURE 1

A MODEL OF CONSUMER COGNITIVE REPRESENTATIONS

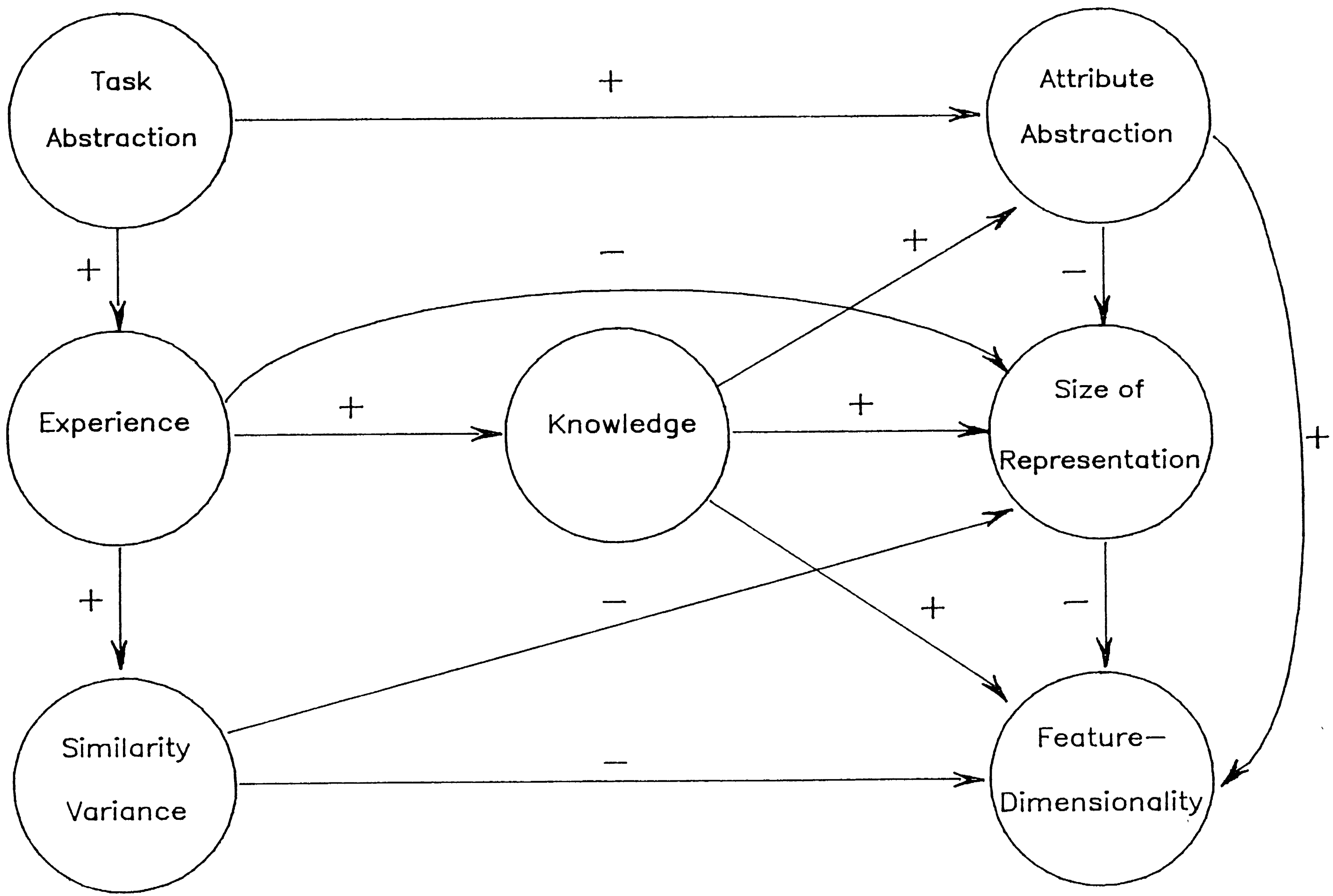


Figure 2
PLS Model Results

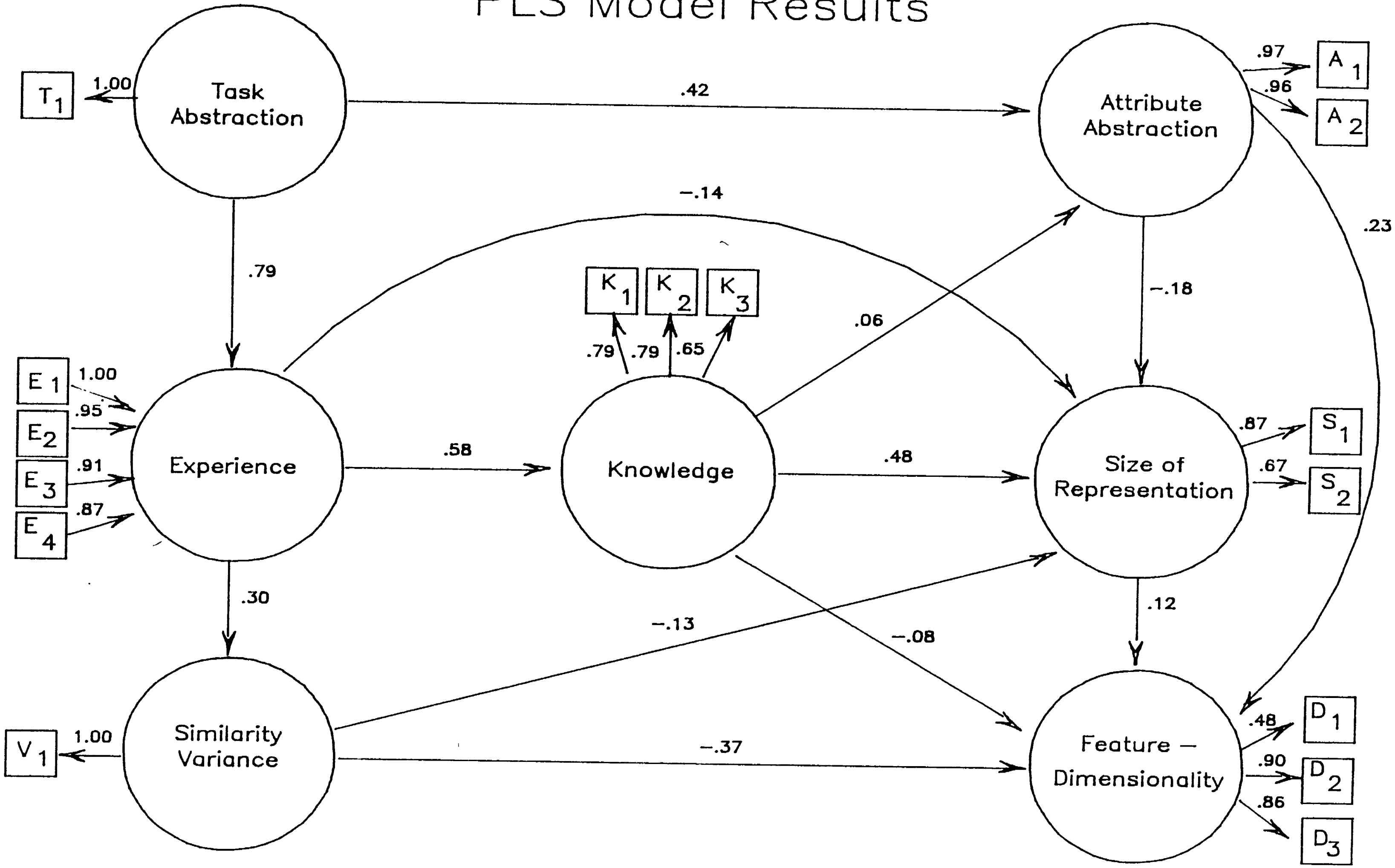
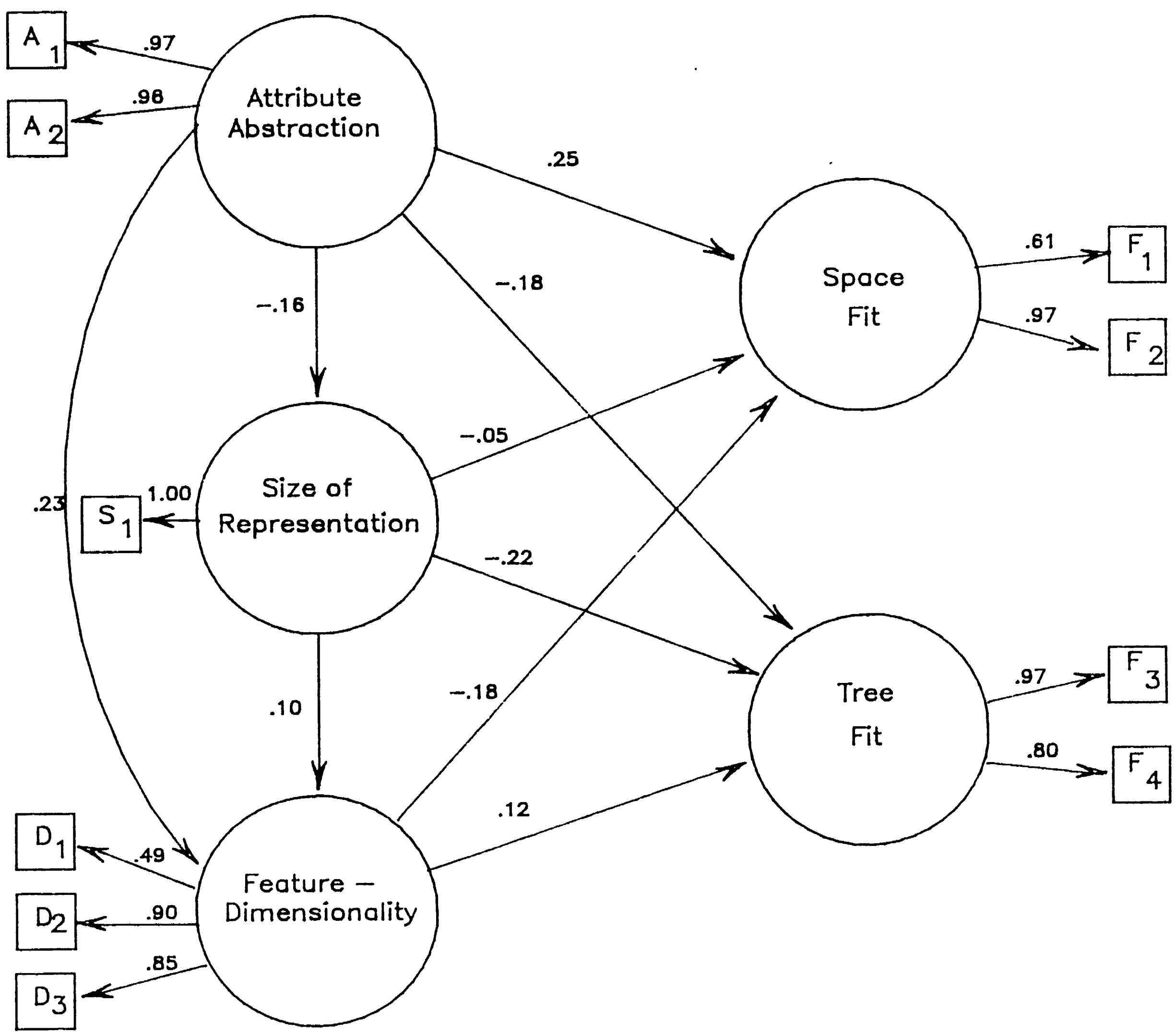


Figure 3
The Methodological Implications of
Cognitive Representations



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