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A STUDY OF CONSUMERS' COGNITIVE STRUCTURE FOR CIGARETTE BRANDS*

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I. INTRODUCTION

In its unrelenting effort to assist consumers in their attempts to make rational decisions, *Consumer Reports* regularly publishes product performance data and product characteristics in the form of long lists of attributes.[1] Each one of a set of alternatives under consideration takes on some value along these attributes. This list, plus accompanying evaluative comments, presumably provide a basis upon which the consumer can make his decision.

Is such a presentation actually useful to the consumer? Can he consult his thirty-six-dimensional utility function for automobiles and determine which auto vector yields maximum utility? Can the human decision maker deal with this degree of complexity, given his demonstrably limited capacity to notice, to remember, and to compute?[2] How *do* consumers compare and evaluate multidimensional alternatives?

The purpose of this paper is to present a methodology that may be useful in finding empirical answers to these important questions. In presenting this collection of theoretical and analytical tools, we shall use some "real" data, but due to limitations set forth below, the reader should bear in mind the fact that this paper is intended to be a methodological contribution, not an empirical investigation.

Our study is limited to certain people —students in a marketing class; to certain alternatives—fifteen brands of cigarettes; and to certain choices—judgments of similarity and preference. It is further limited by the fact that it is based not upon real choices, but upon questionnaire responses. However, the methodological approach presented here may be applied to a wide variety of decision-making situations, and may therefore be of some usefulness to marketing research.

The theoretical position taken here is as follows: A set of alternatives can be represented as a set of points in a multidimensional space. In that same space there exists for each individual an ideal object (i.e., one that, if it existed, would always be preferred to all other objects). The individual's preference ordering of

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[1] For electric ranges, eleven attributes were used; for lawn sprinklers, four; for automobiles, thirty-six, with eighteen additional safety-related attributes (*Consumer Reports*, 1967).

[2] The limits on human processing capacity are well documented. For data and theories, see G.A. Miller, "The Magic Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information," *Psychological Review* 63 (1956): 81–97; R. N. Shepard, "The Analysis of Proximities: Multidimensional Scaling with an Unknown Distance Function. I and II," *Psychometrika* 27 (1962): 125–40, 219–64; H. A. Simon and Allan Newell, "Information Processing in Computer and Man," *American Scientist* 52 (1946): 281–300; D. B. Yntema and G. E. Mueser, "Remembering the Present State of a Number of Variables," *Journal of Experimental Psychology* 60 (1960): 18–22; J. R. Hayes, "Human Data Processing Limits in Decision Making," Technical Documentary Report no. ESD-TDR-62-48, July 1962 (Washington, D.C.: Government Printing Office).

alternatives is simply the inverse of the ordering of distances in the space from the ideal object to all alternatives. The number of dimensions in the space will in general be low (three or fewer) due to the capacity limitations of humans. This position and its similar predecessors have been discussed in more detail elsewhere.[3] In the next section we present a brief formal statement.

II. DEFINITIONS AND THEORY

The psychological space, E, of the decision maker consists of a set of multidimensional objects S, and an ideal multidimensional object O'. A decision consists of the identification of an object in E by the decision maker as being closest to, or most similar to, his subjectively perceived O'. The objects in S and the ideal object O' are composed of many attributes (or dimensions, factors, components, etc.).[4]

For most decisions, no object in E exactly matches O'. If there is an object that is closest to O' on all dimensions, then it is the most preferred or most suitable object. However, the characteristic of most decisions that makes them nontrivial is the fact that different objects are closest to O' along different dimensions. The decision maker must assign to each of the alternatives a number or label according to its overall distance from O'. This is functionally equivalent to mapping some of the multidimensional objects from E into either the set of reals or a set of equivalence classes. The object that obtains the minimum value from the evaluation process is the selected object. The equivalence classes may be as simple as an accept-reject dichotomy, in which case the ideal object is equivalent to a set of acceptable levels along each attribute.

We postulate some evaluation function $F(S_i - O')$ that yields a measure of the proximity of the ith alternative to O'. That is, in a choice between alternatives S_1 and S_2, the decision maker chooses the S_i that minimizes $F(S_i - O')$, $i = 1, 2$; where O' is the ideal object and F is the *preference evaluation function*.

We further postulate a *similarity evaluation function* that is the same as the preference evaluation function. If two pairs of alternatives, (S_a,S_b) and (S_x,S_y), are judged as to relative similarity, the decision maker will designate pair (S_a,S_b) as more alike than pair (S_x,S_y) if $F(S_a - S_b)$ is less than $F(S_x - S_y)$.

We can test this position by empirically obtaining both similarity and preference data on a set of alternatives. The two measures should be related in

[3] The work described in this paper is an extension of David Klahr, "Decision Making in a Complex Environment," *Management Science* 15: 595–618, and represents a synthesis of a theoretical position first posited by C. H. Coombs in "A Method for the Study of Interstimulus Similarity," *Psychometrika* 19 (1954): 183–94, with extension by J. F. Bennett and W. L. Hays in "Multidimensional Unfolding: Determining the Dimensionality of Ranked Preference Data," *Psychometrika* 25 (1960): 27–43, and a data-analysis procedure developed by Shepard (n. 2 above) and by J. B. Kruskal in "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis," *Psychometrika* 29 (1964): 1–27, and "Nonmetric Multidimensional Scaling: A Numerical Method," ibid., pp. 28–48.

[4] In this paper, we use both vector notation and attribute-value notation for describing the objects. The latter is convenient when we explicitly want to name the dimensions under consideration. Thus, we might describe an object as $X = (a_1:v_1, a_2:v_2, \ldots a_n:v_n)$, where the a's are names of attributes and the v's are values of those attributes. These values can range in specificity from ratio scales to equivalence classes. For example, a personnel selection decision might have $O' =$ (age: mid-40s; sex: male; IQ: 129; experience: over twenty years; . . .). For preferences for automobiles, we might have $O' =$ (top speed: 90 mph, cost: O, color: red, . . .). In most empirical work on decision making, O' has the attributes of probability, payoff, and events.

the following way: From the set of similarity measures we can construct a spatial configuration in which each point in the space represents one of the alternatives, and in which the points are arranged so that the inverse rank order of interpoint distances in the space corresponds to the rank order of similarities given in the input data. In this configuration the two closest points (i.e., least

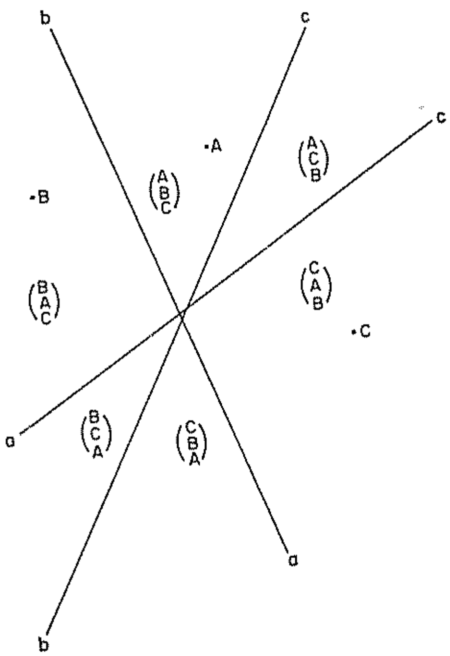

FIG. 1.—Isotonic regions for three points in two dimensions.

interpoint distance) correspond to the two alternatives that were judged most similar, the two points farthest apart correspond to the two alternatives that were least similar, etc. Because we postulate a limited capacity, we expect the number of dimensions in the space to be very low.

Assume that we have obtained such a *similarity*-generated configuration; what should we expect to find when we compare this similarity configuration with the *preference* data? If we locate the ideal object in this same space, we should find that the preference ordering of the alternatives is directly related to the ordering of distances in the space from the ideal object to each alternative. For prediction of preferences we need only a set of similarity judgments and the specification of the ideal object. We describe such an approach in the next sections.

III. ISOTONIC REGIONS: THE RELATIONSHIP BETWEEN PREFERENCES, SPATIAL CONFIGURATIONS, AND IDEAL BRANDS[5]

Suppose that through some procedure we have obtained what is considered to be an accurate representation of a consumer's cognitive structure for a set of brands. Assume that this structure can be represented as a set of points in space, where each point represents one brand, the dimensions represent the important attributes or factors, and the position of each point represents its value on each attribute. If we are correct in stating that preference is simply a function of distance from the ideal brand O' to all other brands, then it is possible to locate the ideal brand, based upon a preference ordering of all existing brands.

Consider the two-dimensional configuration of three points—A, B, and C—shown in figure 1. Suppose that we know that this represents the psychological space of a subject for these three brands. Suppose that the subject's preference ordering for the three brands is ACB. In what region of the space must O', the ideal brand, be located? The preference order requires that the distance from O' to A be less than the distance from O' to

[5] Part of this discussion is based upon a much more general presentation by Bennett and Hays (n. 3 above). Their purpose was to extend Coombs's unfolding technique to multidimensional spaces. Figure 2 of this paper is taken from their figure 6, p. 41.

C. Since the line ac is the locus of points equidistant from A and C, O' must be above ac. Since ba is equidistant from B and A, O' must be to the right of ba; similarly O' must be to the right of cb. Thus, given the preference order ACB, O' must lie in the region $\begin{pmatrix} A \\ C \\ B \end{pmatrix}$ in figure 6. The other five preference orderings determine other regions for O'. Notice that the original brands must not necessarily lie in the same region as O'. If we could manufacture a brand that lay in this region it would always be preferred to the other three brands.

This analysis can get complicated very quickly. In figure 2, we show the location of O' implied by preference ordering for four points in two dimensions. Notice that there are only eighteen regions even though four objects can be ordered in four! = twenty-four different ways. In general, in less than $n - 1$ space all $n!$ orderings are not possible.[6] If certain forbidden orderings occur, the spatial representation is inconsistent with the preference ordering. Bennett and Hays use this fact to construct the spatial configuration on the basis of preferences rather than similarities.

Our ultimate purpose in this research is to construct a spatial configuration based upon *similarity* and then to locate the ideal brand from a set of preferences. Such an effort requires two stages. First, we must test the assumption that preference and similarity judgments occur in the same space. Second, we must demonstrate that the ideal object, when offered as an alternative, actually is preferred to all others. The remainder of this paper is devoted to the first objective. The second remains to be pursued.

[6] See Bennett and Hays.

IV. CONSTRUCTION OF THE SPATIAL CONFIGURATION: NONMETRIC MULTIDIMENSIONAL SCALING

The approach used here is to require only the simplest kind of judgments from the subject, but to require many of them. Subjects are asked to classify all $[n(n-1)]/2$ pairs of n objects according to an eight-point scale of similarity. Thus the basic decision made by subjects is of the form "X and Y are more alike than P and Q." The exact procedure is described in detail in Section V.

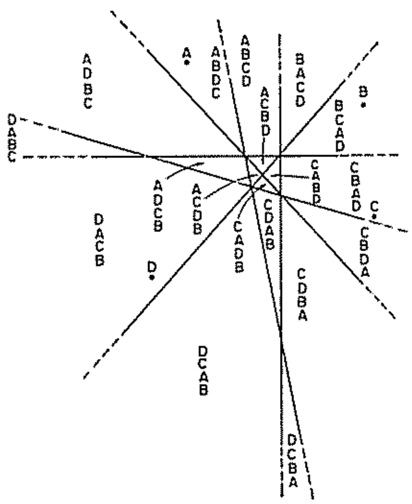

FIG. 2.—Isotonic regions generated by four points in two-space.

The similarity judgment is precisely the thing we want here because it requires the subject to give a single response based upon all the perceived relevant attributes of the objects being compared. (Imagine for yourself the process of deciding upon the relative similarity of Ford and Chevrolet compared with MG and Triumph.) We feel that this procedure captures much of the essential difficulty in consumer decision making. That is, rather than allow endless equivocation about similarity with respect to one thing and then with respect to another, it forces a single decision about overall similarity, whatever that may mean to the subject. Furthermore, it makes only the weakest assumptions about the raw similarity data, that is, that the set of δ_{ij}'s (the perceived similarity between object i and object j) is weakly ordered.

Based upon the set of δ_{ij}'s, we attempt to arrange a set of points in a space where the n points in the space correspond to the n objects, and where the distances between the points in the space (d_{ij}'s) correspond to the similarity measures. More formally, we seek the following: a spatial configuration where the rank of the interpoint distances is maximally inversely correlated with the rank of the similarity measures. We use a procedure developed by Shepard[7] and significantly improved by Kruskal[8] called "Nonmetric Multidimensional Scaling." The procedure starts with an arbitrary configuration of points, and iteratively attempts to find some arrangement of the points in which the interpoint distances correspond to the imput similarity data.

If, in some configuration, the rank order of the interpoint distances is exactly the opposite of the rank order of the similarity measures, we have a perfect fit. As the dimensionality of the space is reduced and the solution becomes more highly constrained, we are apt to get some departures from perfect fit. Some of the distances may be "out of order." A measure of departure from perfect fit, called the "stress" of the configuration has been developed by Kruskal;[9] it is quite similar to a residual sum of squares. From an extensive series of empirical investigations on a variety of data, Kruskal suggests that departures from perfect fit (stress = 0) be interpreted as follows: 0.025—excellent; 0.05—good; 0.10—fair.[10]

The procedure finds the best fit—the minimum stress—in spaces of decreasing dimensionality. We expect minimum stress to increase as the dimensionality decreases, starting in $n - 2$ space with zero stress. The decision as to which configuration is the most appropriate representation of alternatives rests upon scientific judgment, and is not a direct output of the scaling technique. The decision depends upon the stress, the dimensionality of the space, and the meaningfulness of the final configuration.

The process is analogous to an attempt to construct a map of the United States from a table of intercity distances.[11] Given only the *rank order* of distances between all pairs of a set of cities, the nonmetric, multidimensional scaling procedure will produce a two-dimensional configuration of cities that can be overlaid on a map with each city falling precisely where it belongs. If we used major cities of the globe and straight line (through the earth) distances, the procedure would produce a two-dimensional solution with a bad fit (high stress), but a three-dimensional solution with a perfect fit (zero stress). Thus the procedure itself tells us what underlying dimensionality is consistent with the proximity measures.

This apparently magical ability to reconstruct the relative locations of cities, given only the rank order of intercity

7 See n. 2 above.

8 See n. 3 above.

9 "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis."

10 These arbitrary interpretations can be replaced by better estimates of significance (David Klahr, "A Monte Carlo Investigation of the Statistical Significance of Kruskal's Nonmetric Scaling Procedure," *Psychometrika* 34 [1969]: 319–30) and will eventually replace the criteria used here.

11 See L. A. Neidell, "The Use of Nonmetric Multidimensional Scaling in Marketing Analysis," *Journal of Marketing* 33 (1969): 37–43.

distances, derives from the fact that $n(n-1)/2$ interpoint distances are "reduced" to n points in two or three dimensions: a reduction from approximately $n^2/2$ parameters to only $2n$ or $3n$.

Extending this map analogy to the isotonic region analysis described in section 3, we can recast that problem by considering the process of locating someone who has provided us with only a rank ordering of his distances from a dozen U.S. cities.

V. PROCEDURE

A. SELECTION OF OBJECTS TO BE INVESTIGATED

It was decided to investigate a set of objects where a consumer might reasonably be expected to have an "image" of many more brands than those he used personally. For this purpose cigarettes were chosen as the objects to be studied. The primary explicit attributes of cigarette brands are size, filter, and mentholation. The implicit attributes are things like prestige, maleness, etc. It will be seen that the technique used does not distinguish between implicit and explicit attributes of objects. It leaves that decision entirely to the subject. One of the limitations of the procedure we used is that the amount of measurements required goes up with the square of the number of objects. Fifteen objects lead to 105 pairs of objects, and each of these pairs must be evaluated. Therefore, we arbitrarily chose to limit the number of objects to be investigated to fifteen—fifteen of the best-selling regular and king-sized filter cigarettes were used as the set of objects. They are listed in alphabetical order in table 1.

B. SELECTION OF SUBJECTS

Approximately fifty students in a marketing class at the University of Chicago Graduate School of Business were used as unpaid subjects. They were asked at the beginning of a class to participate in an experiment lasting about forty-five minutes during the regular class period.

C. DATA COLLECTION

The data-collection procedure consisted of measures of similarity of brands and measures of individual's preferences for brands. For the similarity part, subjects were read the following instructions:[12]

TABLE 1

ALPHABETICAL LISTING OF CIGARETTE BRANDS USED

Number	Brand Name
1	Camel
2	Chesterfield
3	Herbert Tareyton
4	Kent
5	L & M
6	Lucky Strike
7	Marlboro
8	Old Gold (Filter)
9	Old Gold (Regular)
10	Parliament
11	Philip Morris
12	Raleigh (Filter)
13	Raleigh (Regular)
14	Viceroy
15	Winston

This experiment is part of a marketing research project. We know that for most classes of products there are some brands that are quite similar to one another, while other brands are quite dissimilar. We would like to find out how you perceive the similarities and differences between different brands of a product.

The product we are dealing with is cigarettes. You are to give your opinion as to the relative overall similarity of various brands of cigarettes. It does not matter whether or not you actually smoke any of the brands to be considered; we just want your impression of how much one brand is like another.

Keep in mind the fact that your *preference* for cigarettes is not of importance here. You will be presented with pairs of cigarette brands and

[12] This procedure is based on S. J. Messick, "An Empirical Method of Multidimensional Successive Intervals," *Psychometrika* 21 (1956): 367–76.

asked to decide whether the brands are very similar or very different. You will not be judging either one brand or the other individually, but rather you will be judging the *overall similarity of one brand to the other* relative to the other pairs of brands.

You have in front of you a stack of about 100 cards with pairs of brand names upon them. All the brands are listed alphabetically on the board. You are to divide the cards into 8 approximately equal piles, ranging from high to low similarity, as follows:

1. Skim through the deck quickly to get a feel for the brands with which you are dealing.
2. Go through the deck and divide the cards into two roughly equal piles according to whether the two brands on a card are of relatively high or low similarity. Put the high similarity cards in the pile on your left; the low similarity cards in the pile on your right. Each pile should have about 50 cards in it when you are done.
3. When you have completed the first division, divide each of the two piles into two more piles of higher and lower similarity, yielding four piles. Each pile should have about 25 cards in it ranging, from left to right, from highest similarity to lowest similarity.
4. Once again, each of these piles should be divided roughly in half, according to the relative similarity of the brands. Now you will have eight piles of cards, ranging, from left to right, from highest similarity to lowest similarity. Each pile should have from 10 to 15 cards in it.

At any time you may move a card from one pile to another if it doesn't seem to belong to its current pile. Make your judgments on the basis of your overall impression of the similarity of the two brands.

Each subject had in front of him a deck of regular IBM cards on top of which was printed a pair of cigarette brand names. He had 105 such pairs with the ordering random with respect to which names appeared on the right or left, and also random with respect to the sequence of pairs. Subjects were instructed to work at a comfortable rate and to remain silent during the experiment.

At the end of the similarity judgments each subject had in front of him eight piles of cards ranging, from left to right, from high to low similarity. On top of each pile he then placed a title card. He placed a "1" card on top of the pile on his left indicating that they were the most similar pairs of cigarettes. He placed a "2" card on the second pile from the left, indicating those that were somewhat less similar than those on the left-most pair, etc., until he placed an "8" card on top of the right-most pile, indicating the least-similar pairs of cigarettes or the most-dissimilar pairs of cigarettes. He then stacked these piles into complete decks. Since the cards have identifying information punched on them, this provided a very convenient input for data analysis.

Following the similarity judgments, subjects were asked to indicate their preference for all of the brands used here. A forced-choice paired comparison procedure was used, in which the subject indicated which of each pair he preferred. Data were also collected about age, sex, smoking frequency, and unrestricted first three choices for cigarettes.

VI. ANALYSIS

A. PRELIMINARY ANALYSIS

It is obvious that nonsmokers could not intelligently fill out preference forms. However, many of these subjects could make similarity judgments even though they did not smoke, because they had some image of what brands were similar and what brands were dissimilar. It might be of interest in further studies to compare the structure of those that do not use a product but are exposed to advertising with the structure of those that do use the product. However, in this study, we decided to confine attention to the latter group. Therefore, we chose to look at the similarity and preference results for only those people who were smokers. All those who indicated that they smoked at least one pack per week within the last six months were considered to be smokers. This left us with only ten subjects out of the original forty-five.

At this point, rather than collect a larger sample of smokers, we chose to continue the analysis of this very small data set in order to develop the appropriate procedures for analysis. Due to this small sample, the substantive findings presented later must be regarded as only suggestive.

was greater than .9. For judge 45 it was .56. All the intransitive cycles that do occur are located at the bottom end of the preference ordering. In this table the italicized numbers correspond to nonfilter cigarettes. In general, a judge's preference is based primarily upon the filter-nonfilter dichotomy. This is the most obvious difference between the objects we chose to scale and, as we shall see, its effect just about overwhelms all other variation in the brand images.

TABLE 2

PREFERENCE ORDERING FOR FIFTEEN BRANDS

Judge	Rank Order														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	5	4	7	15	10	*6*	8	3	12	*1*	*2*	14	*9*	*11*	*13*
8	*11*	*1*	*2*	*6*	*9*	*13*	8	15	7	10	3	5	4	14	12
19	7	15	5	14	3	10	8	4	*6*	*9*	*2*	12	*11*	*1*	*13*
23	*1*	*6*	*9*	*2*	7	*11*	15	10	*13*	8	3	14	12	4	5
25	10	14	8	12	*9*	15	7	4	*13*	*11*	5	*2*	*6*	*1*	3
29	*6*	*2*	*1*	*9*	*11*	*13*	7	15	3	10	14	12	8	5	4
32	8	12	3	14	*13*	*9*	10	*1*	*11*	*2*	*6*	15	7	4	5
37	4	5	7	15	10	14	3	*6*	*2*	*1*	12	8	*11*	*9*	*13*
44	15	7	8	3	5	10	14	4	12	*9*	*2*	*11*	*13*	*1*	*6*
45	7	5	14	15	10	8	3	*9*	*2*	4	*6*	12	*13*	*11*	*1*

NOTE.—Italicized numbers correspond to nonfilter cigarettes See table 1 for brand identification.

B. PREFERENCE ORDERINGS

From the paired comparison we get for each judge a measure, P_{ij}, $(i < j, j = 2, 15)$, where $P_{ij} = 1$ if brand i is preferred to brand j, $P_{ij} = 0$ otherwise. We define $P_{ji} = 1 - P_{ij}$. For each judge we construct a rank ordering of brands based upon

$$\sum_j P_{ij} .$$

These derived rank orderings for the fifteen brands are presented in table 2. Although we do not present the entire P_{ij} matrix for each judge, it is clear from such matrices that the judges exhibited a high degree of transitivity. For all but one judge the coefficient of consistency

C. MULTIDIMENSIONAL SCALING OF SIMILARITY MEASURES

The sorting of pairs of brands into different groups according to their overall relative similarity provides us with an eight-level ordinal scale for δ_{ij}^k, the dissimilarity of brand i to brand j, as perceived by judge K. We define $\delta_{ij} = \delta_{ji}$. These sets of raw similarity were treated at two levels of aggregation.

The level of aggregation at which we treat these data depends upon the extent to which the judges are different in their perceptions of the underlying psychological space. It could be the case that the judges all "see" the brands in the same way, although they might be located in different positions in space, or the judges might see the space quite differently.

To determine the amount of correspondence among the judges we can compare either the raw similarity judgments or the spatial configurations generated by those judgments. We have made both kinds of comparisons. In table 3 we present the rank correlations between the similarity judgments of all judges. Each one of these collections of raw data was fed into the multidimensional scaling program, and for each judge we obtained a two-dimensional configuration. The more similar these two-dimensional configurations, the more reasonable it is to say that the judges see the space in the same way. Therefore, we computed the product moment correlation between corresponding interpoint distances in the spaces for each of the individual judges. The results are shown in table 4. We also included an average judge. This average judge is the result of totaling the raw

TABLE 3

INTERJUDGE RANK CORRELATIONS OF RAW SIMILARITY

Judge	Judge: 2	8	19	23	25	29	32	37	44
8	.75								
19	.72	.82							
23	.79	.80	.81						
25	.35	.38	.42	.47					
29	.72	.78	.76	.78	.24				
32	.35	.32	.35	.48	.03	.52			
37	.70	.81	.73	.79	.49	.70	.38		
44	.77	.78	.81	.83	.43	.83	.48	.80	
45	.79	.78	.78	.78	.40	.75	.33	.74	.77

NOTE.—Smokers only: Judges 2, 8, 19, 23, 25, 29, 32, 37, 44, and 45; $\bar{R}=0.63$; $\bar{R}=mW-1/m-1$; $W=\bar{R}(m-1)+1/m=.667=$ coefficient of concordance; $F=(m-1)W/1-W=18$; significant at .001 level.

TABLE 4

PRODUCT-MOMENT CORRELATIONS OF DISTANCES BETWEEN POINTS IN EACH JUDGE'S TWO-DIMENSIONAL CONFIGURATION

Judge	Judge: 2	8	19	23	25	29	32	37	44	45
8	.99									
19	.80	.80								
23	.85	.85	.81							
25	.11	.11	.15	.17						
29	.60	.60	.53	.61	.01					
32	.09	.09	.09	.17	.01	.30				
37	.77	.77	.63	.77	.19	.46	.12			
44	.79	.79	.76	.83	.12	.66	.20	.71		
45	.99	.99	.80	.85	.12	.60	.09	.77	.80	
Average	.99	.99	.80	.86	.12	.60	.10	.78	.80	.99

NOTE.—Smokers only: Judges 2, 18, 19, 23, 25, 29, 32, 37, 44, 45, and Average Judge.

similarity measures (the δ_{ij}'s) before scaling.[13] It is not the average of the spaces after scaling. It seems reasonable to say that all the judges except judge 25 and judge 32 made their similarity judgments in the same way. We will analyze results at both the individual and the aggregate level in the ensuing discussion.

Each judge's similarity data set was scaled by Kruskal's nonmetric multidimensional scaling program in two and three dimensions. The minimum stress in both dimensions for each judge is shown in table 5. In three dimensions it is possible to get a good fit (stress $\leq .05$ for all but judge 25). In two dimensions, only five of the ten judges can be scaled to a good fit. Notice that perfect fit is achieved for judges 2 and 45, and the average judge in two dimensions. In fact, for judge 2 it was possible to get a perfect fit in one dimension.

Recall the interpretation of perfect fit. It means that it is possible to arrange the points in the space such that for all similarity measures (δ_{ij}'s) and all interpoint distances (d_{ij}'s), if $\delta_{ij} \leq \delta_{a,b}$, then $d_{ij} \leq d_{a,b}$. A perfect fit in one dimension means that it has been possible to arrange all 15 points on a line such that the interpoint distances correspond to the similarity measures.

A study of the zero stress one and two-dimensional configurations indicated that they consisted of two clusters in which the within-cluster distances were all much less than the between-cluster distances. (See table 6. The result is seen in most of the configurations, but is most pronounced in the near-zero stress cases.) One cluster corresponds to the filter brands, the other to the nonfilter brands. Although the reasonableness of such a result is somewhat gratifying, this type of clustering is precisely the situation in which the nonmetric scaling breaks down. Instead of being constrained by points distributed throughout the space, the scaling becomes two independent scaling problems, with many more degrees of freedom, This problem is not due to the fact that the subjects attended primarily to a single attribute, but rather to the fact that the most important attribute was dichotomous rather than multivalued or continuous.

TABLE 5

STRESS IN TWO- AND THREE-DIMENSIONAL CONFIGURATIONS FOR ALL SMOKERS (FIFTEEN BRANDS IN EACH CONFIGURATION)

Judge	Dimensions	
	2	3
2	.000	.000
8	.003	.001
19	.064	.040
23	.054	.013
25	.190	.114
29	.067	.006
32	.025	.001
37	.101	.040
44	.036	.026
45	.000	.000
Smoker average	.000	.000

The effect described above was so strong that it made little sense to examine the individual configurations very carefully. However, it is of interest to compare the points in each configuration with the individual preference orderings. The entries in table 6 are the distances from the most preferred brand (used here as a surrogate for the ideal brand) to all other brands. Notice that the filter to filter and nonfilter to nonfilter distances are generally much less than the filter to nonfilter distances. The distances from

[13] For each judge we want to use only the ordering of the similarity measures. Any monotone increasing transformation of a judge's similarities would not change our aggregate results for the average judge.

table 6 were ranked from smallest to largest, and for each judge rank correlations were computed between distances in the configuration and the preference orderings in table 2. The results are shown in table 7. There seems to be some weak evidence that supports our position that preference is related to distance in a spatial configuration based upon similarity. In the specific case we have here, these results say only that, in general, smokers see filters as more like other filters than like nonfilters, and that filter smokers prefer all filters to all non-

TABLE 6

DISTANCES IN TWO- OR THREE-DIMENSIONAL CONFIGURATIONS FROM MOST PREFERRED BRAND TO ALL OTHER BRANDS

PREFERENCE	JUDGE									
	2	8	19	23	25	29	32	37	44	45
Most preferred	5	*11*	7	*1*	10	*6*	8	4	15	7
Other brands:										
1	2.043	0.031	1.616	......	1.409	0.001	0.099	1.915	2.035	2.042
2	2.041	0.023	0.673	0.191	1.411	0.011	0.101	2.323	2.013	2.042
3	0.004	2.050	0.643	1.812	0.200	1.585	0.048	1.043	0.038	0
4	0.005	2.047	1.159	1.907	0.437	1.066	1.858	......	0.030	0
5	......	2.041	0.473	1.759	0.956	1.015	1.743	0.853	0.008	0
6	2.043	0.012	1.153	0.196	1.777	......	0.469	2.306	2.026	2.042
7	0.010	2.037	......	1.788	0.317	1.581	1.739	1.005	0.010	......
8	0.007	2.037	0.533	1.781	0.851	1.598	......	0.962	0.035	0
9	2.044	0.027	1.041	0.918	1.333	0.037	0.453	1.646	2.016	2.042
10	0.006	2.049	1.066	1.888	......	2.474	2.102	0.056	0.038	0
11	2.042	......	0.791	0.838	1.452	0.030	0.009	2.147	2.010	2.042
12	0.010	2.051	1.002	1.933	0.653	1.569	0.446	0.884	0.034	0
13	2.044	0.059	0.483	0.890	1.469	0.010	0.468	1.944	2.013	2.042
14	0.007	2.051	0.928	1.846	0.709	1.596	1.017	0.849	0.001	0
15	0.003	2.043	0.614	1.795	0.902	1.589	1.838	0.950	......	0
Dimensions	2	2	3	3	3	3	3	3	3	2

NOTE.—Figures rounded; 0 values represent distances < .0005. Italicized brands are nonfilters, others are filters (see table 1 for brand identification).

filters, while nonfilter smokers do the opposite (although judge 32 is clearly an exception). Since we have included two brand names as both filters and nonfilters, we see that the filter variable is more important than the brand.

TABLE 7

RANK CORRELATIONS BETWEEN PREFERENCES AND DISTANCES FROM MOST PREFERRED OBJECT IN SPACE

Judge	Preference-Distance Correlation
2	.67*
8	.90*
19	.27
23	.44
25	.33
29	.61*
32	.38
37	.49
44	.76*
45	.70*

* .05 level, 1-tailed *t*-test.

There is one additional analysis we have performed. Working at the aggregate level, we studied the "fine structure" of the clusters for the average judge. The total dissimilarities among filters only and among nonfilters only were scaled separately. For the six nonfilter brands, the stress in one dimension was 0.269, in two dimensions it was zero. The two-dimensional configuration for nonfilters is shown in figure 3. For the nine filter brands, the stress was: one dimension 0.232, two dimensions 0.087, three dimensions 0.001. The three-dimensional configuration for filters is shown in figure 4, and plotted two dimensions at a time in figures 5, 6, and 7.

These configurations can undergo any rigid translation, rotation, or uniform stretching or shrinking of axes. In fact, they have all been normalized so that the centroid is at the origin and the root mean square distance from the origin to all points is unity. *Thus the axes shown in these plots and the units on each dimension are arbitrary and have no necessary "meaning."*

The configurations are merely a summary of the similarity data. Instead of thirty-six interbrand similarity measures for the nine filters, we have a plot of nine points in three-space. The greater the number of points and the lower the dimension of the space, the more parsi-

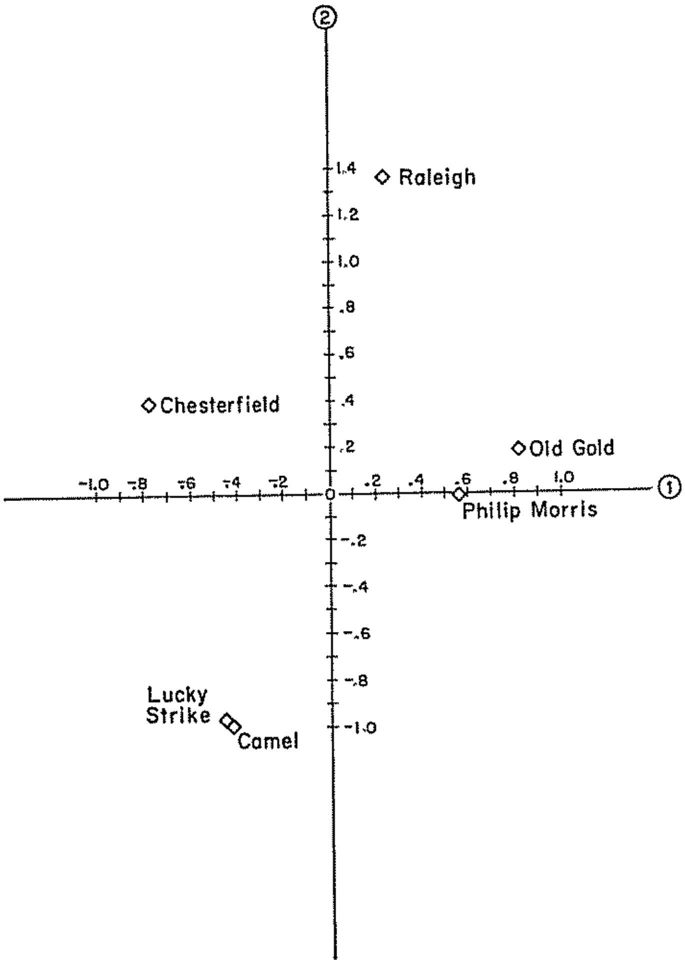

FIG. 3.—Nonfilter cigarettes, smoker average

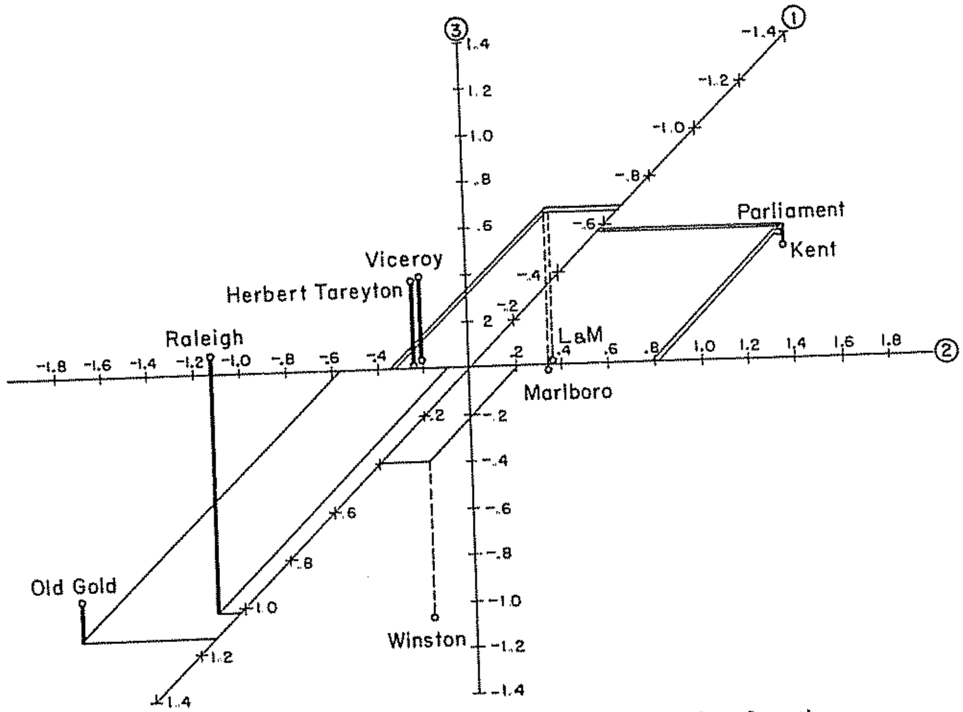

FIG. 4.—Filter cigarettes, smoker average. Three-dimensional configuration

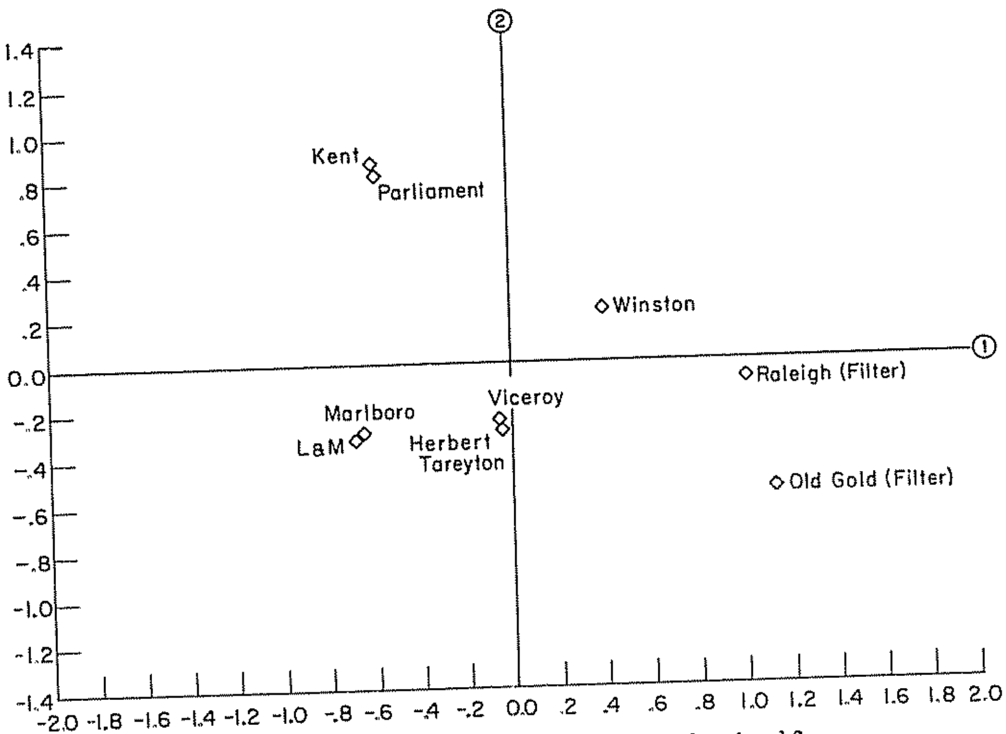

FIG. 5.—Filter cigarettes, smoker average, dimensions 1 and 2

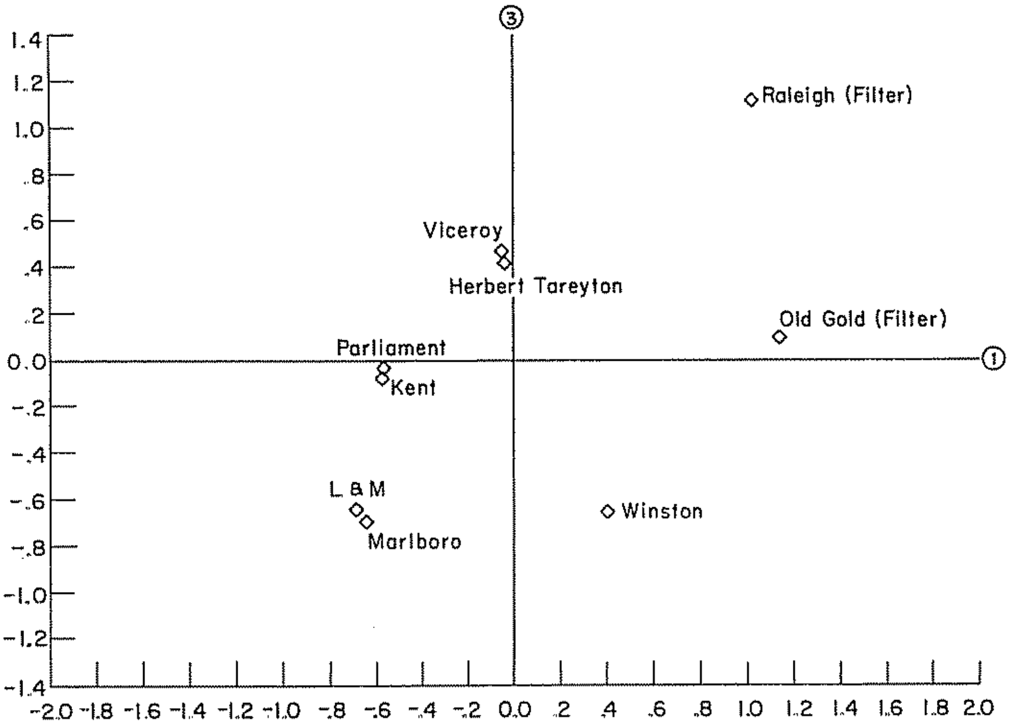

FIG. 6.—Filter cigarettes, smoker average, dimensions 1 and 3

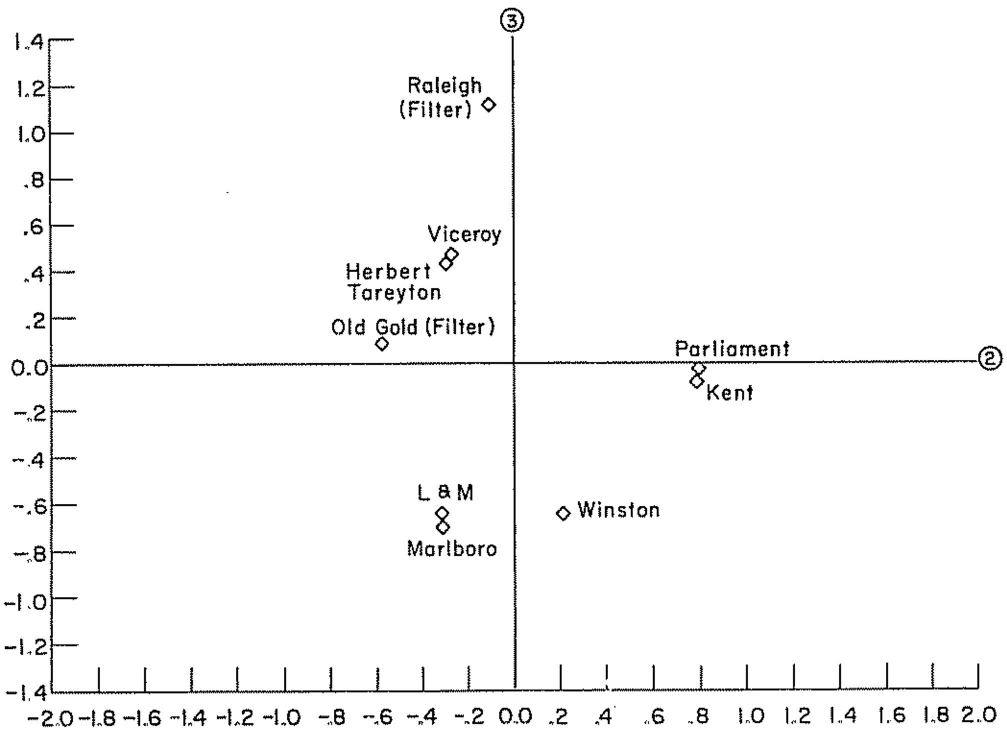

FIG. 7.—Filter cigarettes, smoker average, dimensions 2 and 3

monious is the spatial configuration than the raw-similarity data. The interpretation of the configuration rests upon information that we must provide exogenously. For example, in figure 4 we might postulate a dimension in the 1–2 plane running from Old Gold to Parliament and Kent and call it a hot-cold image. Dimension 3 might correspond roughly to an old-new image. From a behavioral point of view, we might expect the following brand switches to be more likely than any others: Viceroy–Tareyton, L & M–Marlboro, and Parliament–Kent. Similar interpretations can be made of the nonfilter configuration. However, all such interpretations would be premature if based solely upon the data presented here, due to the limitations in the data-collection procedure that have been described above.

VII. CONCLUSION

It appears to be possible to study cognitive structure through the procedures developed here. Our findings, although somewhat limited, seem plausible enough to warrant further investigation under more carefully controlled circumstances. (In particular a larger number of subjects who are smokers should be used; filter smokers should be presented with ten to fifteen filter brands, nonfilter smokers with nonfilter brands. Some measures of reliability should be obtained.) Attention to attributes does appear to be limited to two or three dimensions, both for preference and for similarity judgments. Furthermore, it is possible to predict an approximate preference ordering based only upon the current brand choice and a set of similarity measures.