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A NEW MODEL FOR CONSUMER BUYING BEHAVIOR

by

MOTOKI SHIRASUKA

A dissertation submitted to the Graduate
Faculty in Business in partial fulfillment
of the requirements for the degree of Doctor
of Philosophy, The City University of New York.

1975

This manuscript has been read and accepted for the Graduate Faculty in Business in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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ACKNOWLEDGEMENT

I wish to acknowledge the contribution of all the people and organizations that directly or indirectly made this dissertation possible.

Of those most directly connected particular thanks are extended to Professor Edward H. Wolf, Professor Sidney I. Lirtzman and Professor Ronald Gatty for their work on the dissertation committee. Dr. Wolf, Professor of Statistics and Chairman of the dissertation committee, gave me useful help which improved the content and the form of this study. Dr. Lirtzman, Professor of Management and Dean and Executive Officer of the Ph.D. Program in Business of the City University of New York, gave me warm support and encouragement throughout the study at Baruch. Dr. Gatty, Professor of Marketing, for whom I wish to express special appreciation, gave me the deep insights and valuable research direction. He spent a great deal of time and gave invariable patience in guiding me, which enhanced this study considerably.

Sincere gratitude is extended to Dr. Russell I. Haley, who kindly served as an outside reader and gave his constructive and critical remarks concerning this study.

I am grateful to the education which directly influenced this dissertation : University of Tokyo, University of Illinois (Urbana-Champaign) and City University of New York. To University

of Illinois and City University of New York which provided me with financial aid all through my studies in the U.S., I am deeply indebted.

Recognition is given to our families for their patience during the time spent in my pursuing the graduate studies in a foreign country.

Finally, my greatest debt is to my wife Keiko. She deserves an important share of the recognition of the dissertation. This study was only made possible due to her cheerful patience and continuous encouragement as well as her indispensable secretarial assistance.

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PROPOSITION OF THIS STUDY

Preface

It is the purpose of this dissertation to introduce a new approach to the modelling of consumer brand-choice process. Through the use of a small empirical study it will be demonstrated that the new approach is feasible in practice and may be applied to broad aggregation of consumer populations and to many product markets.

The dependent variable to be "explained" is the choice of brand which, over a population, may be summarized as a matter of a brand's share of market.

Previous research has used a great number of different independent variables but they have not been highly developed in ignoring any sophisticated measurement of consumers' perceptions of the set of competitive brands.

When consumer perceptions of the brands have been measured, it has normally been done with ordinal or at most interval scales. In this study an effort is made to "upgrade" the data to some stronger form of scale. They will be done by multidimensional scaling, a method that has not yet been fully applied to the overall consumer brand-choice process.

We are particularly concerned with the following perceptual variables :

Perceived quality of the brands
Perceived prices of the brands
Perceived dollar advertising per unit sold
Perceived market shares of the brands

With perceived price and perceived advertising, it will be possible to see to what degree there is congruence between the perceptual data and the actual corporate data. Equally important, one may compute measures of the elasticity of advertising and of the conception of quality. Rao has already demonstrated the empirical measurement of price elasticity for safety razors and electric shavers, using essentially the same methods of multidimensional scaling

It is the proposition of this dissertation that we are on the threshold of developing pragmatic models of brand choice if these new variables are introduced into the current state of the art. It is helpful to see these variables in the context of the overall constructs of modelling the consumer brand-choice process.

The organization of chapters

In Chapter 1, an overview of multidimensional scaling methods is discussed with their applicability in consumer behavior, their development, their taxonomy, and their underlying technical meanings.

Chapter 2 is devoted to describing the conceptual foundation and the scheme of the proposed model with the presentation of the hypotheses to be tested in the illustrative sample-problem. Later chapters will deal largely with this sample-problem on which we will demonstrate how the model may be used in a practical marketing situation : modelling consumer brand-choice for automobiles, for example. Data, analyses and interpretation reported here will serve not for any purposes of generalization and projection, but only to demonstrate the feasibility of such an approach with a larger, projectable sample in a pragmatic marketing context.

Chapter 3 describes the design of the data bank for the sample problem. There is a brief description of the questionnaire used to collect data from the respondents.

In Chapter 4, the common perceptual spaces for all brands are obtained after discussing the method of preprocessing the similarities data from the questionnaire. Chapter 5 is devoted to the measurement of perceived brand quality and to the tests of the hypotheses related to price and quality. In Chapter 6, the relation of advertising to price and quality is discussed. One

way of regarding allocation of advertising expenditures is proposed in this chapter.

Chapter 7 deals with the effect of consumers' disposable budget ("endowment"). The purchasing power for perceived quality and marginal utility of it are examined. The utility function will be obtained to predict the price level of brands at which consumers might find most utility.

In Chapter 8, consumers' perception, preferences and attitude are examined. Brand attributes are extrapolated beyond the respondents' present context to other, hypothetical conditions. Fundamental brand properties (underlying the attributes and derived from them) are mapped in terms of brand perception and the nature and direction of each brand property is examined. After the examination of brand properties, these basic attributes of the brand are explored and related to respondents' estimates of their past, present and possible future views.

In Chapter 9, the possibility of market segmentation is demonstrated by checking upon the commonality of perception and preference. Consumers' characteristics data are examined to find homogeneity for segmenting consumers. In Chapter 10, the market shares of brand are predicted by consumers' proximity-preference perceptions. A stochastic model is employed to predict consumers' purchase probabilities.

Chapter 11 presents a summary of findings, discusses the limitation of the study, and considers implications for possible future research.

CHAPTER 1
MULTIDIMENSIONAL SCALING METHODS

Summary

This first chapter gives some background to multidimensional scaling as it is used in this study. In data analysis and interpretation, the particular advantage is in achieving interval or ratio-scale data (which is desirable for analysis) from lower-order data which is more readily obtained from respondents.

At the same time, we determine any underlying structure in the data and can represent that structure graphically or mathematically.

The various types of multidimensional scaling are outlined and briefly explained, pointing up the key features of each major algorithm in commonly available computer programs that were used in this study.

The applicability of multidimensional scaling techniques to
consumer buying behavior

According to Shepard's description (75) , the purpose of these techniques is to determine what structure may lie hidden in our empirical data and to represent that structure by visual presentation. Therefore, the techniques employ a geometrical model or picture. In the perceptual space the stimuli are represented by points such that the significant features of the data about these stimuli are revealed in the geometrical relations among the spatial points in multidimensional space. A model to employ these techniques is able to deal with the situations where the multi-brands positions may be simultaneously presented by points or vectors with respect to their attributes and analyzed for consumer attitudes toward brands.

Consumer buying behavior should be studied with a consideration of a wide range of sociological and psychological constructs such as perception, preferences and attitude. Much of the behavior that interests researchers is a consequence of a complex infusion of many variables, and as such it is multidimensional in nature. The unidimensional approach is too limited in its scope, since it fails to obtain a full and accurate description of complex phenomena. As Gatty says, "For the purposes of marketing research or any other applied field, most of our tools are, or should be, multivariate. One is pushed to a conclusion that

unless a marketing problem is treated as a multivariate problem, it is treated superficially (32)."

In order to develop a programatic model of consumer behavior with good explanatory and predictive power it becomes necessary to use a set of appropriate measures of consumer perception, preferences and attitude toward a set of objects such as brands. Traditional multivariate statistical models are usually limited in the sense that the measurement scales has restrictive assumptions. Therefore, it becomes useful to find a method of converting ordinal scores (which are considered inherent to cognitive data) into cardinal scales or metric scales of either the interval or ratio type. Thus we incorporate the constructs for cognitive processes of perceptions and preferences into a consumer behavior model (69). Multidimensional scaling techniques can be expected to handle these situations.

Development of multidimensional scaling

Multidimensional scaling is a relatively new methodology, having become available in the last several years. However, its original concept might be date back to 1860s. G. Fechner attempted to measure mental energy and compare it to physical energy. He developed a relationship (Fechner's Law), relating a psychological response to a stimulus by means of a logarithmic function (31).

Three major phases could be pointed out for the development of multidimensional scaling. The first of the three major phases in the development of this scaling is referred to as the "classical" or "metric" approach. Torgerson first achieved a generally workable method of multidimensional scaling. In his 1952 work (80), he described several analytical procedures for multidimensional scaling. When a subject's perception of the stimuli was measured, it was done with interval scales which, by definition, have no "zero point". He estimated an unknown constant to convert these relative distances into absolute distances. He determined the dimensionality of the psychological space and obtained the projections of stimuli on the axes of the space by accounting for these absolute distances. In his 1958 work (81), which has long been regarded as the classical treatment of theory and methods of scaling, he described the state of the art of psychological measurements from Fechnerian psychophysics to the then

recent development. However, his way of approach was specified by a rather rigid requirement. That is, the underlying structures of a set of stimuli in the perceptual space should be absolutely known. The metric information in terms of proximity was assumed to be a rigid linearity between the stimulus pairs and the distances between the stimuli in the psychological space.

The second phase began with the concept of "unfolding" models by Coombs in 1958. He developed a new type of scale in which the problem of an equal-interval unit of psychological measurement was avoided. This new scaling was called "ordered metric" and the concept logically falls between an interval scale and an ordinal scale (23). However, this approach considered only non-metric output of only one dimension. His students, Bennet and Hays continued to generalize Coombs' unfolding technique to the multidimensional case. They expanded the theory to more than one dimension in 1961, but they still treated the output of only non-metric scales (7).

The third phase came with the development of the "nonmetric" variety of multidimensional scaling. Shepard applied this approach to the analysis of ranked data by the degree of proximity. He determined the minimum number of dimensions related to the original proximity measures by specifying a monotone distance function. He derived metric output from nonmetric input and recovered a ratio-scaled set of interpoint distances by the aid of a computer program (73). His procedures have given a substantively prac-

tical technique to practitioners.

His mathematical colleague Kruskal contributed to Shepard's approach in conceptual and computational improvement. He established a set of procedures to find the dimensionality of the psychological space by providing a criterion (which is called Kruskal's "stress" measure) which optimizes the goodness of fit of the derived measures to the original input data through a multidimensional algorithm. (See p. 15.)

To deal with data of increasingly diverse types, the Bell Telephone Laboratories have developed numerous methods which are derived from these new approaches mentioned above. J. D. Carroll, J. J. Chang, S. C. Johnson, L. Guttman, F. Young, and others have contributed especially in the development of algorithms of multidimensional scaling techniques.

Taxonomy of multidimensional scaling methods

Multidimensional scaling methods can be classified in many ways. The differences of approaches are quite natural from the nature of marketing research strategies which deal with behavioral data. The approaches differ in the scaling of similarities data (more generally called "proximities" data) as well as in the scaling of preference data (or "dominance" data). One of the classifications is proposed by Green and Rao in their book (35).

There are three important choices in determining the appropriate scaling of similarities data :

1. Response construct : Overall similarities/dissimilarities responses to stimuli (e.g., brands) versus ratings on pre-specified constructs represented by specific attributes and attitude scales.
2. Treatment of subjects : Aggregate or group data versus disaggregate or individual differences.
3. Scaling method : Metric scaling model versus nonmetric scaling model.

For the response construct, direct judgments of overall similarity/dissimilarity are obtained in the perceptual space and the stimuli are jointly represented in it to evoke the appropriate frame of reference. If prespecified attributes are used, derived measures of similarity/dissimilarity are presented in the perceptual

space by calculating conditional scores of each stimulus pair on the prespecified constructs.

For the treatment of subjects, similarities data are averaged across individuals as input, where perceptions are assumed homogeneous for members of the group.

On the other hand, differences among individuals as well as stimuli may be considered for the analysis. The differences in similarities data are observed for different points of view in terms of the evoked dimensions, their relative importance, stimulus scale separations along dimensions, and/or the ordering of stimuli along the dimensions.

For the scaling method, metric models are employed when the similarities data are measured on at least an interval scale. Nonmetric models are used on the assumption that only the rank order of the similarities is known.

Three important choices can also be considered for the appropriate scaling of preference data :

1. Type of preference analysis : Preferences alone versus both preferences and similarities whose perceptual spaces are already obtained.
2. Type of representation : Point-point models versus point-vector models.
3. Scaling method : Metric scaling model versus nonmetric scaling model.

As to the type of preference analysis, a joint space of stimuli and subject points (or subject vectors) can be simultaneously presented from the preference data alone (internal preference analysis). Or, on the other hand, both similarities and preferences could be used in constructing the joint space of stimuli and subjects (external preference analysis). The subject points (or vectors) are fitted into a space which has already been obtained from a prior analysis of the similarities data.

For the type of representation, both stimuli and subjects are represented as points in a common joint-space attribute space (point-point models). As an example of point-vector models, one of Carroll and Chang's unfolding models (a vector model) assumes that a vector direction is found for each subject in the common similarities space whose scale values of preference for each brand agree with the rank order of projections on the vector by maximum correlation of stimulus points with the scale values. (See p. 18 - 21.)

For the scaling method, the same choice of metric or nonmetric approach can be applied as in the scaling of similarities data.

The underlying technical meanings of multidimensional scaling algorithms

The essence of multidimensional scaling methods is the geometric representation of stimuli or subjects by points or vectors derived from all the relations of proximity or dominance. The discussion here covers the underlying meanings and objectives of algorithms which were used in this study.

(a) Models for analysis of similarities data

The major model used in the analysis of similarities data is the distance model, where psychological space is, as in this study, assumed to be Euclidean in nature. Intuition to judge similarity can be connected to the notion of distance. For example, if coffee is considered more similar to tea than to milk, we can assume the distance between coffee and tea is shorter than the distance between coffee and milk. The model assumes that partial similarities do not depend on the actual location of the points but only on their absolute differences, dimension by dimension. When a spatial representation of a set of similarities data is obtained, the interpoint distances are considered to be ratio-scaled. The axes of the configuration are assumed to be interval scales with a common unit.

Various scaling algorithms are available for portraying similarities as relations of points in geometric space. The basic objective of the algorithms is to seek the lowest possible dimensionality which is monotonically consistent with the input data. This is achieved through finding a good configuration in that the ranks of its distances approximately reproduce the input ranks* (33, 50, 53). The criterion used for obtaining a good configuration of coordinates is one of minimizing the regression function called stress (S) given by

$$S = \sqrt{\frac{\sum_{i \neq j}^n (d_{ij} - \hat{d}_{ij})^2}{\sum_{i \neq j}^n (d_{ij} - \bar{d})^2}}$$

where \hat{d}_{ij} is a set of ratio-scaled numbers, chosen to be as close to their respective d_{ij} as possible, subject to being monotone** with the original measure of similarity R_{ij} between pairs of stimuli i and j . \bar{d} is the mean distance. The \hat{d}_{ij} take on the role of fitted values in the monotone regression procedure. Perfect fit will result if all the points fall on the monotone function, and S , then, equals 0. If the stress S of a particular configuration is high, then the monotone fit is poor.

* See p. 226 - 228 in Appendix for further explanation.

** Monotonicity in Kruskal's stress measure means $\hat{d}_{ij} \leq \hat{d}_{kl}$ whenever $R_{ij} < R_{kl}$ $\begin{matrix} i=1,2,\dots,n-1 \\ j=2,3,\dots,n \end{matrix}$

The algorithm to scale similarities data used in this study was Carroll and Chang's INSCAL model* (15, 18). The INSCAL algorithm performs an analysis of proximities data that reveals individual differences among subjects in the weights they apply to a common space. This model assumes that the similarity measure is a linear function of the modified Euclidean distance**. The modified Euclidean distance for the i th individual is given by the formula

$$d_{ij}^{(i)} = \sqrt{\sum_{t=1}^r w_{it} (x_{jt} - x_{it})^2} \quad t = \text{dimension}$$

where x_{jt} is the coordinate value for the j th stimulus on the t th dimension. This formula is different from the usual Euclidean distance formula only in the presence of the weight w_{it} , representing the importance which the i th individual gives to the t th dimension of the perceptual space.

* See p. 229 - 231 in Appendix for further explanation.

** The Euclidean distance function is a special case of the Minkowski p -metric function given by

$$d_{ij}^{(i)}(p) = \left[\sum_{t=1}^r |x_{jt} - x_{it}|^p \right]^{1/p} \quad p \geq 1$$

When $p = 1$, we have the Attneave's city block metric.
 When $p = 2$, we have the usual Euclidean metric.

(b) Models for analysis of preference data only

All models based on preference alone must assume homogeneity of perception so that only differences in preference exist in the perceptual map. The models also assume that the perceived dimensions constitute the arguments of the utility function and that preferences differ across subjects. Then we may classify the major models by type of representation - distance models and vector models. Distance models assume that the preference function is monotonic with (Euclidean) distance between an ideal point and the stimuli points located in the same space. Dimensions of the joint-space are multidimensionally interval-scaled and the interpoint distance between any pair of points - ideal to ideal, ideal to stimulus, stimulus to stimulus - is ratio scaled. All vector model formulations can be viewed as special cases of the distance model in which the ideal points are assumed to extend to infinity. Under this assumption the rank order of a set of stimulus points agrees with the rank order of projections on the vector.

The algorithm for analyzing such data employed in this study was Carroll and Cheng's MDPREF model^{*}. Its basic aim is to determine the stimuli and subjects vectors from the set of dominance judgments so that rankings of stimuli will agree as nearly as possible with the estimated preference scale values of stimuli for subjects (21).

* See p. 231 - 235 in Appendix for further explanation.

Mathematically, the model assumes that stimulus points are projected onto subject vectors and that preference judgments are in agreement with these projected values as expressed :

$$\hat{s}_{ij} = y_i x'_j = \sum_{t=1}^r y_{it} x_{jt} \quad \begin{array}{l} i = 1, 2, \dots, m \\ j = 1, 2, \dots, n \\ t = 1, 2, \dots, r \end{array}$$

where \hat{s}_{ij} represent the estimated preference scale value or subjective utility of stimulus j for subject i , y_i the unit-length vector for subject i and x_j the r -dimensional vector emanating from the origin to the j th stimulus.

The problem is to determine the x 's and y 's from the set of dominance judgments so that the original measures of dominant data will agree as nearly as possible with the matrix of \hat{s} . An iterative procedure and Eckart-Young decomposition theorem are employed to accomplish this task.

(c) Models for analysis of both similarities and preference data

Carroll and Chang developed the set of preference models by a generalization of basic Coombsian unfolding model of preference (18). Subjects do not necessarily have the homogeneity of similarities judgment. Similarities judgment tends to be heterogeneous across the subjects, as does preference judgment. These unfolding models assume the heterogeneity of both similarities and

preferences across the subjects and they allow us to construct the joint-space of stimuli and subjects. This nonmetric version of the Carroll-Chang PREFMAP model assumes only that utility is monotonically related to the weighted squared distance x_j from the ideal point y_i (16, 20). The assumption above is converted to an equation

$$s_{ij} = a_i d_{ij}^2 + b_i + e_{ij} \quad \begin{array}{l} i = 1, 2, \dots, m \\ j = 1, 2, \dots, n \end{array}$$

where s_{ij} represent the scale values of preference of m subjects for the n stimuli, a_i and b_i are constraints ($a_i \geq 0$), and e_{ij} is an error term. The modified Euclidean squared distance is defined with weights as before :

$$d_{ij}^2 = \sum_{t=1}^r w_{it} (x_{jt}^* - y_{it}^*)^2 \quad \begin{array}{l} t = 1, 2, \dots, r \\ (* : \text{transformed data.} \\ \text{See Appendix p. 235 - 239.}) \end{array}$$

This squared distance is substituted into the preference scale equation above to produce the quadratic regression explaining the relationship between s_{ij} and x_{jt} .

$$s_{ij} \approx \sum_t \sum_{t'} r_{tt'}^i (x_{jt} x_{jt'}) + \sum_t b_{it} x_{jt} + c_{ij} \quad (1)$$

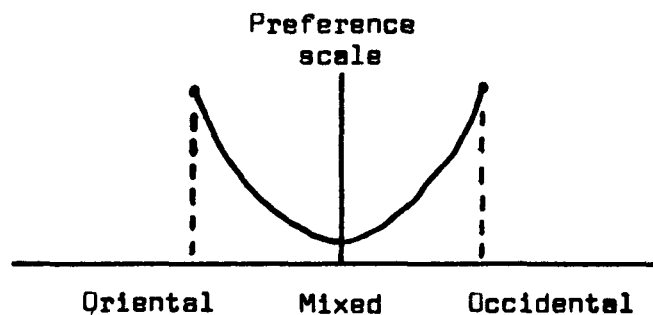
The coordinate values of x_j and y_i are solved by the models after the coefficients are estimated.

This basic monotonic assumption for the formation of the preference scale is common to all four models except for the difference in the way in which d_{ij}^2 is defined.

Both the so-called Models III and IV are employed in this study.*

Model III is a simple unfolding model and utilizes the quadratic regression procedures to estimate the scale value of preference by Equation (1) above. It allows some or all of the dimensions to have negative weight. In the positive model, preference declines with increasing distance from the ideal along each dimension. In the negative model, preference increases with increasing distance from the ideal.

Negativity of the weights w can be explained by the following example. Suppose a person loves both occidental and oriental art, but does not interest himself in a combination of the two. We define this point as the least preferred point. Then, his preference scale along the dimension of "art appreciation" may be described as the farther the art moves from the least preferred point toward the two extremes, the more preferred the art is.



* See pp. 235 - 239 in Appendix for further explanation.

Model IV is the vector model in which scale values are linearly related with stimuli and subjects' coordinates. We define the preference scale values in the product form

$$\begin{aligned} s_{ij} &\approx \sum_{t=1}^r a_{it} y_{it} x_{jt} + c_{ij} \\ &= \sum_{t=1}^r b_{it} x_{jt} + c_{ij} \quad (b_{it} \equiv a_{it} y_{it}) \quad (2) \end{aligned}$$

Equation (2) contains only linear terms. After coefficients b_{it} ($t = 1, 2, \dots, r$) are estimated, the direction cosines of the vector for the i th individual are calculated.

CHAPTER 2
THE CONCEPTUAL FOUNDATION OF THE PROPOSED MODEL

Summary

This chapter describes the scheme of the proposed model, particularly in relation to other models and relevant research in this area. In later chapters, a small-scale case study will illustrate the new approach applied to a specific market (automobiles). In the present chapter we will concentrate on the conceptual foundations, the broad approach and method.

The conceptual foundations of the model are examined by testing eight hypotheses. The analytical methods for our model are provided and the technical problems are discussed in relation to a review of the past studies which are germane to our present research.

As a dominant analytical method, a topological approach is used to examine instantaneous or transient changes in the fields of consumer perception and preferences, and to represent the constantly changing interrelationships among variables in the four morphological fields of the model. In this sense, the multidimensional scaling method is appropriately used as the tool of the topological approach. The derived measures from the multidimensional scaling method are subsequently used for the analysis by the multivariate methods.

Introduction

In the development of brand-choice models both economics and the behavioral sciences have played an important role in the understanding and analyses of the structural complexities of decision process. However, no single area of these sciences can adequately explain consumer buying behavior.

The analysis of consumer behavior in economics has been limited mostly to income and price elasticities of demand, marginal utility analysis, and consumption functions (25, 48). Demand theory has largely ignored the formation and change of consumer perceptions, tastes and preferences. Little attention is given by economists to advertising, to matters of products' status implications or brand imagery, or even to human motivation.

The revealed-preference approach to consumer behavior had begun to be studied in the post war period (42). With this movement, some econometricians have attempted to introduce revealed preferences as new variables, in addition to income. They examined the relative impact of new variables on consumer behavior by employing traditional economic theory and indifference analysis (49). Since they still continued to apply very strict conditions of traditional economic theories to their analysis, most of the results have been disappointing and sometimes even trivial (13).

Social and psychological variables began to be given increasing attention in the 1950s (47). Socio-demographic attributes such as

age, race, place of residence, education, occupation, etc. began to be considered. However, the research was still designed primarily to examine the income-consumption relations.

In 1959 Simon advised that perception and cognition should be studied in relation to consumers' decision-making and the consumers' objective environment (76). Since consumer behavior is based on how and why they behave, it is necessary to study psychological mechanisms and introduce behavioral approaches to consuming activities.

In our present study there is some effort to integrate a behavioral, psychological approach with some of the traditional variables used by economists : price-quality relationship, price-advertising relationship, propensity of consumption, price elasticity, advertising elasticity, utility analysis, and marginal analysis.

The structure of the proposed model

Our proposed model will be illustrated by a small study of eight competing brands of passenger cars in the U.S. market. It attempts to analyze the total scheme of consumer buying decision in the four morphological fields : 1. environment (brand quality, price, and advertising spent) 2. endowment (consumers' disposable budget) 3. consumer perception, preference and attitude and 4. the consumers' future buying behavior (market segments and predicted brand share).

Eight hypotheses are provided to be tested in the four morpho-

logical fields of the model to explore the basic behavioral nature of consumers. Each hypothesis will be followed by discussion of its relevance to the consumer buying behavior model.

The basic conception of the proposed model

The scheme of the model can be conceptualized by the interaction between economic, sociological, and psychological variables for consumer buying behavior. Among and within the four morphological fields of the model, dynamic interrelationships are assumed to exist. All morphological variables are in a state of change. This model adapts Kassarian's concept : "all the psychological reality changes, belief and value systems change, perception and preference change, and habits and loyalties change." No static picture of behavior is realistic (45). Therefore, the field analytical approach is conceptualized in our model in that only the resultant attitude which is existent at a given moment in time is used to explain the behavior of consumers at another moment, in their act of purchase.

In order best to illustrate the dynamic interrelationships of variables which are constantly changing or being cognitively reorganized, a topological approach is incorporated. In our model, the multidimensional scaling methods are employed for this approach in that it is a geometrical and mathematical system to represent dimensionally the stimuli by points or vectors. In addition to that, the

multidimensional methods derive the perceived measurements from the behavioral data. The multivariate methods will be used for further analysis by using the resulting measurements.

Figure 2-1 presents the overall scheme of the new model for consumer buying behavior. The relationships between and within the four morphological fields will be discussed in the following sub-headings.

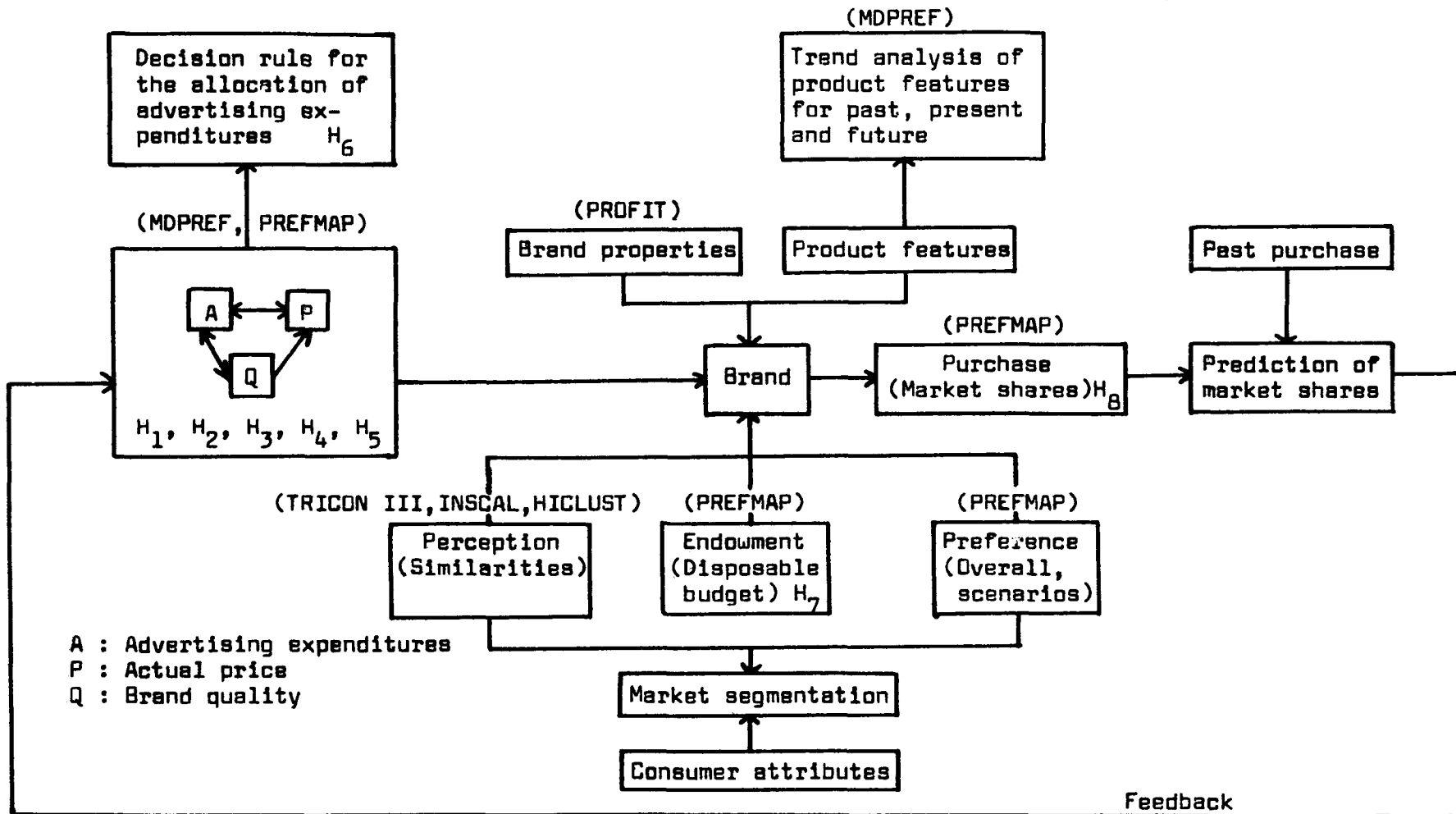
1. Environmental factors* (brand quality, price, and advertising spent)

The casual relationship of price and quality

Within the environmental factors, the proposed model attempts to form the relevant hypotheses, examining the relations between brand quality, price, and advertising expenditures, and test their statistical significance under the formation of normative models. This examination is conducted since brand quality may not always be neglected by price, and advertising may influence and change consumers' preference to provide consumers with some other judgment for brand quality.

To begin with, the existence of price-quality relationship is examined. The following hypothesis is to be tested in the proposed model.

* Availability of products or brands is also an important environmental factor. However, it is not considered in this study. We have had to limit the number of specific environmental factors in the initial study.



Note : H₁, H₂, H₃, H₄, H₅, H₆, H₇, and H₈ are hypotheses to be tested.

The words in the parenthesis are algorithms of multidimensional scaling methods to be used in the new model.

Figure 2-1 Comprehensive scheme of the new model for consumer buying behavior

H_1 : "Do consumers feel that quality of a brand with higher price is better than one with lower price ?"

The previous studies

Some of the relationships between price and quality have been previously studied (55,58). Leavitt (55), for example, using four imaginary consumer brands of products, undertook some price-quality studies. He obtained evidence that the relationship exists in relatively high-priced brands.

Emery developed a mapping method with which the price-quality relationship was evaluated by a paradigm (30) ; Subjective price scale and subjective quality scale are mapped on the same space and the line connecting these two quantity is examined. If its slope is positive, the product is judged as low-priced relative to estimated quality, and vice-versa for the negative slope. This paradigm method, however, gives no information on the degree of relationship between price and quality.

The proposed study

Our study will examine if there is price-quality relationship among such expensive durable products as car brands under a controlled survey situation.

In order to test Hypothesis 1, the MDPREF method can be used

for developing scale-rating scores of perceived quality.* This method can be used for the analysis because the derived scalar value for any brand can be regarded as an evaluative measure of quality of that brand. This scaling algorithm generates as output a geometric configuration of brand points and consumers vectors such that the projection of brand on each consumer's vector correspond optimally with the scale-rating expressed by the consumer. We can relate the value of a brand in quality space to the actual price of the brand and conduct a correlation analysis to examine how well they correlate.

The functional approach to price-quality relationship

To examine further the relationship between price and quality, the proposed model conducts regression analysis to fit the point values between the measures of quality and prices, and the following hypothesis will be tested.

H_2 : "Consumers perceive the quality of a brand as being inelastic in relation to its price."

The previous studies

For relatively inexpensive brands, some attempts to form a functional relationship between price and quality have been made.

* For the definition of perceived quality in this study, see p.60.

McConnell observed perceptual distances on quality, which are not uniformly proportionate between the price ranges. For example, \$1.30 and \$1.20 brands of beer are more separated than the \$1.20 and \$0.99 brands (63). Rao formed the function of price and quality in the product fields of razor blades and electric razors and examined the elasticity among them by employing the measurements from the INSCAL algorithm of multidimensional scaling method (69).

The proposed study

In the proposed model, the psychological transformation between price and quality is to be examined in a nonlinear form. The derived measures of quality by the MDPREF procedure are used as measures of perceived quality in this study.

The analysis is followed by examining the slopes of a nonlinear model. We will test whether or not the psychological evaluation of brand quality will be transformed by price and whether a one percent increase in price tends to contribute to more than one percent increase in brand quality. A possible price inelasticity would be evidence of non-rational buying behavior such as the purchase of a brand for prestige, social status by sacrificing a quality dimension. Reporting on consumer goods, Lambert says that consumers may choose a high-priced brand to enhance or maintain their social image (54) - a result that should hardly surprise us.

The reliability of price estimation

After we determine if there exists some price-quality relationship, we will then examine to what degree consumers' subjective estimate of price can be relied upon, as follows :

H₃ : "Can consumers correctly estimate the rank order of the brand prices and is the reliability of their estimates constant over all eight brands ?"

The previous studies

For relatively inexpensive products such as sweaters and stockings, consumers do not generally try to estimate brand price, but select a higher-priced brand as a means of reducing risk (72). However, the methods of measuring the validity of price perception are still discouraging (11, 12).

The proposed study

The proposed model examined if consumers can estimate the brand price for expensive durable products such as car brands in consumers' choice behavior. In the proposed model, price estimation is examined in two steps. First, the rankings of the estimated prices are examined to see if they correspond to the rankings of the actual

price. Second, the coefficient of variation is used as a criterion to serve as a measure of relative dispersion of the consumers' subjective price from the actual price.

Advertising expenditures and brand price-levels

The environmental factors are further studied by introducing the advertising variable. In the proposed model the advertising expenditures are first examined by the following hypothesis :

H₄ : "Consumers feel that advertising expenditures are, in general, inversely related with brand prices but they are not elastic for inexpensive car brands."

The previous studies

Borden did many studies on the effects of advertising economy. He noticed the relative importance of price and quality of brands upon advertising and studied it empirically for consumer goods in the 1940s (9). He says that one refinement of quality after another by means of product differentiation, is an effective point to stress in advertising. He found that consumers are willing to pay much higher prices for products pertaining to health and beauty when their reputation has been established through advertising.

Dorfman and Steiner studied a general model of advertising-price relationship which optimally determines a firm's profit by continuously differentiable equations (28), but they did not consider consumers' direct responses to advertising.

The proposed study

We derive the measures of perceived advertising expenditures for each brand from consumers' scale ratings for the amounts (from only a little to a great deal) they perceived as being spent. The MDPREF algorithm is used for the derivation of one aspect of the consumers' direct response to advertising. The derived scalar value for any brand can be regarded as an estimate of the advertising expenditures per car for that brand. We relate the scalar value of a brand to the actual price of the brand. Correlation and regression analysis are employed, and the elasticity of advertising expenditures is examined.

The relationship between the amount of advertising expenditures and brand quality

The proposed model examines the effects of advertising dollars on the perceived quality of expensive durable products such as car brands by the following hypothesis :

H₅ : "Consumers' estimates of the car brands' advertising expenditures are negatively related to their perception of the brands' quality."

The previous studies

Borden illustrates the influence of advertising on quality (8). He explains the importance of quality in that manufacturers' short-term advertising efforts can not recover the deteriorated image of quality once they permit apparent product quality to deteriorate. For convenience goods, it is reported that consumers feel there is a great deal of similarity among competing brands regardless of advertising ; they eventually get around to trying most competing products (10).

The proposed study

Consumers' judgments on brand quality based on their advertising perception is normatively investigated for consumer durable goods. In this study, consumers' judgment on advertising expenditures is mapped directly through the PREFMAP procedure by fitting property vectors of both actual and subjectively perceived advertising expenditures in the quality dimension of the perceptual space. The collinearity of the position of the fitted vectors is examined against the evaluative dimension of quality. The measures of cor-

relation of property vectors with quality are calculated by directly correlating the actual and perceived advertising expenditure vectors with the coordinate values on quality dimension which are derived by the MDPREF algorithm.

Congruence of subjective and actual advertising expenditures

Consumers' sensitivity to advertising is a great concern for the management. Therefore, the congruence of consumers' perception of brand advertising expenditures and actual advertising expenditures may be tested with a formal hypothesis :

H_6 : "Consumers correctly perceive the relative advertising expenditures of the brands within the evoked set of brands (the eight brands of car)."

The previous studies

In traditional economic theory, the effects of advertising on consumer response are not operationally defined because there is no way of predicting the cause-effect relationship between consumers' before-after changes in perception. Recently a number of methods of measuring advertising results have been published to investigate consumers' cognitive ability. The techniques to measure

consumers' cognition are still in most part recognition tests, and recall and association tests (58).

The proposed study

The actual and subjective advertising vectors are unfolded in the perceptual space by the PREFMAP model. The collinearity of these two vectors is first examined in the spatial relationship, and a correlation analysis is conducted to fit the values between the measures of the perceived advertising expenditures obtained from the MDPREF model and the actual advertising expenditures.

An approach to the allocation of advertising expenditures

Companies have a problem in advertising policy as to how much expenditure would be appropriate and what decision rule should be used for the allocation of advertising expenditures. The proposed model presents an approach to the allocation of advertising expenditures and creates a criterion to deal with this decision making.

The previous studies

Economic theory explains that the optimal advertising expenditures should be obtained by equating marginal revenue and marginal

cost to maximize the present value of profits from advertising expenditures. In order to accomplish this, we need both revenue (sales) and cost records. Most methods of budgeting advertising expenditures have been approached by relating advertising expenditures to profits or sales, such as some fixed percentage of sales for advertising. Schaffir and Crr proposed one method to take a fixed percent of last year's sales - the advertising-to-sales model (70). Schaffir and Crr's approach is that sales in the next period are a function of the sales in the current (base) period and the ratio of the advertising budget for the next period to the advertising budget in the current (base) period. The parameters are given specific values from the statistical analysis of the historical data. The necessity of historical data on sales and advertising puts a limitation on handling a new brand which is not previously advertised.

Sophisticated approaches have been attempted by complex mathematical formulations, or simulation techniques. Even a simplest econometric model gives us difficulty in establishing appropriate input data (77). The more sophisticated a model is, the more complicated it is (6, 7). The dynamic programming algorithm offers the convenience of handling a discontinuous function, but provides a computational difficulty rather than a conceptual one if many variables are involved (60).

All the methods above need past records on either sales, cost, or advertising expenditures. Furthermore, even though some rela-

tionships among sales, cost, and advertising are specified, they may be distorted and obscured by other factors such as price and quality changes, and even changes in market structures. The crucial point is that those factors are not necessarily an appropriate measure of the value of advertising.

Then, what is an alternative measure of the value of advertising dollars? We admit that the above methods have logical merits but they are complex and time-consuming to handle. There is also a gap between theory and practice. We know that there clearly exists a sales-advertising relationship for brands of cars (14), but more perceptual data in the consumer process should be included in the approach.

The proposed study

The proposed model attempts to provide a criterion or a decision rule for the allocation of advertising expenditures based on consumers' cognitive (perceptual) judgment of advertising on brands.

The coordinate value of a brand which the MDPREF algorithm derives from the rating scores on advertising of each brand can be regarded as measure of the perceived advertising expenditures of that brand. We choose, as a criterion, the maximum value among the ratios of the perceived advertising expenditures from the MDPREF model to the actual advertising expenditures spent for each

brand. The rationale of this approach is as follows : It is more effective for a company that consumers perceive more of its brand advertising expenditures. It is, at the same time, preferable for the company that it spends as little as possible to get the same effect. Therefore, its ratio should be maximized to get an ideal condition for the company.

By employing a new criterion, a revision of the advertising expenditures can be made to determine how much should be spent. The revised point of advertising expenditures for each brand is connected in the perceptual space. The formed curve represents the most effective advertising results based on consumers' perceptual behavior. The curve is not efficient if there is another combination with either a high measure of perceived advertising expenditures and less actual spending on advertising expenditures, a higher measure of perceived advertising expenditures and the same spending of advertising expenditures, or the same measure of perceived advertising expenditures but less spending on advertising expenditures.

2. Endowment

The endowment of consumers is here considered as the purchasing power with which consumers can buy available brands or services. This purchasing power is usually expressed by money. If the concept

of budget is introduced, the endowment represents one of consumers' behavioral constraints, which gives us an index how far consumers can satisfy their preferences by the combination of available goods or services under the budget.

In the proposed study, we examine if consumers are influenced by budgetary considerations in their brand preferences. It is reported for beer that this is the case (79). The following hypothesis is provided :

H₇ : "Consumers believe they would buy a better quality brand if they had more money."

After this is examined, consumers' utility is measured through the perceived quality and a utility function will be formed.

The previous studies

In micro-economics, the theory of consumer behavior has been developed from the early concepts of marginal utility (25). In the traditional consumer analysis, goods themselves are the direct object of utility. A problem arises, then, as to how to measure utility. The work in the empirical derivation of utility functions has been quite sporadic to date (37).

The proposed study

The proposed model will provide a method of deriving a utility function. It is important for the decision maker to obtain a utility index from the consumers' preference for brands and to satisfy consumers with the utility they need to obtain. The measures of preferences for quality are regarded as the indexes of utility.

The analytical method of the proposed model is that budgetary preference vectors representing preference rankings under the monetary constraints are fitted by the PREFMAP model in the perceptual configuration obtained from the INSCAL analysis. The measures of correlating the budgetary vectors with the coordinate values on quality dimension are assumed to represent utility indexes. The utility function is, then, constructed by mapping the brand price directly to the utility indexes.

3. Consumer perception, preference, and attitude

The components of environmental factors provide consumers with physical and social cues of the different brands. The endowment factor provides the framework of utility with which consumers spend their available money. However, for further analysis of consumer behavior, a complex infusion of other variables such as perception, preference, and attitude should be studied.

Perception and preference

The previous studies

In Nicosia's model (67), perception and preference are explained by a search mechanism. That is, internal search and external search are executed to uncover information about consumers' specific needs or wants. An evaluation mechanism starts working by interaction of all the information gathered by these searches. The identification of preferable means-ends relations enables consumers to transform their built-in attitude into motivation by psychological ordering.

The Howard-Sheth model (41) builds a perception-preference construct based on learning. The consumers discriminate brands by employing a set of criteria based on learning which they obtained from actual experiences or other information. Preference can be created at this stage by ranking brands among the alternatives in terms of their want-satisfying capacity or utility. The consumers' preference toward the brands in the evoked set is strengthened by their goal-directed behavior.

The proposed study

Consumer perception leads to perceptual grouping of the brands by proximity or similarity through visual scanning mechanism. In

searching for the similarity attributes among brands, a matching process is executed to find a measure of the brand attributes of each pair. In the proposed model, similarity is related to the formal notion of distance. That is, it is assumed that a brand is more similar to itself than it is to any other brands and the distance of the brand to itself is zero. Preference is determined by ranking brands among the alternatives in terms of consumers' satisfaction or utility. In general, the closer combination of attribute levels of brands is more preferred than the combinations which are farther away in the perceptual space.

In the proposed model, no hierarchical formation of intervening variables is assumed after obtaining the measurements on perception and preference. Accordingly, consumer reactions to the brand and the adjustment to their own reactions can not be functionally specified in our system, though Nicosia did in his model. These consumer reactions must be explained in terms of the properties that exist at the time the event occurs, since interrelationships between variables are "dynamic and constantly changing or being cognitively reorganized (46)." Instantaneous or transient changes of consumer perception or preference can be understood as changing consumers' attitudes. These changes can be studied by the feedback through repetitive use of electronic computers where the changes in the successive periods should be analyzed. Therefore, the concepts of topology and vector theory are much used in the proposed model to represent consumer per-

ception, preference, and attitude.

Consumer attitude

The formation of attitude toward a brand is made by internalization of consumers' perception and preference for the brand, consumers' attributes, and the brand's properties and attributes.

The previous studies

The Nicosia's model assumes that attitude is formed as the transformation of predisposition after the extensive means-ends evaluation. He formulates that attitude is a function of such variables as advertisement and consumers' past experience with brand. However, problems of measurement are involved in specifying the operational definitions of the variables of the model. For advertising expenditures, a metric scale can be used as a measure - dollars, while attitude and motivations are measured on ordinal scales in his model. Therefore, a problem arises when the equation comprises two different sorts of measures, one cardinal and the other ordinal. Also this problem causes us to confront the difficulty in parameter estimation and interpretation of the regression method.

In the Howard-Sheth model, the theory asks for metric information to measure attitude. The graded scale they use is assumed to have equal intervals. However, this assumption may be unreasonable for some criterion. For example, perceived taste intensity, such as sweetness can be expressed by ordinal characteristics, but not by the interval characteristics.

Haley and Gatty studied the question of interval scale and proposed the "usage-weights" method, an empiric way of determining appropriate weighting of the intervals (39). The equal interval scale assumes that "a shift of one point at the lower end of the rating scale is equivalent to a shift of one point at the upper end." However, the fact that a geometric function could be fitted to the percentage of actual brand users and the rating points led them to draw a conclusion that much greater probability of purchasing should be given to a highly favorable attitude toward a brand. They conducted an experimental comparison of attitude measures and concluded that the "usage-weights" method showed greater sensitivity and more reliable than the equal-interval scale method.

The proposed study

The multidimensional scaling methods can handle attitudes on either a nonmetric or metric scale. That is, nonmetric ordinal relations (preference rankings) are transformed to derive the output information consisting of interval scale or stronger. Guttman's

"radex" method (38), one of the multidimensional scaling techniques, indicates the possible handling of nonlinear relations existing among the underlying variables governing the phenomenon under study, while metric factor analysis asks for metric information and assumes a rigid linearity among the underlying variables. It is an advantage of the proposed model that it makes use of some algorithms of the multidimensional scaling methods.

In the proposed model, consumers' changes of perception, preference and attitude are analyzed by three approaches as follows :

1. Analysis of scenario influences* in terms of different levels of budget for the consumers' purchase of car brands and different geographical areas for living and driving (city, town, and suburbs),
2. Analysis of property vectors of brands in the perceptual mapping, and
3. Study of basic attributes of car brands.

* With soft drinks, for example, there might be different responses if they are considered as "mixers" for use with hard liquor, or are considered as drinks to be taken alone. With cars, there might be a different context if one considers them in terms of city driving or country driving. Such contexts are called "scenarios" by Green and Carmone.

1. Analysis of scenario influence : Most preference judgments can be obtained on an unstructured basis by soliciting consumers to give responses regarding overall preference. The rationale for this approach is to identify what dimensions are evoked by the consumers when they are not constrained to make comparisons along any preselected set of scales (33).

The proposed model attempts to evoke the other dimension which is not interpreted by only overall similarity for pairs of brands. This aims to conquer the weakness of the usual multidimensional scaling approach which deals with only overall similarity or overall preference - assumption of a unique ideal point. If consumers search for variety, the position of an ideal point may shift remarkably. In order to examine this multimodel preference function, the hypothetical scenarios are described to the consumers and the changes of consumer preference under several conditions can be elicited and examined. The scenario variables employed in this study are monetary constraints for purchase and types of places where the car would be used (city, town, and suburbs).

The primary input data for this analysis is the ranks of preferences for the nine scenarios concerning monetary constraints and places of residence, and the consumer perception which is obtained by coordinate values from the INSCAL solutions. The nonmetric version of the PREFMAP algorithm is employed for the analysis.

2. Analysis of brand properties : Properties and attributes of a brand may be relevant to one consumer's perception but not to another's, or the same properties or attributes may be perceived positively by one and negatively by another.

In the proposed model, the property vectors are mapped in the conjoint space of brands. That is, property vectors obtained from ratings on prespecified scales on physical, economic, and functional attributes of brands are fitted in the perceptual space for each property vector separately through the PROFIT algorithm.* The linear regression method of the PROFIT algorithm finds the best direction in the brand space for each property scale so that the projection of the brand onto the fitted vector linearly correlates in the maximum degree. The consumers' attitudes toward brand characteristics can be studied by the direction cosines of the fitted outside property vectors in the brand space.

3. Study of the basic attributes of brands : The underlying factors for future changes of brand properties are evoked by factor-analyzing brand attributes, which may affect consumers' estimates of the "expectancies" for information on brands.

In the proposed model we are interested in examining ; Can we identify the factors involved and expose their underlying structure ? Can consumer purchasing behavior be predicted from these

* See P. 244 - 246 in Appendix.

basic attributes of brands ? Can we predict the effect of attribute changes of brands and their influence on potential consumers' purchasing ? How should the future brand be designed ? What may we expect in a new brand's performance ?

In the proposed model, the "importance ratings" for the past, the present, and the future for several brand attributes are factor analyzed to find the basic attributes of brands for each time space. After principal factors are extracted, the brands attributes are superimposed onto the perceptual space by the MDPREF model. By tracing the time-series of vectors of brand attributes, we can predict what brand attributes will be sought, according to various attributes. This gives information that may allow us to predict consumers' potential behavior.

4. Perspectives of consumer buying behavior

In multi-brand companies, it may be the objective to optimize profitability by a good brand-mix strategy through an attempt to uncover segmentation opportunities. Once the market is segmented and established, the evaluation of brand position and brand strategy comes to be of paramount importance. Management can estimate the value of future performance and make decisions concerning the total marketing strategy by some overall measure of utility.

The proposed model discusses marketing segmentation and fac-

tors affecting the consumers' brand purchases based on perception and preference. This approach will identify the underlying process that best describes consumer buying behavior patterns. Following that, "next choice" behavior by later experience - repeat-purchasing and brand-loyalty - will be further studied.

Market segmentation

The previous studies

In economic theory, market segmentation is conducted by product differentiation and price differentiation in monopolistic competition. In market practice, market segmentation is customarily based on the identification and classification of demographically and socioeconomically different consumer groups (40, 65). Massey and Johnson have reported a market analysis by socioeconomic data, using discriminant analysis (44, 61). However, classification by only demographic variables and/or socioeconomic variables is no more appealing for market segmentation. Yankelovich reported that the demographic variables are in some cases outmoded for profitable segmentation and proposed new criteria for segmentation by consumer data such as aesthetic preference, attitude, motivation, and patterns of usage (24, 83). Recently, various quantitative analyses have been applied in segmenting consumers. Multiple re-

gression analysis, factor analysis, canonical analysis, econometric models have been employed, but the results from these methods are sometimes disappointing (69).

The proposed study

In the proposed model, market segmentation is based on the consumers' common perception and preference along with the dimension of their demographic data. Green and Rao have demonstrated this method for fifteen breakfast food items but the perception-preference segments found in their study were not highly associated with consumers' background characteristics (35). The reason might be ascribed to the fact that breakfast foods are relatively cheap consumer goods and are commonly used by many kinds of people regardless of their financial and social status.

In the proposed model, a method of market segmentation will be demonstrated for expensive durable goods such as car brands. It is expected that significant consumer attributes will be explored for these fairly well differentiated brands. The basic approach of Green and Rao is employed in the proposed study. That is, the space of consumers' ideal points and brand positions will be partitioned into reasonably homogeneous subspaces and then the characteristics of consumers will be identified. A subspace of consumers' homogeneous ideal points can be identified as a segment in which they show common perception and preference. If we

focus on the positions of the brands, the brands of one segment may be represented by their competitive position in the market.

The proposed model uses overall preference judgments to fit the nonmetric version of the PREFMAP model to the perceptual configurations obtained by the INSCAL algorithm. We will obtain several main clusters based upon the commonality of perception and preference. Our analysis is, then, turned to see if these cluster members are related in their background characteristics. A multiple discriminant analysis is employed for the background analysis. The component background vectors serve as a set of predictor variables.

Market shares of brands

The previous studies

A useful and common approach to obtain market shares of brands is through the use of consumer panels, where the market shares are directly estimated through data as the ratio of the total sales of all the brands in the test market. However, recent articles have avoided using dollar sales and used demand in number of units as basic data to model the market shares of brands (59, 71). Thus we avoid problems of comparison due to the changing value of the U.S. dollar. A number of market-share models by different approaches

have been reported. A simple model is that a single variable of advertising can be used to affect a company's market share. It assumes that only advertising expenditures determine the share of market gained by each of all the brands in the market (64). Among the complicated mathematical models, Schultz conducted a simultaneous equation model in which brand share proportions were obtained by regression on various decision variables such as price, advertising and environmental conditions (71). Recently psychological data have been used as decision variables for consumers' brand choice behavior. The brand awareness, attitude and attribute change toward a brand have extensively been exposed as predictive variables for market share of a brand (1, 4, 5, 26, 27). Palda presented a model whose predictor variable for the market share was awareness (68). Assael and Day examined the interaction of awareness and attitude with the market share and expressed their relationship as predictor variables of the regression analysis (2). The studies above made by psychological data may reveal some relationship between those variables and choice behavior, but their significant relationship is still under suspect (2).

The proposed study

In the proposed model, it is assumed that a realistic formation of the similarities-preference choice sequence will provide a predictive value for determining the share of brand market, and

consumers' choice behavior is hypothesized as follows :

H_8 : "Share of brand-preference measured by preference and similarity mapping correctly reflects brand-share as determined by unit sales."

To test Hypothesis 8, overall preference rankings data are submitted to the nonmetric version of the PREFMAP model to fit the perceptual configurations whose coordinate values are obtained by the INSCAL program. It is assumed in the algorithm that consumers' motivation to buy a brand can be measured as the function of the squared distance which is measured from a brand to an ideal point in the perceptual space.

Brand switching

The previous studies

Lipstein introduced the first-order stationary Markov process in brand-switching and brand-loyalty in the 1950s (57). Nicosia named a typical stochastic model (which Lipstein studied) "behavioristic" where purchase frequencies and sequences of purchase of brands were specified as input data and no other explanatory variables were included as marketing decision factors (66).

The proposed study

Nicosia noticed the importance of the probability of switching as a measure of direct experience with the brand which links upto psychological and perceptual fields by feedback loops. He argued for the possible application of Markov process to the measurement of consumers' indirect evidence about brand experience.

The proposed model studies the effect of consumers' brand switching behavior by means of preference uncertainty. The future market preferences are regarded as outcome of some probabilistic process which makes conditional predictions for the ultimate market share.

The proposed model employs the first-order Markovian process as car brand-switching model. The employment of the first-order Markovian model is justified by the following reasons which satisfy its requirements.

First, May reported that the past purchases of a particular make of automobile increase the probability of the current purchase for an automobile (62).

Second, no short-term changes in consumer buying behavior can be noticed for such durables as cars. The time interval between the purchases is in most cases more than a year. The changes in brand or product attributes are made in one year cycle due to the annual model change. In addition, the situation of the multi-brand buying rarely occurs in a given period for such expensive durables.

Thus the stationary condition is met, which is a necessary condition for the first-order Markovian process.

The initial transition probabilities of the aggregate matrix will be derived by the PREFMAP algorithm based on consumers' overall preference for brands.

CHAPTER 3
A SMALL SCALE DEMONSTRATION SURVEY

Summary

This chapter outlines an empirical questionnaire survey that provides the data to be used in illustrating the later analyses and interpretations. The empirical study was conducted only to assess and hopefully to demonstrate, the feasibility of gathering and analyzing survey data that could satisfy the requirements of the proposed approach to brand-choice modelling.

Brief description of the questionnaire

An empirical study was conducted only to assess and hopefully to demonstrate, the feasibility of gathering and analyzing survey data that could satisfy the requirements of the proposed approach to brand-choice modelling. The emphasis was on the analytical techniques rather than on the interviewing fieldwork.

For the prototype development of an automobile brand-choice model, a small sample survey (39 graduate and 47 undergraduate students) was conducted at Baruch College.

The inquiry was limited to eight brands of passenger cars considered to have a wide range of brand characteristics such as

prices, quality, advertising expenditures, and brand attributes. These characteristics would make it possible to demonstrate some generalizations as to the model of consumer buying behavior. Brand names are listed in Table 3-1. Individual responses were obtained from the questionnaire which is reproduced in Appendix (p. 217 - 225).

The questionnaire consists of eight question areas, and a brief description of each questionnaire is given as follows :

Question area 1 : Similarity judgments of brands are solicited using the n-dimensional rank ordering on all conjoint pairs of brands.

Question area 2 : Open-ended questions as to what criteria respondents used in judging similarity of brands. This should be useful for the interpretation of axes of underlying attribute-properties.

Question area 3 : The brand ratings on seven-point anchored scales for each brand are asked in order to analyze respondent's attitude toward the brands. The ratings concern price, style and appearance, dependability, frequency of repairs, availability of repair service, amount of advertising, road performance, and overall hedonic rating.

Question area 4 : Respondents' estimated ranking of the manufacturer's retail price are asked. These can be used to see to what degree the actual price and the subjective price may be congruent.

Question area 5 : Respondents' estimated rankings of the advertising expenditures per unit of each brand are asked. These can be used to see to what degree the subjective perception will be congruent with the actual advertising expenditures spent per car for the different brands.

Question area 6 : Each respondent is asked for overall preference rankings of each brand, preference rankings under five budgetary constraints of available money for car purchase, and preference rankings under different geographical situations of living and driving.

Question area 7 : The desirability of various car features are elicited for different time-periods of the respondent's life - past, present, and future. The information from this question area may be used for the examination of respondents' possible attitudinal changes through different phases of life.

Question area 8 : Socio-economic data to provide supplementary information for possible market segmentation.

The data gathered were merely intended to serve as basis to explore the opportunities and problems of implementing the proposed type of brand-choice model.

Definition of some marketing terms used in this study

Price of brand : The median of the price range for each brand was selected as the appropriate representative price for that brand.

Advertising per unit of brand : Manufacturers' spending in media advertising was considered in determining advertising spending per car. Excluded was money spent by the auto companies in corporate advertising programs, promotions and contributions by the auto companies to regional or local advertising associations (3).

Perceived quality : This is the derived measure of consumers' "overall" hedonic brand ratings.

Perceived price : This is the brand price to be estimated by consumers.

Perceived advertising : This is the respondent's estimated advertising expenditures per car before the true figure is revealed to the respondent.

The actual prices and advertising per unit for each brand are listed in Table 3-1.

Table 3-1

Brand names, prices, and advertising expenditures spent per unit.

Brand	Abbreviated notation	Price range*			Advertising per unit**
		Lowest	Highest	Median	
American	A	\$1,999	\$4,437	\$3,218	\$70.31
Cadillac	CA	5,938	11,880	8,826	28.53
Chevrolet	CHE	2,060	5,472	3,766	23.60
Chrysler	CHR	4,035	6,762	5,399	28.57
Ford	F	1,960	5,293	3,627	21.76
Lincoln	L	7,068	8,640	7,854	78.08
Toyota	T	2,056	4,425	3,241	50.27
Volkswagen	V	1,999	3,804	2,902	37.71

* Automotive News, 1972 Almanac Issue.

** Automotive News, November 13, 1972.

THE CONSUMERS' ENVIRONMENT : QUALITY, PRICE AND ADVERTISING
CHAPTERS 4, 5, 6 and 7

The consumers' environment is made up of three components in this study ; perceived quality, perceived price and perceived advertising. The interactions among these three components will be studied in the following three chapters.

After obtaining the common perceptual space for all brands from the directly judged similarities data in Chapter 4, the brand quality dimension is determined in Chapter 5 by consumers' rating scores mapped in the perceptual space. Then, Hypotheses 1, 2, and 3 for brand quality and price are tested in this chapter.

In Chapter 6, with perceived price and perceived advertising, it is possible to see to what degree there is congruence between the perceived and actual advertising expenditures. Hypotheses 4 and 5 will treat this question. Further, this study suggests a method for a decision-making rule in the allocation of advertising expenditures after testing Hypothesis 6.

CHAPTER 4
ANALYSIS OF SIMILARITIES DATA

Summary

In this chapter we determine the dimensionality of the brand space by means of the INSCAL algorithm, using as input the results of the TRICON procedure applied to directly judged brand similarities. Two dimensions suffice : expensive-inexpensive and traditionally popular brands-foreign brands.

Brands are located in this space and studied in terms of clustering, through Johnson's HICLUST program.

Introduction

This chapter is concerned with the scaling the similarities data obtained from the 39 Graduate and 47 Undergraduate students.

The conditional rank-order data* for scaling the respondents' similarities judgment require preprocessing to develop a complete order of similarities and for this purpose the TRICON III program was used (34, 36).

* The raw data are taken from Question area 1 in the questionnaire : taking each brand in turn as the reference-base, all other seven brands out of eight were ranked from 1 to 7 (most similar to least similar). This we call conditional rank ordering.

The matrices of directly judged similarities from the TRICON III algorithms were then submitted to the INSCAL model (15), and solutions were computed in two dimensions. The two-dimensional brand spaces for the Graduate and Undergraduate students (hereafter abbreviate as the G group and the U group, respectively) were tested for congruence.

In order to check the adequacy of the two dimensional solutions for the input data (original similarity), Johnson's hierarchical clustering program (43) was employed.

The flow diagram of the analysis of this chapter appears in Figure 4-1.

Formation of the direct similarities data

The 3-way data matrices were formed with the order of $39 \times 8 \times 8$ and $47 \times 8 \times 8$ by the conditional rank-order data from Question area 1. Since the conditional rank-order require the processing to derive a complete order of similarities, the TRICON III program* was used to preprocess the conditional rank-order data, which yielded a symmetric matrix of similarities for

* See pp. 240 - 241 in Appendix.

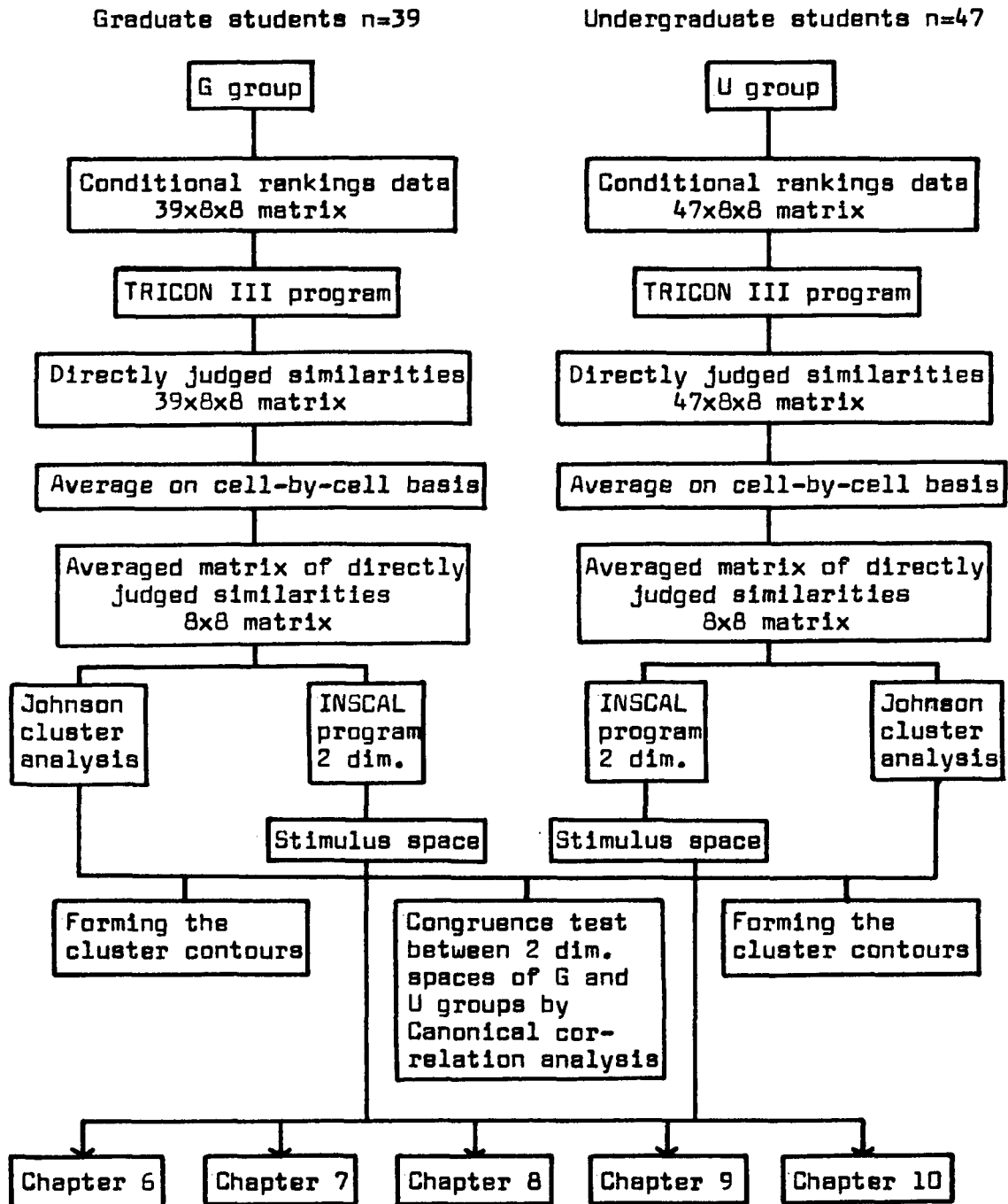


Figure 4-1 Flow diagram of the analysis outlined in Chapter 4.

each subject. The entries of these two sets of 39 and 47 subject matrices were then averaged cell by cell to obtain two sets of the 8 x 8 aggregate matrix of direct similarities.

Table 4-1 shows a tabulation of the frequency of intransitivities from the TRICON processing. Inconsistencies may occur in respondents' judging similarities among brands and these are termed "intransitivities".

Out of 168 implied comparisons*, observed intransitivities ranged from 0 to 28**. In general, the incidence of intransitivities did not exceed 10 percent.

A tabulation of the frequency of Chi-square analysis for stimulus intransitivity table appears in Table 4-2.

Out of 86 (39+47) Chi-square values, only 3 were significant at $\alpha = 0.05$ level, and all were not significant even at $\alpha = 0.025$ level as shown in Table IV-1 in Appendix. That is, in this preprocessing step by the TRICON III program, problems of intransitivities could be safely ignored at these significance levels.

For the aggregate analysis, the half-matrices of similarities were averaged on a cell-by-cell basis for both groups. The averaged direct similarities will become the input data for the analysis of this chapter. The lower half matrix of averaged direct similarities is shown in Table IV-2 in Appendix.

* The number of implied comparisons in the n-dimensional rank order procedure is given by :

$${}^n C (n-1,2) = \frac{1}{2} n (n-1)(n-2)$$

** See Table IV-1 in Appendix.

Table 4-1
Intransitivities frequency from
the TRICON III procedure.

Class interval (C)	Number of frequency	
	G	U
$C \leq 5$	25	31
$5 < C \leq 10$	11	11
$10 < C \leq 15$	2	5
$C > 15$	1	0
Total	39	47

G : Graduate students
U : Undergraduate students

Table 4-2
Frequency of Chi-square analysis for
brand intransitivity table.

d.f. = 7

Class interval (C)	P α	Frequency	
		G	U
$C \leq 2.83$	$P \leq 0.10$ $\alpha \geq 0.90$	10	6
$2.83 < C \leq 12.01$	$0.10 < P < 0.90$ $0.10 < \alpha < 0.90$	28	37
$12.01 < C \leq 14.06$	$0.90 \leq P < 0.95$ $0.05 < \alpha \leq 0.10$	0	2
$14.06 < C \leq 16.00$	$0.95 \leq P < 0.975$ $0.025 \leq \alpha \leq 0.05$	1	2
$C > 16.00$	$P \geq 0.975$ $\alpha \leq 0.025$	0	0
Total		39	47

The perceptual space from the direct similarities data

The two averaged 8×8 matrices of directly judged similarities from the TRICON III algorithm were submitted to the INSCAL program. In this run, the algorithm was set for 50 iterative computations and 0.001 criterion value for terminating the iterations.* The criterion value 0.001 was reached at the 34th and 32nd iterations in three dimensions for the G and the U groups, respectively, and at the first iteration in two dimensions for both groups. The stimulus space was found in two and three dimensions for each group. The program computed a global measure of goodness of fit : the proportion of variance in the scalar products matrix (computed from the input data) accounted for by the model - for both three and two dimension solutions.

Table 4-3 shows the percentage of variance accounted for by the INSCAL model, the average of the individual correlation coefficients between computed scores and original respondent data, and the correlations between the dimensions of the group stimulus spaces. These summary statistics were obtained from the analysis of the $39 \times 8 \times 8$ and $47 \times 8 \times 8$ matrices of the G and the U groups' directly judged similarities. The correlation coefficients for the individual subject of each group are shown in Table IV-3 in Appendix.

* The iterative computations stop when

where $\hat{Y}(I)$ is estimated Y 's on the I th iteration (15).

$$\sum (Y - \hat{Y}(I-1))^2 \leq \text{a criterion value}$$

Table 4-3

Summary statistics from the INSCAL analysis of directly judged similarities in three and two dimensions : Goodness of fit of the INSCAL model.

Measure of goodness of fit	3 dim.		2 dim.	
	G	U	G	U
Percentage of variance accounted for by the INSCAL model	86.8	87.6	78.2	75.5
Average correlation coefficient across subjects	0.932	0.936	0.884	0.869
Correlation between axes				
1 and 2	0.574	-0.641	0.574	-0.641
1 and 3	0.405	0.719		
2 and 3	0.716	-0.396		

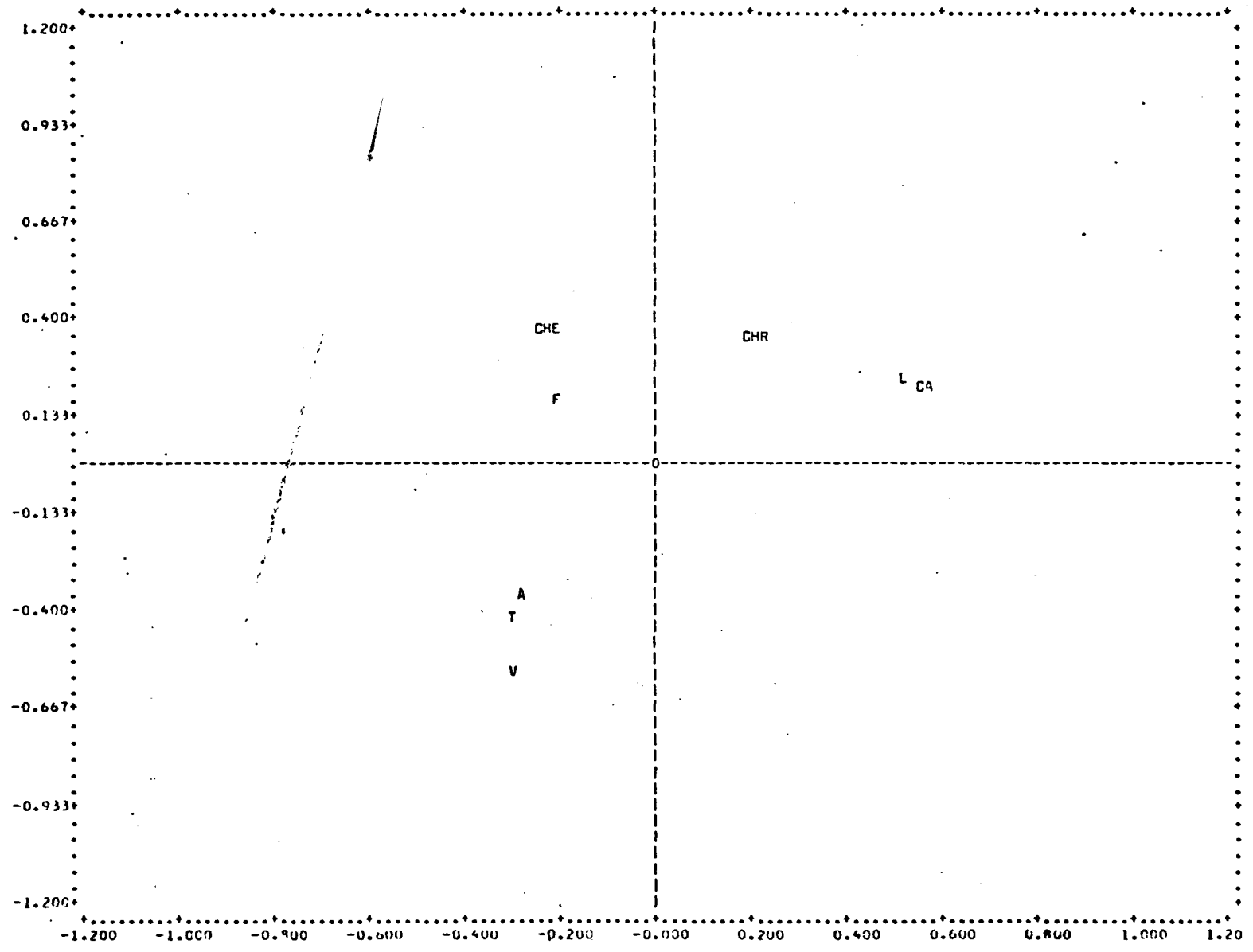
An examination of Table 4-3 suggests that some improvement of fit occurs with three dimensions rather than two dimensions. However, the improvement in goodness of fit is on the order of only 10 percentage points of variance accounted for. For parsimony and easy interpretation for our practical demonstration of the theory, further analysis is restricted to the two dimensional solutions from the INSCAL model.

The three and two dimensional stimulus coordinates are presented in Table IV-4 in Appendix. The stimulus spaces in two dimensions are shown in Figure 4-2(a) and (b).

On the configuration of the G group, the horizontal dimension appears to describe the sophisticated and expensive brand of cars. The most expensive brands like Cadillac and Lincoln are positioned at the extreme right and the least expensive brands like Volkswagen and Toyota are positioned at the extreme left. The vertical axis appears to show traditional popularity among American brands. The Chevrolet and Ford are positioned in the upper portion of the space, while recent new market invaders like Volkswagen and Toyota are located in the lower portion of the space.

In the configuration of the U group, a 90° counterclockwise rotation from the origin provides a similar perceptual configuration to that of the G group and gives the same interpretation to the U group as to the G group.

THIS IS PLOT OF DIMENSION 1 VS. DIMENSION 2 FOR TABLE NO. 2



71

Figure 4-2 (a) Two-space brand configuration from the INSCAL analysis of direct similarities for Graduates.

THIS IS PLOT OF DIMENSION 1VS.DIMENSION 2FOR TABLE NO. 2

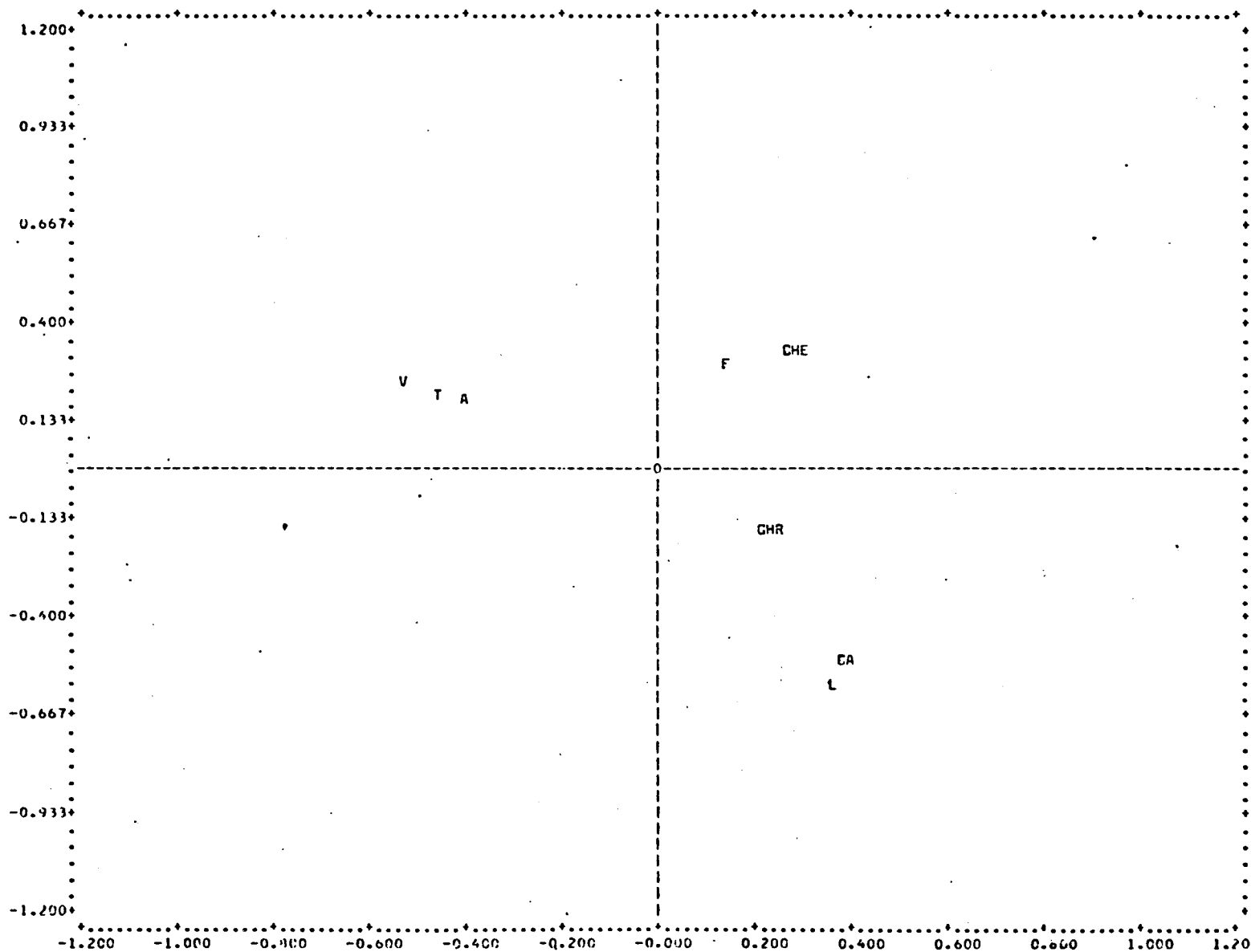


Figure 4-2 (b) Two-space brand configuration from the INSCAL analysis of direct similarities for Undergraduates.

The above dimensional interpretation is also confirmed by the subjects' response to Question area 2 - the open-ended question on the criteria used in making similarity judgments. Table 4-4 shows the frequency count of the criteria mentioned by the respondents. The criteria can be roughly classified into two factor groups - a group of price, size, style and looks, and performance (Factor group 1) and a group of cost of operation and domestic or foreign brands (Factor group 2). For the G group, Factor group 1 explains the nature of the brands along the horizontal axis, and Factor group 2 well explains that of the brands along the vertical axis. For the U group, Factor group 1 describes the nature of the brands along the vertical axis, and Factor group 2 describes that of the brands along the horizontal axis. These interpretations provide some additional support to interpret the nature of dimensions (brand attributes) in perceptual configuration.

Cluster analysis

A cluster analysis was conducted to determine how well the low-dimensional scaling solutions (two dimensions in this study) preserved the original relationships in the input data.

The averaged two 8×8 direct similarities data (Table IV-5 in Appendix) were submitted to Johnson's nonmetric clustering

Table 4-4
Criteria used by respondents in making similarity judgments.

Factor group	Criterion used	Frequency of mentions					
		G	%	U	%	Total (G+U)	%
1	Price	20	23.8	36	26.1	56	25.2
	Size	19	22.6	18	13.0	37	16.7
	Style and looks	17	20.2	28	20.3	45	20.3
	Performance	10	11.9	28	20.3	38	17.1
	Sub-total	66	78.5	110	79.7	176	79.3
2	Cost of operation	8	9.6	24	17.4	32	14.4
	Domestic or foreign	10	11.9	4	2.9	14	6.3
	Sub-total	18	21.5	28	20.3	46	20.7
Grand total		84	100.0	138	100.0	222	100.0

program (43).^{*} This method was used to obtain a series of nested clusters on the two dimensional space of the stimuli.

Figure 4-3 shows the resulting hierarchies which expressed the clusters in the form of trees obtained from the HICLUST program. In each figure the strength of clusters is given in the left-hand column. The same row gives the clusters associated with that diameter and X portions indicate clusters which contain more than one stimulus. Stimulus numbers appear in the top row.

The top row in Figure 4-3 shows a clustering with seven clusters, the set of (Toyota and Volkswagen) is one cluster, and the other six brands are themselves clusters. Cluster strength at this level is 2.08 and 2.00 for the G and the U groups, respectively. Next, we have a clustering with six clusters (Chrysler), (Cadillac and Lincoln), (American), (Chevrolet), (Ford), and (Toyota and Volkswagen) at the level of 9.92 and 9.07 for the G and the U groups, respectively. Each cluster grows with the new addition of new members as the cluster's strength (Johnson's α) increases. And, finally we have the strongest clustering which includes all brands in the same cluster at the level of 26.64 and 27.06 for the G and the U groups, respectively.

The selected cluster contours obtained from the hierarchical grouping program can be plotted in the reduced-space solutions.

* See pp. 241 - 243 in Appendix.

DIAMETER METHOD

0 0 0 0 0 0 0 0
4 2 6 1 3 5 7 8

Cluster strength

2.08 XXX	1 : A
9.92	. XXX . . . XXX	2 : CA
17.71	. XXX . XXX XXX	3 : CHE
22.99	. XXX XXXXX XXX	4 : CHR
25.44	XXXXX XXXXX XXX	5 : F
26.35	XXXXX XXXXXXXXX	6 : L
26.64	XXXXXXXXXXXXXXXX	7 : T
		8 : V

END OF METHOD

Graduates

DIAMETER METHOD

0 0 0 0 0 0 0 0
4 2 6 1 3 5 7 8

Cluster strength

2.00 XXX
9.07	. XXX . . . XXX
18.22	. XXX . XXX XXX
20.50	. XXX XXXXX XXX
25.47	XXXXX XXXXX XXX
26.86	XXXXX XXXXXXXXX
27.06	XXXXXXXXXXXXXXXX

END OF METHOD

Undergraduates

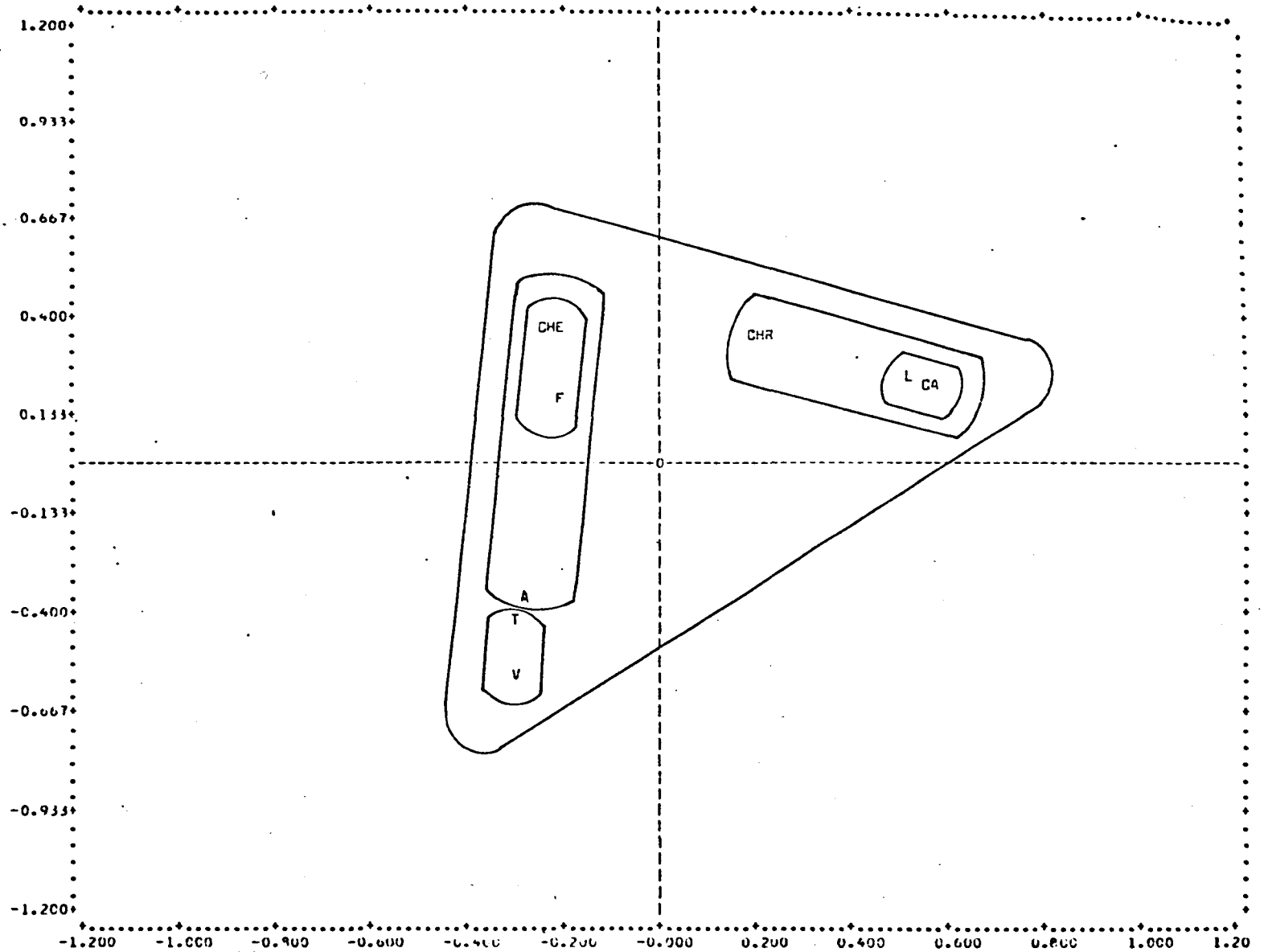
Figure 4-3 Tree diagrams by the diameter method of the hierarchical grouping algorithm for direct similarities data.

Now we can see how the original relationships have been sacrificed by the dimensional reduction to two dimensions through the scaling algorithm. The examination was made for the INSCAL solution (See Figure 4-2 (a) and (b)) by the cluster composition of the diameter option. Figure 4-4 (a) and (b) show the nested clusters of brands superimposed on the perceptual map, wherein the stronger clusters are embedded in larger weaker clusters.

Two types of clusters were obtained for each of the groups. The examination of Figure 4-3 and Figure 4-4 (a) and (b) reveals that Toyota and Volkswagen clustered first and therefore were perceived to be the most similar. On the other hand, Chrysler was different from all other brands, and tended to cluster with more expensive brands (Cadillac and Lincoln), implying that it might substitute for other expensive brands.

We found that for both groups three clusters were formed in the perceptual map based on similarities judgment ; one is a cluster of foreign cars of cheaper brands, another is a cluster of traditionally popular cars of middle-priced brands, and the other is a cluster of luxurious cars of expensive brands. The examination of these clusters also support the previous interpretation of axes in our analysis.

THIS IS PLOT OF DIMENSION 1 VS. DIMENSION 2 FOR TABLE NO. 2



7B

Figure 4-4 (a) Two-space brand configuration from the INDEAL analysis of direct similarities and the nested clusters of brands by the MICLUST program for Graduates.

THIS IS PLOT OF DIMENSION 1 VS. DIMENSION 2 FOR TABLE NO. 2

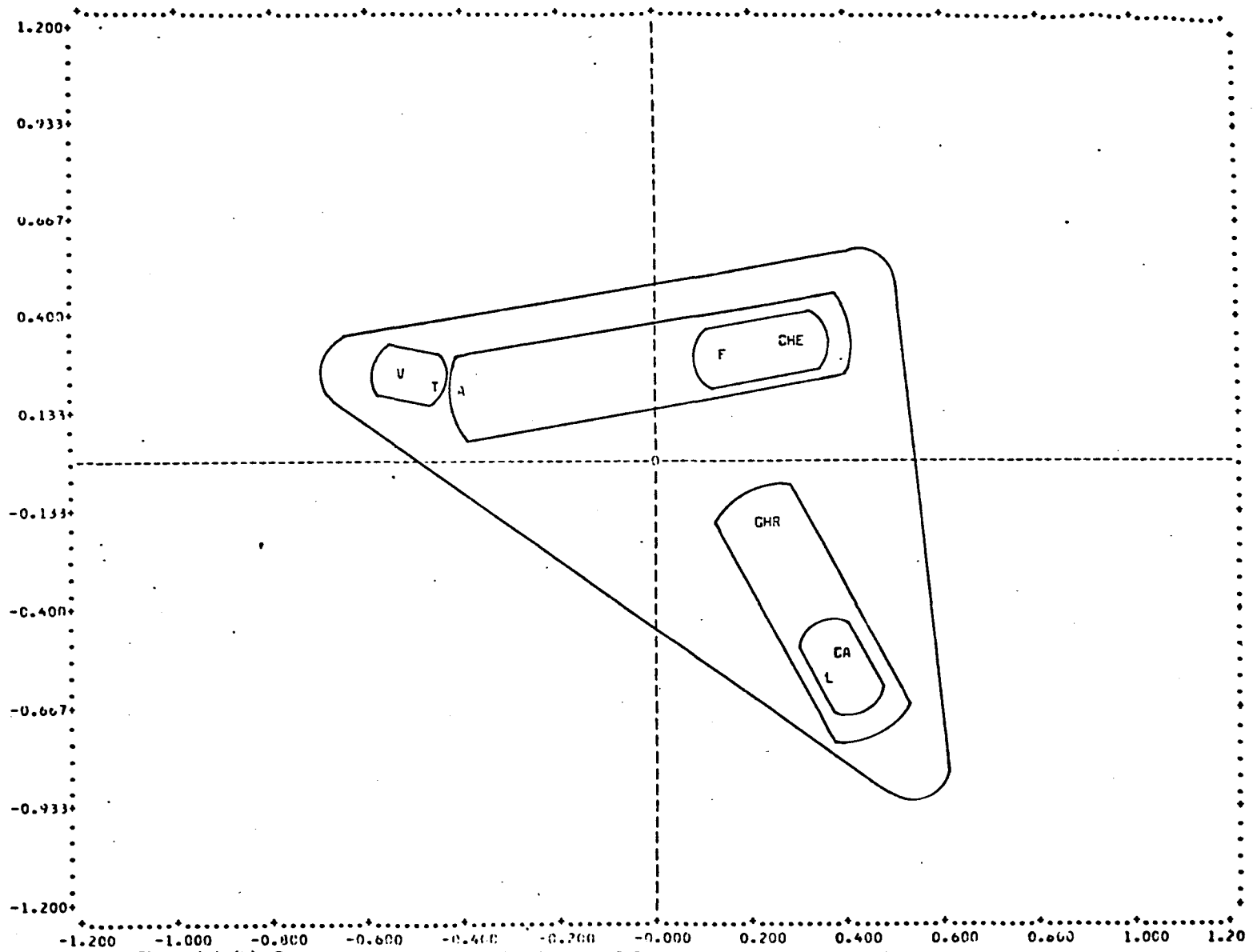


Figure 4-4 (b) Two-space brand configuration from the INSCAL analysis of direct similarities and the nested clusters of brands by the HICLUST program for Undergraduates.

The congruence testing of the perceptual spaces between the
Graduate group and the Undergraduate group

The comparison of the percentage of variance accounted for and the average correlation coefficients across subjects presented in Table 4-3 indicates that the INSCAL model fitted better for the G group than for the U group. The correlations between the two axes are 0.574 and -0.641 for the two dimension case in the G group and the U group, respectively.

The two INSCAL configurations of (a) and (b) of Figure 4-2 can be compared for congruence by canonical correlation. The results are shown in Table 4-5. As the table shows, the two configurations are very highly congruent. We can conclude that both groups provide similarity judgments for brands of cars which are highly congruent in their perceptions.

Table 4-5

Results of canonical correlation analysis between the two-dimensional configurations of the Graduates and the Under-graduates groups obtained from the INSCAL model.

Statistic of measure	Latent root number	
	1	2
Canonical correlation	0.99930	0.97508
Wilks lambda	0.00007	0.04921
Chi square (χ^2)	52.70378	16.56417
Degrees of freedom	4	1
Probability	< 0.0001	< 0.0001

Both latent roots are statistically significant.

CHAPTER 5
THE MEASUREMENT OF THE PERCEIVED BRAND QUALITY

Summary

In this chapter we apply the MDPREF method to scale the average subject's "overall" hedonic brand rating to obtain the measures of perceived brand quality. The scalar value from the rating scores via the MDPREF algorithm can be regarded as a measure of perceived quality of the brand.

We find that quality is perceived as better as price increased. (Hypothesis 1). This is determined by correlation analysis.

To examine further this relationship, a nonlinear model is applied. The fit of the model is extremely good for both groups. We can assert that the psychological evaluation of brand quality will be nonlinearly transformed by price, and the elasticity of brand quality with respect to brand price is inelastic for both groups. (Hypothesis 2).

The consistency of perceived price ranking and actual price ranking is tested by (a) the Spearman rank order correlation analysis and (b) a significance test of the rate of change in the coefficient of variation plotted against the actual price.

The findings in this section indicate that the consumers' judgment on brand prices is quite reliable. (Hypothesis 3).

Introduction

The perceived brand quality can be obtained from the average subject's "overall" hedonic brand rating. That is, the scalar values for any brand on the quality dimension will be obtained by the MDPREF technique (21) from respondents' ratings. These scalar values can be regarded as representing an evaluative measure of the quality of that brand. We can relate this measure of a brand with the actual price of the brand to execute our analysis.

By forming a nonlinear model between quality and price and by examining the parameters of the equation, the rate of change of quality to price is studied with a marginal analysis. This is conducted to test Hypothesis 2.

Finally, a comparison of ranking of the actual price with that of estimated (subjective) price of each brand leads to the congruence test of the consumers' subjective judgment of price. Spearman's rank order correlation method is used for this test. The price distortion between the actual and estimated values is further analyzed.

The analytical flow chart of this chapter is shown in Figure 5-1.

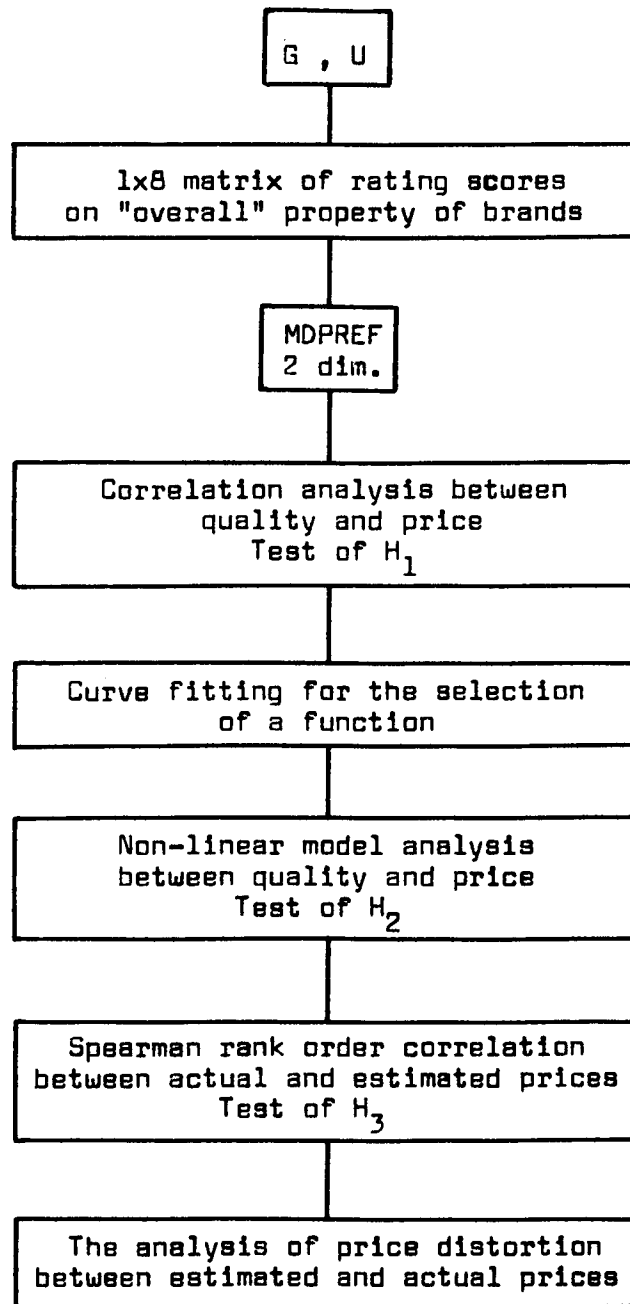


Figure 5-1 Analytical diagram for testing H_1 , H_2 , and H_3 .

Hypotheses 1, 2, and 3 are restated below :

- H₁ : "Do consumers feel that quality of a brand with higher price is better than one with lower price ?"
- H₂ : "Consumers perceive the quality of a brand as being inelastic in relation to its price."
- H₃ : "Can consumers correctly estimate the rank-order of the brand prices and is the reliability of their estimates constant over all eight brands ?"

Perception of quality with respect to actual price - Test of H₁

The MDPREF method is used to scale rating-scores. The average overall hedonic ratings of each brand was calculated for each of the two population sub-groups (Graduates and Undergraduates) and submitted to the MDPREF program. The input data are presented in Table V-1 in Appendix.

The MDPREF scaling algorithm generates as output a geometric configuration of stimulus-points and subject-vectors such that the projections of stimuli on each subject's vector correspond optimally with the subject's rating scale. The algorithm employs Eckart-Young decomposition theorem.*

* See p. 231 in Appendix for further explanation.

In this point-vector model, representing rating data, the algorithm assumes that utility increases monotonely with increases along each dimension. Based on this nature of the MDPREF method, the scalar value for scores on "overall" ratings can be regarded as an evaluative measure of the perceived quality of that brand. We can relate the measures of quality to the actual prices of the brands. Price and the measure of perceived quality for each brand obtained from the MDPREF model are presented in Table 5-1. These relationship is graphically displayed in Figure 5-2 (a) and (b). Conclusions may be drawn from Figure 5-2 : There appears to be an increase in quality as price increases. That is, the higher the price, the more highly consumers evaluate the quality of a brand.

To examine how price and quality were correlated, a correlation analysis was made. Correlation was 0.9525 and 0.9453 for the G and the U groups, respectively. The correlations were significant, thus meriting further analysis of the relationship between price and quality. Hypothesis 1 was thus tested and accepted affirmatively.

Table 5-1

Measures of perceived quality from the MDPREF analysis and their corresponding prices.

Brand	Price	Derived measure of quality	
		Graduates	Under-graduates
A	\$3,218	-0.3660	-0.3423
CA	8,826	0.5408	0.5751
CHE	3,766	0.0219	0.0886
CHR	5,399	0.0983	0.1952
F	3,627	-0.1311	-0.2589
L	7,854	0.5244	0.4361
T	3,241	-0.2130	-0.2820
V	2,902	-0.4752	-0.4117

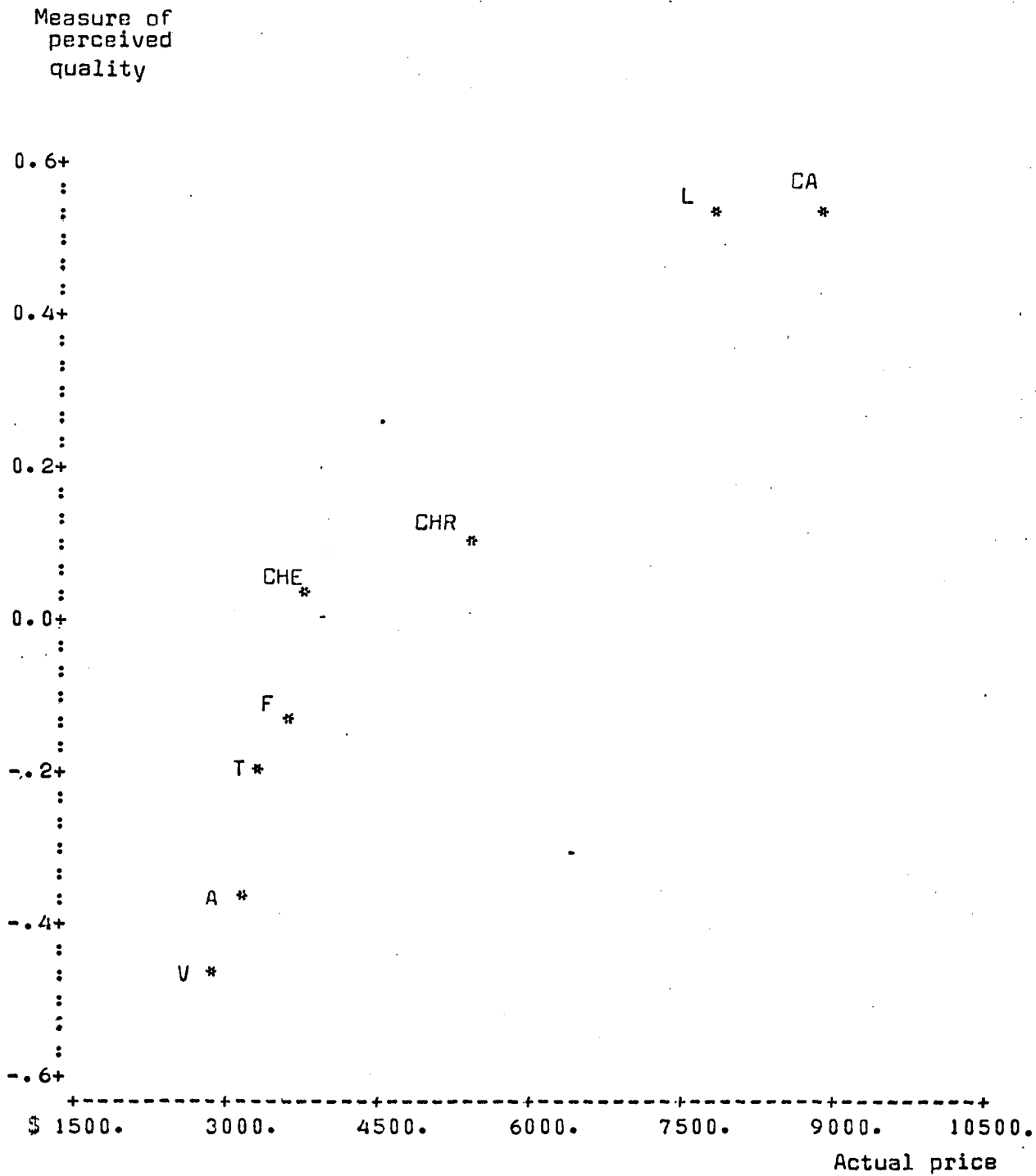


Figure 5-2 (a) Relationship between the measures of perceived quality and actual prices for Graduates.

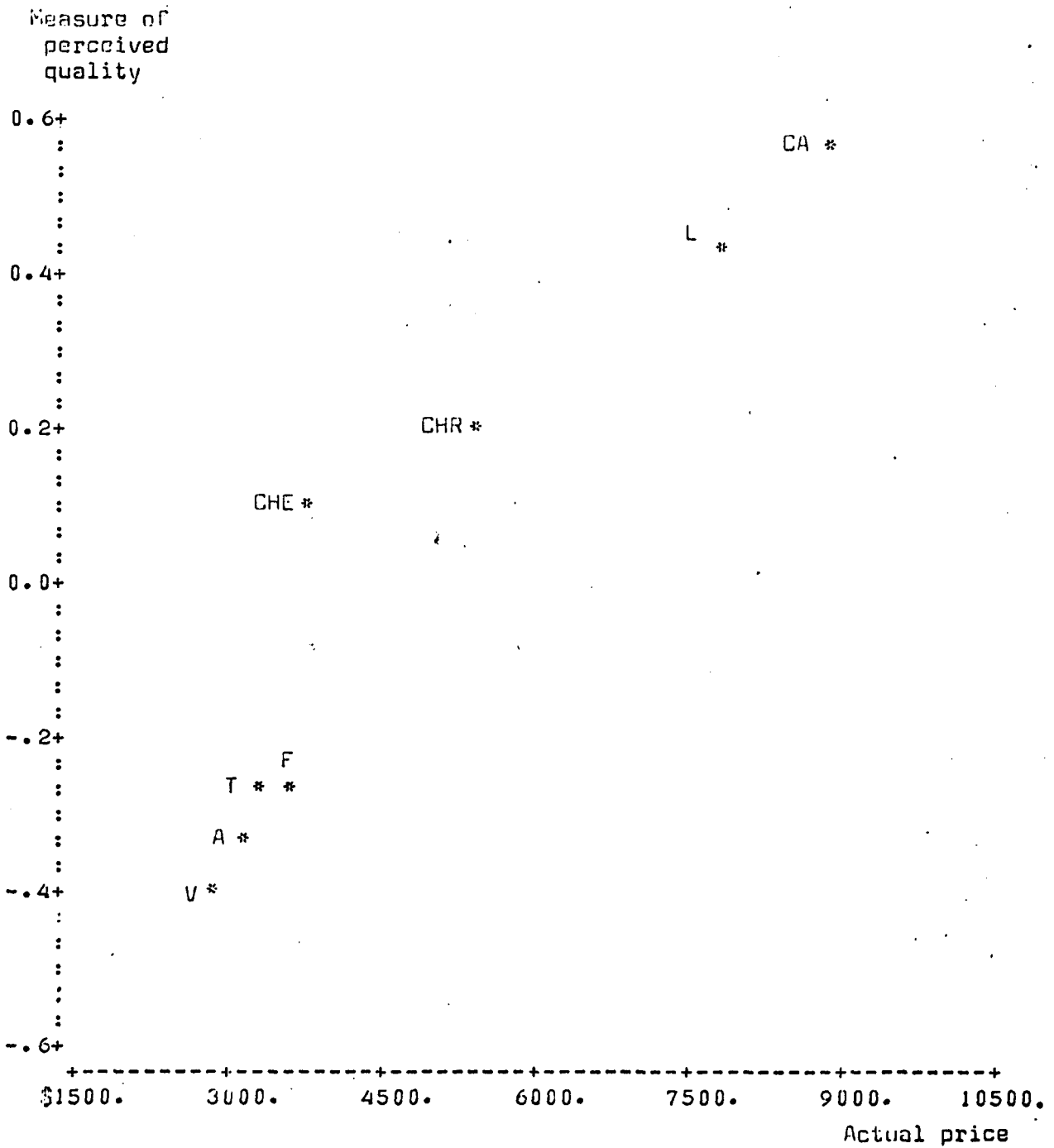


Figure 5-2 (b) Relationship between the measures of perceived quality and actual prices for Undergraduates.

Test of H₂

Hypothesis 2 is restated below :

H₂ : "Consumers perceive the quality of a brand as being inelastic in relation to its price."

To examine further the relationship between price and quality, curve fittings were conducted to determine a function to which the point values between the measures of quality and prices would be best fitted. A linear, a semi-logarithmic, and a logarithmic function were submitted for the regression analysis. The results are presented in Table 5-2.

Both a linear and a semi-logarithmic functions showed statistical significance at the 1 percent level both in computed t-statistics of parameters a and b and computed F-values with 1 and 6 degrees of freedom, but a logarithmic function was not significant. Therefore, a logarithmic function was rejected as inapplicable. The coefficient of determination of a semi-logarithmic function was higher for both groups than that of a linear function, which led us to adopt a semi-logarithmic function for our analysis.

With cardinal measures of quality in Table 5-1, we could fit the point values to a nonlinear model given by :

$$Q = a \log_e P + b$$

Table 5-2

Parameter estimates of quality-price relationship and goodness of fit of a linear, a semi-logarithmic, and a logarithmic model by a regression analysis.

Form of the Function	Group	Parameters						Coefficient of determination	Computed F-value	d.f.
		b			a					
		Estimate	Standard error	t-statistic	Estimate	Standard error	t-statistic			
Linear $Q = b + aP$	G	-0.7616	0.1087	-7.0041*	0.0157×10^{-2}	0.0205×10^{-3}	7.6583*	0.9072	58.650*	1,6
	U	-0.7560	0.1164	-6.4919*	0.0156×10^{-2}	0.0219×10^{-3}	7.0983*	0.8936	50.385*	1,6
Semi-logarithmic $Q = b + a \log_e P$	G	-3.2437	0.3372	-9.6184*	0.8544	0.0883	9.6720*	0.9397	93.547*	1,6
	U	-3.2263	0.3647	-8.8463*	0.8499	0.0955	8.8956*	0.9295	79.131*	1,6
Logarithmic $\log_e Q^{**} = \log_e b + a \log_e P$		$\log_e b$								
	G	-7.6438	3.9126	-1.9536	4.1401	2.3600	1.7543	0.3390	0.0775	1,6
	U	-8.3132	3.6657	-2.2678	4.4770	2.2111	2.0248	0.4059	4.0999	1,6

* : Statistically significant at the 1 percent level.

** : 0.4753 and 0.4118 were added to Q for G and U groups, respectively so that all derived measures of brand quality will be positive.

where Q is the measure of brand quality, P is the actual price, and "a" and "b" are parameters. In such a semi-logarithmic regression model, the exponent of P has a particular significance, in that "a" represents the elasticity of Q with respect to P . That is, if "a" is not equal to zero we can prove that the psychological evaluation of brand quality will be nonlinearly transformed by price. When "a" is greater than unity, one percent increase in price contributes to more than one percent increase in brand quality. When "a" is less than unity, the situation is vice versa. Thus, if price has an elastic "importance" in the evaluation of brand quality, then the value of "a" should be greater than unity.

As we can see in Table 5-2, the fit of the model is good for both groups. The regression coefficient "a" is less than unity for both groups, which indicates an inelastic quality-price relationship. This finding supports Hypothesis 2.

Test of H₃

Hypothesis 3 is represented below :

H₃ : "Can consumers correctly estimate the rank-order of the brand prices and is the reliability of their estimates constant over all eight brands?"

To test Hypothesis 3, the estimated rankings of brand prices obtained from Question area 4 (a) were averaged over the respondents of each group. The Spearman rank order correlation was employed to examine whether the rankings of the estimated prices corresponded to the rankings of the actual prices. The result is presented in Table 5-3. The Spearman rank order correlations of 0.9524 for the G group and 0.9762 for the U group shown in Table 5-3 indicate a good congruence between the estimated and actual prices.

It was noted that respondents' estimated rank order of brand prices corresponded fairly well to the rank order of actual prices for both groups. Next, in order to know the degree of distortion of the estimated prices from the actual prices, the respondents were asked to estimate the price of each brand by Question area 4 (b). The coefficient of variation was used as a criterion, serving as a measure of relative dispersion of the estimated prices from the actual prices. (See Table 5-4.)

Table 5-3
Rank order of perceived and actual prices.

Brand	Graduates		Undergraduates		Actual ranking
	Estimated		Estimated		
	Yielding score	Ranking	Yielding score	Ranking	
A	5.98	6	5.69	6	7
CA	1.53	1	1.51	1	1
CHE	4.63	5	4.41	4	4
CHR	3.23	3	3.20	3	3
F	4.53	4	4.76	5	5
L	1.60	2	1.53	2	2
T	7.03	7	7.27	7	6
V	7.05	8	7.67	8	8
Spearman rank order correlation	0.9524*		0.9762*		

* Statistically significant at 1 percent level.
Critical value = 0.833

The significance test of the changes in the coefficient of variation against the actual prices was conducted. When the computed t-ratios were compared with the critical value of the t-statistic of 2.365 (at 1 percent level with 7 degrees of freedom), insignificant differences were noted for both groups as shown in Table 5-5.

The relationship between the coefficient of variation and actual price for each brand is graphically presented in Figure 5-3 (a) and (b).

The conclusion can be drawn that the consumers' ranking of brand prices was significantly estimated and the reliability of their estimates was constant over all eight brands.

Table 5-4
 Estimated prices, standard errors,
 and coefficients of variation.

Brand	Graduates			Undergraduates		
	Average estimated price \bar{P}_G	σ_G	$\frac{\sigma_G}{\bar{P}_G}$	Average estimated price \bar{P}_U	σ_U	$\frac{\sigma_U}{\bar{P}_U}$
A	\$3,560	\$625	0.1755	\$3,539	\$580	0.1638
CA	8,258	948	0.1148	7,784	1,240	0.1595
CHE	4,275	853	0.1995	4,170	545	0.1307
CHR	5,559	1,204	0.2165	5,249	1,155	0.2201
F	4,386	799	0.1821	4,035	650	0.1612
L	8,049	895	0.1112	7,771	1,267	0.1627
T	2,926	976	0.3337	2,655	525	0.1976
V	2,685	585	0.2180	2,473	502	0.2031

Table 5-5
 Parameter estimates between the coefficients
 of variation and actual prices.

d.f. = 7

Group	Estimated rate of change	t-statistic
G	-0.002128	-2.3873*
U	-0.002218	-0.4322*

* Statistically insignificant at the 1 percent level.

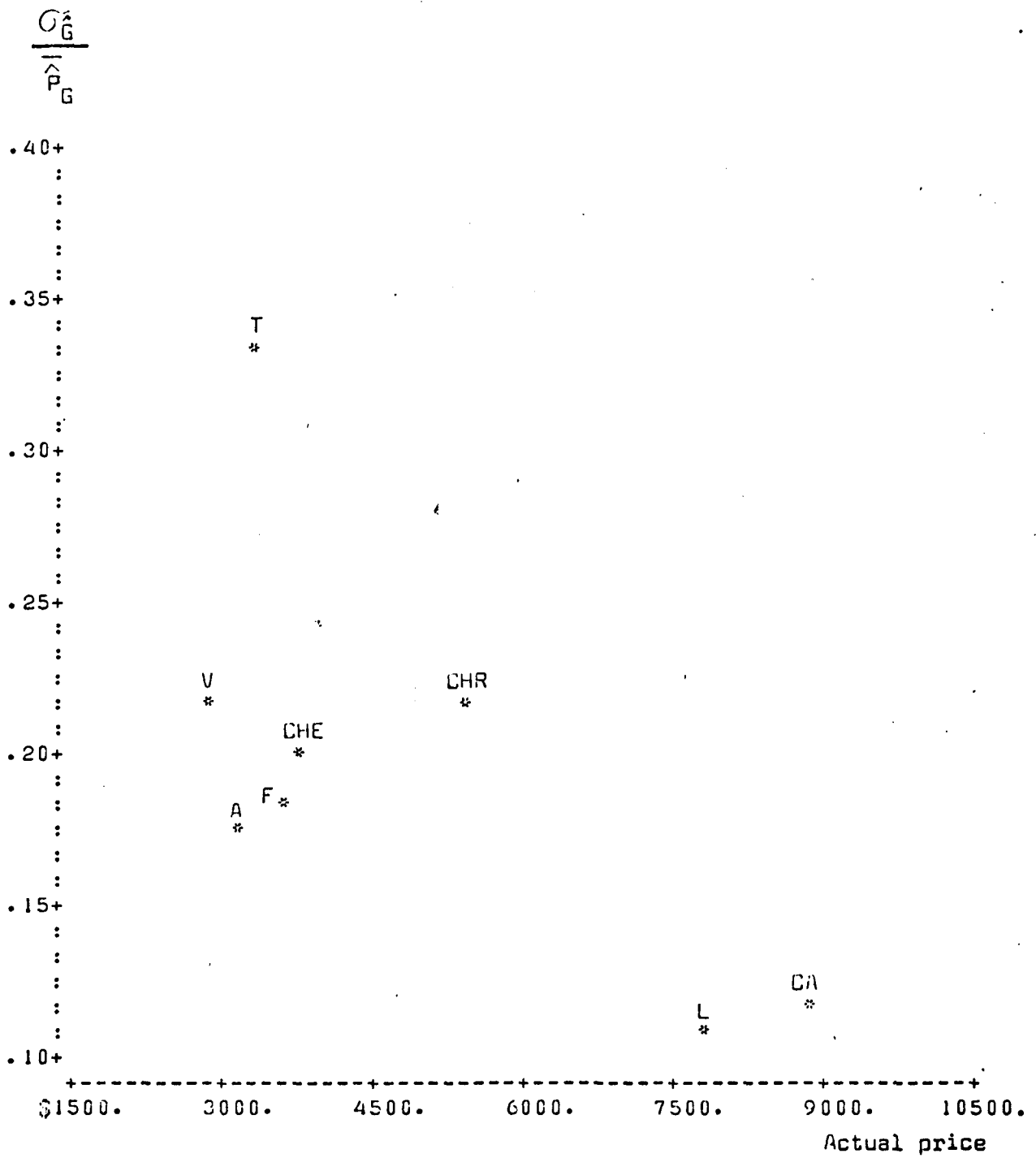


Figure 5-3 (a) Relationship between the coefficients of variation and actual prices for Graduates.

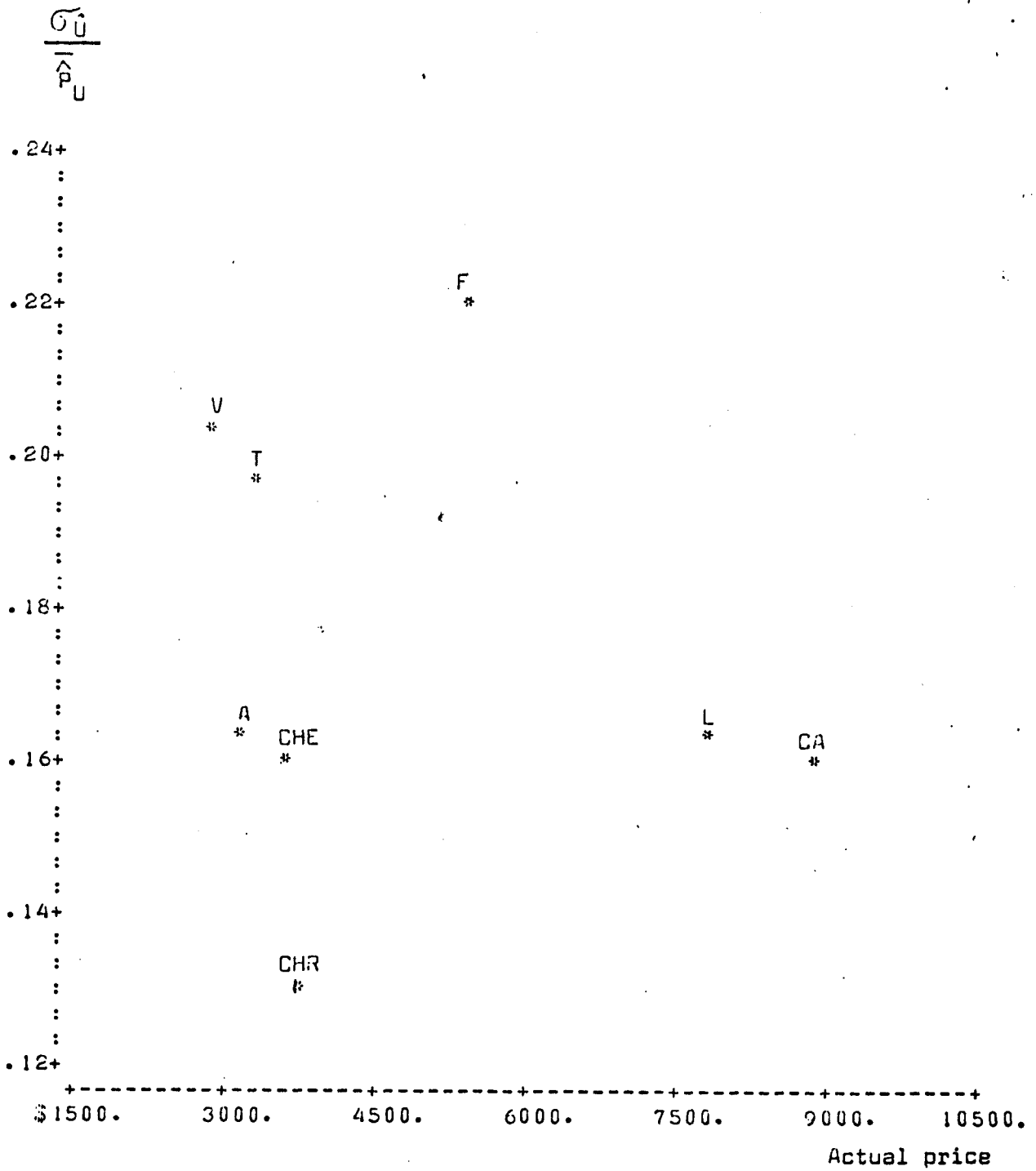


Figure 5-3 (b) Relationship between the coefficients of variation and actual prices for Undergraduates.

CHAPTER 6
THE MEASUREMENT OF THE PERCEIVED
ADVERTISING EXPENDITURES

Summary

The MDPREF algorithm is used to scale rating-scores on the perceived amount of advertising per unit. We test by a nonlinear model whether consumers perceive little difference in advertising expenditures for inexpensive car brands. (Hypothesis 4).

The PREFMAP model presents the collinearity of perceived amount of advertising with the negative quality dimension. The negative value of the correlation coefficient of the perceived amount of advertising with perceived quality provides additional evidence : consumers' estimate of the brands' advertising expenditures are negatively related to their perception of the brand quality. (Hypothesis 5).

After testing consumers' correct perception of the relative advertising expenditures of the brands (Hypothesis 6), a criterion for judging advertising efficiency is suggested based on measures of perceived advertising expenditures and actual advertising expenditures.

Introduction

This chapter discusses the relationships among advertising expenditures, price and quality of brands.

In Hypothesis 4, the relationship between the perceived advertising expenditures and brand prices is tested. It is attempted to find the advertising elasticity which Green and Rao have suggested to doing (35).

In Hypothesis 5, it will be tested how consumers perceive brand quality based on the perceived and actual advertising expenditures.

After testing the reliability of consumers' estimates of advertising expenditures by Hypothesis 6, a decision rule for the allocation of advertising expenditures will be proposed.

The analytical flow-chart of this chapter is presented in Figure 6-1.

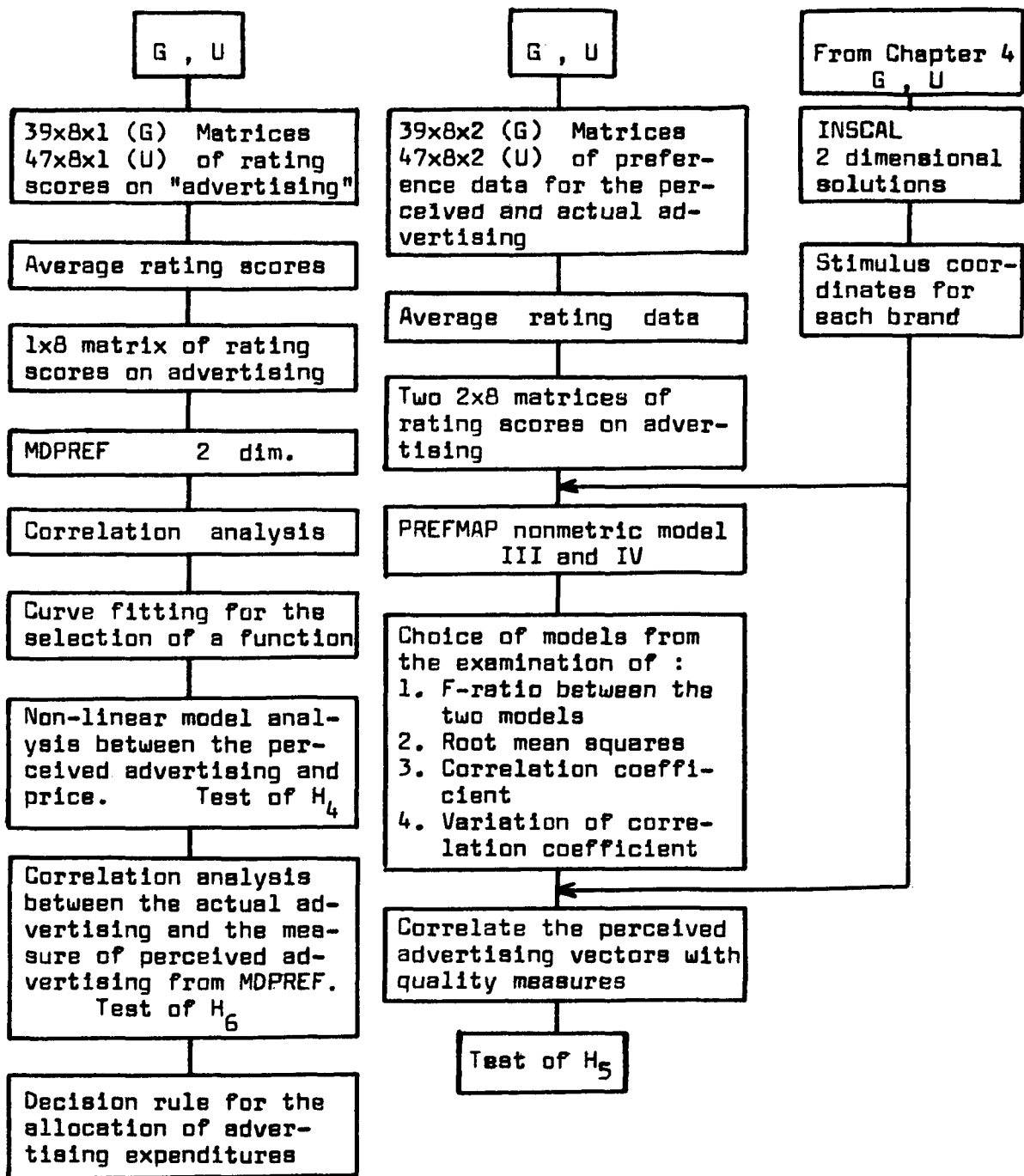


Figure 6-1 Analytical flow-chart for testing H_4 and H_5 .

The Hypotheses 4, 5, and 6 are recaptulated below :

- H₄ : "Consumers feel that advertising expenditures are, in general, inversely related with brand prices but they are not elastic for inexpensive car brands."
- H₅ : "Consumers' estimates of the brands' advertising expenditures are negatively related to their perception of the brands' quality."
- H₆ : "Consumers correctly perceive the relative advertising expenditures of the brands within the evoked set of brands (the eight brands of car)."

The measure of perceived advertising expenditures and actual price - Test of H₄

The MDPREF method was used to develop the scalar values of the perceived advertising expenditures from respondents' ratings on the amount of advertising spent for each brand (data from Question area 3 in the questionnaire). This is a seven-point scale on which the amount of advertising spent on each brand is rated from "only a little" to "a great deal". Data are presented in Table VI-1 in Appendix for the average scale-ratings for each brand, by population sub-group (Graduates and Undergraduates).

The resultant values from the MDPREF procedure are shown in Table 6-1. We can relate these scalar values of each brand to the actual brand price, as in Figure 6-2 (a) and (b).

The actual price and its corresponding measure of perceived advertising expenditures for each brand is presented in Table 6-1. The regression analysis was employed to examine the elasticity of advertising expenditures for the eight brands. In order to determine a functional form of a regression analysis, curve fittings were conducted* so that the point values between the measures of advertising expenditures and prices of brands might be best fitted. The curve forms and coefficients of determination to fit the model are shown in Table 6-2. The examination of the coefficient of determination value of each curve form suggested that there was no relationship between prices and measures of perceived advertising expenditures. This finding does not support Hypothesis 4.

If there were some theoretical grounds for removing Cadillac and Lincoln from the data set, we would observe from Table 6-3 (a) that an exponential model would fit the remaining values extremely well. Therefore, with the cardinal measures of perceived advertising expenditures in Table 6-1**, we built a model given by :

$$A = be^{aP} \quad (1)$$

* This was conducted through the Rapidata system at the Baruch Computer Center.

** See Table VI-2 in Appendix for the transformation of data.

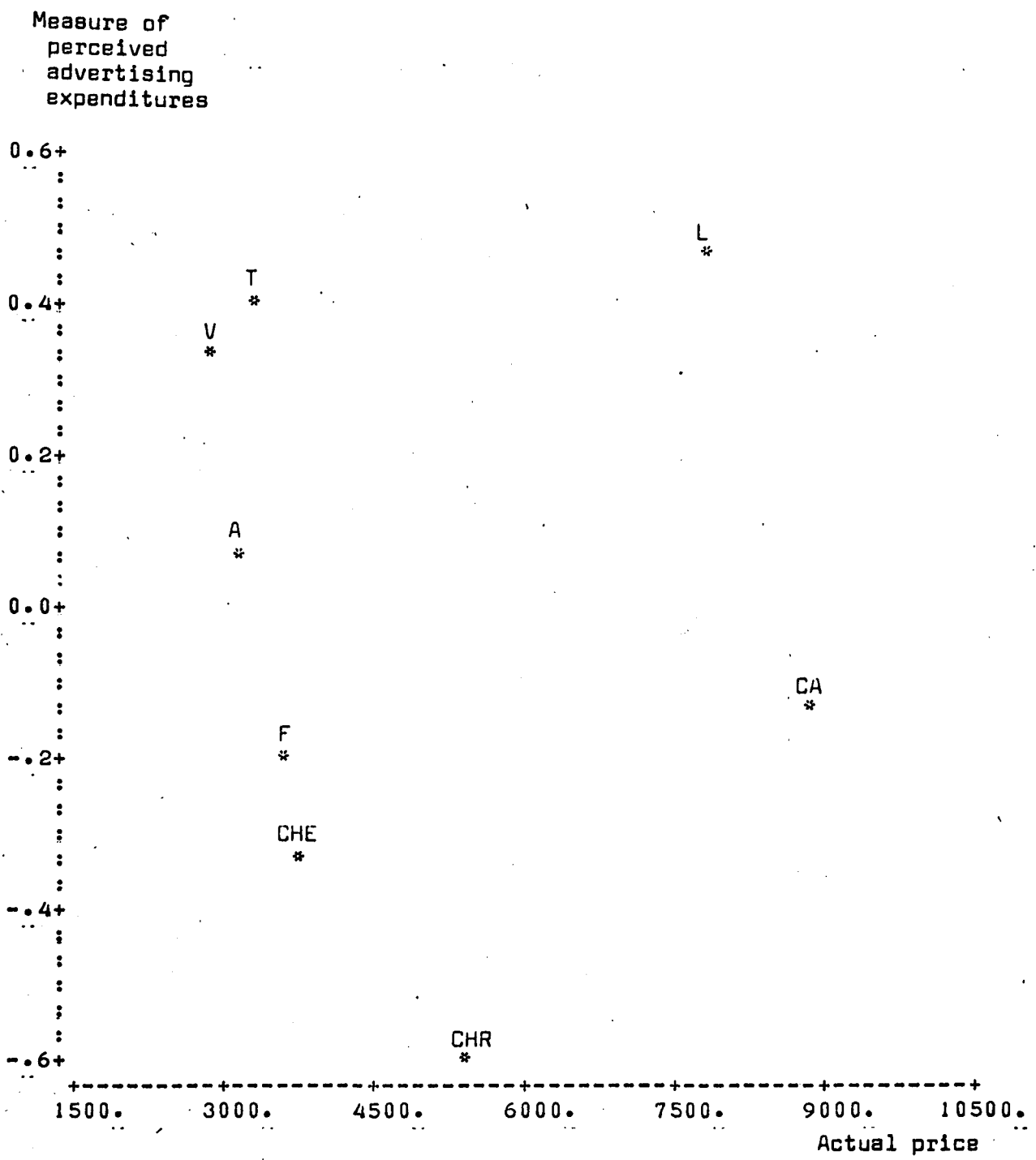


Figure 6-2 (a) Relationship between the measures of perceived advertising expenditures and actual prices for Graduates.

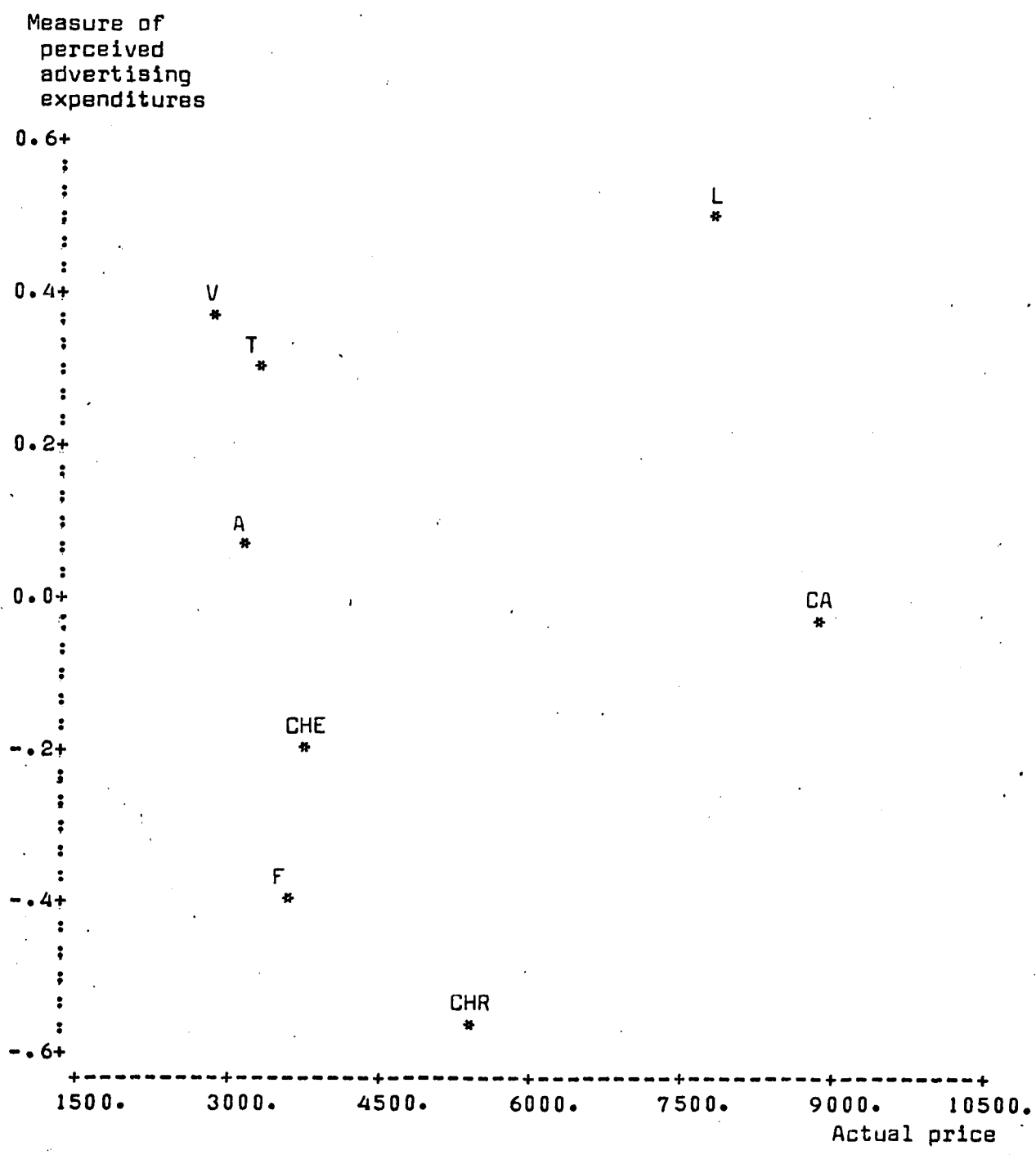


Figure 6-2 (b) Relationship between the measures of perceived advertising expenditures and actual prices for Undergraduates.

Table 6-1

Measures of perceived advertising expenditures from the MDPREF analysis.

Brand	Graduates	Under-graduates	Price
A	0.0807	0.0757	\$3,218
CA	-0.1237	-0.0214	8,826
CHE	-0.3481	-0.2063	3,766
CHR	-0.5926	-0.5717	5,399
F	-0.1919	-0.4144	3,627
L	0.4533	0.4873	7,854
T	0.3972	0.2838	3,241
V	0.3251	0.3670	2,902

Table 6-2

Least squares fit of six curve types between the measures of advertising expenditures and the actual prices - eight brands.

Curve form	Group	Coefficient of determination
$A = b + aP$	G	0.0017
	U	0.0051
$A = be^{aP}$	G*	0.0077
	U**	0.0094
$A = bP^a$	G*	0.0319
	U**	0.0343
$A = b + \frac{a}{P}$	G	0.0429
	U	0.0463
$A = \frac{1}{b + aP}$	G	0.0092
	U	0.0092
$A = \frac{P}{b + aP}$	G	0.0664
	U	0.0664

* 0.5927 was added to the advertising measure.
 ** 0.5718 was added to the advertising measure.

Table 6-3 (a)

Least squares fit of six curve types between the measures of advertising expenditures and the actual prices - six brands (Cadillac and Lincoln excluded).

Curve form	Group	Coefficient of determination
$A = b + aP$	G	0.7427
	U	0.6967
$A = be^{aP}$	G*	0.9490
	U**	0.9478
$A = bP^a$	G*	0.9038
	U**	0.9068
$A = b + \frac{a}{P}$	G	0.8244
	U	0.8028
$A = \frac{1}{b + aP}$	G	0.8795
	U	0.8795
$A = \frac{P}{b + aP}$	G	0.7391
	U	0.7392

* 0.5927 was added to the advertising measure.

** 0.5718 was added to the advertising measure.

where A is the measure of perceived amount of advertising, P is the actual price, and " a " and " b " are parameters. Logarithmic transformation was made of equation (1) to its equivalent form :

$$\log_e A = \log_e b + aP \quad (2)$$

If Hypothesis 4 is true, the parameter " a " must be less than zero, making the perceived advertising expenditures a decreasing function of brand price. Further " a " can be interpreted as the elasticity of the perceived advertising expenditures to the brand price change. If " a " is between 0 and -1 (0 and -1 exclusive), then one percent increase in price causes less than one percent decrease in the perceived advertising expenditures. If " a " is less than minus unity, then one percent increase in price contributes to more than one percent decrease in the perceived advertising expenditures.

Table 6-3 (b) presents the estimates of parameters and the tests of goodness of fit of the model to data by the regression analysis. As is seen in Table 6-3 (b) the fit of the model is good for both groups. The regression coefficient " a ", elasticity of perceived advertising expenditures to price, is $-1 < a < 0$ for both groups. This finding supports Hypothesis 4. Unfortunately, no theoretical justification can be found for removing these two values of Cadillac and Lincoln.

Table 6-3 (b)

Parameter estimates for the relationship between the measures of perceived advertising expenditures and the actual prices, and goodness of fit to data by a semi-logarithmic model.

Group	Parameters						Coefficient of determination	Computed F-value	d.f.
	log _e b			a					
	Estimate	Standard error	t-statistic	Estimate	Standard error	t-statistic			
G	12.395	1.7086	7.2544*	-0.3900	0.0452	-8.6297*	0.9490	74.471*	1,4
U	12.133	1.7132	7.0824*	-0.3860	0.0453	-8.5196*	0.9478	72.584*	1,4

* : Statistically significant at 1 percent level

Test of H₅

Hypothesis 5 is restated below :

H₅ : "Consumers' estimates of the brands' advertising expenditures are negatively related to their perception of the brands' quality."

Nonmetric versions of the Models III and IV of the PREFMAP procedure were employed to fit two advertising expenditure vectors in the perceptual space.* Data were obtained from Question area 5 in the questionnaire.

* For the nonmetric versions of the PREFMAP program, the maximum number of iterations was set at 15 and the criterion for stopping the iterative procedure was the value of 0.01.

If $\sum_I (S_I - \hat{S}_{I-1})^2 \leq 0.01$, the iteration is terminated

where \hat{S} is the estimated scale value and I denotes I th iteration (20).

In order to obtain parsimony and ease of interpretation it is desirable to fit a simple model rather than a complex one. In the PREFMAP algorithm, Model IV is a simpler model than Model III. (See p. 235 in Appendix.)

We prepared two 8×2 matrices of coordinate values for the average subject in the G group and the U group separately, which were obtained from the INSCAL analysis in Chapter 4. Next, we prepared two matrices of 1×8 of the average-subject rating scores on perceived and actual advertising expenditures.

The first step in the analysis for the G group and the U group separately, was to fit the non-metric versions of Models III and IV of the PREFMAP program to the perceptual configuration whose coordinate values were obtained in Chapter 4, appearing in Table IV-4 in Appendix.

The measures of goodness of fit (multiple correlation coefficients) for Models III and IV and the value of the F-ratio for testing the contribution of Model III over Model IV appear in Table 6-4 for each property vector.

When the computed F-ratios were compared with the critical value at 5 percent level of the F-statistic of 5.79 (with 2 and 5 degree of freedom), no significant differences were noted between Models III and IV for the G group.

Furthermore, the root mean square of the individual goodness of fit measures (multiple correlations) for Model III is 0.9381 for the G group. This value drops to 0.9161 in Model IV for

the G group. This small amount of difference (0.0220) indicates that relatively little improvement can be obtained by employing Model III (the ideal point model) for the G group. Accordingly, Model IV (the vector model) was used for the G group. Since significant difference was recognized between Models III and IV for the U group, Model III (the ideal point model) was used for the U group. In the ideal point model, the property vectors are represented as ideal points.

The direction cosines of the property vectors in the perceptual space are presented in Table 6-5. Figure 6-3 (a) and (b) show the joint-space configurations of the vector model for the G group and the ideal point model for the U group.

We can interpret the vertical axis of Figure 6-3 (a) as representing the brand quality from the same inference as we did for the horizontal axis of Figure 4-2 (a). Similarly, we can also interpret the horizontal axis of Figure 6-3 (b) as representing the brand quality from the same inference as we did for the vertical axis of Figure 4-2 (b).

We can draw conclusions from the analyses as follows.

For the G group, the position of the fitted vector of the perceived advertising expenditures is not collinear with the quality dimension. This observation gives a cue that the perceived advertising expenditures are against brand quality but for some other attributes - e.g., more advertising expenditures spent in less traditional brands in this study.

Table 6-4

Goodness of fit of Models III and IV of the PREFMAP procedure for perceived and actual advertising expenditures spent.

Property vector	Graduates			Undergraduates		
	Correlation coefficient		F-ratio between the two models d.f.= 2.5	Correlation coefficient		F-ratio between the two models d.f.= 2.5
	Model III	Model IV		Model III	Model IV	
Perceived	0.9661	0.9345	3.6140	0.9948	0.8872	77.8154*
Actual	0.9092	0.8972	0.4989	0.9851	0.9623	5.9779*
Root mean square	0.9381	0.9161		0.9899	0.9255	

* : Statistically significant at 5 percent level

Table 6-5

Direction cosines by the vector model for perceived and actual advertising expenditures.

Property vector	Direction cosines			
	Graduates		Undergraduates	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
Perceived	-0.9990	0.0443	-0.3910**	1.0483**
Actual	-0.9990	0.0437	-0.4413**	1.1315**

** : Those are coordinate values of ideal points.

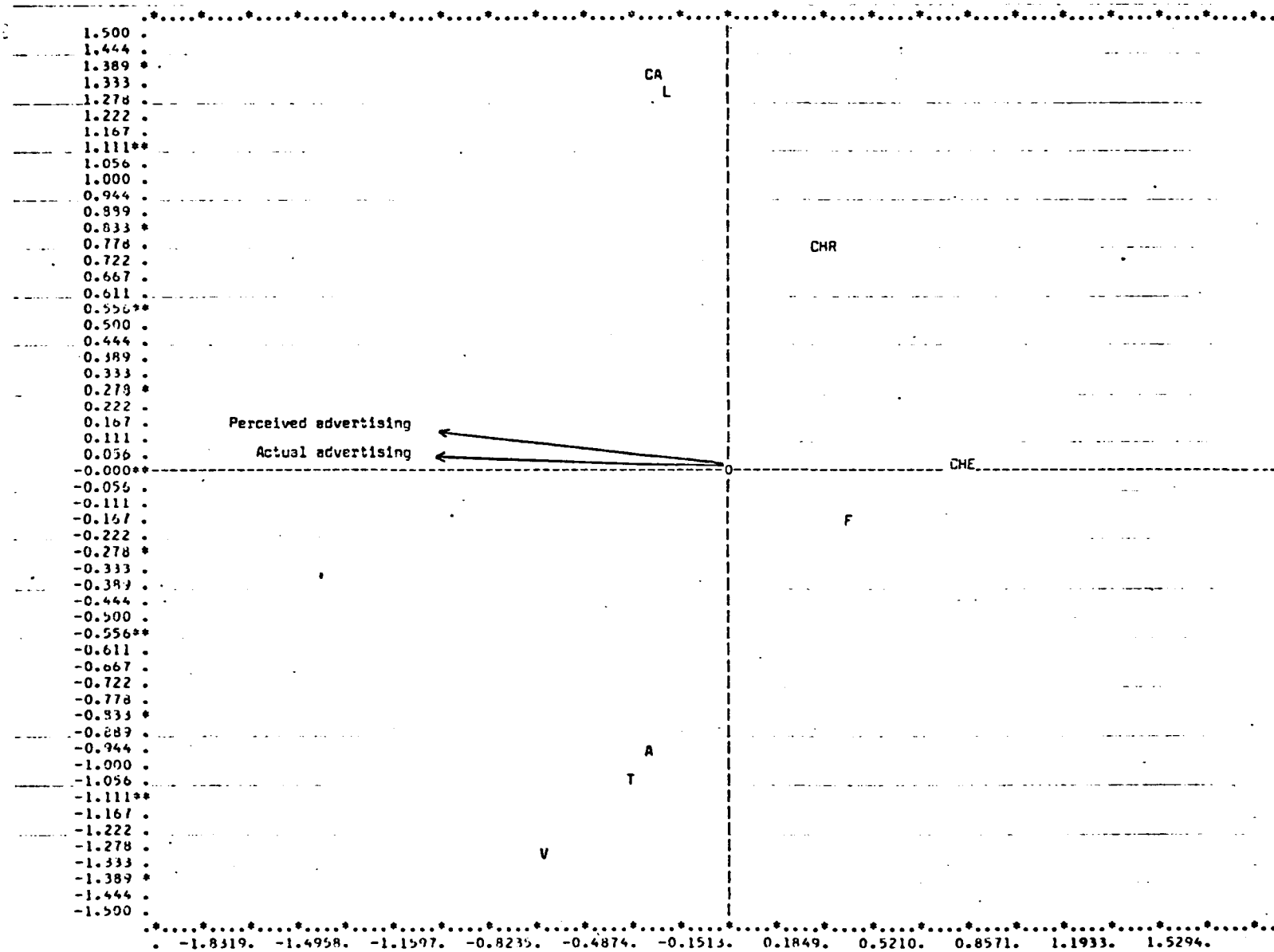


Figure 6-3 (a) Joint-space configuration of brands and vectors of actual and perceived advertising expenditures for Graduates.

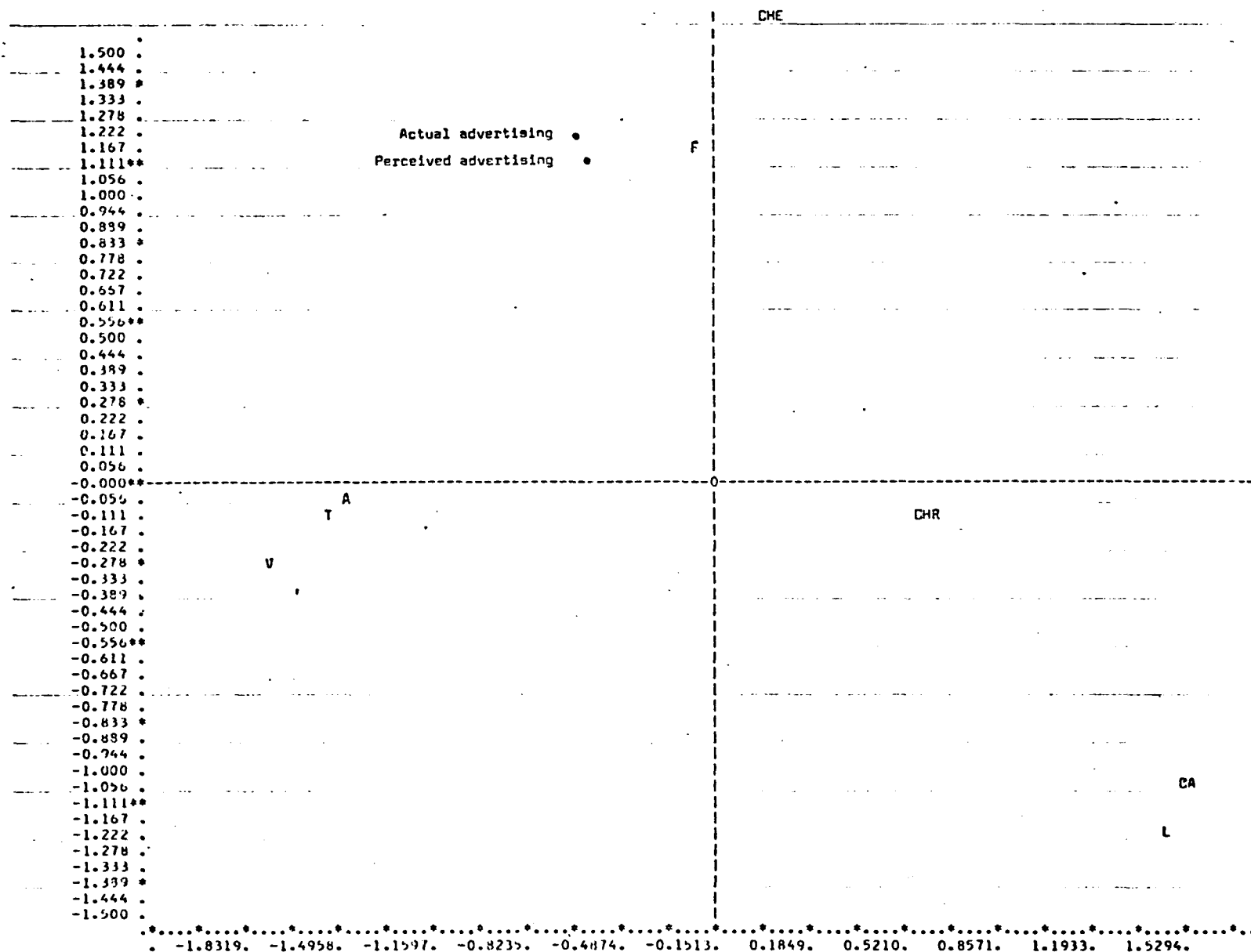


Figure 6-3 (b) Joint-space configuration of brands and points of actual and perceived advertising expenditures for Undergraduates.

For the U group, perceived advertising point is not situated close to the dimension representing "quality".

In order to prove these visual examinations that the perceived amount of advertising is negatively indicative of brand quality for both groups, the correlation of property vectors (points) with the quality dimension was made for each group by directly correlating the perceived and actual advertising expenditure vectors with the coordinate values on the brand quality measures. The brand quality measures were already obtained from the MDPREF procedure in Chapter 5. The results are shown in Table 6-6.

The advertising expenditure vectors are negatively correlated with the quality dimension for both groups. The positions of advertising expenditure vectors in Figure 6-3 and the correlation coefficients in Table 6-6 both support Hypothesis 5.

Table 6-6

Correlations between perceived and actual advertising expenditure vectors with the quality measures.

Correlation between quality measures and			
Graduates		Undergraduates	
Estimated advertising vector	Actual advertising vector	Estimated advertising point	Actual advertising point
-0.82633	-0.75935	-0.449985	-0.567421

Test of H_6 and the decision rule for the allocation of advertising expenditures

Hypothesis 6 is restated below :

H_6 : "Consumers correctly perceive the relative advertising expenditures of the brands within the evoked set of brands (the eight brands of car)."

In the previous section, it was noted that both perceived advertising vector and actual advertising vector were collinear with each other. Therefore we can say that the consumer can perceive advertising effects on brands as spent by a company. To further examine this hypothesis, the correlation analysis was conducted to fit the values between the measures of perceived advertising expenditures obtained from the MDPREF model and the actual advertising dollars. Input data for this analysis are presented in Table 6-7. The correlation coefficients are 0.7042 and 0.7077 for the G group and the U group, respectively. The results were fairly good for both groups, with the additional visual evidence that both vectors are collinear in Figure 6-3 (a) and (b). These findings support H_6 .

It was concluded that a company's advertising expenditures were relatively well reflected in consumers' perceptions of amount of advertising spent per car. This study attempts to provide a

Table 6-7

Measures of perceived advertising expenditures from the MDPREF program and actual advertising expenditures spent per unit.

Brand	Measure of advertising $f(A_1)$		Advertising* spent per unit A_1
	Graduates	Undergraduates	
A	0.0807	0.0757	\$70.31
CA	-0.1237	-0.0214	28.53
CHE	-0.3481	-0.2063	23.60
CHR	-0.5926	-0.5717	28.57
F	-0.1919	-0.4144	21.76
L	0.4533	0.4873	78.08
T	0.3972	0.2838	50.27**
V	0.3251	0.3670	37.71**

* Automotive News, November 13, 1972.

** Estimated.

criterion or a decision rule for the allocation of advertising expenditures based upon consumers' cognitive (perceptual) judgment of the amount of advertising spent. An efficiency curve will present a locus of optimal advertising expenditures to be allocated.

As the MDPREF algorithm assumes, the coordinate value of a brand can be regarded as the measure of the perceived amount of advertising spent per unit of that brand. Figure 6-4 (a) and (b) plot the coordinate values of brands in the perceived advertising space and the actual advertising expenditures of the brands.

Examination of Figure 6-4 (a) reveals that Chrysler, for instance, was perceived to spend least in advertising. But it actually spent more in advertising (per car) than Chevrolet, Ford, and Cadillac. So we can say that every dollar spent for these brands was more effective than for Chrysler. Therefore Chrysler should not have spent so much advertising per unit or it should improve the effectiveness of the dollars spent.

The question arises as to whether more advertising dollars be spent if the perceived measure could be increased accordingly. There is of course, a practical limitation on the amount that can or will be spent on advertising. But what criterion should be employed to measure the effective amount of advertising?

We could suggest that it might be more effective for a company that consumers perceive more of its advertising, and that it is, at the same time, preferable that the company spend as little as possible to get the same effect. To achieve this, the ratio

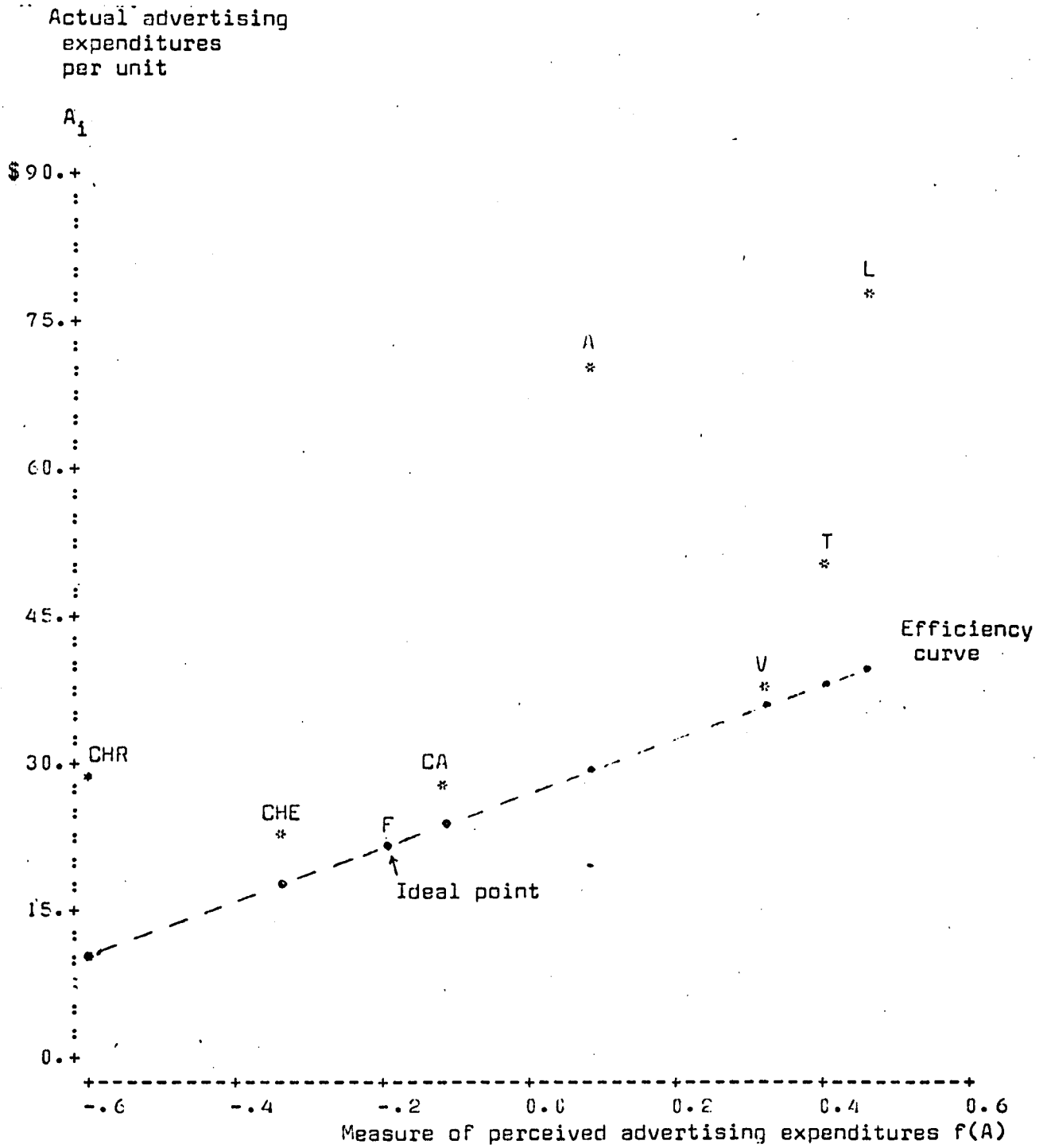


Figure 6-4 (a) Relationship between the measures of perceived advertising expenditures and actual advertising expenditures per unit for Graduates.

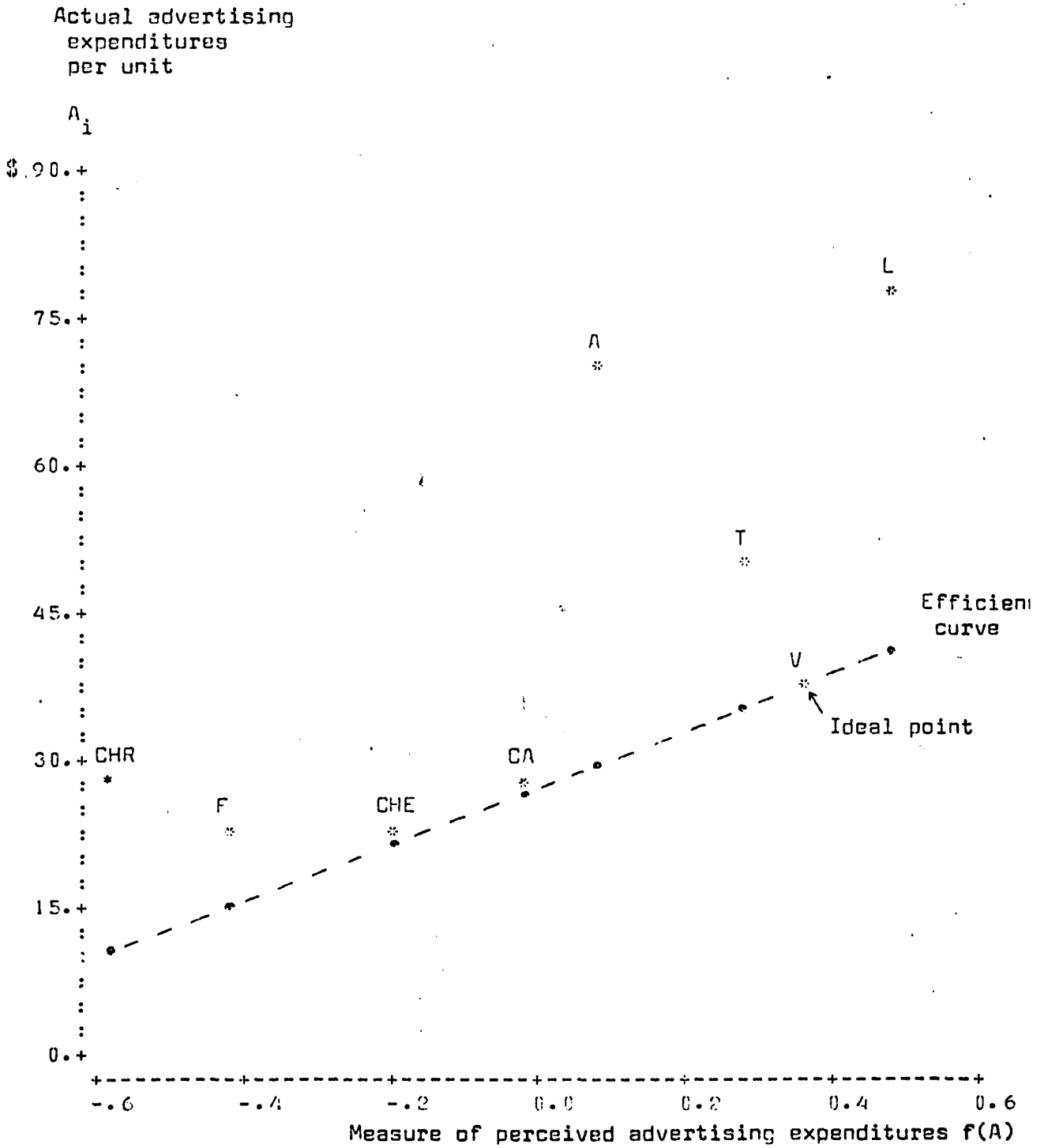


Figure 6-4 (b) Relationship between the measures of perceived advertising expenditures and actual advertising expenditures per unit for Undergraduates.

of the measure of perceived advertising to the actual advertising expenditures should be maximized. The criterion can be given by the following formula ;

$$f_{\max} = \max \left[f_i = \frac{f(A_i) + C}{A_i} \right] \quad (A_i \neq 0)$$

- f_i : Ratio value for brand i .
- $f(A_i)$: Measure of perceived advertising expenditures for brand i .
- A_i : Actual advertising expenditures for brand i .
- C : Constant. ($\geq -f(A_i)$)

f_i was calculated for each brand, and the criterion value f_{\max} for all brands was obtained as shown in Table 6-8. This maximum value of 0.0371 for the G group indicates an ideal value to balance the actual advertising expenditures spent with the measure of perceived advertising expenditures to obtain the most effective spending.

It is obviously desirable for a company to spend the advertising expenditures as effectively as possible. For the G group, Ford obtained an ideal position. It spent \$21.76 per unit and its measure of perceived advertising expenditures was -0.1919 , which turned out to be the best among all brands.

For the U group, the maximum value is 0.0363 . Volkswagen obtained an ideal position. It spent \$37.71 per unit and its

Table 6-8
Revised advertising expenditures based
on the new criterion.

Brand	β_i		Revised A_i (\$)		Difference (\$)	
	G	U	G	U	G	U
A	0.0154	0.0153	29.13	29.63	41.18	40.68
CA	0.0307	0.0343	23.62	26.96	4.91	1.57
CHE	0.0276	0.0336	17.57	21.87	6.03	1.73
CHR	0.0143	0.0150	10.98	11.80	17.59	16.77
F	0.0371	0.0269	21.76	16.13	0	5.63
L	0.0186	0.0191	39.17	40.97	38.91	37.11
T	0.0278	0.0255	37.66	35.37	12.61	14.90
V	0.0351	0.0363	35.72	37.71	1.99	0
$\max\{\beta_i\}$	0.0371	0.0363				

+1.0000 was added to the measures
of advertising for both groups.

perceived advertising measure was 0.3670 . The advertising expenditures were the most effective for Ford in the G group and for Volkswagen in the U group.

The revision of the actual advertising expenditures spent could be made by employing a new criterion to determine how much should be spent. The revised advertising expenditures* based on this new criterion and the difference between the actual and the revised advertising expenditures are also presented in Table 6-8. The revised advertising expenditures were also plotted in Figure 6-4 (a) and (b). The curve connecting the most effective point for each brand is called an efficiency curve for advertising expenditures.

We might seek a combination of the advertising expenditures and the consumers' perception that lies on this efficiency curve. A combination is not efficient if there is another combination with either a higher measure of perceived advertising expenditures and less actual expenditure, a higher measure of perceived advertising expenditures and the same actual advertising expenditures, or the same measure of perceived advertising expenditures but less actual expenditure.

* The revised advertising expenditures are expressed as ;

$$A_i = \frac{1}{0.0371} \left[f(A_i) + 1.0 \right] \quad \text{for Graduates.}$$

$$A_i = \frac{1}{0.0363} \left[f(A_i) + 1.0 \right] \quad \text{for Undergraduates.}$$

$f(A_i)$: Measure of perceived advertising expenditures for brand i .

CHAPTER 7
PROPENSITY TO CONSUME IN RELATION TO
BRAND QUALITY

Summary

Five vectors for possible car-buying budgets (\$4,000, \$6,000, \$8,000, \$10,000, and \$12,000) are fitted in the perceptual configuration.

We find that the vectors of higher budgeted preferences come closer to the quality dimension in both groups. (Hypothesis 7).

By constructing a utility function in which the prices are directly mapped to the utility indices, we can theorize that consumers might realize the best utility by Mercedes-Benz when we consider all five possible budgets.

Introduction

This chapter is concerned with the "endowment" of consumers which, in this study, consists of available purchasing power. In Chapter 5 the analysis indicated that the effect of price on the perception of quality was clear. Our concern here is to determine the importance of price, from the point of consumers' budgets, in the evaluation of brand quality.

The hypothesis to be tested is restated below.

H₇ : "Consumers believe they would buy a better quality brand if they had more money."

The analytical steps in this chapter are presented in Figure 7-1.

Test of H₇ and utility analysis

First we see how property vectors for budgets were fitted in the perceptual space of brands ; five preference vectors of the average subject which represented his preference rankings under the monetary limits of \$4,000, \$6,000, \$8,000, \$10,000, and \$12,000 were fitted in the perceptual configuration obtained from the INSCAL analysis in Chapter 4. Nonmetric version of Models III and IV of the PREFMAP algorithm was employed for the analysis. Table 7-1 presents the goodness of fit (correlation coefficients of the estimated preference values and the nonmetric transform of the original preference ranks) for Models III and IV.

Even though there are wider variations among correlation coefficients in Model IV than in Model III, correlation coefficients are even better in certain vectors than those in Model III for both groups. Furthermore, the differences in the correlation

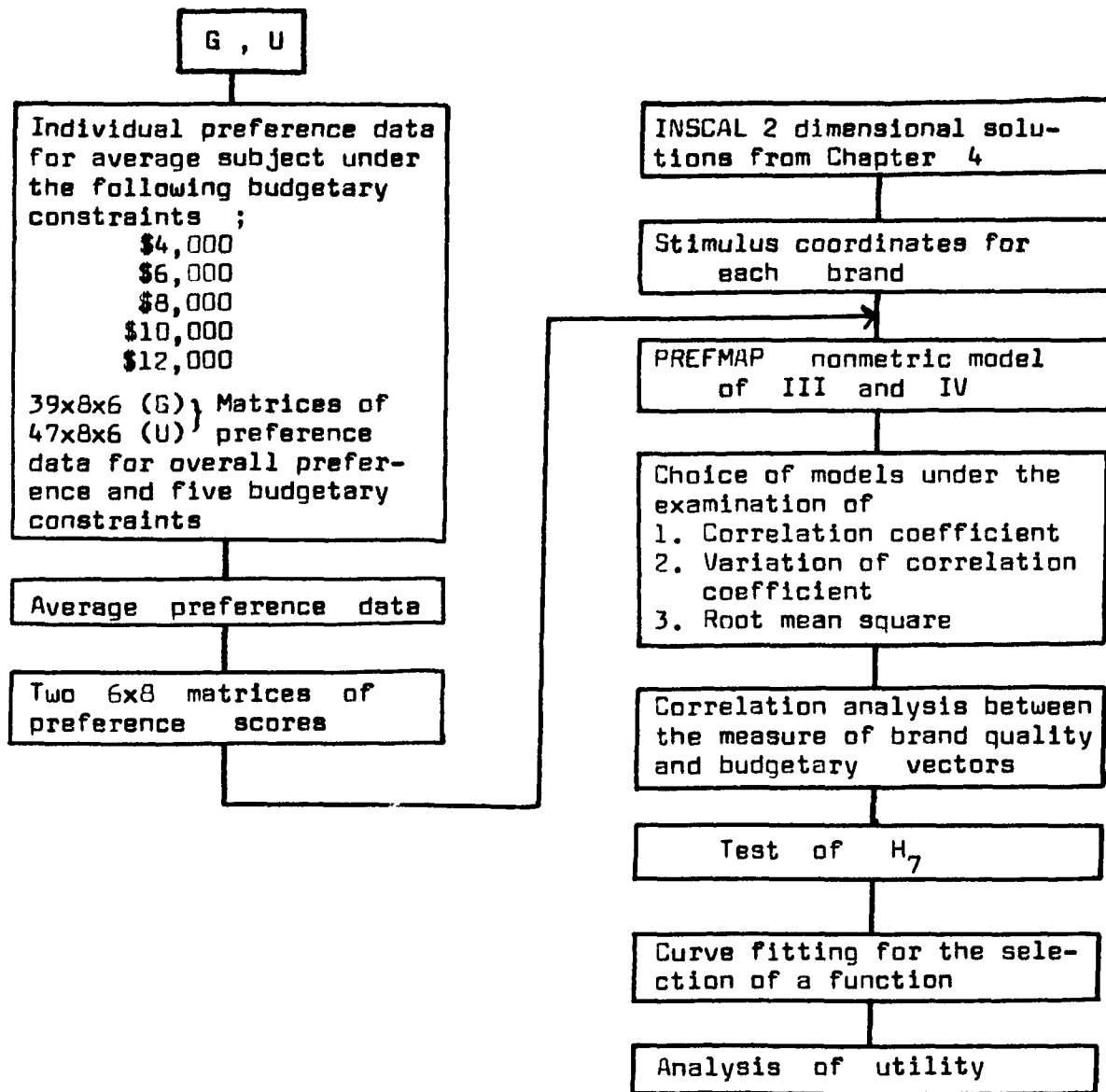


Figure 7-1 Analytical procedures for testing H_7 .

coefficients in absolute value between Model III and Model IV are less than 0.1 in all cases and so they may be considered negligible.

Accordingly little improvement in the goodness of fit from Model IV to Model III was to be expected. Therefore, the analysis was made by Model IV for all vectors.

The direction cosines of the property vectors in the perceptual spaces of both groups are presented in Table 7-2. Figure 7-2 (a) and (b) show the joint-space configuration by the vector model for each group.

The vectors of higher budgeted preferences were positioned closer to the quality dimension in both groups* (or, closer to dimension 1 for the G group and to dimension 2 for the U group). That is, the vectors for the G group moved clockwise, being directed toward better quality of brand from lower budgeted preferences to higher budgeted preferences. The \$12,000 budgeted vector was collinear with the dimension which represented higher quality of brand. Vectors for the U group moved counter-clockwise, being directed toward better quality of brand from lower budgeted preferences to higher budgeted preferences. The \$12,000 budgeted vector showed the same nature as for the G group with regard to the quality dimension. The overall preference vector was located between the \$4,000 and the \$6,000 vectors in both groups. Since

* In interpretation of axes, see Chapter 4, and this interpretation was confirmed in Chapter 5.

Table 7-1

Goodness of fit of Models III and IV of the PREFMAP procedure with vectors of overall preference and five disposable budgets.

Preference budgetary condition	Graduates			Undergraduates		
	Correlation coefficient		Difference in correlation coefficient between the two models	Correlation coefficient		Difference in correlation coefficient between the two models
	Model III	Model IV		Model III	Model IV	
Overall preference	0.9888	0.9037	0.0851	1.0000	0.9652	0.0348
\$4,000	0.9906	0.9466	0.0440	0.9517	0.9445	0.0072
\$6,000	0.9791	0.9794	-0.0003	0.9388	0.9130	0.0258
\$8,000	1.0000	1.0000	0	0.9994	0.9999	0.0005
\$10,000	0.9971	0.9999	-0.0028	0.9999	1.0000	0.0001
\$12,000	0.9996	0.9996	0	0.9998	1.0000	0.0002
Root mean square	0.9925	0.9722		0.9820	0.9710	

Table 7-2

Direction cosines of the fitted vectors of overall preference and five disposable budgets by the vector model.

Property vector	Direction cosines			
	Graduates		Undergraduates	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
Overall preference	-0.1321	0.9912	0.9955	0.0952
\$4,000	-0.8109	0.5852	0.8121	-0.5836
\$6,000	0.1021	0.9948	0.9025	0.4308
\$8,000	0.9792	0.2030	0.3711	0.9286
\$10,000	0.9874	0.1584	0.2553	0.9669
\$12,000	0.9942	0.1074	0.1784	0.9840

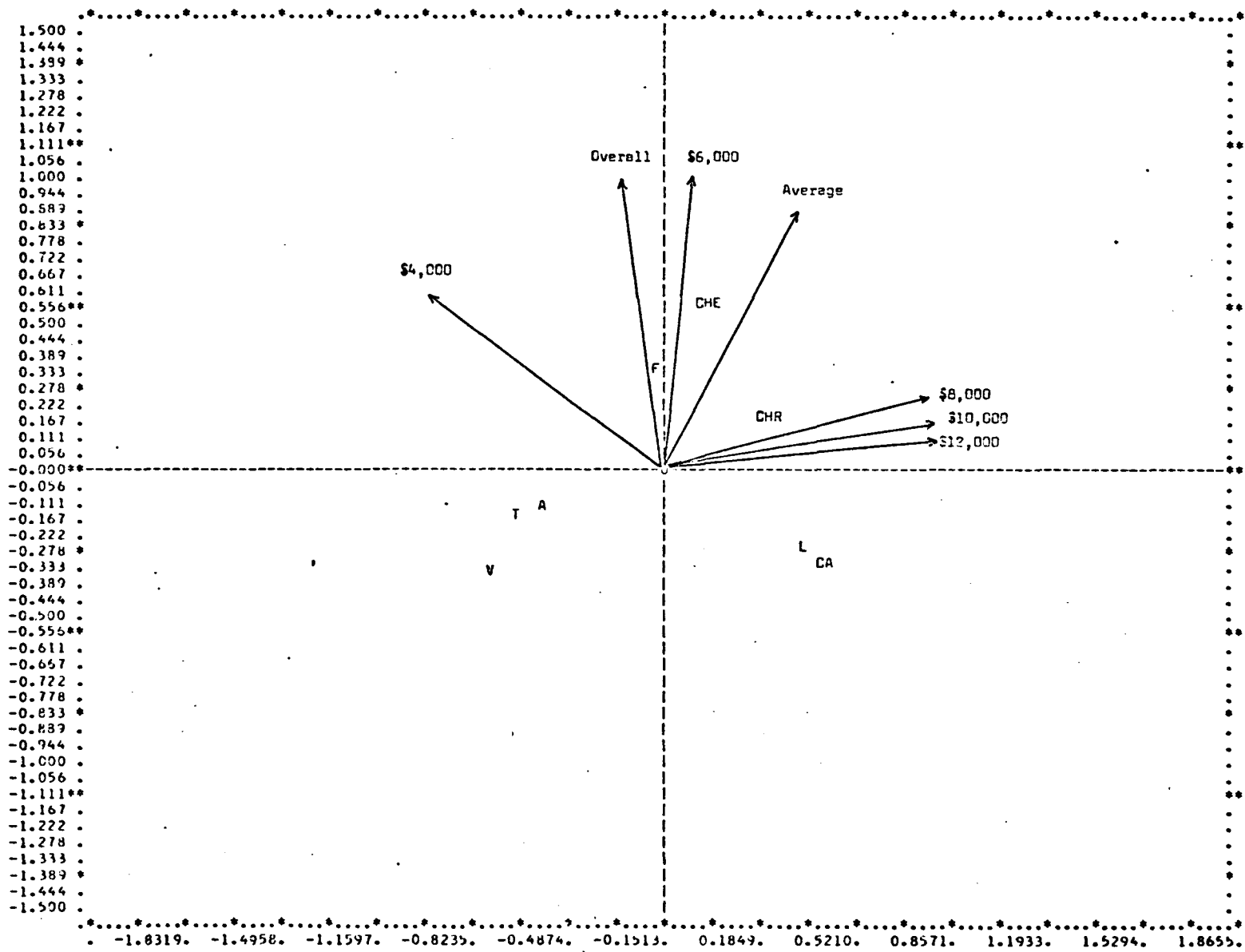


Figure 7-2 (a) Preference vectors (overall and five disposable budgets) in the brand perception space for Graduates.

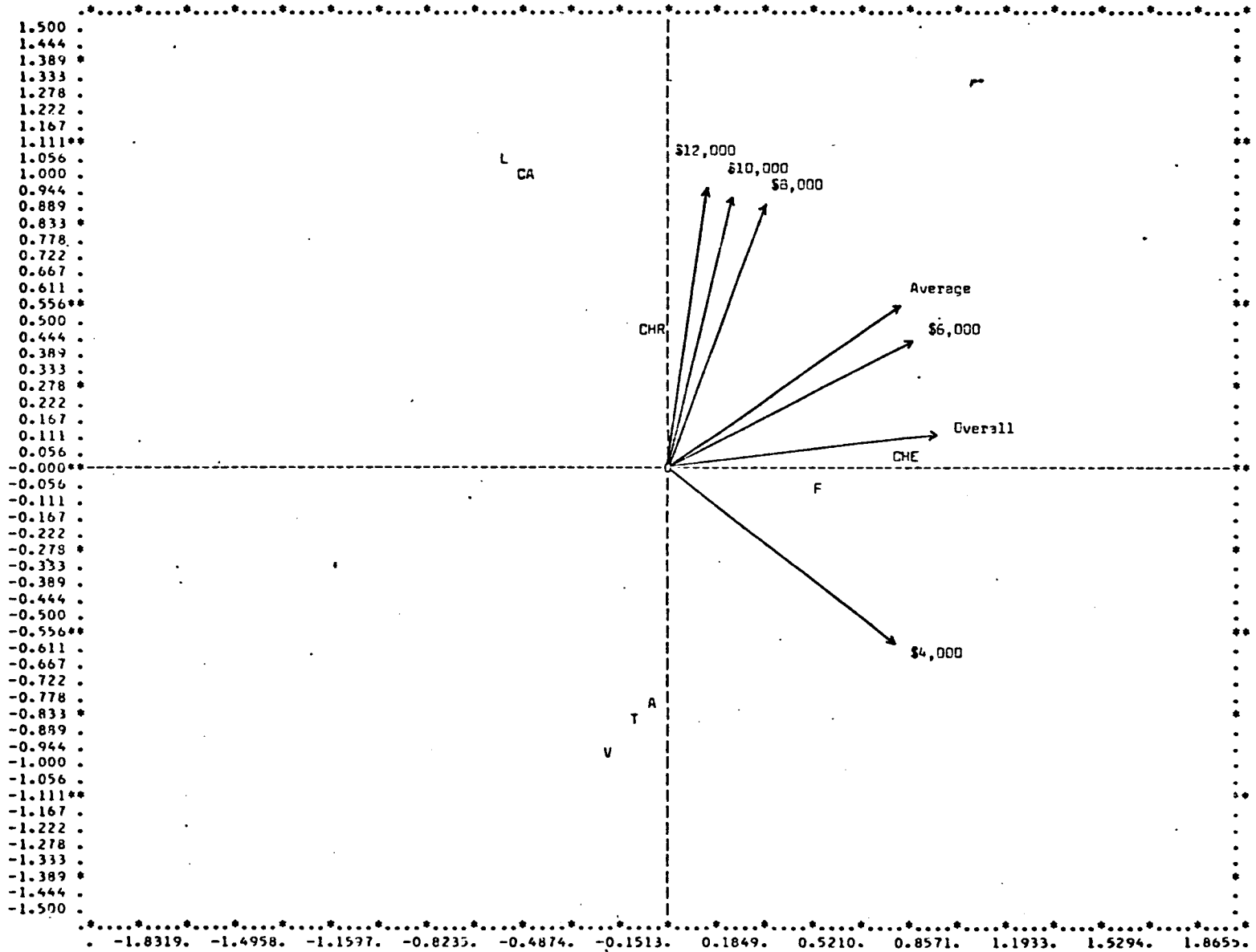


Figure 7-2 (b) Preference vectors (overall and five disposable budgets) in the brand perception space for Undergraduates.

the average budgetary vector was found between the \$6,000 and \$8,000 budgetary vectors for both groups, we may say that they were trading off brand quality for some other use of the money.

The measure of correlation of property vectors with the quality dimension was made by directly correlating the five budgetary vectors with the coordinate values on the quality dimension. Results are shown in Table 7-3. The relationship between the budgets and their degree of correlation with brand quality was graphed for both groups in Figure 7-3.(a) and (b).

It is noted again that the high monetary budget caused the respondents to show a greater propensity for brand quality. These findings support Hypothesis 7.

However, "saturation" of quality was reached with higher monetary budgets. Between the Budgets of \$10,000 and \$12,000, consumers' utility for quality was not remarkably increased. This suggests that consumers may purchase expensive brands not for strictly utilitarian motives but for other factors such as prestige or social status.

If we regard the correlation between budgetary constraints and quality as the expected utility obtained from the value of the brand price, we could construct a utility function by mapping the prices directly to the utility indices.

Table 7-3

Correlations between the vectors of five disposable budgets with the quality dimension.

Correlation with the quality measure		
Vector	Graduates	Undergraduates
\$4,000	-0.27411	-0.38598
\$6,000	0.28995	0.21664
\$8,000	0.95635	0.95223
\$10,000	0.96578	0.95721
\$12,000	0.97358	0.96264

Correlation between
the disposable budget
and the brand quality

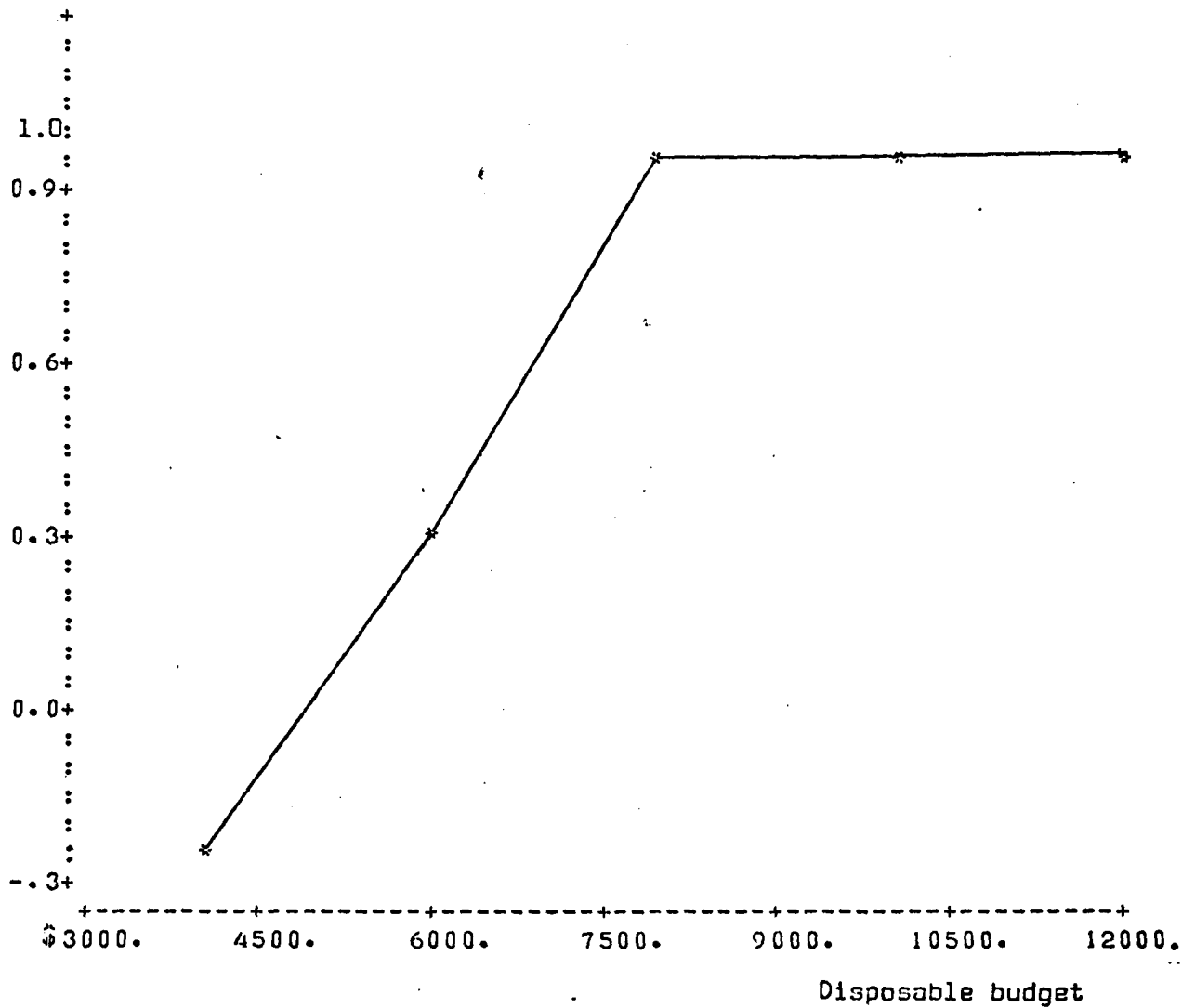


Figure 7-3 (a) Relationship between five disposable budgets and their corresponding correlations with the brand quality for Graduates.

Correlation between
the disposable budget
and the brand quality

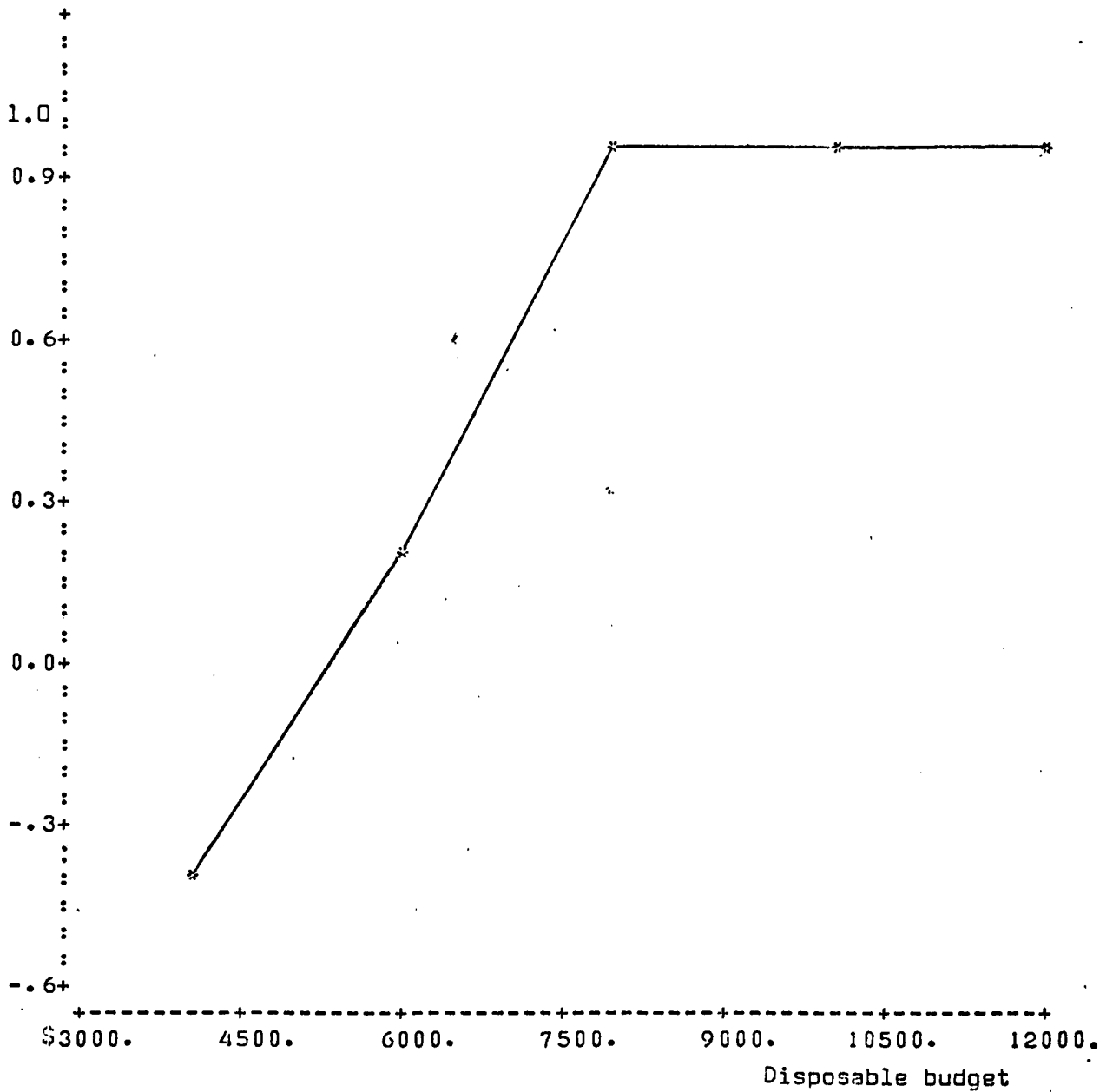


Figure 7-3 (b) Relationship between five disposable budgets and their corresponding correlations with the brand quality for Undergraduates.

In order to determine the form of a function, curves were fitted*. The assumption of the nature of utility led us to examine three asymptotic curve forms. Table 7-5 (a) presents the results of curve fittings. Since a reciprocal transformation showed the best fit to the data for both groups, it was used for our analysis. Detailed analysis was made with the form given by :

$$U = b + \frac{a}{D} \quad (D \neq 0)$$

where U is the measure of brand utility. D is the budget, and "a" and "b" are parameters.

The model was applied in its reciprocal form to the data given in Table 7-4. The estimates of "a" and "b" by the least squares fit and the tests of goodness of fit of the model to data are presented in Table 7-5 (b). The utility function is shown by curve in Figure 7-4 (a) and (b). The fit of the model was very good for both groups.

From the curve obtained, we could predict how much of their budget consumers would have to use to reach a utility index of, say, 1. \$10,639 and \$10,725 were calculated for the G and the U groups, respectively. Mercedes-Benz would fall into this price range, for which consumers would realize the best utility.

* This was done through the Rapidata system at the Baruch Computer Center.

Table 7-4

Five disposable budget vectors and their corresponding utility indices.

Budget vectors	Utility measure	
	Graduates	Undergraduates
\$4,000	-0.27411	-0.38598
6,000	0.28995	0.21664
8,000	0.95635	0.95223
10,000	0.96578	0.95721
12,000	0.97358	0.96264

Table 7-5 (a)

Least squares fit of three curve types with an asymptotic level for the utility analysis.

Curve form	Group	Coefficient of determination
$U = b + \frac{a}{D}$	G	0.9439
	U	0.9406
$U = \frac{1}{b + aD}$	G	0.1800
	U	0.0052
$U = \frac{D}{b + aD}$	G	0.4071
	U	0.2009

Table 7-5 (b)

Parameter estimates for the reciprocal form of the utility function of disposable budgets and goodness of fit to data.

Group	Parameters				Coefficient of determination
	b		a		
	Estimate	95% confidence limit	Estimate	95% confidence interval	
G	1.770	$1.305 \leq b \leq 2.234$	-8188.81	$-11152.6 \leq a \leq -5225.0$	0.9439
U	1.828	$1.308 \leq b \leq 2.347$	-8876.76	$-12189.1 \leq a \leq -5564.4$	0.9406

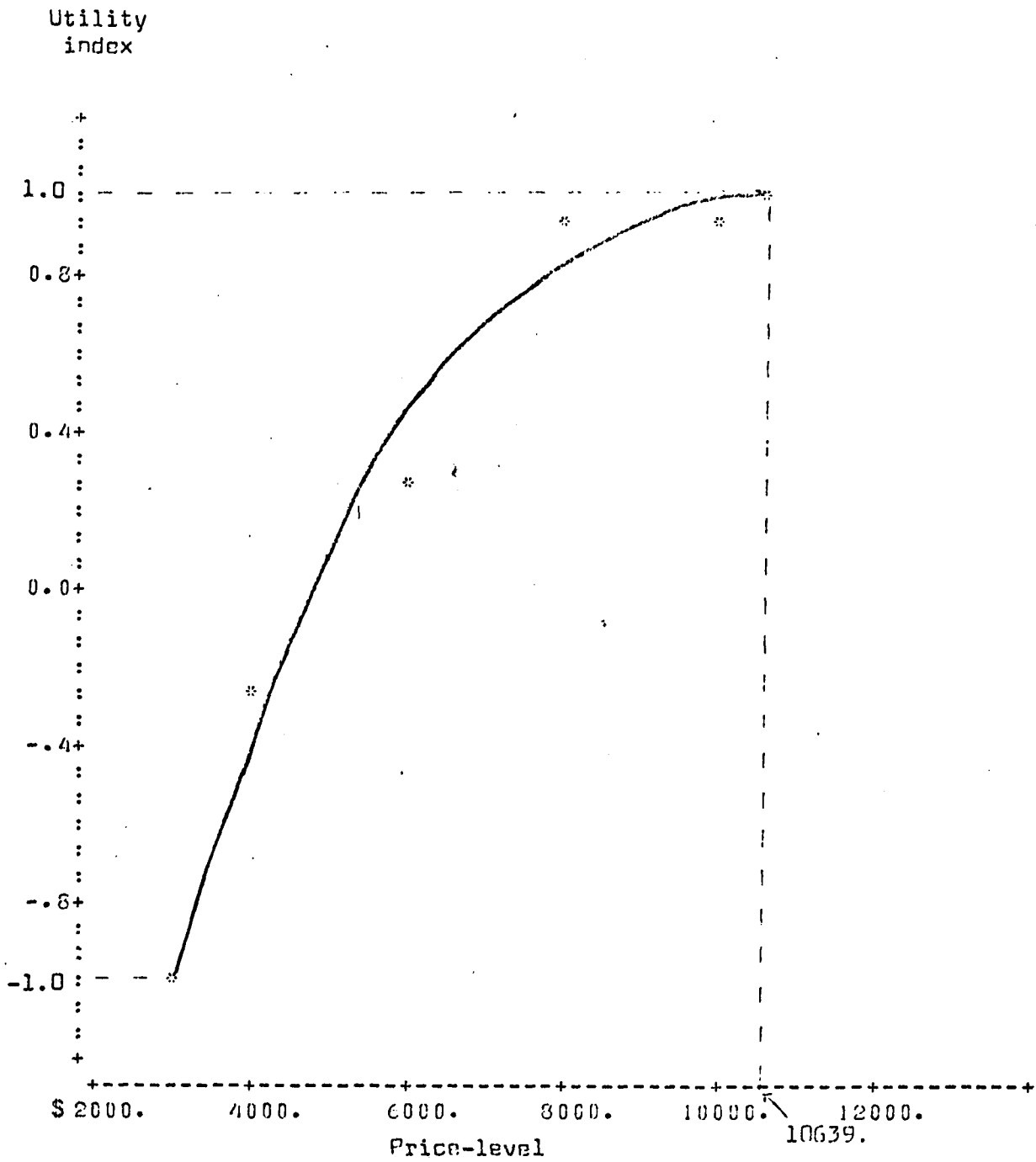


Figure 7-4 (a) Utility function for cars at various price-levels (\$4, \$6, \$8, \$10 and \$12 thousand) for Graduates.

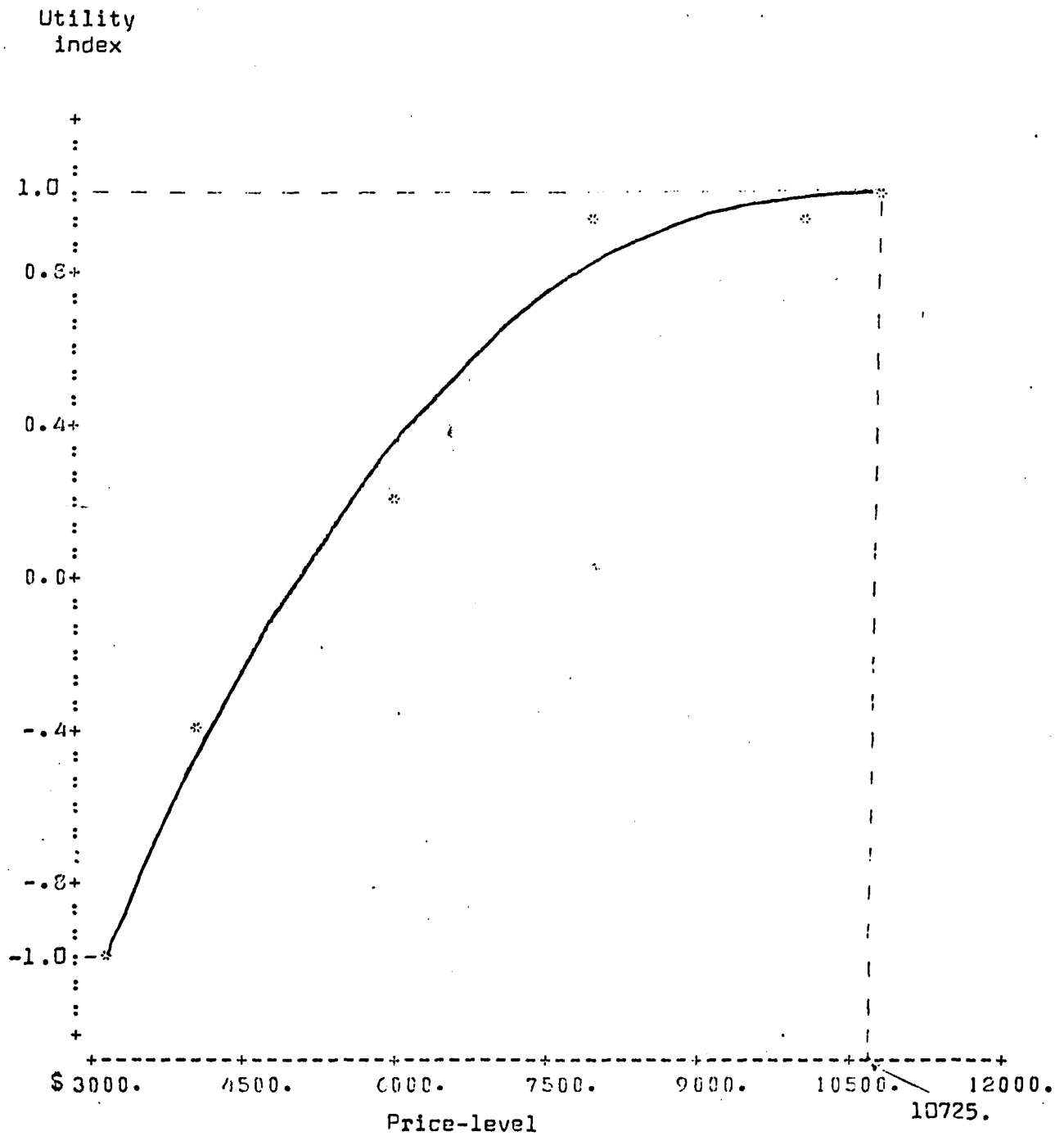


Figure 7-4 (b) Utility function for cars at various price-levels (\$4, \$6, \$8, \$10 and \$12 thousand) for Under-graduates.

CHAPTER 8
CONSUMERS' CHANGE OF PERCEPTION, PREFERENCE
AND ATTITUDE TOWARD BRANDS

Summary

Chapter 8 is divided into three sections.

In the first section we conduct the analysis of scenario influences in terms of monetary constraints and places of residence. We find that the city preference-vector is collinear with the \$4,000 monetary vector. We also conclude from the data that the more spacious places to live in are appropriate for owning the larger and the more expensive cars.

The second section deals with the analysis of basic attribute vectors (property vectors) of brands in the perceptual map.

We find that the property vectors which represent "Styling and appearance", "Price", "Road performance", and "Overall rating" are directed around more expensive brands of cars. The property of "Availability of repair service" is more relevant to the domestic brands. It is confirmed that the property of "Overall rating" can be used as a good index for perceived quality.

The third section studies the basic product features in relation to time.

For the Luxury concept of the product features, there is no difference between Graduates and Undergraduates in their three

vectors of the past, the present and the future.

For the Economy concept of the product features, there are some significant differences discerned between vectors of Graduates and Undergraduates. Both have the similar perception for future importance of economy. But they perceive past and present importance of economy differently. Generally, Graduates give less importance to the economy factor.

In terms of the change through time from the past into the future we recognize little change in perception of the importance of luxury. Most of the change through time is to be found in a much greater importance given to economy with the passage of time.

Introduction

Chapter 8 is divided into three sections as follows ;

Analysis of scenario influences in terms of monetary constraints (\$4,000, \$6,000, \$8,000, \$10,000, and \$12,000) and places of residence (city, suburbs and small town).

Analysis of basic attribute vectors (property vectors) of brands in the perceptual map.

Study of the basic product features of brands in relation to time.

In the first section, we attempt to evoke what were not interpreted by only overall preference. When the scenarios are given, the changes of consumer preference under conditions might be elicited. The scenario variables used in this study are monetary constraints for purchase and types of places where the car would be used (city, suburbs, and small town).

The second section analyzes consumer attitude toward a brand by rated scales of brand properties. Since Question area 3 provided us with the unidimensional construct ratings on eight properties, it is possible to fit these outside property vectors in the perceptual map of brands and study consumers' attitudinal direction on each property.

In the third section, efforts are made to find basic attributes of brands by factor analysis. Consumers form their perceptual frame about attributes of a brand which they are motivated to purchase. Our aims here are to examine these questions : Can we identify the factors involved and expose their underlying structure? Can consumer purchasing behavior be predicted from these basic brand attributes? Can we predict the effect of attribute changes of brands and their influence on potential consumers' purchasing? How should a future brand be designed? What may we expect in a new brand's performance?

The analytical flow for Chapter 8 is diagrammed in Figure 8-1.

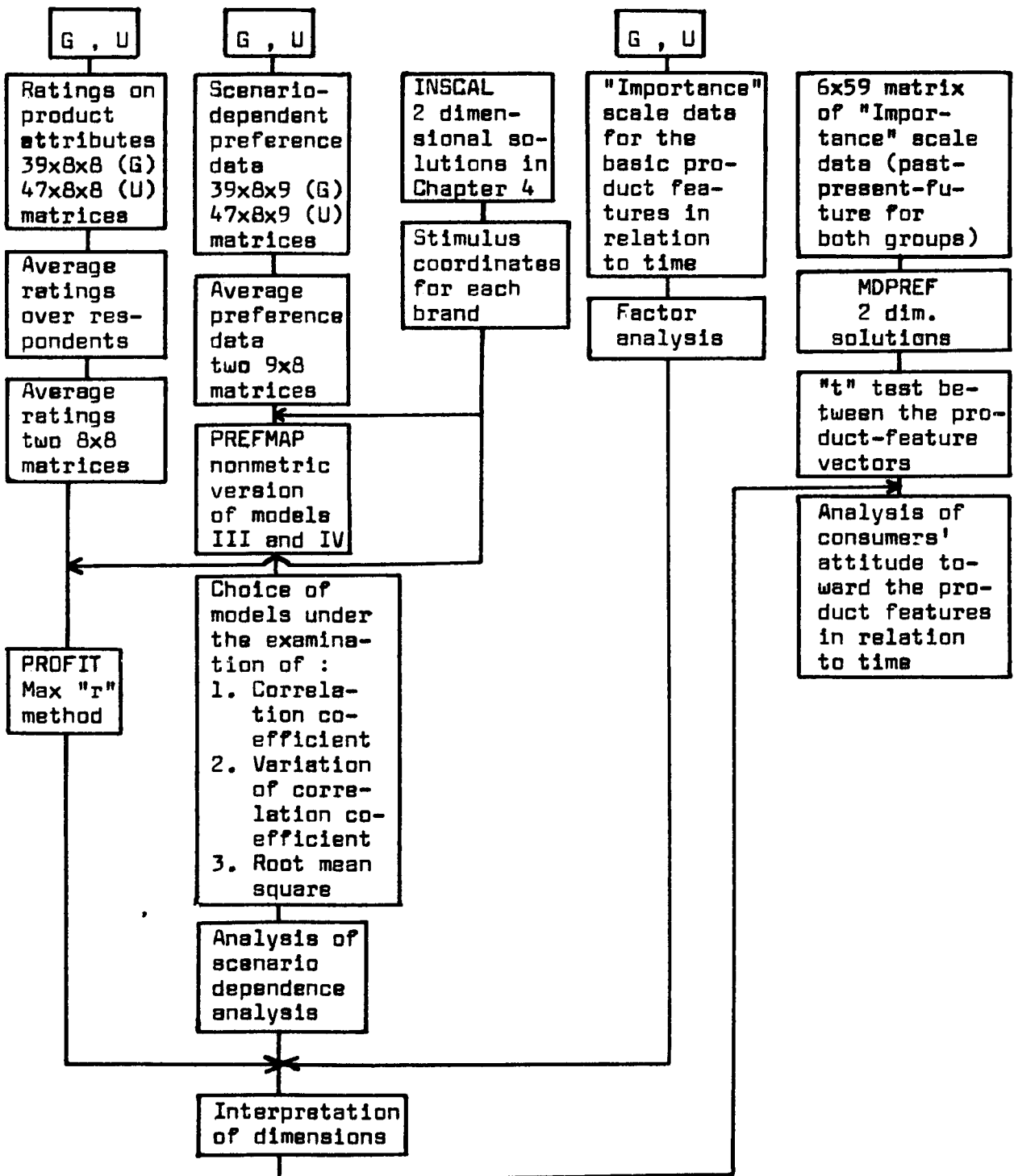


Figure 8-1 Flow diagram of the analysis outlined in Chapter 8.

Analysis of Scenario influence in terms of monetary constraints
and places of residence

We are here considering the data from Question area 6 (a) and (b) in the questionnaire. The respondent is asked to rank the eight brands. First he ranks them by overall preference. Then he is asked to rank them in eight separate and different contexts within which he might buy or use a car.

There are five contexts (scenarios) of budgetary constraints ; i.e., \$4,000, \$6,000, \$8,000, \$10,000, and \$12,000.

There are three geographical contexts of living ; i.e., in the city, in the suburbs and in a small town.

Average ranks was computed for each brand. These averages and the coordinate values from our Chapter 4 INSCAL solutions were submitted to the nonmetric versions of both Models III and IV of the PREFMAP procedure. The input data are summarized in Table VII-1 in Appendix.

The goodness of fit measures (individual-scenario multiple correlations) is presented in Table 8-1. The root mean squares for Model IV which were applied to the original INSCAL spaces were 0.9797 and 0.9750 for the G group and the U group, respectively. Model III whose root mean squares for the G group and the U group were 0.9942 and 0.9906 , respectively.

Table 8-1

Goodness of fit measures of Models III and IV of the PREFMAP procedure for nine scenario-dependent preferences.

Scenario dependent vector	Graduates			Undergraduates		
	Correlation coefficient		Difference	Correlation coefficient		Difference
	Model III	Model IV		Model III	Model IV	
Overall	0.9900	0.9019	0.0881	0.9982	0.9671	0.0311
\$4,000	0.9856	0.9469	0.0387	0.9925	0.9440	0.0385
\$6,000	0.9796	0.9799	-0.0003	0.9640	0.9146	0.0494
\$8,000	1.0000	0.9956	0.0044	0.9964	0.9940	0.0024
\$10,000	0.9969	1.0000	-0.0031	0.9995	1.0000	-0.0005
\$12,000	0.9996	0.9997	-0.0001	0.9996	1.0000	-0.0004
City	0.9968	0.9977	-0.0009	0.9683	0.9558	0.0125
Suburbs	0.9996	0.9923	0.0073	1.0000	1.0000	0.0000
Town	0.9995	0.9991	0.0004	0.9959	0.9958	0.0001
Root mean square	0.9942	0.9797		0.9906	0.9750	

The absolute differences in the correlation coefficients between Models III and IV were less than 0.1 for all cases, and were thus considered negligible. For the above reasons therefore, Model IV was used in the analysis.

The direction cosines of the scenario dependent vectors in the perceptual space are shown in Table 8-2. The joint-space configuration is presented in Figure 8-2 (a) and (b).

In the conjoint space of the G group, it was noted that the city preference vector was closer to the \$4,000 monetary vector, indicating that city dwellers liked smaller-sized brand of cars. Town and suburbs dwellers preferred more expensive cars whose prices ranged between \$6,000 and \$8,000. Understandably, the more spacious places to live in were appropriate for owning the larger and the more expensive cars.

The U group followed the same pattern of preferences as the G group. Only difference was the direction of the suburbs vector, which was located near the \$10,000 monetary vector.

Table 8-2

Direction-cosines of nine fitted
scenario-dependent vectors.

Scenario dependent vector	Direction cosines			
	Graduates		Undergraduates	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
Overall	-0.1793	0.9838	0.9835	0.1809
\$4,000	-0.8199	0.5725	0.8543	-0.5197
\$6,000	0.0578	0.9983	0.8850	0.4656
\$8,000	0.9724	0.2331	0.3161	0.9487
\$10,000	0.9824	0.1871	0.2034	0.9791
\$12,000	0.9909	0.1342	0.1277	0.9918
City	-0.8030	0.5959	0.8473	-0.5310
Suburbs	0.9213	0.3887	0.2204	0.9754
Town	0.7168	0.6973	0.3797	0.9251
Average	0.4306	0.9025	0.7766	0.6300

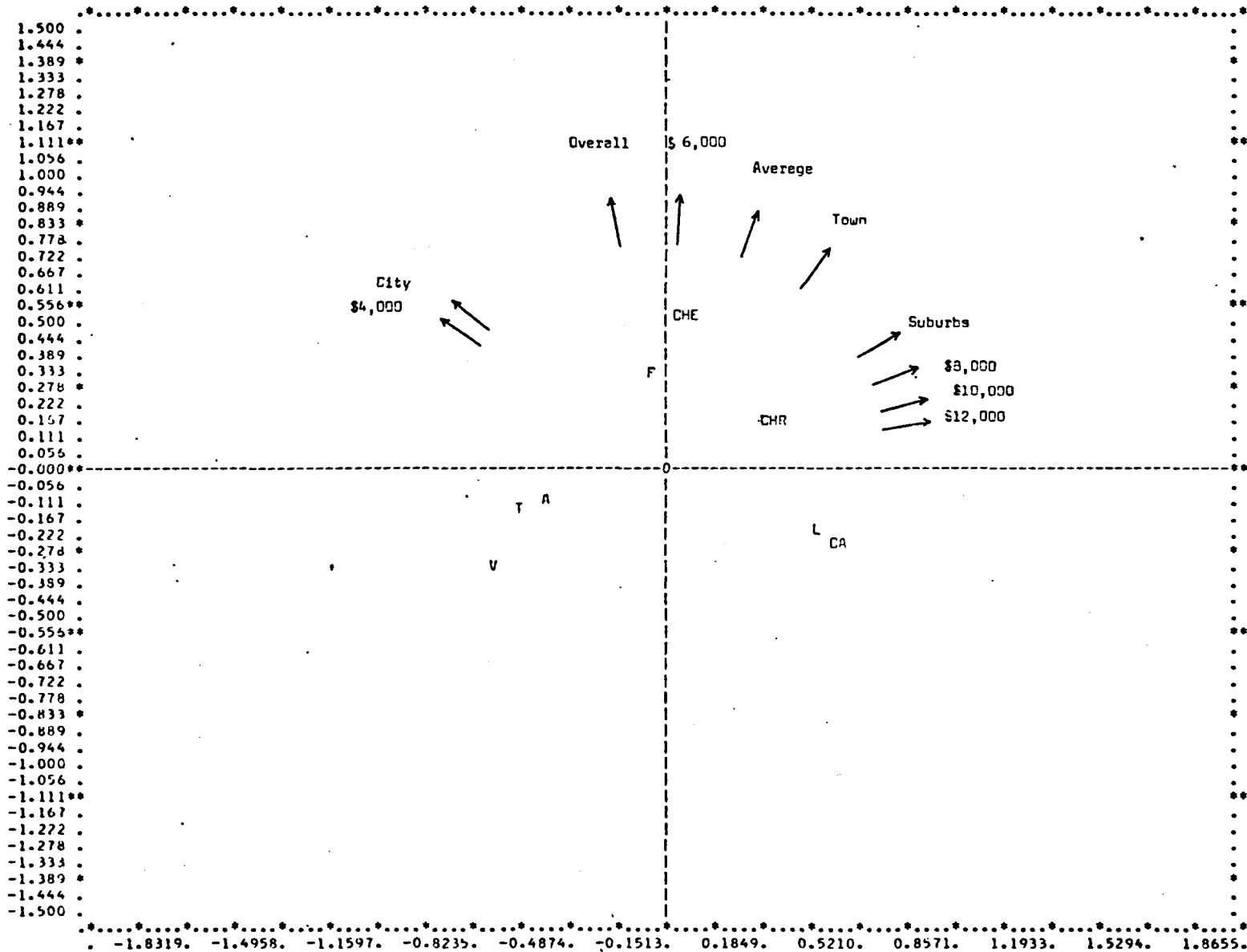


Figure 8-2 (a) Joint-space configuration of brands and scenario-dependent preferences (overall, five contexts of budgetary constraint, and three geographical contexts of living for Graduates.

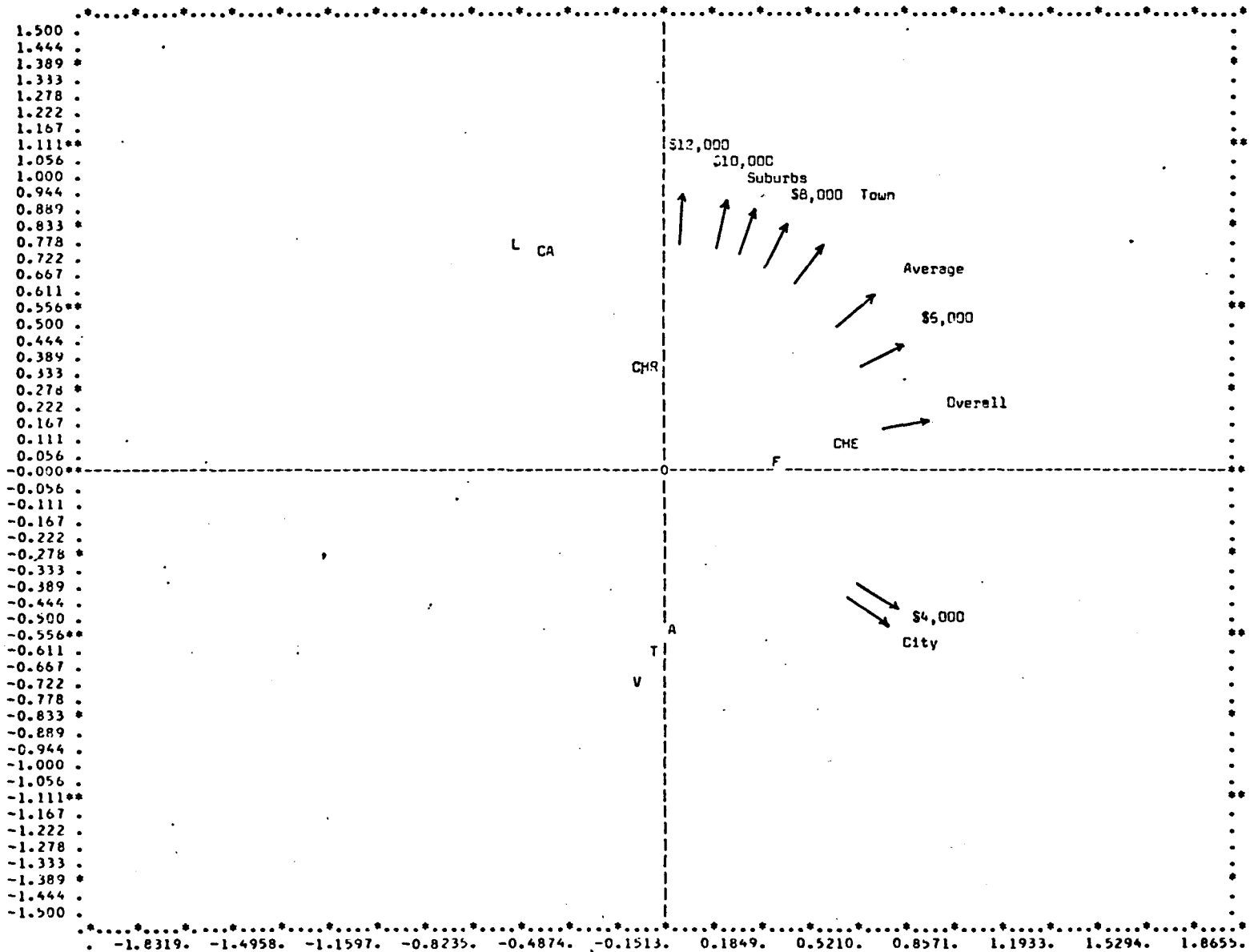


Figure 0-2 (b) Joint-space configuration of brands and scenario-dependent preferences (overall, five contexts of budgetary constraint, and three geographical contexts of living for Undergraduates.

Analysis of basic attribute vectors (property vectors) of brands
in the perceptual map

We are here considering the data from Question area 3 in the questionnaire. The respondent is asked to use a seven-point scale to give an overall hedonic rating to each of eight brands. Then, still with a seven-point scale, he is asked to rate the brands separately on seven characteristics or attributes ; i.e., price, styling and appearance, dependability, frequency of repairs, availability of repair service, amount of advertising, and road performance.

A summary of the resultant averages is shown in Table VIII-1 in Appendix. These averages and the corresponding INSCAL coordinates were used as input in the present analysis.

Using a plot of the INSCAL coordinates and the previously identified loci of the eight brands, we wish to draw in a vector to represent each of the scales mentioned above.

We will call these vectors "property vectors". We will see how consumers perceive each of the eight brands in terms of their perception of brand properties (Figure 8-3 (a) and (b)). Technically, the objective was to fit the outside property vectors which represented the unidimensional ratings in the perceptual dimensions. The method of max "r" of the PROFIT algorithm was

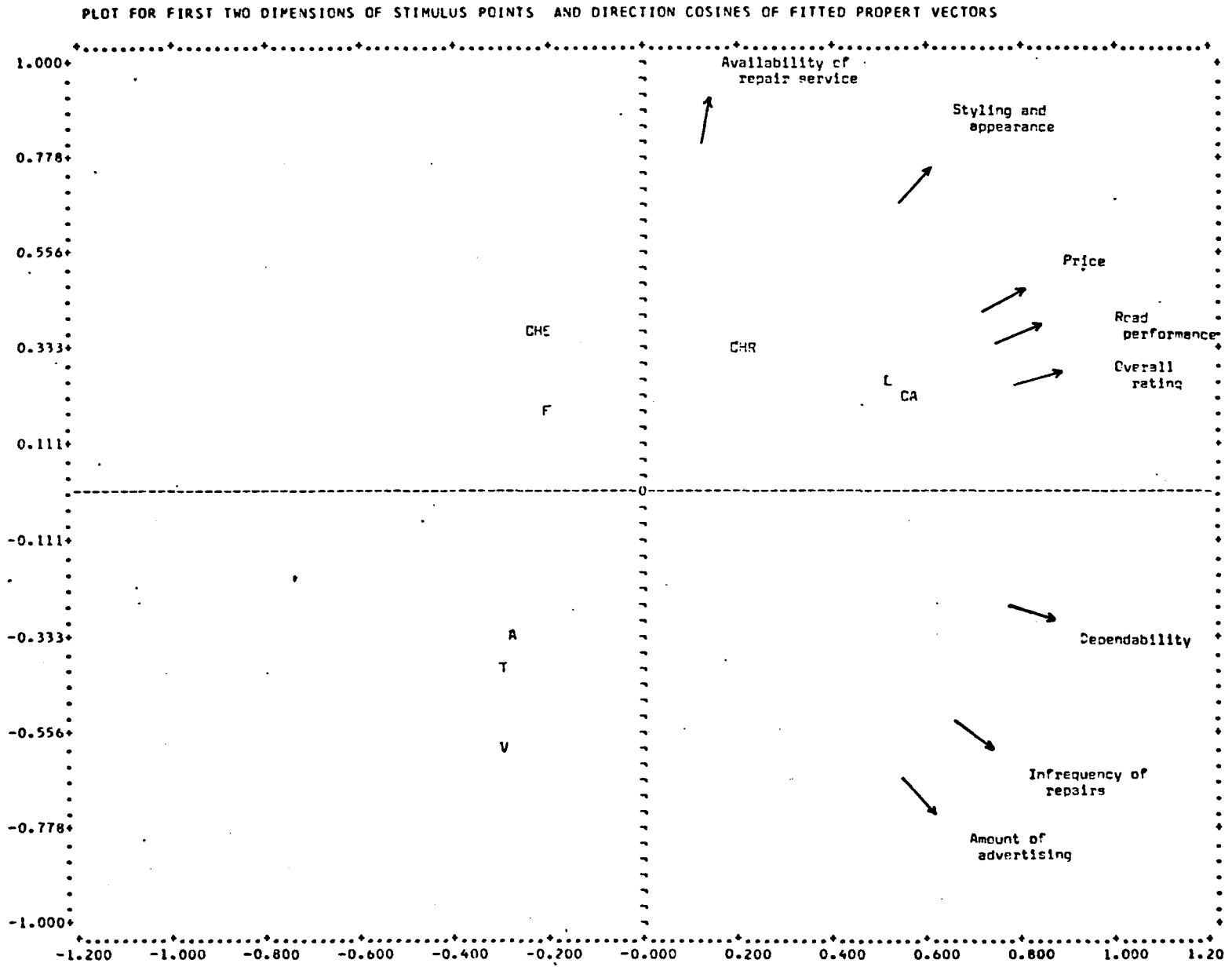


Figure D-3 (a) Eight brand property vectors fitted in the brand space by max "r" method for Graduate.

PLOT FOR FIRST TWO DIMENSIONS OF STIMULUS POINTS AND DIRECTION COSINES OF FITTED PROPERTY VECTORS

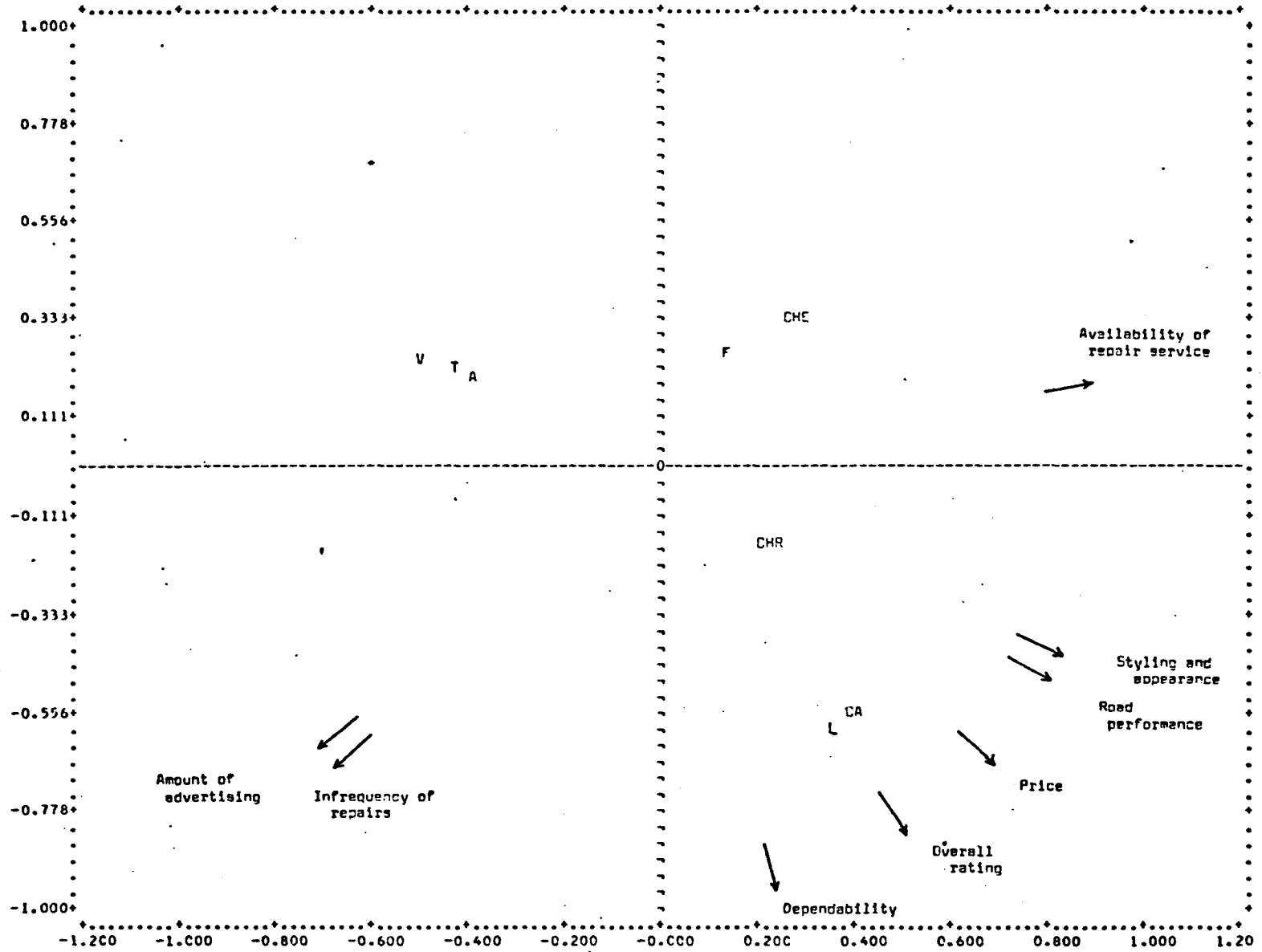


Figure 8-3 (b) Eight brand property vectors fitted in the brand space by max "r" method for Undergraduates.

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employed for the analysis of this study. This method finds the best direction in the stimulus space for each property scale so that the projections of the stimuli onto the fitted vector are linearly correlated with the original ratings of the candidate property vector in the maximum degree. Resulting goodness of fit (multiple correlation) for each fitted vector and the direction cosines are presented in Table 8-3 for both groups.

The goodness of fit measures (the multiple correlation coefficients in Table 8-3) represented the degree of congruence of the construct represented by the property scale with the dimensions of the configuration linearly related. Correlation coefficients of each property for both groups were quite similar, but the G group generally showed higher correlations with the perceptual map than the U group. The property 4 in both groups and property 6 in the U group were not highly correlated with the perceptual configurations.

Figure 8-3 (a) and (b) revealed little differences in the configurations of both groups. "Styling and appearance", "Price", "Road performance", and "Overall rating" property vectors were directed around more expensive brands of cars such as Chrysler, Lincoln and Cadillac. Both groups indicated that "Availability of repair service" was more relevant to the domestic brands. The fitted vector labeled "Overall rating" was positioned close to the quality dimension (dimension 1 for the G group and dimension 2 for the U group), supporting our interpretation of the axes in Chapters

Table 8-3

Goodness of fit measures of eight brand property vectors by max "r" method of the PROFIT algorithm.

Property vector	Graduates			Undergraduates		
	Correlation coefficient*	Direction cosine		Correlation coefficient*	Direction cosine	
		Dimension 1	Dimension 2		Dimension 1	Dimension 2
1. Price Low/High	0.9937	0.9003	0.4352	0.9715	0.7167	-0.6974
2. Styling and appearance Not at all attractive/ Very attractive	0.9711	0.6241	0.7813	0.9748	0.8779	-0.4788
3. Dependability Undependable/ Dependable	0.7188	0.9576	-0.2882	0.6868	0.1914	-0.9815
4. Frequency of repairs Frequent/ Infrequent	0.5426	0.7900	-0.6131	0.5289	-0.7013	-0.7128
5. Availability of repair service Poor/Excellent	0.8514	0.1231	0.9924	0.8277	0.9845	0.1756
6. Amount of advertising Only a little/ A great deal	0.8540	0.6429	-0.7659	0.5162	-0.7300	-0.6834
7. Road performance Poor/Excellent	0.9826	0.9515	0.3076	0.9530	0.8504	-0.5262
8. Overall rating Poor/Excellent	0.9638	0.9530	0.3031	0.9607	0.5276	-0.8495

* : The maximum correlation between the property and the projections on fitted vector

4 and 5. Also, it was confirmed that "Overall rating" could be used as a good index for perceived quality.

Study of the basic product features in relation to time

Here we are using data from Question area 7 in the questionnaire concerned with 59 specific car features. On a seven-point "importance" scale (Unimportant-Important) respondents are asked to rate the specific car features in terms of importance to them in the past, at the present, and in the future.

The 59 specific features appear in the full questionnaire in Appendix. The raw data are summarized in Table VIII-2 in Appendix.

The data were submitted to six principal component analyses* : Graduates and Undergraduates each for the three different time periods (past, present and future). In each case a varimax rotation was made and the first two factors were extracted. The factor loadings for the three time periods of each group are shown in Table VIII-3 through VIII-5 in Appendix.

Interpretation of the two factors of product features was made by considering the extracted main factor loadings, appearing

* BMD72-Factor Analysis-Revised, April 5, 1972, Health Science Computing Facility, UCLA.

in Tables 8-4 (a) and (b). The two factors of product features were interpreted as first, a "luxury" concept and second, an "economy concept".

In the resultant two-factor space, we plotted three vectors (past, present and future) separately for Graduates and Undergraduates. (See Figure 8-4.) Three vectors were derived by the MDPREF model using the raw seven-point interval-scale data as input which are presented in Table VIII-2 in Appendix. The objective was to represent the consumers' perceptual changes in the product features for the three time periods - past, present and future.

For the Luxury axis, there was no significant difference between Graduates and Undergraduates in their three vectors. We determined this by inter-t test of distances between the projected points from the vectors onto the axis. (See Table 8-5.)

For the Economy axis, some significant differences were discerned between vectors of Graduates and Undergraduates. Both perceive future importance of economy similarly. But their perceptions of economy-importance in their past and present fairly differ. In general, Graduates give less importance to the economy factor.

In terms of the change through time from the past into the future we see little change in perception of the importance of luxury, only perhaps a very small (non-significant decline).

Most of the change through time is to be found in a much greater importance given to economy from the past through the

Table 8-4 (a)

Extracted main factor loadings for the past-present-future
product features : Factor 1.

Variable	Factor 1					
	Graduates			Undergraduates		
	Past	Present	Future	Past	Present	Future
Low insurance rate	0.8732	0.2314	0.1001	0.1941	-0.2454	0.2552
Resale value	0.8428	0.0270	0.0499	-0.0761	-0.0700	-0.1305
Warranty/Guarantee	0.8241	0.2572	0.2581	0.0083	-0.0366	-0.0634
Trade-in allowance	0.7962	-0.0082	0.0677	0.1315	-0.0906	0.0317
Convenient service facility	0.7897	0.1571	0.1901	-0.2086	-0.1210	0.1078
Air conditioning	0.2603	0.8418	0.7620	0.6989	0.1100	-0.1381
Smoothness of operation	0.3772	0.8599	0.7759	0.8103	0.2255	0.0020
Driving comfort	0.3331	0.8179	0.8141	0.7077	0.0508	-0.0720
Silent running	0.2344	0.8480	0.8507	0.6864	0.0378	-0.0301
Strong protective bumpers	0.2520	0.3579	0.7195	0.5675	0.1241	0.0636
Power steering	0.3602	0.6810	0.7308	0.0182	0.0831	0.2846
Automatic transmission	-0.1953	0.6628	0.7671	0.7409	0.2704	0.1201
Power disk brakes	0.3725	0.0551	0.0143	0.7608	-0.0112	0.2744
Rear window defogger	0.3817	0.3635	0.2668	0.7062	-0.0603	0.0312
Map light	0.1461	0.0896	-0.0122	0.7115	0.1487	-0.0350
Front seat roominers	0.4803	0.4954	0.3726	0.7880	0.1947	-0.0138
V8 engine	-0.1126	0.1722	0.0225	0.3455	0.7518	0.0256
Front engine	0.2695	0.0171	0.0746	0.1760	0.8610	0.0927
Sporty styling	0.1540	-0.0260	-0.0323	-0.0268	0.7225	0.7225
Percentage of explained variance	24.0	17.6	18.6	30.1	14.4	16.2
Label	"Luxury" concept					

Table 8-4 (b)

Extracted main factor loadings for the past-present-future product features : Factor 2.

Variable	Factor 2					
	Graduates			Undergraduates		
	Past	Present	Future	Past	Present	Future
Resale value	0.0946	0.0581	0.1966	0.8317	0.7542	0.1598
Warranty/Guarantee	0.0915	-0.0528	0.1490	0.7624	0.8666	0.0506
Trade-in allowance	0.0476	0.0464	0.1336	0.8042	0.7635	0.2166
Convenient service facility	0.0498	-0.0256	0.0732	0.6500	0.8135	-0.1574
Strong protective bumpers	-0.0343	0.0571	0.0043	0.3442	0.0547	0.8096
Mini size	0.7306	0.0158	0.0446	0.0945	-0.0193	0.1379
Compact size	0.8461	0.1191	0.0397	0.1454	0.0247	0.0161
Vinyl roof	-0.0208	0.7491	0.0625	0.0184	-0.0020	-0.1549
Cloth seat	-0.1049	-0.1510	0.8606	0.1159	-0.1883	0.0887
Low cost of operation	0.2265	-0.0053	-0.0976	0.7828	0.2796	0.8731
Ease of parking	0.3214	0.0363	-0.2290	0.6763	0.2481	0.7441
Percentage of explained variance	10.2	11.7	11.6	8.7	12.3	11.2
Label	"Economy" concept					

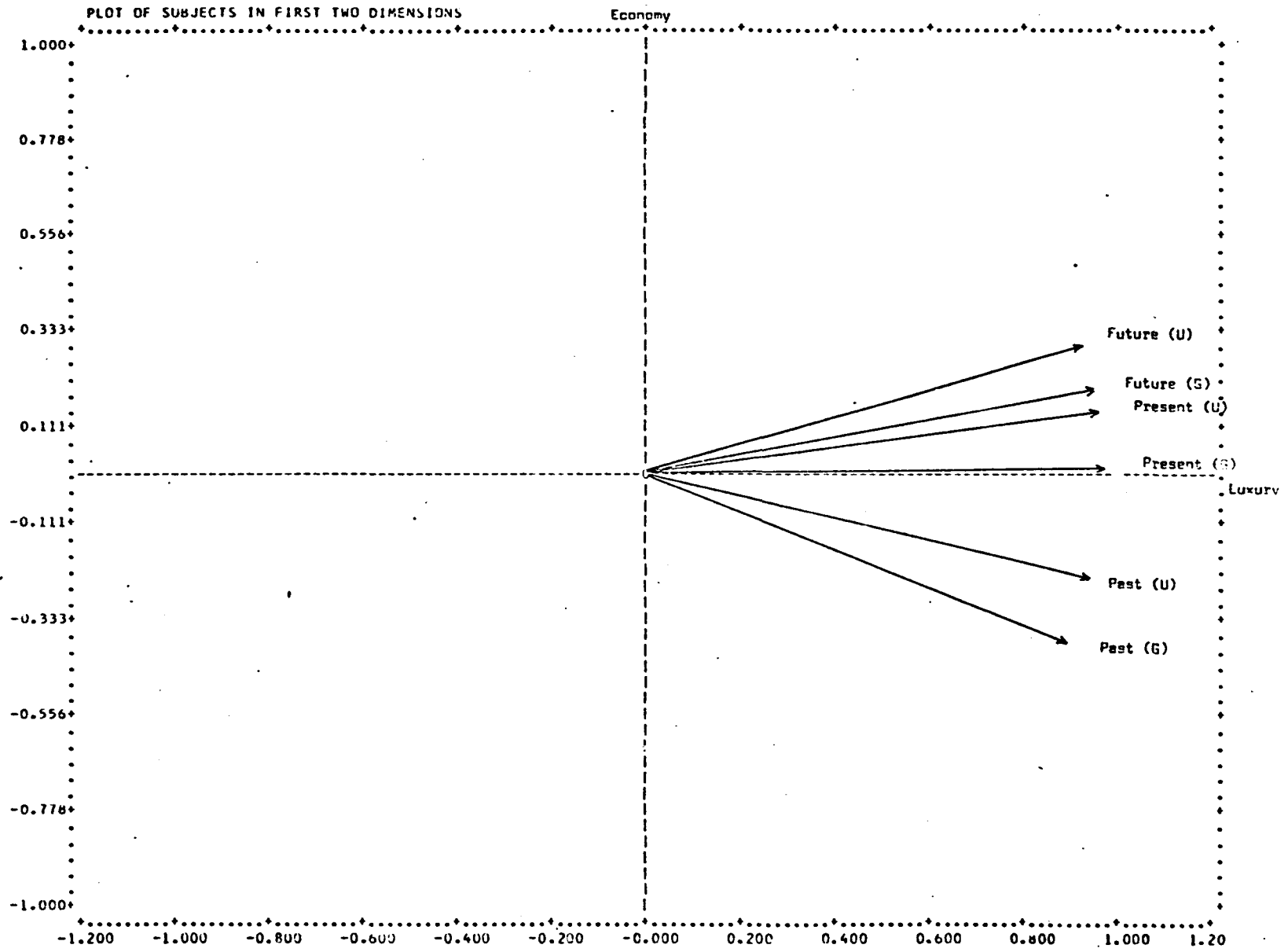


Figure 8-4 Product feature space for the past, the present and the future derived from the MOPREF model.

Table 8-5
 Inter-t values of time vectors (past, present, future)
 against product-feature axes (luxury, economy)

Luxury axis

	Past(G)	Past(U)	Present(G)	Present(U)	Future(G)	Future(U)
Past(G)	-					
Past(U)	-0.0197	-				
Present(G)	-1.0774	-0.9283	-			
Present(U)	-1.2268	-1.0452	-0.0841	-		
Future(G)	-1.6721	-1.4405	-0.5282	-0.4689	-	
Future(U)	-1.5148	-1.3001	-0.3701	-0.3022	0.1672	-

Economy axis

	Past(G)	Past(U)	Present(G)	Present(U)	Future(G)	Future(U)
Past(G)	-					
Past(U)	-0.2613	-				
Present(G)	-2.3223	-2.1513	-			
Present(U)	-5.1707*	-5.1317*	-2.5547	-		
Future(G)	-3.5536*	-3.4306*	-1.1771	1.2967	-	
Future(U)	-5.5640*	-5.5330*	-3.0674*	-0.7231	-1.8803	-

* : Statistically significant at 0.01 level

present and on to the future.

These conclusions are confirmed by the questionnaire (Question area 8, item 13) in which respondents were asked what model of car they intended to buy next. Mainly, they named economy models : Audi, Capri, Gremlin, Toyota, Vega, Volkswagen and Volvo. The result was presented in Table IX-3 in Appendix.

The trend is anyway, quite apparent. Further support carries in the comment in the Advertising Age (56).

"One important factor is a growing inclination to regard the motor vehicle as an appliance, rather than a symbol of affluence or status

Past-performance charts on the auto market indicate clearly that Americans are opting for smaller cars,"

CONSUMER BUYING BEHAVIOR

CHAPTERS 9 and 10

It is designed to identify the underlying process that best describes consumer buying behavior patterns in the following two chapters.

In Chapter 9, market segmentation is conducted based on the consumers' common perception and preference along with the dimension of their characteristics data.

A subspace by consumers' homogeneous ideal points can be identified as a segment in which they present their common perception and preference. Therefore, the brands of one segment may represent their competitive position in the market with the brands of other segments. This segmentation is made in terms of perception and preference regardless of the brands' similarity with respect to physical or other particular characteristics (35).

Chapter 10 discusses a stochastic model to allow a multitude of the factors that affect consumer buying behavior by means of preference uncertainty. That is, future market preferences are regarded as outcome of some probabilistic process which makes conditional predictions for the ultimate market share. This application will be directed at determining the best descriptor of consumer behavior in marketing decision process.

The analytical steps for Chapters 9 and 10 are presented in Figure 9-1.

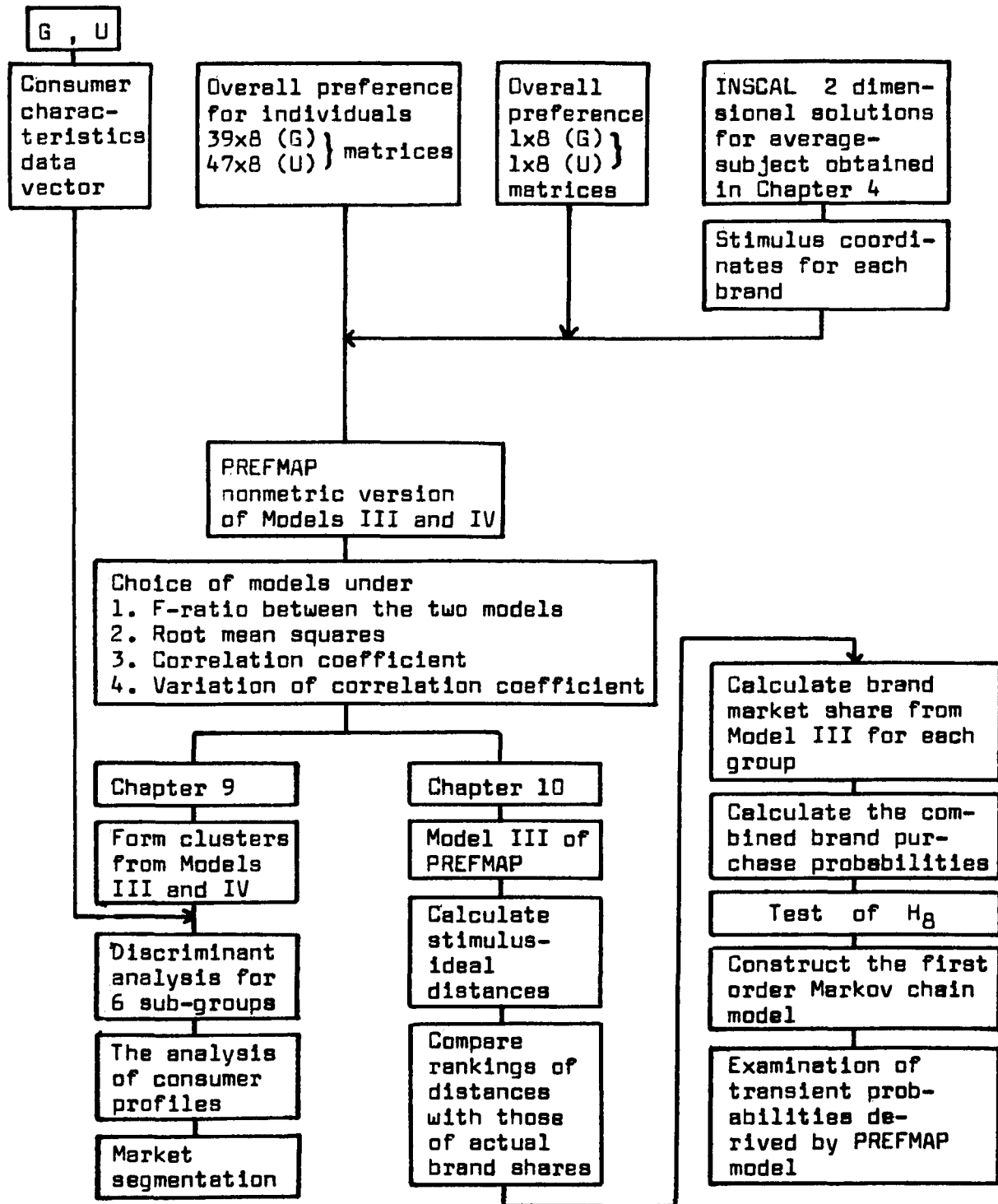


Figure 9-1 Analytical step for Chapter 9 and Chapter 10.

CHAPTER 9
MARKET SEGMENTATION

Summary

Two sub-population groups can be divided into six reasonably homogeneous groups with each having different preferences for brands of car.

The above results are confirmed by the discriminant analysis and the classification matrix in which ten demographics served as predictor variables.

There are essentially important factors in determining membership in the specific preference clusters : "Age", "Place of residence", "Degree of use of car at weekend", "Expectation of income increase" are positively associated with the membership classification, but "Marital status" and "Number of children" are negatively associated with the membership classification.

We can draw conclusions as follows ; the consumers of older age and with more income are inclined to buy more expensive cars. They live in the suburbs or a town with family and have a considerable possibility of income increase during the next three years.

Introduction

It is the purpose of this chapter to see to what extent our two sub-populations can be divided into homogeneous groups with each having definably different preferences within the already defined perceptual map.

Chapter 4 has already described the development of the perceptual space within which brands are located by means of the INSCAL procedure.

In the present chapter we locate each individual person's preference in this same space and examine any possible grouping that becomes apparent.

Method and analysis

The raw data are taken from Question area 6 (a) in the questionnaire in which the respondents are asked to rank the eight brands according to their overall preference. Individual person's overall preference rankings for each brand are presented in Table IX-1 in Appendix.

Nonmetric versions of Models III and IV were employed for the analysis. The goodness of fit to the model (multiple correlation coefficients) for Models III and IV and the F-ratios between the two models for individuals of each group are shown in Table 9-1 (a) and (b).

Table 9-1 (a)

Goodness of fit measures of Models III and IV of the PREFMAP algorithm for 39 subjects for Graduates.

Subject	Correlation coefficient		F-ratio between the two models d.f. = 1,4
	Model III	Model IV	
101	0.9978	0.8178	295.7754*
102	0.9861	0.8890	26.4301*
103	0.9681	0.8424	14.5008
104	0.9696	0.9467	2.9245
105	0.7555	0.6788	1.0247
106	0.9469	0.9443	0.1909
107	0.9661	0.9624	0.4196*
108	0.9851	0.8937	23.1637
109	0.8523	0.8016	1.2269*
110	0.9893	0.8888	35.3711
111	0.8267	0.4812	5.7116
112	0.8006	0.7743	0.4607
113	0.9088	0.8854	0.9684
114	0.9273	0.9083	0.9971
115	0.6920	0.6614	0.3177
116	0.8710	0.7270	3.8141*
117	0.9985	0.9337	166.2231
118	0.9682	0.9605	0.9441
119	0.8132	0.8092	0.0773*
120	0.9889	0.8529	45.4328
121	0.8362	0.8056	0.6678**
122	0.9024	0.9037	-0.0505
123	0.7116	0.6849	0.3029
124	0.8389	0.7161	2.5779*
125	0.9972	0.9067	121.1174
126	0.9705	0.7266	8.4647
127	0.9152	0.9043	0.4882
128	0.8541	0.8534	0.0192*
129	0.9852	0.8888	24.6347
130	0.8479	0.8441	0.0917**
131	0.9627	0.9664	-0.3879* , ***
132	0.9995	0.8892	1000.0000 , ***
133	0.9174	0.9005	0.7751
134	0.7439	0.4846	2.8538
135	0.9617	0.9512	1.0598
136	0.8479	0.8384	0.2277
137	0.7991	0.5097	4.1905
138	0.9759	0.9593	2.6895
139	0.8893	0.8223	2.1893
Root mean square	0.9059	0.8357	

Table 9-1 (b)

Goodness of fit measures of Models III and IV of the PREFMAP algorithm for 47 subjects for Undergraduates.

Subject	Correlation coefficient		F-ratio between the two models d.f. = 1,4
	Model III	Model IV	
201	0.9715	0.9592	1.6966
202	0.9738	0.9530	3.1064*
203	0.9575	0.8326	10.7665
204	0.9529	0.9427	0.8411
205	0.9738	0.9530	3.1064
206	0.9852	0.9579	7.2322*
207	0.8817	0.5854	7.8121
208	0.8714	0.7960	2.0870*
209	0.9508	0.7671	13.1378
210	0.9942	0.9861	5.6177
211	0.7846	0.5978	2.6868
212	0.7808	0.7777	0.0483
213	0.9672	0.9448	2.6448
214	0.5463	0.5355	0.0665
215	0.9796	0.9527	5.1259
216	0.9751	0.9468	4.4253
217	0.7846	0.2350	5.8314* ***
218	0.9999	1.0000	1000.0000
219	0.9782	0.9697	1.5290
220	0.9743	0.9598	2.1954
221	0.9671	0.9378	3.4541*
222	0.9783	0.6345	51.6608
223	0.8694	0.7048	4.2443
224	0.9715	0.9592	1.6966*
225	0.9972	0.9691	39.5435*
226	0.9553	0.8528	8.4765*
227	0.9975	0.9540	68.5527*
228	0.9928	0.9705	12.2044
229	0.9205	0.7522	7.3813*
230	0.9964	0.9644	34.8066
231	0.9644	0.9443	2.2018
232	0.9751	0.9485	4.1577**
233	0.8896	0.8900	-0.0130
234	0.9743	0.9598	2.1954*
235	0.9841	0.9341	12.1904*
236	0.9975	0.9574	62.0939**
237	0.9943	0.9969	-1.8433
238	0.7711	0.6838	1.2519*
239	0.9994	0.9691	195.8719

(Continued)

Subject	Correlation coefficient		F-ratio between the two models d.f. = 1,4
	Model III	Model IV	
240	1.0000	0.9990	10000.0000*,***
241	0.8597	0.8456	0.3683
242	0.9823	0.9594	5.0749
243	0.8259	0.7747	1.0331
244	0.8195	0.7891	0.5947
245	0.9300	0.7113	10.6358*
246	0.9271	0.7779	7.2466
247	0.8850	0.8351	1.5829
Root mean square	0.9341	0.8716	

- * Statistically significant at 5 percent level.
- ** Negative F-ratios are due to rounding error in the computation of product-moment correlations. These should be interpreted as zero values.
- *** F-ratio of 1000.0000 is due to R very close to 1.00.

F-ratios serve to ascertain the statistical significance of the contribution of Model III over Model IV.

When the computed F-ratios were compared with the critical value of 7.71 at the 5 percent level of 1 and 4 degrees of freedom, significant differences among subjects were noted between Models III and IV for both groups. It was noted that for the G group, F-ratios of Model III markedly exceeded those of Model IV for ten subjects (marked *), and, for the U group, so did fifteen subjects (marked *). Therefore, Model III was employed for these ten and fifteen subjects, and Model IV was employed for the remaining 29 and 32 subjects of the G and the U groups, respectively.

The dimension weights in Table IX-2 (a) and (b) in Appendix were checked to see whether these subjects belonged to a positive or a negative ideal point model. The dimension weights of ten subjects of the G group were all negative. The dimension weights for these fifteen subjects of the U group were positive or partially negative. The PREFMAP specifies that along with the dimension of the negative weight, preference increases with increasing squared distance from the ideal point. With this specification in mind, these ten negative ideal points of the G group and these fifteen mixed ideal points of the U group were also plotted in Figure 9-2 (a) and (b), respectively.

The direction cosines of the fitted subject vectors in the perceptual space of each group are presented in Table 9-2.

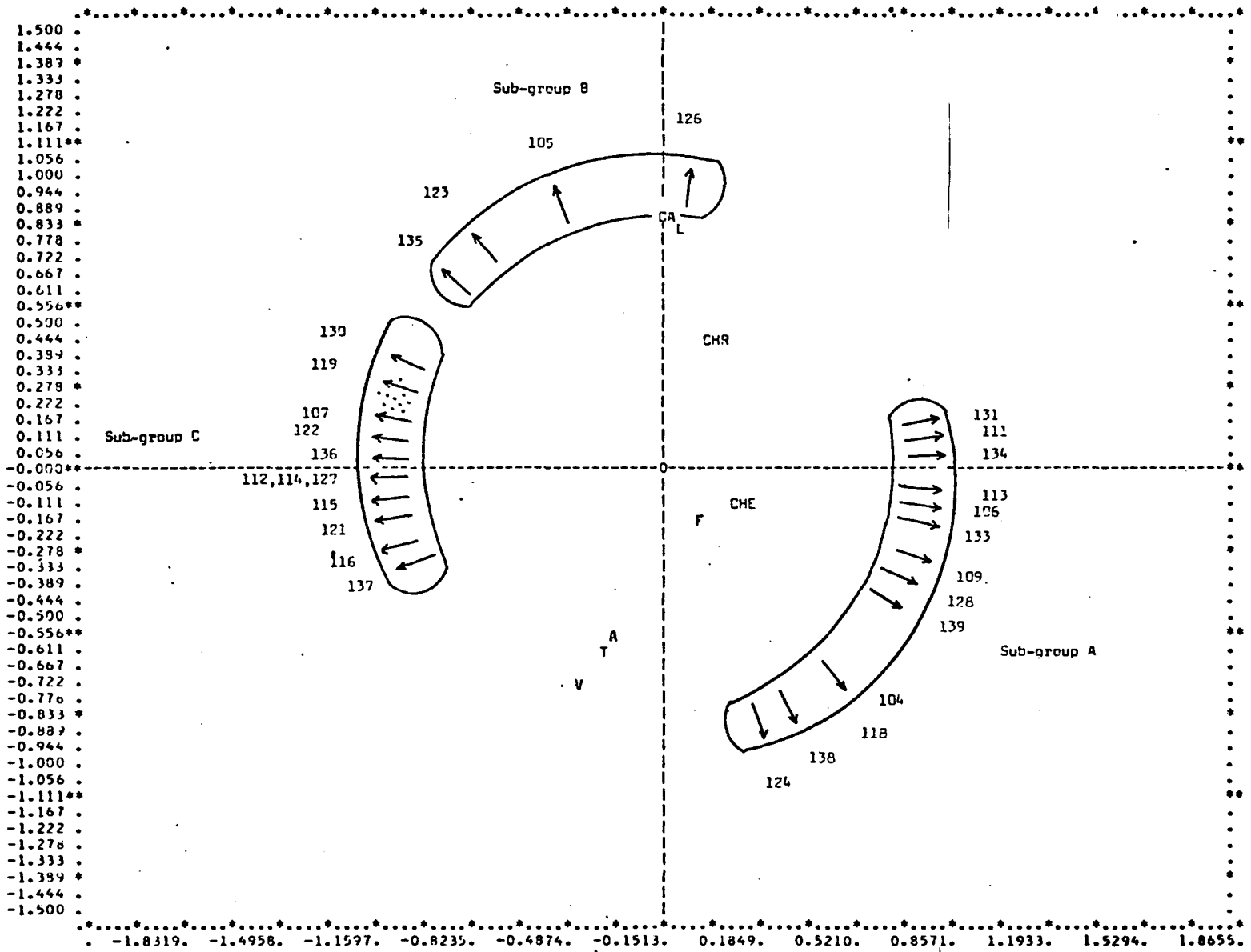


Figure 9-2 (a) Joint-space configuration of brands and subjects by Models III and IV of the PREFMAP procedure for Graduates.

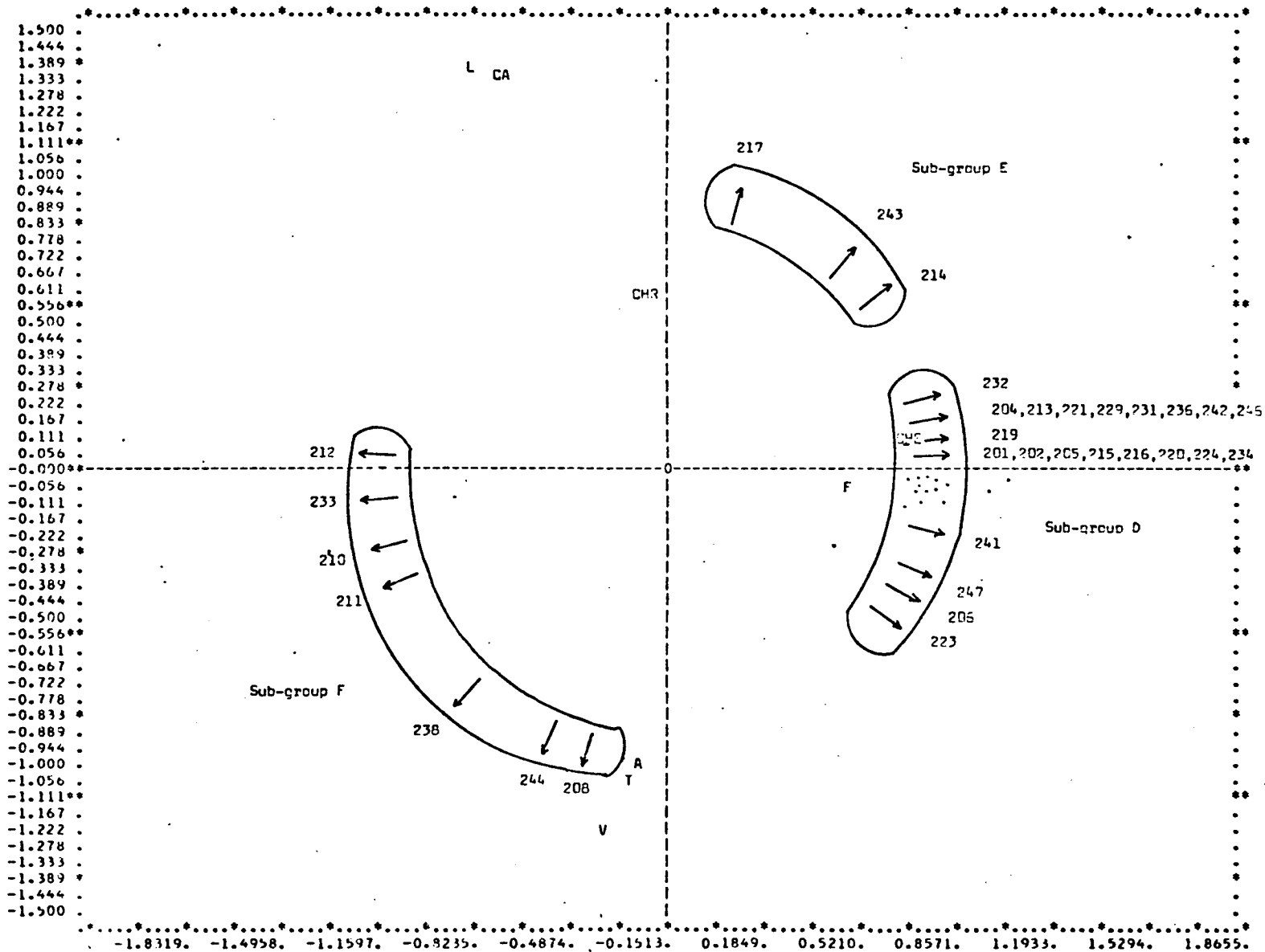


Figure 9-2 (b) Joint-space configuration of brands and subjects by Models III and IV of the PREFMAP procedure for Undergraduates.

Table 9-2
 Direction cosines of individual subjects
 for overall preference.

Direction cosines of fitted subject vectors					
Graduates			Undergraduates		
Subject	Dimension 1	Dimension 2	Subject	Dimension 1	Dimension 2
101	0.9774	-0.2115	201	0.9986	0.0529
102	0.9828	-0.1845	202	0.9977	0.0678
103	0.9909	-0.1349	203	0.9854	-0.1701
104	0.6597	-0.7515	204	0.9873	0.1588
105	-0.3531	0.9356	205	0.9977	0.0678
106	0.9804	-0.1971	206	0.8612	-0.5083
107	-0.9851	0.1720	207	0.7599	-0.6501
108	0.9839	-0.1791	208	-0.3025	-0.9531
109	0.9232	-0.3843	209	-0.7032	-0.7110
110	0.9857	-0.1683	210	-0.9574	-0.2886
111	0.9941	0.1086	211	-0.9105	-0.4135
112	-0.9994	-0.0344	212	-0.9999	0.0164
113	0.9816	-0.1910	213	0.9884	0.1518
114	-0.9973	-0.0738	214	0.7758	0.6310
115	-0.9956	-0.0937	215	0.9978	0.0660
116	-0.9527	-0.3039	216	0.9979	0.0650
117	0.8901	-0.4558	217	0.3084	0.9512
118	0.6605	-0.7508	218	0.9747	-0.2235
119	-0.9468	0.3218	219	0.9952	0.0976
120	0.9692	-0.2461	220	0.9983	0.0577
121	-0.9845	-0.1752	221	0.9878	0.1560
122	-0.9931	0.1174	222	0.6744	0.7384
123	-0.6251	0.7805	223	0.8194	-0.5732
124	0.3743	-0.9273	224	0.9986	0.0529
125	0.9747	-0.2237	225	0.9959	0.0900
126	0.1125	0.9937	226	-0.7758	-0.6309
127	-0.9992	-0.0412	227	0.9835	0.1809
128	0.9222	-0.3867	228	0.9949	0.1010
129	0.9858	-0.1681	229	0.9845	0.1753
130	-0.9074	0.4204	230	0.9981	0.0608
131	0.9915	0.1297	231	0.9885	0.1511
132	0.9829	-0.1840	232	0.9798	0.2001
133	0.9753	-0.2210	233	-0.9944	-0.1056
134	1.0000	0.0036	234	0.9983	0.0577
135	-0.6279	0.7783	235	0.9923	0.1236
136	-1.0000	-0.0067	236	0.9894	0.1453
137	-0.9355	-0.3533	237	0.8378	-0.5460
138	0.4912	-0.8710	238	-0.6041	-0.7969
139	0.8856	-0.4644	239	0.9959	0.0900
			240	-0.7553	0.6553
			241	0.9835	-0.1808
			242	0.9868	0.1620
			243	0.6819	0.7314
			244	-0.3528	-0.9357
			245	0.9950	-0.1001
			246	0.9833	0.1817
			247	0.8868	-0.4622

The ten negative ideal point subjects of the G group and fifteen partially negative ideal point subjects of the U group were set aside for the analysis as being ideosyncratic from the remaining subjects in preference nature.

As far as the vector portion was concerned, we obtained by inspection three main clusters for each group. Thus, we could define six reasonably homogeneous sub-groups of vector model designating as A, B, and C for the G group, and D, E, and F for the U group. The subjects who fell into these sub-groups are tabulated in Table 9-3.

From Figure 9-2 (a) the subjects in the G group were divided into three kinds of subjects ; those who preferred Chevrolet and Ford (assigned to A), those who preferred Cadillac, Lincoln and Chrysler (assigned to B), and those who preferred no specific brands (assigned to C).

Similarly, from Figure 9-2 (b), the U group was clustered into three sub-groups ; those who preferred Chevrolet and Ford (assigned to D), those whose closest preference was Chrysler (assigned to E), and those whose closest preference was American, Toyota and Volkswagen (assigned to F).

Our interest was turned to see the relationship between clusters and respondents' background characteristics data. Table IX-3 in Appendix presents data on respondents' background characteristics.

Table 9-3

Segmented subjects obtained from the PREFMAP vector model for the analysis of overall preference.

Group	Graduates			Undergraduates		
Sub-group	A	B	C	D	E	F
Subject	104	105	107	201	214	208
	106	123	112	202	217	210
	109	126	114	204	243	211
	111	135	115	205		212
	113		116	206		233
	118		119	213		238
	124		121	215		244
	128		122	216		
	131		127	219		
	133		130	220		
	134		136	221		
	138		137	223		
	139			224		
				229		
				231		
				232		
				234		
				236		
				241		
				242		
			246			
			247			
Sub-total	13	4	12	22	3	7
Total	29			32		
Grand total	61					

Six-group stepwise discriminant analysis* was conducted to identify their distinctive characteristics. The ten background variables, such as the various demographics (see Table IX-3 in Appendix) were used as a set of predictor variables to predict the six clusters of respondents. (Also see Table IX-4 in Appendix for supporting output of the six-group discriminant analysis.)

The results of the discriminant analysis are presented in Table 9-4. This classification matrix contains the output for the ten-variate six-group stepwise discriminant analysis of sixty-one respondents (twenty-nine and thirty-two from the G group and the U group, respectively). The run was made assuming the sample population frequencies as a priori probabilities. From the entries on the main diagonal of the matrix, we can see how correctly the respondents are classified, while the off-diagonal components represent respondents' misclassification. The percentage of correct classification was 73.8 . Wilks' Λ to test equality of group means** was 0.03940 . In testing the significance of Wilks' Λ , the F approximation is used. The appropriate F statistic derived from Wilks' Λ to test equality

* BMD07-Stepwise Discriminant Analysis-Revised, April 10, 1972 Health Sciences Computing Facility, UCLA.

** Wilks' $\Lambda = \frac{|W|}{|T|}$ d.f. = (r, g-1, n-g)
 where W is the pooled within-groups deviation score cross-products matrix and T is the total sample deviation score cross-products matrix. r is number of predictor variables, g number of groups, and n number of subjects.

Table 9-4

Classification matrix for ten characteristics variates by 6-group stepwise discriminant analysis. (The sample population frequencies are assumed as a priori probabilities.)

Actual group	Predicted group						Total
	A	B	C	D	E	F	
A	11	0	0	2	0	0	13
B	0	3	0	0	1	0	4
C	0	0	9	2	0	1	12
D	4	0	2	16	0	0	22
E	1	1	0	0	1	0	3
F	0	0	2	0	0	5	7
							61

Total hits = 45

Percent hits = 73.8%

Wilks' Λ = 0.03940 (d.f.= 10, 5.55)

F = 4.40005 (d.f.= 50, 213.16)

Statistically significant at the 0.01 level.

Table 9-5

Normalized classification matrix of Table 9-4.

Actual group	Predicted group						Total
	A	B	C	D	E	F	
A	0.85	0	0	0.15	0	0	1.00
B	0	0.75	0	0	0.25	0	1.00
C	0	0	0.75	0.17	0	0.08	1.00
D	0.18	0	0.09	0.73	0	0	1.00
E	0.33	0.33	0	0	0.33	0	1.00
F	0	0	0.29	0	0	0.71	1.00

of group means was 4.40005 and that exceeded the critical F-value of 1.62 at the 0.01 level (with 50 and 213.16 degrees of freedom). Therefore, the differences between the means among these six groups were found to be significant at the 0.01 level. There was at least one pair of sub-group of respondents who were different on at least one of their ten variables.

Figure 9-3 shows a plot of respondents in discriminant function space based on the first two linear components. The space is separated with group means in each quadrant. Therefore, the conclusion was drawn that the perceptual-preference segments were found to be associated with respondents' background characteristics fairly well.

The normalized classification matrix was obtained by dividing each component of each row by its row sum. The new entries in Table 9-5 represent the probabilities that a respondent would be so classified correctly or mistakenly by chance. Now, we are in a position to talk about the probability of consumers' membership profile by the normalized classification matrix as follows.

Sub-group A was clearly and correctly identified in 85 per cent of the cases. There was a distinct membership profile. The only "confusion" was with sub-group D and only to an extent of 15 per cent of the members.

Sub-group B had a fairly distinct membership profile (75 per cent correct classification) and association with only one other group, sub-group E, with 25 per cent "confusion".

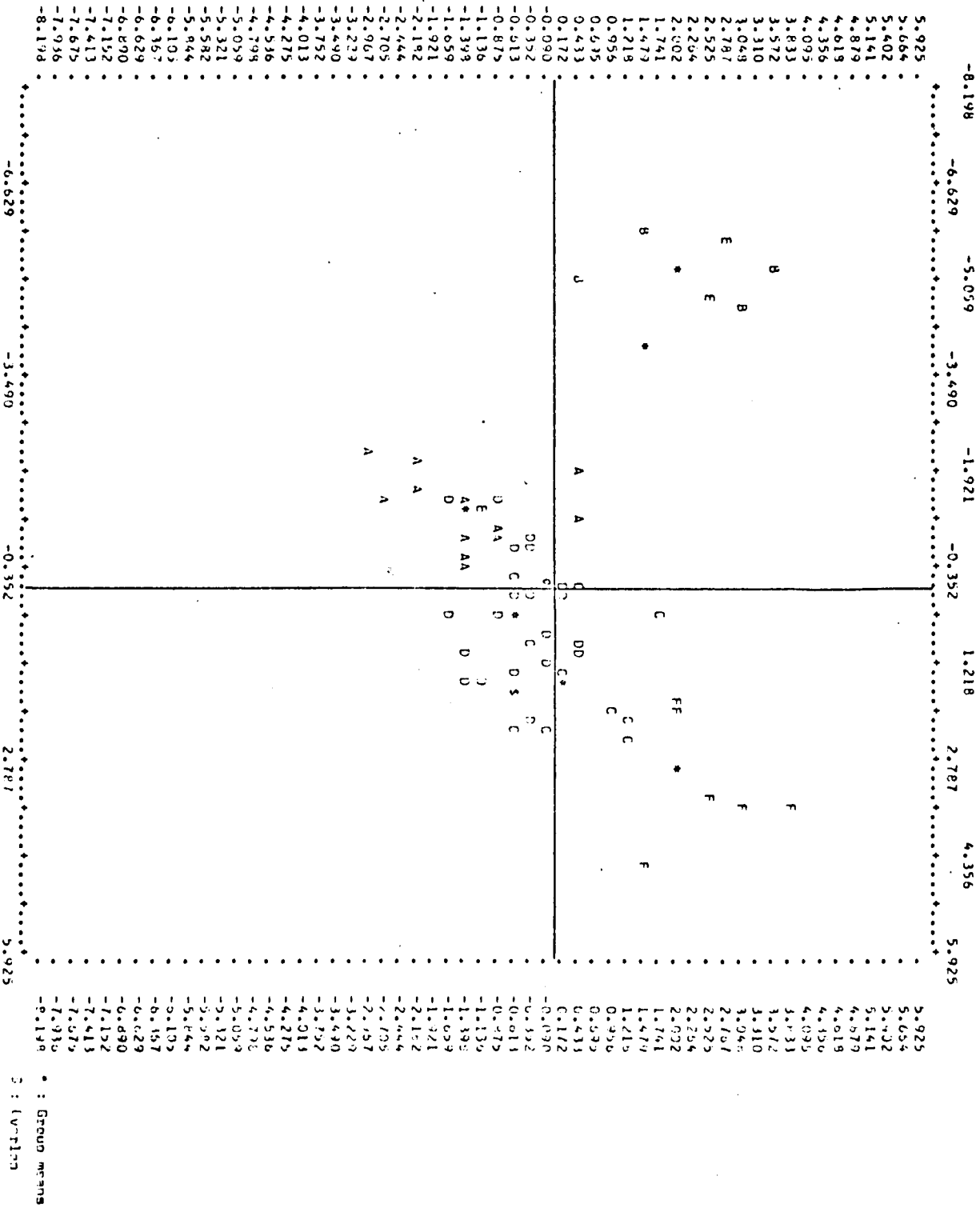


Figure 9-3 Discriminating space based on perception-preference consisting of the first two linear components.

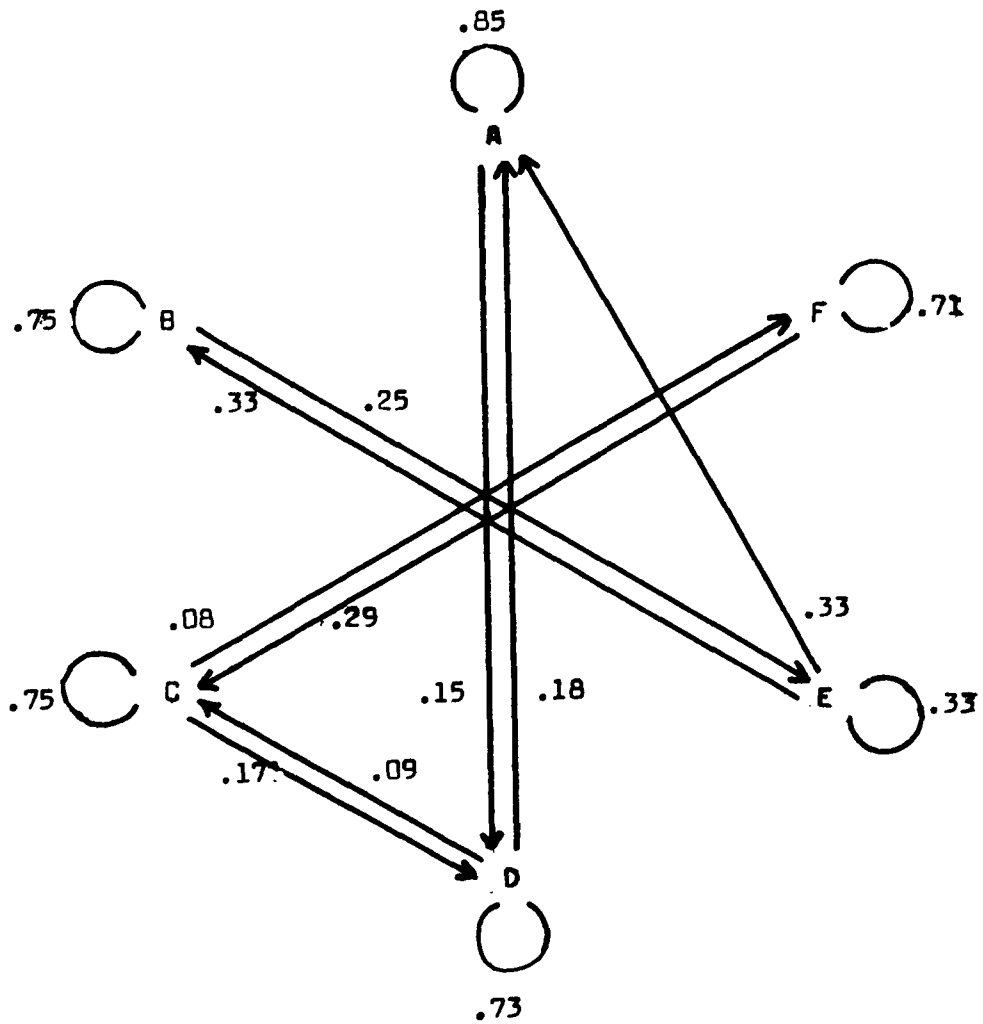
The other sub-groups were moderately well defined with the single exception of sub-group E, which was evenly divided amongst sub-groups A, B and E.

In sum, we can consider the cluster definition to be relatively good in general.

Based upon the relations between sub-groups above, the direction of association could be diagrammed with their respective probabilities (Figure 9-4). An arrow loop in the sub-group represents correct classification. By following the direction of the arrow, we can see the possible misclassification of members in one group into a second group and the misassignment, on the other hand, of members of the second group to the first group.

In order to see the possible effects of misclassification, the coefficients of the ten variables were examined as to their relative importance. Table 9-6 presents the multiple discriminant coefficients for ten variables and six discriminant functions.

The extreme values of the discriminant coefficients for each variable reveals certain characteristics in the sub-group. The most positive variable contributes most to the probability of classification in that sub-group. Conversely, negative coefficients contributes less to the classification probability in the group members. The coefficients which are near zero for any sub-group do not contribute to determining membership in the individual groups.



Arrows indicate the direction of misclassification.
 Loops indicate the correct classification.

Figure 9-4 Association diagram between 6 sub-groups.

The coefficients of the following variables were large for each sub-group (Table 9-6), suggesting that these are essentially important factors in determining membership in the specific preference clusters : "Age", "Place of residence", "Degree of use of car at weekend", "Expectation of income increase", "Marital status", and "Number of children".

"Marital status" and "Number of children" were negatively associated with the membership classification. The possible reason was that the survey samples consisted of students, some of whom had not yet considered marriage or children.

The average value of characteristics data are shown in Table 9-7 to explain the relevant values of the coefficients of the variables.

We may briefly highlight the average figures of sub-groups B and F which make a wider contrast with their characteristic data.

The membership of sub-group B consists of Graduate students. They are the oldest among six sub-groups (28.8 years old). Their yearly income is the largest (\$21250.0). All of them are married and half of them are most likely to have a child. Most of them live in the suburbs or town. They have owned about 4.8 cars. They are interested in buying expensive cars with great expectation of income increase during the next three years. (See also Table IX-3 in Appendix.)

Group members of sub-group F are Undergraduate students. They are the youngest among six sub-groups (19.9 years old). Their

Table 9-6

Multiple discriminant coefficients for 6 sub-groups and 10 variates.

Variable	Function					
	A	B	C	D	E	F
1 Age :	15.10859	14.72069	13.60478	14.07939	14.99061	11.59749
2 Income :	-0.00114	-0.00085	-0.00124	-0.00098	-0.00105	-0.00104
3 Sex :	0.21452	1.48077	1.13950	1.21468	2.33760	3.44529
4 Marital status :	-4.96308	-5.48125	-9.13257	-9.67521	-6.04736	-8.97677
5 Number of children :	-5.06976	-2.99364	-4.31478	-2.97993	-4.89635	-3.30712
6 Place of residence :	8.22982	7.34730	10.50856	9.88178	4.60651	11.45205
7 Frequency of car used :	2.19587	1.80855	3.69326	3.10240	1.81010	3.50088
8 Degree of usage at weekend :	8.11990	4.40441	6.28899	6.18213	4.93857	3.36275
9 Number of cars owned :	-1.60801	5.26255	-0.47077	-1.10222	1.79288	-0.11291
10 Possibility of income increase :	5.76825	14.50176	7.00815	6.42766	14.96766	6.15283
Constant	-200.19032	-221.26633	-170.72923	-180.52568	-210.81010	-130.82939

Table 9-7

The average values of characteristics data for six sub-groups.

Group		Graduates			Undergraduates			
Variable	Sub-group	A	B	C	D	E	F	Grand mean
1 Age :		26.5	28.5	23.2	24.7	27.3	19.9	24.6
2 Income :		16634.6	21250.0	11458.3	15340.9	18750.0	8750.0	14651.6
3 Sex :		0.8	1.0	0.9	0.9	1.0	1.0	0.9
	(Male=1, Female=0)							
4 Marital status :		0.4	1.0	0.1	0.1	0.7	0.0	0.2
	(Married=1, Single=0)							
5 Number of children :		0.2	0.5	0.0	0.5	0.0	0.0	0.2
6 Place of residence :		0.8	0.3	0.9	0.8	0.3	1.0	0.8
	(City=1, Town or suburbs=0)							
7 Frequency of car used per week :		3.1	1.3	6.0	4.9	1.7	5.4	4.4
8 Degree of usage at weekend :		0.9	0.3	0.8	0.8	0.3	0.4	0.7
	(Heavy=1, Otherwise=0)							
9 Number of cars owned :		2.0	4.8	1.4	1.5	3.3	1.1	1.9
10 Possibility of increase in income :		0.2	0.8	0.2	0.1	1.0	0.1	0.2
	(Yes=1, No=0)							

yearly income is the smallest (\$8750.0). They are all single and live in the city. They have almost no possibility in income increase during the next three years. They choose inexpensive brands of car as their next choice.

CHAPTER 10
CONSUMER PROBABILITIES OF PURCHASE

Summary

It is assumed that consumers' motivation to buy a brand can be measured by their perceptions and preferences for the brand.

The nonmetric version of Model III of the PREFMAP model is a good predictor of the rank order of brand shares for Graduates. It correctly estimated the first four brands. If foreign brands are excluded for Undergraduates, this model is also a good predictor of the rank order of brand shares.

We calculated the brand shares for the total (student) consumer population from these two sub-population groups. There is little difference between the actual and the calculated market shares. (Hypothesis 8).

A first-order Markov chain model provides the predicted market shares of brands. Among the two biggest market-share brands, Chevrolet and Ford, it would be predicted - if we had a representative sample - that the former will decrease its market share and the latter will increase its market share.

Introduction

Chapter 10 discusses the last component of the consumer decision process ; buying a certain brand which is available in market.

In this part of the study, we will provide a predictive value for determining the share of brand market, based on our knowledge of perception and preference.

After assuming that preference determines subsequent sales and therefore estimating the market share for each brand, an evaluation of the potentiality of brands will be made.

The relevant hypothesis is restated below :

H_8 : "Share of brand-preference measured by preference and similarity mapping correctly reflects brand-share as determined by unit sales."

Test of H_8

Overall preference rankings data on the average-subject level for the G group and the U group, separately, were submitted to the nonmetric versions of Models III and IV of the PREFMAP algorithm to fit the perceptual configurations whose coordinate values were obtained in Chapter 4. Data were obtained from Question area

6 (a) in questionnaire.

Table 10-1 shows goodness of fit measures for Models III and IV. The F-ratios testing the contribution of Model III over Model IV exceeded the critical value of 7.71 at the 5 per cent level (with degrees of freedom of 1 and 4) for both groups. Therefore, the difference between Models III and IV was statistically significant. Accordingly Model III was employed for the analysis for both groups. Stimuli coordinates, ideal point coordinates, and signs of the axes weights from the model are presented in Table 10-2.

For the G group, both dimensions were negatively weighted, suggesting that along these dimensions a monotonically ascending relationship exists between preferences and inter-distances of stimulus-ideal points.

For the U group, both dimension weights were positive. Therefore in this case, preference declines with increasing distances from the ideal point. It was assumed that consumers' motivation to buy a brand could be measured as a function of distance from the ideal point in the perceptual mapping. The stimuli-ideal point-perceptual map is shown in Figure 10-1 (a) and (b).

To test Hypothesis 8, the distances between a stimulus and an ideal point were calculated. The rankings of these distances and those of the actual brand shares were first examined by the Spearman rank order correlation method. The results are presented in Table 10-3. From the tabulated results, we note that Model III

Table 10-1

Goodness of fit measures of Models III and IV
of the PREFMAP procedure for overall preference.

Property vector	Graduates			Undergraduates		
	Correlation coefficient		F- ratio between the two models d.f.= 1,4	Correlation coefficient		F-ratio between the two models d.f.= 1,4
	Model III	Model IV		Model III	Model IV	
Overall preference	0.9954	0.9029	76.7927*	1.0000	0.9648	1000.000*,**
Root mean square	0.9954	0.9029		1.0000	0.9648	

* : Statistically significant at 5 percent level

** : Because R is 1.0000.

Table 10-2
 Coordinate values of brands, ideal points
 and signs of axes weights from Model III
 of the PREFMAP procedure.

Brand	Graduates		Undergraduates	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
A	-0.59829	-0.15992	-0.01794	-1.45361
CA	0.63664	0.83731	-0.91624	1.87145
CHE	0.30112	-0.81823	1.39831	0.17120
CHR	0.53804	0.01690	-0.10541	0.84619
F	0.08570	-0.54823	0.93021	-0.03958
L	0.64127	0.78427	-1.03905	1.86178
T	-0.69241	-0.16037	-0.04912	-1.51893
V	-0.91209	0.04827	-0.20076	-1.73846
Ideal point	-0.01528	0.42710	1.32280	-0.27694
Weight	Negative	Negative	Positive	Positive

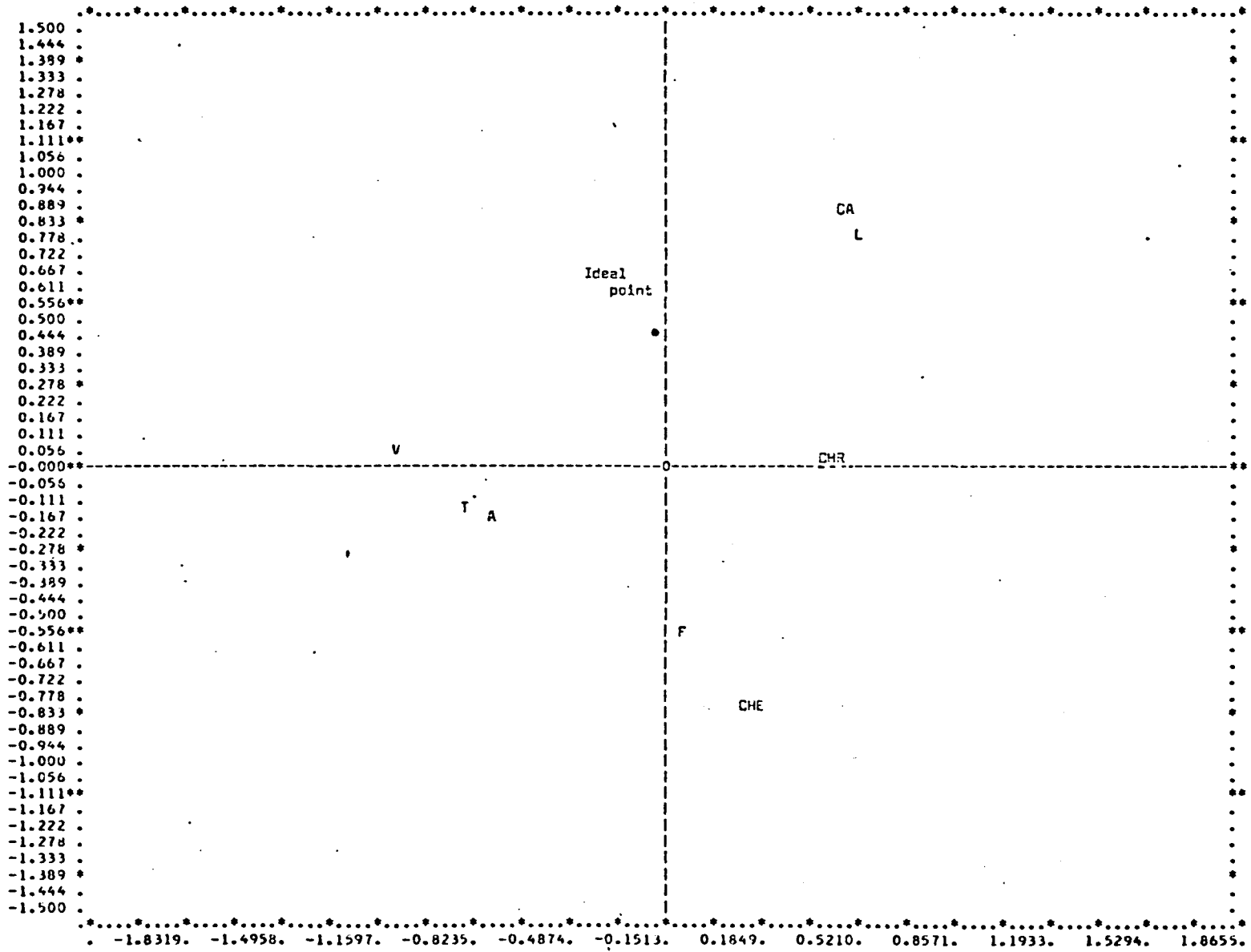


Figure 10-1 (a) Joint-space configuration of brands and an ideal point from the negative ideal point model of the PREFMAP procedure for Graduates.

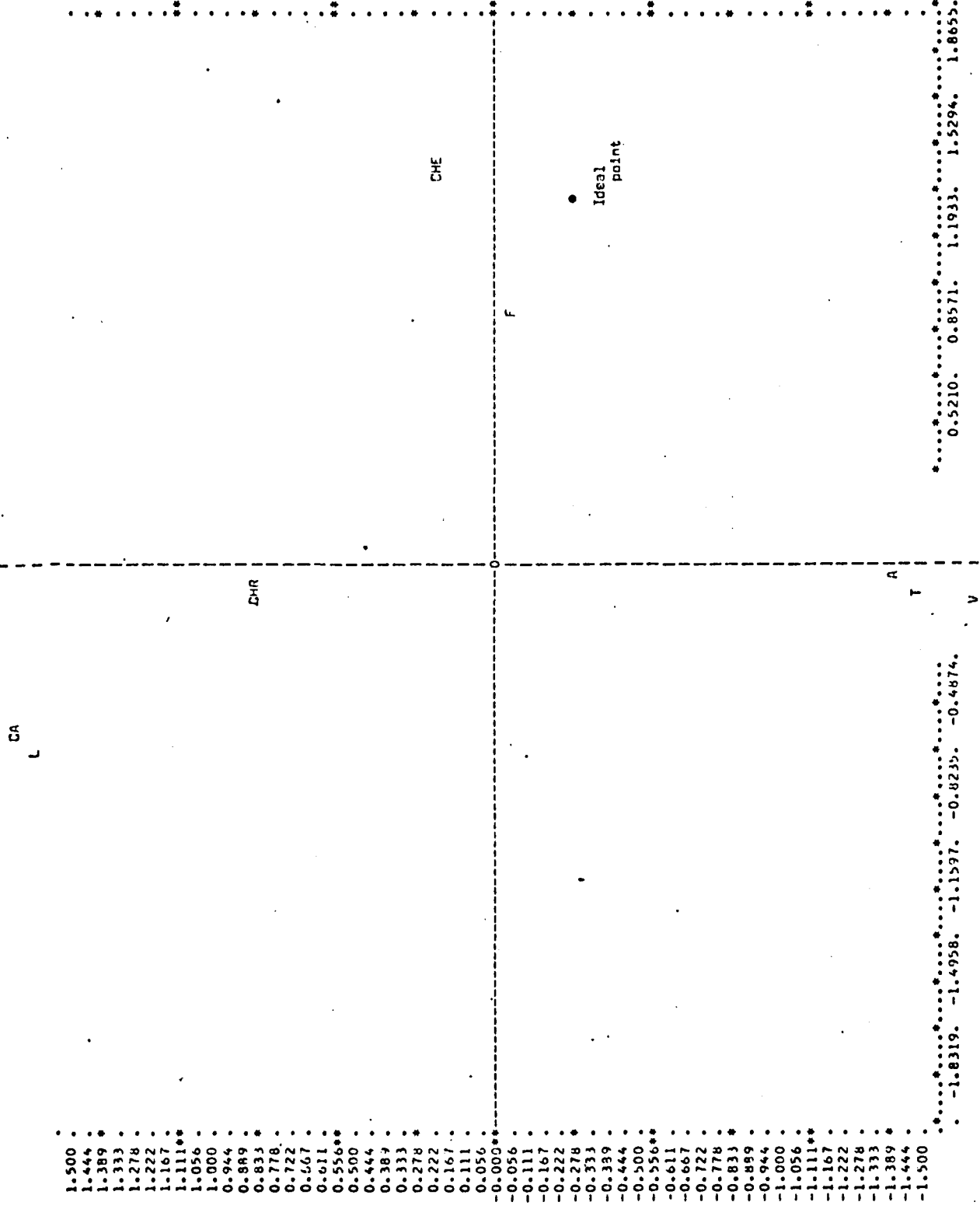


Table 10-3

Actual and calculated rank order of the market shares of brands.

Brand	Actual rank * order	Calculated rank order of market share for each brand : 8 brands included		Undergraduates	
		G	U	Calculated rank order of market share : Except foreign brands	Actual rank order except foreign brands
		A	6		
CA	5	6	7	5	3
CHE	1	1	1	1	1
CHR	7	8	4	4	5
F	2	2	2	2	2
L	8	7	8	6	6
T	4	4	5		
V	3	3	6		
Spearman rank order correlation coefficient		0.95 **	0.62	0.93 **	

Automotive News, 1972 Almanac Issue and March 5, 1973.

* The actual rank order was adjusted under the assumption that only these eight brands were on the market.

** Statistically significant at 0.05 level. Critical value = 0.643

was a good predictor of the rank order of brand market shares for the G group. The Spearman rank order correlation coefficient was 0.95 and was highly significant at the 5 per cent level. It accurately estimated the first four brands - Chevrolet, Ford, Volkswagen and Toyota. However, this model was not quite so good a predictor for the U group. It predicted the first two brands - Chevrolet and Ford. The Spearman rank order correlation was 0.62 and was not significant at the 5 per cent level. If foreign brands were not considered for the U group, this model would also become a good predictor of the order of brand market shares as shown on the right side of Table 10-3. The Spearman rank order correlation coefficient improved from 0.62 to 0.93, which is highly significant at the 5 per cent level.

After the rankings of the brand market shares were examined, the percentage of the market share of each brand was calculated separately for each group.* The actual market share for each brand, the calculated brand market share for each brand from Model III, and the differences between the actual and the calculated market shares are presented in Table 10-4 for both groups.

These market shares for each brand obtained separately for both groups were combined into a single market share for each brand so that a prediction of the market shares from the total consumer population could be made.

* See p. 273 in Appendix for the calculation methods.

Table 10-4

Actual and estimated market shares of brands obtained from Model III of the PREFMAP procedure and the difference between them in percentage points.

Brand	Actual market share *	Market share estimated by preference model		Difference between actual and estimated market shares (percentage points)	
		G	U	G	U
A	4.36 %	10.26 %	2.88 %	5.90 p.p.	1.48 p.p.
CA	4.50	8.89	0.95	4.39	3.55
CHE	38.99	24.74	44.30	14.25	5.31
CHR	2.99	7.11	2.77	4.12	0.22
F	34.00	14.41	43.47	19.59	9.47
L	1.18	8.35	0.90	7.17	0.28
T	4.85	12.04	2.67	7.19	2.18
V	9.13	14.20	2.06	5.07	7.07
Average				8.46 p.p.	3.70 p.p.
Total	100.00 %	100.00 %	100.00 %		

* The actual market shares were adjusted under the assumption that only these eight brands were on the market.

We had a population consisting of the two groups - the G and the U groups in this study. The market shares of brands were obtained separately for each group as shown in Table 10-4. Our next task was to estimate brand choice probabilities :

Some statistical notation for the analysis are given as follows :

$p(G) = \frac{39}{86} = 0.453$: the probability that a consumer belonged to the G group.

$p(U) = \frac{47}{86} = 0.547$: the probability that a consumer belonged to the U group.

$p(A_{i,t}/G)$: the probability that a consumer from the G group purchased brand i at time t .
 $i=1,2,\dots,8$ (See Table 10-4.)

$p(A_{i,t}/U)$: the probability that a consumer from the U group purchased brand i at time t .
 $i=1,2,\dots,8$ (See Table 10-4.)

$p(A_{i,t+1}/A_{i,t})$: the probability that a consumer would purchase brand i at two successive periods.
 $i=1,2,\dots,8$

The probability that a consumer buys brand i at time t is :

$$p(A_{i,t}) = p(A_{i,t}/G) p(G) + p(A_{i,t}/U) p(U) \quad i=1,2,\dots,8$$

For the "American" brand as an example,

$$\begin{aligned} p(A_{1,t}) &= p(A_{1,t}/G) p(G) + p(A_{1,t}/U) p(U) \\ &= (0.1026) (0.453) + (0.0288) (0.547) \\ &= 0.0622 \end{aligned}$$

For the other seven brands, the same procedure was applied to obtain $p(A_{2,t})$, $p(A_{3,t})$, ..., $p(A_{8,t})$. The results are presented in Table 10-5.

It is noted that the accuracy of the probabilities for a consumer's brand purchase increased remarkably due to the above transformations. The average difference in absolute value between the actual and combined probabilities of brand purchase (market shares) was 0.020, and none of the differences between corresponding brands exceeded 0.04 in absolute value. From the newly estimated market shares, the change of market shares was predicted as follows; Chevrolet, Ford, and Volkswagen would decrease in their market shares by 3.55%, 3.69%, and 1.57%, respectively. The other five brands were predicted to improve the market shares of the magnitude from 0.05% (Cadillac) to

Table 10-5

Probabilities that a consumer from the total population would purchase a brand on the purchase time t .

Brand	Actual market share	Probability	Difference between the actual and combined probability
A	0.0436	0.0622	+ 1.86
CA	0.0450	0.0455	+ 0.05
CHE	0.3899	0.3544	- 3.55
CHR	0.0299	0.0474	+ 1.75
F	0.3400	0.3031	- 3.69
L	0.0118	0.0427	+ 3.09
T	0.0485	0.0691	+ 2.06
V	0.0913	0.0756	- 1.57
			Absolute average 2.20

3.09% (Lincoln). The results of both the calculated market shares and their rankings support H_8 .

Our final interest was to predict how the market shares at present would change at the time of the consumers' next choice. We could calculate the probability that a consumer would purchase a brand at two successive periods. For, we had already obtained the probability that a consumer would buy a brand at t .

The probability that a consumer buys brand i at two successive periods is :

$$p(A_{i,t+1}/A_{i,t}) = p(A_{i,t+1}/G) p(G/A_{i,t}) + p(A_{i,t+1}/U) p(U/A_{i,t}) \quad (1)$$

$$i=1,2,\dots,8$$

However, we must compute the probability that a consumer who bought brand i at the previous period belongs to the G (or the U) group. By the Bayes' theorem, the following transformations are conducted.

$$p(G/A_{i,t}) = \frac{p(A_{i,t}/G) p(G)}{p(A_{i,t}/G) p(G) + p(A_{i,t}/U) p(U)}$$

$$= \frac{p(A_{i,t}/G) p(G)}{p(A_{i,t})} \quad (2)$$

$$i=1,2,\dots,8$$

$$p(U/A_{i,t}) = \frac{p(A_{i,t}/U) p(U)}{p(A_{i,t})} \quad (3)$$

$$i=1,2,\dots,8$$

Substituting (2) and (3) into (1), we can determine the probability defined in Equation (1).

For the "American" brand,

$$p(G/A_{1,t}) = \frac{(0.1026) (0.453)}{0.0622} = 0.7460$$

$$p(U/A_{1,t}) = \frac{(0.0288) (0.547)}{0.0622} = 0.2540$$

Therefore, the probability that a consumer buys "American" at two successive periods was :

$$p(A_{1,t+1}/A_{1,t}) = (0.1026) (0.7460) + (0.0288) (0.2540) = 0.0839$$

We could calculate a 8 x 8 matrix for all combinations of eight brands to produce a first order Markov chain model. The aggregate transition matrix is shown in Table 10-6.

This aggregate transition matrix is a special type of a forecasting model. We could examine a brand-power situation between the brands by this matrix. The diagonal entries can be interpreted as a measure of a brand's retentive or holding power, while other entries are a measure of one brand's power to attract consumers from another brand. Stronger holding powers from time 0 to 1 were Chevrolet and Ford, whose values are 0.3811 and 0.3721, respectively and they are eminent among others.

Table 10-6
Aggregate transition matrix of the first-order Markov chain.

$t + 1$

Brand	A	CA	CHE	CHR	F	L	T	V	Total
A	0.0839	0.0688	0.2969	0.0601	0.2177	0.0646	0.0967	0.1113	1.0000
CA	0.0942	0.0798	0.2698	0.0661	0.1773	0.0750	0.1097	0.1281	1.0000
CHE	0.0521	0.0346	0.3811	0.0414	0.3428	0.0326	0.0563	0.0590	1.0000
CHR	0.0790	0.0635	0.3100	0.0572	0.2371	0.0597	0.0904	0.1032	1.0000
F	0.0447	0.0266	0.4009	0.0370	0.3721	0.0250	0.0469	0.0467	1.0000
L	0.0941	0.0798	0.2699	0.0661	0.1776	0.0749	0.1096	0.1280	1.0000
T	0.0870	0.0721	0.2887	0.0619	0.2055	0.0678	0.1006	0.1164	1.0000
V	0.0916	0.0771	0.2766	0.0646	0.1874	0.0724	0.1064	0.1239	1.0000

202

t

It was noted that Chevrolet would decrease its market share from the present 38.99% to 38.11% by 0.88% , while Ford would increase its market share from the present 34.00% to 37.21% by 3.21%.

CHAPTER 11
SUMMARY OF FINDINGS AND LIMITATIONS OF THE STUDY,
AND IMPLICATIONS FOR FUTURE RESEARCH

The final chapter discusses the findings, limitations of the study conducted, and the implications of the model for the further research.

The substantive findings obtained in the small scale automobile case-study model and the tests of hypotheses can be summarized as follows :

1. Two dimensional solutions were appropriate in portraying most of the information in the data. The two main dimensions of the group brand spaces were interpreted as the axes of expensive/inexpensive, and traditionally popular/foreign brands of cars.
2. Quality was perceived as better as price increased. Furthermore, it was found that the psychological evaluations of brand quality was nonlinearly transformed by price.
3. Consumers' judgment on ranking brand prices (perceived price) was proved to be reliable. And insignificant distortion between the perceived and actual prices was noticed.

4. The brand in which more advertising was spent was perceived to be negatively related to quality. Consumers proved to be able to rank the brands in order of advertising expenditures. Given this fact, a decision rule for the allocation of advertising expenditures was proposed. The criterion was based upon cognitive judgment for budgeting advertising expenditures.
5. It was found (with no surprise) that the more the discretionary budget allowed, the more consumers spent for quality. However, saturation of utility for quality was noticed in the budget range of \$10,000 and \$12,000. This might show consumers' motivation to purchase expensive brands for prestige or social status. The price level of brands at which consumers had best utility was between \$10,639 and \$10,725. Mercedes-Benz fell in this category.
6. Consumers who lived in the city preferred the \$4,000 budgeted brand. As the place of residence shifted from the city to the suburbs, more would be spent.
7. "Luxury" and "Economy" were extracted as leading factors of product features. However, liking for the luxurious type of car did not differ markedly from the past, the present, and to the future, while attitude toward the economical type of car differed markedly from the past to the future. It was

predicted that a future car would be smaller, less costly, and safety oriented.

8. Market segmentation based on the measures of perception and preference yielded six sub-groups. They revealed that "Age" contributed most strongly to classification, and "Place of residence", "Degree of use of car at weekend", and "Expectation of income increase" were highly related to membership classification. "Marital status" and "Number of children" were negatively associated with classification.
9. Market shares of brands were reasonably well predicted by the proximity-preference choice behavior model. The ranking measure derived by the Graduate students was a much better predictor than it was for the Undergraduate students. However, if foreign brands were excluded, the Undergraduate students also provided a good prediction of market shares. The combination of market shares of both groups showed a remarkable improvement in prediction. The average difference between the actual and predicted market shares was only 2.20 percentage points.
10. A prediction was made as to how the market shares would change from the combined purchase probabilities. Chevrolet, Ford, and Volkswagen would decrease in percentage points of

their market shares by 3.55 , 3.69 , and 1.57 , respectively. Five other brands were expected to increase their market shares by a magnitude of 0.05 (Cadillac) to 3.09 (Lincoln) percentage points.

11. Through Bayes' theorem, we obtained the first order Markov chain matrix, which is a special type of forecasting model. We could examine a "brand power" situation among the brands. Stronger holding powers from time 0 to 1 were Chevrolet and Ford, whose values were 0.3811 and 0.3721 , respectively. It was noted that Chevrolet would decrease its market share from the present 38.99% to 38.11% by 0.88 percentage points, while Ford would increase its market share from the present 34.00% to 37.21% by 3.21 percentage points.

Now, to review briefly the essential points of the proposed consumer model that is illustrated by the small-scale automobile case-study : Green and Carmone have listed a series of research problems such as advertisement measurement, market segmentation, and probability of choice model that could utilize multidimensional scaling (33). This study attempted to introduce all of the suggested applications mentioned above.

Reo demonstrated the empirical relationship between price and quality using essentially the same methods of multidimensional scaling (62). However, it should be noted that the way of

obtaining the evaluative measures of quality differs between Rao's model and the proposed model. Rao obtained the evaluative dimension from the INSCAL solution of similarity data, and interpreted it as representing the quality measures after examining the brand attributes in the perceptual configuration. This dimensional interpretation was also confirmed by the subjects' responses to the open-ended question on the criteria for similarity judgments. In the proposed model, the evaluative measures were obtained from conditional dominance data ; The quality measures for brands were obtained by the MDPREF algorithm where quality judgments were in agreement with the projected values of the stimulus points onto the subject vectors. In both models, the subjects' responses to the open-ended question on the criteria for similarity judgment gave added confirmation for interpretation in the perceptual space.

The primary objectives of this study for consumer buying behavior were to demonstrate

1. the development of the model,
2. a preliminary, small-scale illustration, and
3. the plan how to generalize the model.

We believe that the model and the techniques are applicable to the complex decision processes for other consumer goods, industrial goods, and services.

However, some criticisms and limitations should be mentioned and openly discussed. They will fall into conceptual, computational, and empirical categories.

Conceptual problems :

1. The underlying assumption employed by all the algorithms in this study was that perceptual space is Euclidean in nature. If the constructs of cognition and preference are Euclidean, then attribute-space of stimuli by the multidimensional scaling algorithms are appropriate for use. But, if dimensional differences in perception should be established for the exact differences of stimulus attributes, then the city block metric might be appropriate since it gives an equal weight to each dimensional difference.
2. All the analyses were conducted on an aggregate (average-subject) basis except the market segmentation. However, it is quite likely that different respondents adopt different criteria in making judgments on overall similarity and/or overall preference. Therefore, if there is serious question of the homogeneity of the respondents, the aggregate analysis should be avoided. Some advantages are credited for the use of the average-subject data ; less fieldwork is necessary, and the missing data in individual matrices can be overcome

by averaging relevant cell entries. We should consider the trade-offs as to the time to be taken for the survey, number of subjects, and the possible existence of the missing data for our experimented design.

3. Overall preference and perception were used as a basis for estimating the brand's share of purchase in conjunction with perception in this study. However, consumers do not necessarily select the most preferred brand. Some other factors (e.g., accessibility of brands, time-pressure on consumers) and policy variables (product, price, promotion, or distribution) should be considered as important factors in consumers' perception, preference, choice, and ultimately, market share.

Computational problems :

1. A small number of stimuli may not fully recover known configurations. In general, as the number of points increases, the more "uniqueness" of solution can be obtained for a specific dimensionality. However, Shepard found that a perfect recovery can be obtained with as few as only eight points and the lowest coefficient for that case was about 0.99 (74). Therefore, the eight stimuli taken for this study may be justified for the use of multidimensional scaling analysis.

Dangers of extrapolation may, however, be involved due to the lack of the number of data points. The balance between the number of stimuli and the accuracy of questionnaire response should be considered in the application of multidimensional scaling methods. When the number of stimuli is increased, the necessary experimental matrices will become overwhelmingly large in size, and consequently this may lead to cause respondents' fatigue and produce "noise" in data. Furthermore, it is reported that more than twenty data points do not contribute to significant configuration recovery (22).

2. In this study, two dimensions were determined in the perceptual mapping for easiness of interpretation and parsimony. This was made after the examination of the possible improvement of goodness of fit to the data in three dimensions compared with that in two dimensions. In general, the lowest possible dimensionality consistent with data should be obtained so that we can recognize the underlying structure of proximity and/or dominance. However, we should not reduce the number of dimensions only for convenience, at the cost of violating the original data. The trade-off between the practical significance and the statistical reliability should be determined by some criterion, for instance, a goodness of fit to data.

3. The PREFMAP program can analyze preference data up to a maximum of 49 subjects, which limits the number of respondents for an experimental design and jeopardizes the adequacy of sample size in the statistical sampling theory. Of course the program itself can be expanded. And it may be used for national samples, based on clusters of more than 49 people.

4. There were missing data from the respondents ; every respondent did not fill all the cells of ratings, similarity, or preference matrices, resulting in smaller sample sizes than the presently allowable 49 subjects of the PREFMAP program. In this study, the thirty-nine of Graduate and forty-seven of Undergraduate students with no missing data were submitted for the analysis.

Empirical problems :

1. In our particular automobile case-study, the median price range within each brand-class of cars was selected as the objective, representative price-base. With any product class or service, we must face the problem of selecting some price on set of prices to represent each brand. This can be a difficult choice, given the proliferation of product and brand variations differing in size, style, packaging flavour, or other characteristics.

2. Labelling of axes is subjective and intuitive rather than objective and deductive. It must be made through external information obtained from respondents and through experience and judgment on the part of experimenters. In this study, we used open-ended questioning of respondents' criteria in judging similarity of brands. These aid in the interpretation of axes.
3. Respondents were asked to rate the specific car features in terms of importance to them in the past, at the present, and in the future. It is problematical as to whether or not consumers can provide valid information on very different phases of their life. With some product categories the data may be more accurate and valid than with others.
4. Market segmentation was based on the consumers' common perception and preference along with the dimension of their demographic data. Properly, one might well consider not only demographics but also personality, life style and product benefits sought, as in "benefit segmentation."
5. Only perceptual measurement was used as a criterion of advertising in this study. Also possible would be the use of perception/preference measurements as a new source of data in advertising. Additionally, other important factors such as sales, brand shares, time-lag effects, and media selections should be considered for the problem of effective advertising.

6. Markov process was employed for the analysis of consumers' brand switching behavior under the assumption that their previous experience enhance the probability of repurchase for a specific make of automobiles. But other factors, such as consumer satisfaction, availability in distribution of brands, or the price changes of brands, may play an important part in their ultimate brand choice behavior.

7. Within the limitation of time and money, a small sample survey was conducted. In order to test the theory of the proposed model, more replications among the population sub-groups should be conducted. Furthermore, more sample with a variety of socio-economic and geographical distributions should be chosen to validate the model for any particular product class.

The research conducted on the proposed model has provided some implications for further investigations :

1. Carroll and Chang's unfolding model was used as the basis of a predictive tool for consumers' purchase behavior. Other predictive models among the multidimensional scaling techniques (e.g., using preference data only) should be compared with our model and their predictive performance determined.

2. It would be possible to submit other sorts of data to the multidimensional scaling method : Examples are psychogalvanometer, tachistoscope data, and eye-camera data.
3. To make the proposed model more practical as an adaptive model of consumer buying behavior, a post-purchase analysis should be made, and the theory of cognitive dissonance be introduced to analyze a disequilibrium between the two pieces of knowledge of before and after purchases. But several years would be necessary to survey the post-purchase behavior for such durable goods as cars. It is nevertheless entirely possible to apply the multidimensional scaling models to the analysis of cognitive dissonance and the post-purchase behavior.
4. Experimentation may be done with different representation of the product class (in our case car brands) to be studied. While we have simply named brands to the consumer, it would be possible to provide also pictures, word descriptions, or even exposure to the product itself to study consumer perceptions and preferences. Experimental design might be suggested for the analysis of individual consumer behavior, using analysis of variance. The MANOVA algorithm of the multidimensional scaling methods can be employed for this purpose. The INSCAL data can be appropriate in that it remains the individual differences in scaling proximities data. The combination of experimental design and the INSCAL data should provide a useful approach for understanding consumer buying behavior.

APPENDIX

Questionnaire

I would like to ask you a few questions about your attitudes to some major brands of cars. We will be talking mainly about the standard passenger cars.

Graduate student ()

Undergraduate student ()

June, 1973

1. Please rank each brand on how similar it is to the one at top. Give a "1" to the most similar and a "7" to the least similar.

AMERICAN

CADILLAC ()
 CHEVROLET ()
 CHRYSLER ()
 FORD ()
 LINCOLN ()
 TOYOTA ()
 VOLKSWAGEN ()

FORD

AMERICAN ()
 CADILLAC ()
 CHEVROLET ()
 CHRYSLER ()
 LINCOLN ()
 TOYOTA ()
 VOLKSWAGEN ()

CADILLAC

AMERICAN ()
 CHEVROLET ()
 CHRYSLER ()
 FORD ()
 LINCOLN ()
 TOYOTA ()
 VOLKSWAGEN ()

LINCOLN

AMERICAN ()
 CADILLAC ()
 CHEVROLET ()
 CHRYSLER ()
 FORD ()
 TOYOTA ()
 VOLKSWAGEN ()

CHEVROLET

AMERICAN ()
 CADILLAC ()
 CHRYSLER ()
 FORD ()
 LINCOLN ()
 TOYOTA ()
 VOLKSWAGEN ()

TOYOTA

AMERICAN ()
 CADILLAC ()
 CHEVROLET ()
 CHRYSLER ()
 FORD ()
 LINCOLN ()
 VOLKSWAGEN ()

CHRYSLER

AMERICAN ()
 CADILLAC ()
 CHEVROLET ()
 FORD ()
 LINCOLN ()
 TOYOTA ()
 VOLKSWAGEN ()

VOLKSWAGEN

AMERICAN ()
 CADILLAC ()
 CHEVROLET ()
 CHRYSLER ()
 FORD ()
 LINCOLN ()
 TOYOTA ()

2. What criteria did you use in making these judgments of overall similarity in the question above ?

3. Indicate your feeling about each brand even though you have not bought nor used, nor are currently using any of the brands. (Circle one number for each brand.)

	<u>Price</u>							<u>Availability of repair service</u>						
	Low			High				Poor			Excellent			
AMERICAN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CADILLAC	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHEVROLET	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHRYSLER	1	2	3	4	5	6	7	1	2	3	4	5	6	7
FORD	1	2	3	4	5	6	7	1	2	3	4	5	6	7
LINCOLN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
TOYOTA	1	2	3	4	5	6	7	1	2	3	4	5	6	7
VOLKSWAGEN	1	2	3	4	5	6	7	1	2	3	4	5	6	7

	<u>Styling and appearance</u>							<u>Amount of advertising</u>						
	Not at all attractive			Very attractive				Only a little			A great deal			
AMERICAN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CADILLAC	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHEVROLET	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHRYSLER	1	2	3	4	5	6	7	1	2	3	4	5	6	7
FORD	1	2	3	4	5	6	7	1	2	3	4	5	6	7
LINCOLN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
TOYOTA	1	2	3	4	5	6	7	1	2	3	4	5	6	7
VOLKSWAGEN	1	2	3	4	5	6	7	1	2	3	4	5	6	7

	<u>Dependability</u>							<u>Road performance</u>						
	Undependable			Dependable				Poor			Excellent			
AMERICAN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CADILLAC	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHEVROLET	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHRYSLER	1	2	3	4	5	6	7	1	2	3	4	5	6	7
FORD	1	2	3	4	5	6	7	1	2	3	4	5	6	7
LINCOLN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
TOYOTA	1	2	3	4	5	6	7	1	2	3	4	5	6	7
VOLKSWAGEN	1	2	3	4	5	6	7	1	2	3	4	5	6	7

	<u>Frequency of repairs</u>							<u>Overall rating</u>						
	Frequent			Infrequent				Poor			Excellent			
AMERICAN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CADILLAC	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHEVROLET	1	2	3	4	5	6	7	1	2	3	4	5	6	7
CHRYSLER	1	2	3	4	5	6	7	1	2	3	4	5	6	7
FORD	1	2	3	4	5	6	7	1	2	3	4	5	6	7
LINCOLN	1	2	3	4	5	6	7	1	2	3	4	5	6	7
TOYOTA	1	2	3	4	5	6	7	1	2	3	4	5	6	7
VOLKSWAGEN	1	2	3	4	5	6	7	1	2	3	4	5	6	7

4. Please rank the brands, 1 through 8, as to how expensive you think these are.

"1" is most expensive, and "8" is least expensive.

Then please estimate the average price of each brand.

(The average price of the most expensive brand is \$8,826.)

Please guess even if you are very uncertain.

	Your estimated <u>rank</u>	Your estimated <u>average price</u>
AMERICAN	()	(\$)
CADILLAC	()	(\$)
CHEVROLET	()	(\$)
CHRYSLER	()	(\$)
FORD	()	(\$)
LINCOLN	()	(\$)
TOYOTA	()	(\$)
VOLKSWAGEN	()	(\$)

5. Please rank the brands, 1 through 8, as to how much advertising expenditure you think is spent per car for each of these brands.

"1" is highest, and "8" is lowest.

Then please estimate the advertising expenditure per car of each brand.

(The highest advertising expenditure per car is \$78.08.)

Please guess even if you are uncertain.

	Your estimated <u>rank</u>	Your estimated <u>advertising expenditure per car</u>
AMERICAN	()	(\$)
CADILLAC	()	(\$)
CHEVROLET	()	(\$)
CHRYSLER	()	(\$)
FORD	()	(\$)
LINCOLN	()	(\$)
TOYOTA	()	(\$)
VOLKSWAGEN	()	(\$)

6. Please give rankings by your personal preference.

(a) Overall preference for each brand.

"1" is most preferred, and "8" is least preferred.

	<u>Rank</u>
AMERICAN	()
CADILLAC	()
CHEVROLET	()
CHRYSLER	()
FORD	()
LINCOLN	()
TOYOTA	()
VOLKSWAGEN	()

(b) Possible preference under budgetary constraints. Please rank all of them even if you do not prefer.

"1" is most preferred.

	\$4,000	\$6,000	\$8,000	\$10,000	\$12,000
	<u>Rank</u>	<u>Rank</u>	<u>Rank</u>	<u>Rank</u>	<u>Rank</u>
AMERICAN	()	()	()	()	()
CADILLAC	XXXXX	()	()	()	()
CHEVROLET	()	()	()	()	()
CHRYSLER	XXXXX	()	()	()	()
FORD	()	()	()	()	()
LINCOLN	XXXXX	XXXXX	()	()	()
TOYOTA	()	()	()	()	()
VOLKSWAGEN	()	()	()	()	()

(c) Please rank your preference for the brands, if you were to have the car in the city, the suburbs, or a small town.

"1" is most preferred, and "8" is least preferred.

	In the city	In the suburbs	In a small town
	<u>Rank</u>	<u>Rank</u>	<u>Rank</u>
AMERICAN	()	()	()
CADILLAC	()	()	()
CHEVROLET	()	()	()
CHRYSLER	()	()	()
FORD	()	()	()
LINCOLN	()	()	()
TOYOTA	()	()	()
VOLKSWAGEN	()	()	()

7. Indicate your feeling about the desirability of various car features even though you have not bought nor used, nor are currently using, nor even plan to buy a car.

(Circle one number for each feature.)

	<u>Past</u>		<u>Present</u>		<u>Future</u>	
	Unimport- ant	Import- ant				
1. Sporty styling	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
2. Simple but husky styling	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
3. Hardtop	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
4. European styling	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
5. 2 door sedan	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
6. 4 door sedan	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
7. Mini size	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
8. Compact size	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
9. Intermediate size	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
10. Standard size	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
11. Bright body color	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
12. Vinyl roof	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
13. Convertible	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
14. Undercoating	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
15. Strong protective bumpers	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
16. V4 engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
17. V6 engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
18. V8 engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
19. Front engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
20. Rear engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
21. Piston engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
22. Rotary engine	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
23. Power disk brakes	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
24. Power steering	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
25. Emission control system	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
26. Automatic transmission	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
27. Automatic speed control	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
28. Engine tachometer	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
29. Safety belt warning system	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
30. Air conditioning	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
31. Reheat system air conditioning	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
32. Power window	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
33. Remote-control outside mirror	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
34. Rear window defogger	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
35. Tinted glass	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
36. Map light	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
37. AM radio	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
38. FM stereo radio	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
39. TV installation	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7

	<u>Past</u>		<u>Present</u>							<u>Future</u>											
	Unimport- ant	Import- ant	1	2	3	4	5	6	7	1	2	3	4	5	6	7					
40. Low seating position	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
41. Bucket seat	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
42. Front seat roominess	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
43. Rear seat comfort	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
44. Synthetic fiber seat	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
45. Cloth seat	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
46. Interior luxury	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
47. Trunk space	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
48. Smoothness of operation	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
49. Driving comfort	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
50. Silent running	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
51. Fuel economy	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
52. Low cost of operation	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
53. Ease of parking	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
54. Low purchase price	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
55. Low insurance rate	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
56. Resale value	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
57. Warranty/Guarantee	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
58. Trade-in allowance	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
59. Convenient service facility	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7

Kruskal's multidimensional scaling algorithm (MDSAL 5M) (33, 51, 52, 53)

Kruskal's concept is to derive a configuration of stimuli in a prespecified number of dimensions, given a set of proximities data among pairs of stimuli. Let us suppose that we have a set of ranked pairs R_{ij} ($i=1,2,\dots,n-1$ and $j=2,3,\dots,n$). Then R_{ij} represent the original measure of similarity between pairs of stimuli i and j . We can call the R_{ij} similarities, or psychological distances. Our objective is to represent the n stimuli by n points in a r -dimensional space, so that the rank order of distances between pairs of points best reproduces the rank order of the R_{ij} . Let the coordinates of the i th point be $x_i = (x_{i1}, x_{i2}, \dots, x_{ir})$ and the distance from x_i to x_j be d_{ij} . Now, we can denote $X = (x_1, x_2, \dots, x_n)$, which consists of n vectors in a space of r dimensions. For each x_i, x_j in X we can compute a distance d_{ij} . If X is a good configuration in that the ranks of its distances d_{ij} approximately reproduce the input ranks R_{ij} , then that configuration should be final or close thereto for representing the R_{ij} in a specified dimensionality.

The criterion used for obtaining a good configuration of X is one of minimizing the regression function called stress (S) given by the formula,

$$S = \sqrt{\frac{\sum_{i+j}^n (d_{ij} - \hat{d}_{ij})^2}{\sum_{i+j}^n (d_{ij} - \bar{d})^2}}$$

where \hat{d}_{ij} is a set of ratio-scaled numbers, chosen to be as close to their respective d_{ij} as possible, subject to being monotone with the R_{ij} . \bar{d} is the mean distance. The \hat{d}_{ij} take on the role of fitted values in the monotone regression procedure. Perfect fit will result if all the points fall on the monotone function, and S , then, equals to 0. If the stress S of a particular configuration is higher, then the monotone fit is poorer. The algorithm keeps finding a new configuration X in which the ranks of interpoint distances are more closely monotone to the original R_{ij} than the previously ranked distances. The new configuration X is obtained by the numerical method called "steepest descent".

Let the coordinates of the gradient of stress be $g_i = (g_{i1}, g_{i2}, \dots, g_{ir})$. Then the next configuration is formed by moving along the gradient the distance which is proportional to the step-size c . If d_{ij} is larger than \hat{d}_{ij} , the point i starts toward point j by the distance specified by c . If d_{ij} is smaller than \hat{d}_{ij} , then the point i starts away from the point j by the distance specified by c .

The new configuration X'_{it} measured by the Euclidean distance is given by the following formula :

$$x'_{it} = x_{it} + \frac{c}{\text{mag}(g)} g_{it}$$

$$\text{mag}(g) = \sqrt{\frac{\sum_{i,t} g_{it}^2}{n}} \quad (\text{normalized})$$

$$g_{it} = s \sum_{i,j}^n (U^i - U^j) \left[\frac{d_{ij} - \hat{d}_{ij}}{\sum_{i \neq j}^n (d_{ij} - \hat{d}_{ij})^2} - \frac{d_{ij}}{\sum_{i \neq j}^n d_{ij}^2} \right] \frac{x_{it} - x_{jt}}{d_{ij}}$$

$$U^i = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$$

All (n-1) points which effect on the point 1 are considered and the process is repeated until successive configurations $x_0, x_1, x_2, \dots, x_p$ converge S value to be less than or equal to a criterion value (usually 0.01). If the stress value is not satisfactorily achieved, the same process is repeated in the next lower dimensionality which satisfies S.

Carroll and Cheng's INSCAL model (15, 16, 18)

The INSCAL algorithm performs an analysis of proximities data that reveals individual differences among subjects in the weights they apply to a common space.

A set of r dimensions or factors underlying the n stimuli is assumed. These dimensions are assumed to be common for all m individuals making similarity judgments. Let x_{jt} represent the value of the j th stimulus on the t th dimension ($j=1,2,\dots,n$ and $t=1,2,\dots,r$).

Similarity judgments for each individual are assumed to be related in a simple way to a kind of modified Euclidean distance in this space, and the relationship is to be linear. That is, the similarity measure, $s_{jk}^{(i)}$, the pair of j th and k th stimuli for the i th individual, is a linear function of the modified Euclidean distance $d_{jk}^{(i)}$ such as

$$s_{jk}^{(i)} = L (d_{jk}^{(i)})$$

The modified Euclidean distance for the i th individual is given by the formula :

$$d_{ij}^{(i)} = \sqrt{\sum_{t=1}^r w_{it} (x_{jt} - x_{kt})^2}$$

where x_{jt} is the coordinate value for the j th stimulus on the t th dimension. This formula is different from the usual Euclidean distance formula only in the presence of the weights w_{it} , which represent the saliences or importances which the i th individual gives to the t th dimension of the perceptual space. The above model is sufficiently general. It can accommodate individuals with widely divergent perceptions of a set of stimuli in terms of a common perceptual space.

The procedures by which the parameters of the model are estimated from similarities judgments on all possible $\frac{n(n-1)}{2}$ distinct pairs of stimuli by m individuals will be discussed as follows. The model consists of the $n \times r$ elements of the X matrix ($X = (x_{jt})$ represent the matrix of stimulus coordinates in the common space) and the $m \times r$ elements of the matrix $W = (w_{it})$.

The method to analyze data in terms of this model uses a procedure called "canonical decomposition of N-way tables." In the present case, we start with a 3-way table of distances (derived from similarities or dissimilarities) between stimuli for individuals. This table of data will be $m \times n \times n$, for m individuals and n stimuli. By using procedures described by Torgerson (82), this cube of distances data is converted to a cube of scalar products data. That is, the procedures estimate an additive constant which converts the comparative distances (that is, the original similarities judgments) into absolute distances

between pairs of stimuli. The distance estimates are then converted for each individual to scalar products of vectors. If we let $b_{jk}^{(i)}$ denote the scalar product between the vectors $(y_{j1}^{(i)}, y_{j2}^{(i)}, \dots, y_{jr}^{(i)})$ for the pair of the j th and k th stimuli, then this relation can be shown by the equation :

$$b_{jk}^{(i)} = \sum_{t=1}^r y_{jt}^{(i)} y_{kt}^{(i)} = \sum_{t=1}^r w_{it} x_{jt} x_{kt}$$

The similarities data will generate the 3-way matrix which consists of stimulus pairs for individuals. The problem is to estimate values of the X matrix and the w matrix, whose elements enter into the right-hand side of the preceding equation so that the estimates satisfy the equation.

Carrroll and Chang's MDPREF model (21, 29)

MDPREF is designed to perform an internal analysis of preference (or any other type of dominance) data. The objective of the program is to maximize a measure of agreement between projections of points on subject vectors and the initial paired comparisons data for each subject. The program develops simultaneously the vector directions for the subjects and configuration of stimuli

in a common space. The preferences are assumed to be described by a vector model.

The data to be assumed is the dominance judgments of either paired comparisons or rankings of stimuli. Thus a set of paired comparisons matrices may be assumed, one for each subject. These matrices can be considered to be of the form :

$$P_i = \parallel P_{i,jk} \parallel \quad \begin{array}{l} i=1,2,\dots,m \\ jk=1,2,\dots,n \end{array}$$

where

$$P_{i,jk} = \begin{cases} +1 & \text{if subject } i \text{ judges } j > k \\ 0 & \text{if no response or indifference} \\ -1 & \text{if subject } i \text{ judges } j < k \end{cases}$$

The model assumes that stimulus points are projected onto subject vectors and that preference judgments are in agreement with these projected values. Let $x_j = (x_{j1}, x_{j2}, \dots, x_{jr})$ represent the r -dimensional vector emanating from the origin to the j th stimulus and $y_i = (y_{i1}, y_{i2}, \dots, y_{ir})$ represent the unit-length vector for subject i . Then, \hat{s}_{ij} , the estimated preference scale value (or "subjective utility") of stimulus j for subject i is defined by the scalar product :

$$\hat{s}_{ij} = y_i \cdot x_j = \sum_{t=1}^r y_{it} x_{jt}$$

If $X \equiv \parallel x_{jt} \parallel$ is the $n \times r$ matrix of stimulus coordinate values, and $Y \equiv \parallel y_{it} \parallel$ is the $m \times r$ matrix of coordinates of the termini of subject vectors, the $m \times n$ matrix of preference scale is defined by

$$\hat{S} = Y X'$$

The problem is to determine the matrices Y and X' from the set of paired comparison judgments so that the P matrix will agree as nearly as possible with the \hat{S} matrix. An iterative procedure and Eckart-Young decomposition are used to accomplish this task

Given any such matrix \hat{S} of scale values. The following preference differentials are defined.

$$D_{i,jk} \equiv \hat{s}_{ij} - \hat{s}_{ik}$$

Perfect agreement of the matrix of scale values with the original paired comparison data causes $D_{i,jk}$ to possess exactly the same sign as $p_{i,jk}$ for all i, j , and k ($p_{i,jk} \neq 0$). In this case, therefore, the product $p_{i,jk} D_{i,jk}$ will always be positive or zero. Then, the following criterion of agreement between the data and the given configuration is suggested :

$$C = \sum_i w_i \left[\frac{(\sum_{j \neq k} p_{i,jk} D_{i,jk})^2}{\sum_{j \neq k} D_{i,jk}^2} \right]$$

As values of +1, 0, and -1 are assigned to the p 's, the criterion simply adds up, for each subject, the D 's agreeing with his data, subtracts the sum of the D 's disagreeing, squares the resulting number and normalizes by dividing by the sum of squares of the D 's to get a measure of agreement for that subject. These individual agreement indices are then weighted (if desired) and this weighted sum forms the overall measure of agreement. The goodness of fit to the paired comparison data can be found by maximizing C .

The procedure for maximizing C can be described as follows. First, define $S \equiv \|s_{ij}\|$ by

$$s_{ij} = (w_i)^{\frac{1}{2}} \sum_{k \neq j} (p_{i,jk} - p_{i,kj})$$

And S is expressed by a product form :

$$S = UbV'$$

set $Y = U_r b_r$

and $X = V_r$

U_r and V_r are matrices whose first r columns are made up of U and V . b_r is the diagonal matrix whose first r rows and columns are made up of b .

Mathematically, the elements in U_r of each row represent the projected points on the unit-length principal vectors of S , and the elements in V_r of each column similarly represent the projected points on the same unit-length principal vectors of S . Matrix Y , the product of U_r and b_r , represents the underlying factors, and the number of factors are expressed in the number of columns in the matrix. Matrix X , equated by V_r , contains the preference scores for the subject i in column i . ($i=1,2,\dots,m$) The Eckart-Young procedure produces matrices X and Y such that the matrix $S = YX'$ is the rank r matrix which gives best least-squares approximation to S .

MDPREF program can also accept directly judged preference scale values as input (S is directly defined, by bypassing paired-comparisons matrices).

Carroll and Chang's Model III and IV of PREFMAP algorithm (16, 20)

Carroll and Chang have developed the set of preference models called "external analysis" for relating preference data to a given stimulus space. It consists of a hierarchy of models ranging from the vector model (Model IV) to the generalized unfolding model (Model I). In this study, however, only Model III and IV are discussed.

PREFMAP algorithm has two versions : metric and nonmetric. The metric version assumes that a monotone function is linear between the preference scale values and the squared Euclidean distances, while the nonmetric version assumes an arbitrary monotone function which is nondecreasing. The metric version will first be discussed.

Let us assume that a matrix is given :

$$x \equiv \left\| \left\| x_{jt} \right\| \right\| \quad \begin{array}{l} j = 1, 2, \dots, n \\ t = 1, 2, \dots, r \end{array}$$

representing the coordinates of n stimuli in r dimensions (as determined by a multidimensional scaling solution). Also $X_j \equiv (x_{j1}, x_{j2}, \dots, x_{jr})$ is used to represent the j th point in r dimensions. Since we obtain the scale values of preference of m individuals for the n stimuli, we can define :

$$s \equiv \left\| \left\| s_{ij} \right\| \right\| \quad \begin{array}{l} i = 1, 2, \dots, m \\ j = 1, 2, \dots, n \end{array}$$

The unfolding model of the PREFMAP algorithm assumes that the preference scale value is monotonically related to the square of the Euclidean distance between X_j and the ideal point Y_i in psychological space. The assumption above is converted to an equation,

$$s_{ij} = a_i d_{ij}^2 + b_i + c_{ij} \quad (1)$$

where a_i and b_i are constants ($a_i \geq 0$) and e_{ij} is an error term.

We assume that original X_j and Y_i can be orthogonally transformed through matrix T_i as follows :

$$\begin{aligned} X_j^* &= X_j T_i \\ Y_i^* &= Y_i T_i \end{aligned}$$

Since the squared distance is invariant by the transformation, our modified Euclidean squared distances are expressed by the new coordinate values :

$$d_{ij}^2 = \sum_{t=1}^T w_{it} (x_{jt}^* - y_{it}^*)^2 \quad (2)$$

If we substitute Equation (2) in Equation (1) and arrange a newly defined preference value by matrix form, then we have :

$$s_{ij} \approx X_j K_i X_j' + B_i X_j' + c_i \quad (3)$$

where $R_i = a_i T_i W_i T_i'$, $B_i = -2Y_i R_i$, and $c_i = \text{constant}$.

Equation (3) is of a form of the quadratic regression between s_{ij} and x_{jt} .

This basic assumption for the formation of preference scale is common to Models I, II, and III. These models differ in the

way in which d_{ij}^2 is defined. s_{ij} 's are estimated by quadratic or linear regression methods in all four models, and coordinate values of vectors X_j and Y_i are solved by the models after the coefficients are estimated.

Model III : This is a simple unfolding model. The concept of negative weight can be introduced in this model. Some or all of the dimensions are allowed to have negative importance. Preference scale is expressed in the quadratic regression :

$$s_{ij} \approx a_i X_j R'_i X'_j + c_{ij}$$

where R'_i consist of the components of ± 1 .

Model IV : This is a simple linear or vector model. We define the preference scale values in the product form :

$$\begin{aligned} s_{ij} &\approx a_i Y_i X'_j + c_{ij} \\ &\approx b_{it} X'_{jt} + c_{ij} \quad (b_{it} = a_i Y_{it}) \quad (4) \end{aligned}$$

where X_j represents an inverse matrix of the j th point of stimulus in r dimensions. Equation (4) contains only linear terms. After coefficients b_{it} ($t=1,2,\dots,r$) are estimated, the direction cosines of the vector for the i th individual are calculated in the form of a unit length.

In the nonmetric version, the model fits nondecreasing monotone functions between the preference scale values and the square of Euclidean distance. Therefore, we can assume to replace equation (1)

with
$$\tilde{s}_{ij} = d_{ij}^2 + e_{ij}$$

and
$$\tilde{s}_{ij} = M_1(s_{ij})$$

where M_1 is an arbitrary monotone function which is nondecreasing.

In order to predict the values of s_{ij} 's, the parameters of the appropriate linear regression are solved. Suppose a first estimate of the monotone function M_1 is found, which is called $M_1^{(1)}$. Then we compute $\tilde{s}_{ij}^{(1)} = M_1^{(1)}(s_{ij})$ and replace s_{ij} with $\tilde{s}_{ij}^{(1)}$ to compute a new set of regression coefficients. We use the new set of $\tilde{s}_{ij}^{(1)}$, compute a new monotone function $M_1^{(2)}$ and a new set of $\tilde{s}_{ij}^{(2)}$. This iterative process is repeated until it converges (that is, until no more change occurs in the monotone function or regression coefficients). The feature of this nonmetric scheme is that it is quite general and can be applied to a multiple regression whose predictor variables are measured on interval scales while the criterion variable is measured only on an ordinal scale.

TRICON III - Triangularization III of Conjoint Data (34, 35, 36)

Coombs proposed a triangularization procedure for converting conjoint data to a complete order of ranks over all pairs of stimuli. Conjoint data can be obtained by ranking the $(n-1)$ remaining stimuli out of a set of n stimuli due to the degree of similarity to a reference stimulus i . Each i , in turn, serves as a reference item. Name "conjoint" is derived by that all pairwise similarities have a stimulus in common.

TRICON algorithm first develops a $\frac{n(n-1)}{2} \times \frac{n(n-1)}{2}$ matrix of all possible tetradic comparisons from the input data. In this step all direct comparisons are made. Either 1 or 0 is entered into this new matrix according to whether or not the row pair is more similar than the column pair. If the row pair is judged as more similar than the column pair, 0 is entered in the cross-cell of the matrix.

The row sums of this pairs-by-pairs matrix are calculated. The more sum a row has, the more dissimilar the pair corresponding to the row is regarded than other pairs. If a perfect consistency arose in judgment, no 1's below the major diagonal in the permuted matrix could be found. A 1 below the major diagonal means that there exists an intransitive pair. Slater's i and the determination of nearest adjoining orders are employed to render the data transitive (78).

After intransitivities are removed, the matrix is powered to obtain higher-order (assumed to be transitive) connections between the pairs. Powering is repeated until no higher-order relationship can be obtained. The final matrix can be obtained by ranking the pairs in a decreasing order of row sums to end up with a lower-half matrix. The resulting form of order of all possible pairs can be treated as measures of direct similarity and used as input to various multidimensional scaling programs. (e.g., INSCAL algorithm in this study.)

Johnson Hierarchical Cluster Program (12)

Johnson's algorithm is based upon hierarchical in that each object starts out in its own cluster. A similarity matrix of stimuli or subjects is used as input to this program.

The hierarchical clustering algorithm has two methods - connectedness and diameter methods. The connectedness method will be first discussed.

Let us suppose that we have n stimuli and a sequence of $(m+1)$ clusterings such as C_0, C_1, \dots, C_m . Each clustering C_i has a number a_i , its value. Our problem is to find a set of numbers a_0, a_1, \dots, a_m subject to

$$\begin{array}{ll}
 a_{j-1} \leq a_j & \text{for } j=1,2,\dots,m \quad (a_0 = 0) \\
 C_{i-1} < C_i & \text{for } i=1,2,\dots,m
 \end{array}$$

If we define $d(x,y)$ as the measure of similarity between the pair of stimuli x and y ($x,y = 1,2,\dots,n$; $x \neq y$),

$$d(x,z) \leq \max [d(x,y), d(y,z)]$$

can hold for perfect data. (Ultrametric inequality)

Johnson proves the existence of a hierarchical clustering scheme (HCS) for every matrix of distance measures under a metric d , satisfying the ultrametric inequality which is stronger than the triangle inequality. Steps of HCS are summarized as follows :

Given a similarity function d on n stimuli,

Step 1. Clustering C_0 with value 0 which means the weak clustering.

Step 2. Assuming that the clustering C_{j-1} is given with the similarity function d , define a_j as the smallest nonzero entry in the matrix. Merge all pairs of points and/or clusters with distance a_j , generating C_j with a_j .

Step 3. Creating a new similarity function for C_j as follows ;
if x and y are clustered in C_j and not in C_{j-1}
(i.e., $d(x,y) = a_j$), define the distance from the cluster
(x,y) to any third stimulus or cluster, z , by
$$d((x,y), z) = \min [d(x,z), d(y,z)] .$$

Step 4. Obtaining a new similarity function d for C_j .

Step 5. Repeating Steps 2 through 4 until all stimuli are included
in one cluster.

The diameter method only differs in its function of Step 3.

That is,

$$d((x,y), z) = \max [d(x,z), d(y,z)]$$

Carroll and Chang's PROFIT program (17, 19)

This program fits outside property vectors into stimulus spaces. That is, it will find for each property a vector, or direction, in the r dimensional space such that the stimulus projections of the n points on the vector are maximally correlated with the scale values of the candidate property vector. There are two approaches to be employed in finding the vectors : the max "r" procedure and the nonlinear correlation method.

Let us define matrices as follows ;

$X \equiv \{ x_{ij} \}$: the matrix of the coordinates of n stimuli
in r dimensional space
 $i = 1, 2, \dots, n$
 $j = 1, 2, \dots, r$

$P \equiv (p_i)$: the ratings of the n stimuli on an attribute
 $i = 1, 2, \dots, n$

$T \equiv (t_j)$: the direction cosines of the fitted vector
 $j = 1, 2, \dots, r$

$H \equiv (h_i)$: the projections of n stimuli on the fitted vector
 $i = 1, 2, \dots, n$

Max "r" linear regression : The criterion in the max "r" approach is :

$$\min (P - H)^2$$

The solution for the transformation t is given by the least square method.

$$T = (X' X)^{-1} X' P$$

and

$$H = X T = X (X' X)^{-1} X' P$$

Nonlinear correlation method : The criterion is defined to minimize an index value :

$$k = \frac{1}{S^2} \sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n w_{ij} (x_i - x_j)^2$$

where $w_{ij} = f (| p_i - p_j |)$, f is a monotone decreasing function, and

$$S^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 .$$

The direction cosines (T) of the fitted vectors and the projections (H) of stimuli on the vector can be obtained by constructing a $r \times r$ symmetric matrix $X'AX$, where the element of A are defined by

$$A_{ij} = -w_{ij} \quad \text{for } i \neq j$$

$$A_{ij} = \sum_{i \neq j}^n w_{ij}$$

The smallest characteristic root of $X'AX$ is the minimum value of k , and the direction cosines (T) of the fitted vector (the new vector) are given by the corresponding characteristic vector. Once we obtain T , the projections (H) can be calculated by $H = XT$.

Table IV-1
Observed intransitivities and Chi-squares
from the TRICON III procedure.

Subject number	Total intransitivities	χ^2	Subject number	Total intransitivities	χ^2
101	3	2.5556	201	1	5.0000*
102	1	5.0000	202	5	14.3333
103	2	4.6667	203	1	5.0000
104	3	4.3333	204	4	8.0000
105	4	6.6667	205	2	7.3333
106	14	11.7143	206	4	4.0000
107	6	5.1111	207	4	2.6667
108	10	5.2000	208	4	9.3333*
109	0	0.0000	209	8	14.6667
110	3	7.8889	210	0	0.0000
111	0	0.0000	211	5	3.6667
112	0	0.0000	212	11	6.0303
113	12	8.4444	213	9	8.8518
114	6	8.6667	214	11	9.4242
115	9	6.4815	215	0	0.0000
116	28	2.2857	216	1	5.0000
117	2	7.3333	217	2	7.3333
118	7	9.0952	218	2	4.6667
119	5	3.6667	219	0	0.0000
120	6	5.1111	220	14	7.1429
121	7	4.5238	221	2	4.6667
122	2	7.3333	222	3	7.8889
123	6	6.8889	223	2	7.3333
124	3	4.3333	224	5	12.2000
125	2	7.3333	225	8	8.6667
126	3	4.3333	226	2	4.6667
127	0	0.0000*	227	3	9.6667
128	5	14.3333*	228	3	9.6667
129	7	2.2381	229	1	5.0000
130	5	3.6667	230	10	13.7333
131	3	5.0000	231	9	9.4444
132	6	11.3333	232	6	8.6667
133	5	9.0000	233	6	1.5556
134	3	5.0000	234	8	6.6667
135	6	6.8889	235	4	6.6667
136	3	2.5556	236	3	7.8889
137	0	0.0000	237	0	0.0000

(Continued)

Subject number	Total intran-sitivities	χ^2	Subject number	Total intran-sitivities	χ^2
138	4	5.3333	238	4	6.6667
139	0	0.0000	239	9	5.2963
			240	7	4.5238
			241	4	8.0000
			242	2	7.3333
			243	4	6.6667
			244	10	9.4667
			245	11	9.4242
			246	12	6.6667
			247	4	8.0000

* : Statistically significant at 5 percent level

Table IV-2
 Input lower-half matrix of the averaged
 direct similarities data.

Graduates

Brand	A	CA	CHE	CHR	F	L	T	V
A	0							
CA	19.54	0						
CHE	7.92	14.74	0					
CHR	13.64	9.92	8.76	0				
F	7.13	16.13	3.73	8.87	0			
L	19.71	2.10	14.03	9.23	14.85	0		
T	10.31	25.44	15.31	20.51	14.83	24.54	0	
V	11.55	26.64	17.49	22.99	17.71	26.35	2.08	0

Undergraduates

Brand	A	CA	CHE	CHR	F	L	T	V
A	0							
CA	19.55	0						
CHE	8.59	13.83	0					
CHR	12.81	8.85	8.39	0				
F	7.62	14.77	5.10	8.96	0			
L	19.09	2.11	15.30	9.07	14.64	0		
T	10.29	25.47	15.63	20.50	14.63	24.63	0	
V	12.01	27.06	18.22	22.83	17.23	26.86	2.00	0

Table IV-3
Individual-subject correlation coefficients
from aggregate level INSCAL analysis of direct
similarities in two and three dimensions

Graduates			Undergraduates		
Correlation			Correlation		
Subject	2 dim.	3 dim.	Subject	2 dim.	3 dim.
1	0.928757	0.932989	1	0.925806	0.967757
2	0.808590	0.907247	2	0.935657	0.951820
3	0.955528	0.960371	3	0.757954	0.965511
4	0.747539	0.956343	4	0.946924	0.969588
5	0.929747	0.949801	5	0.819527	0.968124
6	0.918100	0.924020	6	0.697769	0.948759
7	0.868008	0.943607	7	0.763984	0.945216
8	0.882849	0.890568	8	0.858399	0.913093
9	0.973626	0.975897	9	0.930270	0.936845
10	0.864412	0.962732	10	0.938289	0.954117
11	0.771119	0.968906	11	0.952665	0.958549
12	0.986582	0.990263	12	0.861364	0.861428
13	0.608528	0.814825	13	0.814494	0.931822
14	0.909126	0.983400	14	0.754674	0.928127
15	0.879115	0.917123	15	0.945238	0.952538
16	0.600867	0.674138	16	0.931232	0.960810
17	0.921708	0.962699	17	0.961202	0.969281
18	0.933224	0.972973	18	0.927603	0.962692
19	0.838191	0.927070	19	0.933011	0.984403
20	0.956527	0.957083	20	0.576239	0.706866
21	0.894887	0.919184	21	0.934378	0.953086
22	0.933272	0.957833	22	0.851102	0.958223
23	0.944827	0.946342	23	0.944710	0.968667
24	0.898866	0.926794	24	0.923262	0.943199
25	0.966206	0.982461	25	0.850637	0.932559
26	0.835948	0.882435	26	0.937817	0.954028
27	0.962171	0.969015	27	0.303453	0.803766
28	0.846927	0.876187	28	0.957461	0.982261
29	0.940421	0.951645	29	0.958078	0.962518
30	0.720765	0.889274	30	0.940800	0.957475
31	0.953907	0.957005	31	0.893057	0.915011
32	0.836022	0.922909	32	0.837283	0.867553
33	0.917585	0.934002	33	0.727223	0.944944
34	0.953436	0.959833	34	0.725563	0.885724
35	0.821001	0.838822	35	0.866589	0.888080
36	0.888127	0.957298	36	0.904750	0.924538
37	0.969945	0.972210	37	0.973928	0.978653

(Continued)

Graduates			Undergraduates		
Correlation			Correlation		
Subject	2 dim.	3 dim.	Subject	2 dim.	3 dim.
38	0.793189	0.903941	38	0.878106	0.979814
39	0.947125	0.957929	39	0.941785	0.947995
			40	0.817819	0.950589
			41	0.906301	0.916593
			42	0.918293	0.967593
			43	0.913496	0.975749
			44	0.757191	0.891018
			45	0.647856	0.919768
			46	0.607154	0.841376
			47	0.923843	0.981111

Table IV-4

Stimulus coordinates from aggregate level
INSCAL analysis of direct similarities
in two and three dimensions.

	Brand	2 dimensions		3 dimensions		
G	A	-0.27250	-0.34089	-0.27250	-0.34089	0.31471
	CA	0.56479	0.21212	0.56479	0.21212	0.16415
	CHE	-0.23307	0.37448	-0.23307	0.37448	0.15181
	CHR	0.19278	0.33522	0.19278	0.33522	0.16556
	F	-0.19624	0.17778	-0.19624	0.17778	0.25394
	L	0.54454	0.22701	0.54454	0.22701	0.16065
	T	-0.30519	-0.40010	-0.30519	-0.40010	-0.61640
	V	-0.29511	-0.58563	-0.29511	-0.58563	-0.59440
U	A	-0.40286	0.23718	-0.40286	0.23718	0.26266
	CA	0.37274	-0.54680	0.37274	-0.54680	0.20694
	CHE	0.26434	0.33094	0.26434	0.33094	0.15226
	CHR	0.21652	-0.16785	0.21652	-0.16785	0.28908
	F	0.13361	0.24568	0.13361	0.24569	0.13992
	L	0.35100	-0.57676	0.35100	-0.57676	0.16034
	T	-0.42568	0.24003	-0.42568	0.24003	-0.56920
	V	-0.50966	0.23757	-0.50966	0.23757	-0.64200

Table IV-5
 Input to HICLUST of lower-half matrix of
 the average direct similarities data*

Graduates

Brand	A	CA	CHE	CHR	F	L	T	V
A	0							
CA	9.23	0						
CHE	22.99	14.83	0					
CHR	15.31	17.71	20.51	0				
F	24.54	11.55	25.44	19.71	0			
L	8.87	26.35	14.85	19.54	14.03	0		
T	17.49	3.93	13.64	8.76	14.74	7.13	0	
V	16.13	2.08	10.31	7.92	9.92	2.10	26.64	0

Undergraduates

Brand	A	CA	CHE	CHR	F	L	T	V
A	0							
CA	8.85	0						
CHE	20.50	14.77	0					
CHR	15.30	19.55	22.83	0				
F	24.63	13.83	25.47	19.09	0			
L	8.96	26.86	12.81	18.22	14.63	0		
T	17.23	5.10	12.01	8.59	14.64	7.62	0	
V	15.63	2.00	9.07	8.39	10.29	2.11	27.06	0

* The more similar, the larger rank orders are given.

Table V-1

Preference scores on overall ratings by
the average subject

Brand	Graduates	Undergraduates
A	4.00	4.12
CA	5.66	6.10
CHE	4.43	4.30
CHR	4.85	5.28
F	4.71	5.05
L	5.63	5.80
T	4.28	4.25
V	3.80	3.97

Table VI-1

Rating scores on advertising - the average subject

Brand	Graduates	Undergraduates
A	4.83	4.40
CA	4.80	4.39
CHE	3.55	4.35
CHR	3.40	2.71
F	3.83	3.41
L	5.65	6.06
T	5.00	4.57
V	4.95	5.84

Table VI-2

Actual prices and their corresponding measures of perceived advertising for logarithmic transformation. (CA and L excluded.)

Brand	Price (\$)	Measure of perceived advertising*		$\log_e A$	
		Graduates	Under-graduates	Graduates	Under-graduates
A	3,218	0.6734	0.6475	-0.3954	-0.4346
CHE	3,766	0.2446	0.3655	-1.4081	-1.0065
CHR	5,399	0.0001	0.0001	-9.2103	-9.2103
F	3,627	0.4008	0.1574	-0.9143	-1.8490
T	3,241	0.9899	0.8556	-0.0102	-0.1560
V	2,902	0.9178	0.9388	-0.0858	-0.0632

* A constant of 0.5927 and 0.5718 were added to the original projections of brands on fitted vectors of advertising preference ratings to yield positive measures for graduate and undergraduate groups, respectively.

Table VII-1

Average-subject scenario dependent preferences

Dependent condition for scenario	Brand															
	Graduates								Undergraduates							
	A	CA	CHE	CHR	F	L	T	V	A	CA	CHE	CHR	F	L	T	V
Overall	5.55	4.35	3.48	5.70	3.53	5.88	3.80	3.73	5.41	4.69	2.92	5.71	3.24	6.16	3.86	3.63
\$4,000	3.28	7.00	2.30	7.00	2.75	7.00	3.25	3.38	3.51	7.00	1.98	7.00	2.78	7.00	3.16	3.67
\$6,000	4.43	3.35	2.73	2.93	3.18	8.00	5.03	5.48	4.47	3.37	2.86	3.29	3.84	8.00	5.00	5.29
\$8,000	5.08	2.22	3.48	3.35	4.35	3.03	6.33	6.80	5.65	3.43	3.82	3.55	4.31	3.08	5.67	6.37
\$10,000	5.05	2.93	3.78	3.30	4.68	2.75	6.35	6.78	5.76	2.92	3.78	3.53	4.55	2.57	5.90	6.98
\$12,000	5.43	2.80	3.80	3.38	4.90	2.63	6.33	6.95	6.04	2.73	3.94	3.45	4.49	2.14	6.10	7.08
City	4.15	6.00	3.50	5.38	4.05	6.08	3.30	3.75	4.67	6.00	3.71	4.63	4.06	6.04	3.18	3.69
Suburbs	5.45	3.43	3.53	3.73	4.33	3.18	6.98	5.85	5.47	2.94	3.73	3.63	4.67	3.04	5.78	6.53
Town	5.13	4.33	3.45	3.53	3.95	3.68	5.75	6.20	5.45	3.47	3.61	3.51	4.43	3.35	5.69	6.49

Table VIII-1
Average ratings on the 7 rating scales.

Group	Property	Brand							
		A	CA	CHE	CHR	F	L	T	V
Gradu- ates	1	2.80	6.63	4.34	5.35	4.22	6.45	3.15	2.68
	2	2.95	5.37	4.59	4.76	4.46	5.98	3.22	2.27
	3	4.15	5.63	4.83	4.98	4.02	5.34	4.15	5.37
	4	4.00	4.40	4.20	4.66	4.05	4.68	4.32	4.90
	5	4.70	5.33	5.26	5.03	5.05	5.02	3.20	3.80
	6	4.83	4.80	3.55	3.40	3.83	5.65	5.00	4.95
	7	4.10	5.93	4.83	5.24	4.49	5.93	4.39	4.00
	8	4.00	5.66	4.43	4.85	4.71	5.63	4.28	3.80
Under gradu- ates	1	2.77	6.23	4.30	4.82	4.12	6.21	3.72	2.58
	2	3.22	6.20	4.76	4.91	4.53	6.44	3.56	2.36
	3	4.09	5.61	5.14	4.95	4.10	5.46	4.47	5.19
	4	3.61	4.40	4.07	4.03	3.41	4.22	4.54	4.69
	5	4.85	5.15	5.32	4.91	4.91	5.19	3.31	3.79
	6	4.40	4.39	4.35	2.71	3.41	6.06	4.57	5.84
	7	3.81	5.97	5.30	5.21	4.67	5.98	4.29	4.32
	8	4.12	6.10	4.30	5.28	5.05	5.80	4.25	3.97

Table VIII-2

59 car feature scores by the average subject
for the past-present-future analysis.

Car feature variable	Past		Present		Future	
	G	U	G	U	G	U
1	4.40	4.63	4.13	4.92	4.10	5.06
2	3.68	3.35	3.65	3.57	3.43	3.65
3	4.05	4.61	4.48	5.14	4.50	5.14
4	3.00	3.37	3.25	3.96	3.48	3.98
5	3.15	3.95	3.30	3.88	3.15	4.06
6	4.18	3.86	3.98	4.06	4.10	4.57
7	2.83	2.63	3.33	3.69	3.80	3.80
8	3.48	3.16	4.30	4.20	4.70	4.45
9	3.90	3.78	3.93	4.39	3.95	4.39
10	4.08	3.96	3.80	4.22	3.60	4.31
11	3.50	3.06	3.60	3.76	3.43	3.88
12	2.63	3.49	3.33	4.27	3.38	4.41
13	4.13	3.16	3.28	3.20	3.05	3.04
14	4.73	4.63	5.13	5.47	5.00	5.59
15	4.73	4.76	5.93	5.92	6.43	6.27
16	2.70	2.78	3.23	3.24	3.70	3.51
17	3.43	3.78	3.68	4.04	3.95	4.33
18	4.80	4.47	4.98	5.20	4.85	4.94
19	4.45	4.71	4.53	5.29	4.53	4.96
20	2.90	2.73	2.93	3.18	3.03	3.20
21	4.13	4.29	4.15	4.47	3.88	3.96
22	2.58	3.02	3.65	4.73	4.45	5.24
23	4.38	4.47	5.28	5.76	5.83	5.84
24	4.70	4.82	5.53	6.00	5.73	6.22
25	3.45	3.80	5.18	5.55	6.00	5.88
26	4.35	4.55	4.88	5.71	5.18	5.86
27	2.98	3.39	3.38	4.39	3.55	4.71
28	3.28	3.08	3.55	3.76	3.75	3.94
29	3.23	4.04	4.45	3.39	4.75	5.76
30	3.78	3.94	5.13	5.57	5.50	6.00
31	3.13	3.49	3.90	4.65	4.13	5.20
32	2.25	2.59	2.65	3.18	3.05	3.84
33	2.18	2.88	3.03	4.06	3.30	4.31
34	3.53	3.94	5.23	5.67	5.88	6.10
35	3.63	3.68	4.93	5.33	5.28	5.61
36	3.30	3.18	3.93	4.35	4.20	4.47
37	4.83	4.16	5.13	5.24	5.38	5.29
38	3.88	4.20	5.10	5.47	5.35	5.71

(Continued)

Car feature variable	Past		Present		Future	
	G	U	G	U	G	U
39	1.58	1.76	1.63	2.27	1.90	2.71
40	2.15	2.86	2.48	3.69	2.65	3.92
41	3.58	3.49	3.90	4.49	4.13	4.69
42	4.75	4.98	5.38	5.96	5.40	6.22
43	4.03	4.63	4.50	5.29	4.53	5.51
44	2.73	3.08	3.18	5.67	3.35	3.88
45	2.68	2.86	2.90	3.57	3.05	3.71
46	3.58	3.94	4.30	5.00	4.58	5.12
47	4.30	4.55	5.40	4.88	5.35	5.57
48	5.48	5.63	5.98	5.98	5.95	6.57
49	5.43	5.49	4.00	6.35	6.15	6.57
50	4.88	5.00	5.68	5.84	5.95	6.35
51	4.78	4.90	5.48	5.98	5.83	6.27
52	5.08	5.53	5.88	6.00	6.20	6.02
53	4.83	4.96	5.75	5.61	6.10	6.06
54	5.50	5.00	5.63	5.27	5.50	5.24
55	5.60	5.00	6.00	6.63	5.83	5.94
56	5.28	5.14	5.65	5.88	5.65	5.98
57	5.58	5.69	5.93	6.27	6.13	6.27
58	5.18	5.39	5.58	5.90	5.40	5.88
59	5.63	5.49	6.18	6.22	6.05	6.37

Table VIII-3
Factor loadings for the car features
for the past

Car feature variable	Graduates		Undergraduates	
	Factor		Factor	
	1	2	1	2
1	0.15398	-0.19360	-0.02684	0.11554
2	0.15941	-0.14875	-0.04961	-0.06865
3	-0.13455	-0.08646	-0.00718	-0.16128
4	0.17104	0.29516	-0.12340	0.00644
5	-0.02006	-0.08010	0.22069	0.10971
6	0.12972	0.10734	-0.15497	0.16726
7	0.22259	0.73056	0.02554	0.09449
8	0.14391	0.84611	0.06213	0.14535
9	0.17870	0.15515	-0.22194	0.28178
10	0.05654	0.00667	0.14782	0.07673
11	0.01057	0.45173	0.05238	0.06512
12	0.13714	-0.02078	0.21292	0.01843
13	0.21488	0.08567	0.03803	0.10997
14	-0.04571	0.27359	-0.02025	0.24943
15	0.25204	-0.03427	0.16992	0.34420
16	0.06094	0.15475	0.00080	0.19323
17	-0.08791	0.17314	0.14150	0.20669
18	-0.11262	0.21312	0.34546	-0.07634
19	0.26947	0.00082	0.17604	-0.05184
20	-0.03602	0.24362	0.05229	0.12163
21	0.13274	0.07042	-0.04126	-0.00096
22	-0.08458	0.07032	0.03312	0.15840
23	0.37252	0.54112	0.16407	0.32708
24	0.36016	-0.19280	0.01824	0.21956
25	0.30143	0.51788	0.47302	0.23365
26	-0.19526	0.19766	0.23679	0.27425
27	0.07768	0.00243	0.80102	0.22062
28	0.07150	0.16425	0.66024	0.34097
29	0.19799	-0.12278	0.28382	0.24868
30	0.26026	-0.01801	0.00412	0.14965
31	0.17175	0.13986	0.37097	-0.05343
32	-0.03203	0.07714	-0.04808	0.12722
33	-0.02479	0.05528	0.18657	0.21093
34	0.38170	-0.17927	0.31171	0.11537
35	0.45528	0.16573	0.03670	0.28459
36	0.14605	0.25867	0.20577	0.22019
37	-0.00198	0.01079	0.01086	0.08780
38	0.38682	0.02616	0.14827	0.03905

(Continued)

Car feature variable	Graduates		Undergraduates	
	Factor		Factor	
	1	2	1	2
39	-0.12190	0.07175	0.07716	-0.07940
40	-0.05936	-0.16376	-0.13671	-0.11526
41	0.18829	0.30737	-0.05462	0.02317
42	0.48027	0.37635	0.03218	0.29348
43	0.37646	0.38167	0.18221	0.42399
44	0.20319	-0.19115	0.23810	0.23379
45	0.09306	-0.10494	0.06695	0.11591
46	0.05291	-0.16165	-0.06118	-0.01579
47	0.53196	0.20799	0.19938	0.22311
48	0.37723	-0.00278	0.04371	0.40653
49	0.33311	-0.03799	0.01399	0.43529
50	0.23441	-0.09321	0.16331	0.32042
51	0.61651	0.24263	0.07516	0.72371
52	0.62400	0.22649	0.25471	0.78284
53	0.54571	0.32135	0.22431	0.67633
54	0.66623	0.11695	-0.03184	0.64069
55	0.87320	0.01630	0.19405	0.82298
56	0.84276	0.09461	-0.07613	0.83174
57	0.82409	0.09151	0.00825	0.76243
58	0.79624	0.04757	0.13152	0.80424
59	0.78965	0.04981	-0.20863	0.64997
Percentage of explained variance	23.96	10.92	30.12	8.74

Table VIII-4
Factor loadings for the car features
for the present

Car feature variable	Graduates		Undergraduates	
	Factor		Factor	
	1	2	1	2
1	-0.02602	0.20549	0.21080	0.01564
2	-0.03852	-0.05595	-0.10114	0.02053
3	0.17050	0.10578	0.10462	0.06015
4	-0.33133	0.02968	-0.22306	-0.13264
5	0.14770	0.42166	0.05622	-0.07815
6	0.25333	-0.10739	0.04314	-0.04353
7	-0.31424	0.01577	-0.33954	-0.01934
8	-0.09045	0.11905	-0.30531	0.02466
9	-0.05697	0.10371	-0.01632	0.11740
10	0.24461	0.06561	0.03582	-0.03531
11	-0.08112	-0.19105	-0.06423	0.07886
12	0.00553	0.74906	0.40790	-0.00199
13	-0.46304	-0.06909	0.00074	-0.17121
14	-0.09096	0.12411	0.32096	0.43677
15	0.35789	0.05706	0.12412	0.05469
16	-0.05707	-0.15406	0.11151	0.17024
17	-0.13818	0.03615	0.00758	0.11057
18	0.17216	-0.27206	0.75182	-0.24777
19	0.01706	0.01461	0.86102	-0.04941
20	-0.52450	-0.09947	0.00641	-0.03282
21	0.09403	0.27959	0.31185	0.25361
22	0.08068	0.20681	0.03495	0.13322
23	0.05505	0.04988	-0.01122	0.22690
24	0.68096	0.29831	0.08308	-0.06316
25	-0.02072	-0.03786	-0.04138	-0.05435
26	0.66279	0.16383	0.27035	-0.05233
27	0.20257	0.12445	0.09226	-0.18435
28	-0.23104	0.30108	0.06746	-0.12929
29	0.12177	0.07464	-0.33702	0.06860
30	0.84182	-0.01278	0.10997	0.09765
31	0.34961	-0.09276	0.17215	-0.06945
32	0.02810	0.03500	0.15451	0.03289
33	0.10283	0.15198	-0.12800	-0.06841
34	0.36349	-0.21655	-0.06030	0.16077
35	0.37868	-0.18655	-0.11884	0.09517
36	0.08964	-0.14946	0.14874	0.24528
37	0.40984	0.10609	0.25470	0.25194
38	0.35383	0.13821	0.19829	0.06325

(Continued)

Car feature variable	Graduates		Undergraduates	
	Factor		Factor	
	1	2	1	2
39	-0.17173	-0.07599	-0.16528	-0.02458
40	-0.19411	0.20517	0.26323	-0.08047
41	-0.11785	0.41904	-0.02055	0.02896
42	0.49536	0.16408	0.19471	0.13370
43	0.16873	-0.13433	0.07178	0.07773
44	0.20489	0.19499	0.05045	0.16238
45	0.18870	-0.15096	0.16022	-0.18883
46	0.43913	0.05171	-0.00218	0.06597
47	0.49475	-0.14260	0.19876	0.36358
48	0.85985	-0.00273	0.22554	0.44303
49	0.81793	-0.12912	0.05077	0.13094
50	0.84804	-0.09821	0.03780	0.38537
51	0.10396	-0.10374	-0.05053	0.20271
52	0.12998	-0.00525	-0.04279	0.27961
53	0.12991	0.03633	0.11399	0.24809
54	-0.05828	-0.15468	-0.34316	0.37319
55	0.23136	-0.13450	-0.24536	0.27522
56	0.02696	0.05809	-0.06996	0.75418
57	0.25722	-0.05283	-0.03664	0.86664
58	-0.00817	0.04636	-0.09059	0.76349
59	0.15709	-0.02560	-0.12103	0.81351
Percentage of explained variance	17.6	11.7	14.4	12.3

Table VIII-5
 Factor loadings for the car feature
 for the future

Car feature variable	Graduates		Undergraduates	
	Factor		Factor	
	1	2	1	2
1	-0.03230	0.02208	0.72248	-0.17484
2	-0.05940	-0.00593	0.31180	0.24714
3	0.15203	0.17636	0.24125	0.18387
4	-0.19118	0.30372	0.06275	0.08675
5	0.01895	0.03104	0.06941	0.08924
6	0.25472	0.11956	-0.10237	0.06799
7	-0.21982	0.04463	-0.00239	0.13785
8	0.09224	0.03973	0.05776	0.01610
9	0.05315	-0.27880	-0.11863	-0.08161
10	0.18092	-0.08642	-0.04729	-0.07327
11	-0.15619	0.13511	0.55187	-0.05149
12	0.08901	0.06251	0.30784	-0.15489
13	-0.36112	-0.01826	0.33528	-0.14319
14	-0.07443	0.02136	-0.17642	0.24286
15	0.71948	0.00426	0.06356	0.80963
16	-0.05395	0.27723	0.11714	0.19001
17	0.00192	-0.17037	-0.01241	0.03570
18	0.02249	-0.16226	0.02562	0.08541
19	0.07464	0.00875	0.09274	0.20715
20	-0.46353	0.20502	-0.00148	0.01674
21	0.04602	0.01864	0.16014	-0.15069
22	0.28474	-0.10658	-0.08080	0.22056
23	0.01429	-0.09984	0.27438	0.09404
24	0.73077	-0.17032	0.28456	-0.01459
25	0.10651	0.04084	0.17959	0.22660
26	0.76709	-0.19751	0.12010	-0.04288
27	0.31313	0.01742	0.18912	0.40313
28	-0.17098	0.17471	0.62340	0.25619
29	0.39185	-0.05189	-0.14189	0.10897
30	0.76198	0.19642	-0.13805	-0.16663
31	0.37889	0.04334	0.07072	-0.13084
32	0.16261	0.10648	0.03732	0.00828
33	0.10369	0.17154	0.08964	0.32762
34	0.26680	-0.04779	0.03116	0.00910
35	0.06337	0.09705	0.03061	-0.13450
36	-0.01224	0.06086	-0.03501	0.17632
37	0.40895	-0.05380	0.14225	0.01709
38	0.33730	0.07760	0.21951	-0.00622

(Continued)

Car feature variable	Graduates		Undergraduates	
	Factor		Factor	
	1	2	1	2
39	-0.08309	0.20772	0.07730	-0.19945
40	-0.18848	0.52650	-0.09858	0.15481
41	-0.06342	0.12661	0.27942	0.04866
42	0.37256	0.02027	-0.01380	0.20681
43	0.35393	0.15674	0.04550	0.16865
44	0.29353	0.52617	0.14782	0.07008
45	0.17957	0.86063	-0.03577	0.08868
46	0.44978	0.42477	-0.14348	-0.39181
47	0.56283	0.10785	-0.14638	0.25164
48	0.77594	0.00015	0.00199	0.18157
49	0.81406	0.20544	-0.07202	0.02773
50	0.85068	0.15827	-0.03010	0.03536
51	0.09159	-0.14726	-0.02326	0.50627
52	0.21367	-0.09761	-0.11990	0.87310
53	0.32842	-0.22899	-0.01678	0.74409
54	-0.05461	-0.41464	0.27123	0.28834
55	0.10011	-0.07217	0.25524	0.37907
56	0.04992	0.19657	-0.13047	0.15983
57	0.25808	0.14901	-0.06337	0.05055
58	0.06774	0.13361	0.03167	0.21664
59	0.19011	0.07319	0.10778	-0.15738
Percentage of explained variance	18.56	11.59	16.21	11.21

Table IX-1
Overall preference rankings at the individual-
subject level

Graduates									Undergraduates								
Subject	Brand								Subject	Brand							
	A	CA	CHE	CHR	F	L	T	V		A	CA	CHE	CHR	F	L	T	V
101	8	4	1	7	3	6	2	5	201	7	6	2	5	1	8	4	3
102	5	4	1	8	2	7	3	6	202	7	5	2	6	1	8	3	4
103	6	7	1	5	4	3	2	8	203	1	4	2	7	3	8	6	5
104	5	6	2	8	1	7	4	3	204	5	7	2	8	1	4	6	3
105	8	6	7	2	3	1	5	4	205	7	5	2	6	1	8	3	4
106	7	8	2	4	1	5	3	6	206	2	7	3	5	4	8	1	6
107	6	2	8	5	7	4	1	3	207	2	8	3	4	6	1	5	7
108	3	5	1	8	2	7	6	4	208	2	8	4	7	5	3	6	1
109	4	5	2	8	3	7	1	6	209	7	3	5	8	4	6	1	2
110	6	3	1	8	2	7	4	5	210	2	6	8	5	7	3	4	1
111	3	1	2	8	4	7	6	5	211	1	6	5	8	4	2	7	3
112	4	3	7	2	6	8	5	1	212	7	4	6	3	8	5	1	2
113	6	4	2	7	1	8	5	3	213	8	6	2	5	1	7	3	4
114	4	3	7	5	6	8	1	2	214	4	5	2	8	6	1	3	7
115	7	1	4	8	3	6	5	2	215	6	4	2	7	1	8	3	5
116	7	3	6	5	2	8	4	1	216	7	4	2	6	1	8	3	5
117	6	4	3	8	2	7	5	1	217	4	3	5	1	8	7	6	2
118	5	6	1	7	2	8	4	3	218	4	7	1	6	2	8	3	5
119	5	6	2	7	1	8	3	4	219	7	5	2	4	1	8	3	6
120	8	5	6	2	7	1	3	4	220	7	6	2	5	1	8	3	4
121	6	4	1	7	3	8	2	5	221	8	4	2	6	1	7	3	5
122	8	7	5	6	4	3	1	2	222	8	1	2	7	4	5	6	3
123	6	3	7	4	8	5	1	2	223	4	8	1	7	6	3	5	2
124	3	6	5	2	8	1	7	4	224	7	6	2	5	1	8	4	3
125	3	5	6	4	1	8	7	2	225	6	4	1	7	2	8	5	3
126	6	5	1	7	2	8	3	4	226	1	3	5	7	6	8	4	2
127	6	1	2	8	5	3	4	7	227	7	3	1	8	2	6	4	5
128	2	3	6	7	5	8	4	1	228	7	4	1	6	2	8	5	3
129	1	5	3	7	2	8	4	6	229	6	3	1	8	7	5	2	4
130	7	4	1	6	2	5	8	3	230	8	1	6	4	5	7	2	3
131	6	4	7	2	5	1	8	3	231	7	5	1	6	2	8	3	4
132	8	5	2	4	1	3	6	7	232	8	5	2	6	1	7	4	3
133	6	5	1	8	2	7	3	4	233	8	3	2	5	1	7	4	6
134	6	8	2	7	1	4	3	5	234	1	4	8	5	6	3	7	2
135	6	4	5	1	3	8	7	2	235	7	6	2	5	1	8	3	4
136	7	2	5	1	8	3	6	4	236	6	5	2	8	1	7	4	3
137	4	2	5	7	6	8	1	3	237	6	4	1	8	2	7	3	5

(Continued)

Graduates								Undergraduates									
Subject	Brand							Subject	Brand								
	A	CA	CHE	CHR	F	L	T		V	A	CA	CHE	CHR	F	L	T	V
138	6	2	3	5	8	7	1	4	238	5	8	1	6	4	7	3	2
139	5	8	4	7	2	6	3	1	239	2	6	4	8	5	3	1	7
									240	6	3	1	7	2	8	5	4
									241	8	1	7	3	5	2	6	4
									242	7	6	3	4	1	8	2	5
									243	8	5	1	7	2	6	4	3
									244	1	6	3	5	4	2	8	7
									245	7	3	4	5	6	8	1	2
									246	6	4	2	8	3	5	7	1
									247	8	2	1	6	5	7	3	4

Table IX-2 (a)
 Ideal-point coordinates and dimension weights-
 overall preferences

Graduates

Subject	Ideal point		Dimension weight**	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
1	-0.98779	0.24014	-3.29110	-3.29110*
2	-1.01279	0.25994	-3.00048	-3.00048*
3	-1.10732	0.24990	-2.56876	-2.56876
4	-1.06440	0.51996	-0.92751	-0.92751
5	-0.81733	0.30318	1.84346	1.84346
6	-4.33495	0.92190	-0.29308	-0.29308
7	-4.90491	0.92844	0.26416	0.26416*
8	-1.07843	0.25970	-2.71748	-2.71748*
9	-0.95084	0.30528	-2.13935	-2.13935*
10	-0.96312	0.24358	-3.36816	-3.36816
11	-0.77588	0.19899	-3.59539	-3.59539
12	-1.15428	0.18057	1.66557	1.66557
13	-1.84926	0.41021	-0.91062	-0.91062
14	0.19756	0.27494	-0.83113	-0.83113
15	-0.14851	0.27237	-0.87542	-0.87542
16	-0.58124	0.24100	-2.42802	-2.42802*
17	-1.04331	0.32937	-2.14442	-2.14442
18	-1.14981	0.52433	-0.92730	-0.92730
19	1.29566	-0.49161	-0.34832	-0.34832*
20	-1.08354	0.27047	-2.64696	-2.64696
21	-0.17052	0.30597	-0.97687	-0.97687
22	-5.29006	0.66913	0.22803	0.22803
23	-0.80992	0.35010	1.27889	1.27889
24	-0.73629	0.15225	3.00225	3.00225*
25	-1.06078	0.27760	-2.69186	-2.69186
26	-0.79703	0.15456	-3.32634	-3.32634
27	0.59931	0.25846	-0.62516	-0.62516
28	3.14995	-1.45518	0.16211	0.16211*
29	-1.10071	0.25150	-2.64267	-2.64267
30	-2.26790	0.89646	0.38547	0.38547
31	-3.71394	-0.08887	-0.27470	-0.27470*
32	-0.97149	0.25900	-3.20440	-3.20440
33	-1.85161	0.45691	-0.87314	-0.87314
34	-0.66095	0.20040	2.97369	2.97369
35	-1.13241	0.58906	0.76266	0.76266
36	0.67964	0.22159	-0.57606	-0.57606
37	-0.69093	0.20943	-3.24432	-3.24432
38	-0.91045	0.53204	-0.86327	-0.86327
39	-0.97758	0.31638	-2.08111	-2.08111

Table IX-2 (b)
 Ideal-point coordinates and dimension weights-
 overall preferences

Undergraduates

Subject	Ideal point		Dimension weight**	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
1	1.21875	-0.12621	0.84645	-0.84645
2	1.23314	-0.13250	0.82613	-0.82613*
3	0.89665	-0.09399	2.23218	-2.23218
4	1.32987	-0.20368	0.68208	-0.68208
5	1.23314	-0.13250	0.82613	-0.82613
6	0.64383	-0.27478	-0.82880	0.82880*
7	0.80378	-0.15147	-2.29671	2.29671
8	0.84116	-0.21072	-1.60378	1.60378
9	0.80999	-0.10643	2.57916	-2.57916
10	1.26902	-0.27667	-0.76620	0.76620
11	0.85173	-0.11593	2.32590	-2.32590
12	1.92878	-0.12354	-0.23952	0.23952
13	1.35980	-0.21150	0.65320	-0.65320
14	1.05825	-0.29078	0.57308	-0.57308
15	1.00110	-0.11918	1.73393	-1.73393
16	1.21883	-0.15055	0.87665	-0.87665
17	0.85173	-0.11593	-2.32590	2.32590*
18	1.49273	0.01067	0.43382	0.43382
19	1.30205	-0.15774	0.72718	-0.72718
20	1.23739	-0.13373	0.81933	-0.81933
21	1.27132	-0.20006	0.78426	-0.78426*
22	0.88564	-0.17254	2.57857	-2.57857
23	0.79810	-0.17295	-1.93054	1.93054
24	1.21875	-0.12621	0.84645	-0.84645*
25	0.98224	-0.12339	1.94874	-1.94874*
26	0.81572	-0.07311	2.07807	-2.07807*
27	0.96287	-0.16316	2.23561	-2.23561
28	1.13363	-0.15147	1.14118	-1.14118
29	0.85375	-0.11621	2.73026	-2.73026*
30	1.24704	-0.15036	0.83456	-0.83456
31	1.26747	-0.19398	0.78864	-0.78864
32	1.02447	-0.19421	1.61012	-1.61012
33	1.30569	-0.18632	-0.66713	0.66713
34	1.23739	-0.13373	0.81933	-0.81933*
35	0.95880	-0.11328	2.04511	-2.04511
36	0.98595	-0.12536	1.93027	-1.93027
37	1.70861	0.36762	0.23054	-0.23054
38	0.85188	-0.11534	2.27900	-2.27900

(Continued)

Subject	Ideal point		Dimension weight**	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
39	0.97255	-0.13979	2.14012	-2.14012*
40	0.50939	-0.42739	0.45505	-0.45505
41	1.26030	-0.05534	0.59619	-0.59619
42	1.19061	-0.18204	0.97147	-0.97147
43	0.75813	-0.09466	-1.82771	1.82771
44	0.79957	0.06357	0.73878	-0.73878*
45	0.89007	-0.13289	2.75783	-2.75783
46	0.91851	-0.15225	2.51484	-2.51484
47	1.00879	-0.03616	1.01859	-1.01859

* Subjects whose Model III goodness of fit values markedly exceed those of Model IV

** Only the algebraic sign of the dimension weights is relevant for the simple ideal-point model.

Table IX-3

The background data of the respondents for
discriminant analysis

Variable										Re- spond- ent	Sub- group	
1	2	3	4	5	6	7	8	9	10			Next car
25	18750	1	1	0	1	3	1	2	1	Dodge	104	A
26	16250	1	1	0	1	6	1	1	1	Porsch	106	A
28	21250	1	1	0	1	5	1	2	0	Volkswagen	109	A
26	16250	1	0	0	1	2	1	2	0	Valiant	111	A
26	18750	1	0	0	1	0	1	2	0	Ford	113	A
26	13750	1	0	0	1	3	1	2	0	Capri	118	A
29	18750	1	0	0	1	4	1	2	0	Pontiac	124	A
28	13750	0	0	0	1	0	0	2	0	Dodge	128	A
29	13750	1	1	1	1	3	1	2	0	Plymouth Duster	131	A
25	16250	1	0	0	1	0	1	2	0	An old MG	133	A
25	16250	1	0	0	0	4	1	3	0	Grand Prix	134	A
26	18750	1	1	1	0	7	1	2	0	Ford Mustang	138	A
25	18750	0	0	0	1	3	1	2	0	Ford	139	A
28	21250	1	1	1	0	2	0	5	1	Station wagon	105	B
26	18750	1	1	0	0	0	0	4	1	Mercedez	123	B
29	23750	1	1	0	1	0	1	5	1	Mercedez	126	B
31	21250	1	1	1	0	3	0	5	0	Porsch	135	B
25	13750	1	0	0	1	3	1	2	0	Audi	107	C
22	11250	1	0	0	1	6	1	1	0	Chevy Vega GF	112	C
23	08750	1	0	0	1	7	1	1	0	Toyota	114	C
24	16250	1	0	0	1	7	1	2	0	Volkswagen	115	C
23	06250	1	0	0	1	5	1	2	1		116	C
22	11250	1	0	0	1	6	0	1	0	Monte Carlo	119	C
24	16250	0	0	1	0	0	7	2	0	Toyota	121	C
22	06250	1	0	0	1	6	0	0	1	Mazda	122	C
23	11250	1	0	0	1	7	1	1	0	Datsun	127	C
25	18750	1	0	0	1	7	1	2	0	Pontiac	130	C
23	11250	1	0	0	1	5	1	1	0	Volkswagen	136	C
22	06250	1	0	0	1	6	1	2	0	Toyota	137	C
26	18750	1	0	0	1	5	0	2	0	Dodge Charger	201	D
23	16250	1	0	0	1	4	1	2	0	Toyota	202	D
25	03750	1	0	0	1	2	0	2	0	Volvo	204	D
25	06250	1	0	0	1	6	0	2	0	Audi	205	D
26	13750	1	1	2	1	7	1	2	0	Gremlin	206	D
27	18750	1	0	0	1	4	1	2	0	Datsun sportscar	213	D
25	13750	1	1	2	1	3	1	2	0	Chevrolet	215	D
24	13750	1	0	0	1	5	1	2	0	Toyota	216	D
25	21250	1	0	0	0	7	1	2	0	Capri	219	D
23	13750	0	0	0	1	5	1	1	0	Audi	220	D
25	21250	1	0	0	1	4	1	1	0	Vega	221	D

(Continued)

Variable										Re- spond- ent	Sub- group	
1	2	3	4	5	6	7	8	9	10			Next car
27	21250	1	0	0	1	4	0	2	0	Mustang	223	D
23	11250	1	0	0	1	4	1	1	0	Valiant	224	D
24	13750	1	0	0	1	5	1	2	0	Toyota	229	D
23	13750	1	0	0	1	7	1	1	0	Volkswagen	231	D
25	13750	1	0	0	1	7	1	1	0	Volvo	232	D
26	18750	1	0	0	1	2	1	1	1	Porsch	234	D
23	16250	1	0	0	1	7	1	1	0	Ford Cinger	236	D
24	13750	0	0	1	0	7	1	1	0	Plymouth Duster	241	D
25	21250	1	0	0	1	3	1	1	1	Volvo	242	D
23	16250	1	0	2	1	3	1	1	0	Toyota	246	D
27	16250	1	0	3	0	7	0	1	0	Volkswagen	247	D
27	18750	1	1	0	0	1	0	4	1	Mercedez	214	E
29	21250	1	1	0	0	2	0	5	1	BMW 2002	217	E
26	16250	1	0	0	1	2	1	1	1	Cadillac	243	E
19	06250	1	0	0	1	7	0	0	0	Mazda	208	F
23	11250	1	0	0	1	5	1	1	0	Volkswagen	210	F
18	06250	1	0	0	1	4	0	1	0	Toyota	211	F
21	11250	1	0	0	1	7	1	1	1	Chevrolet	212	F
19	06250	1	0	0	1	7	0	2	0	Volkswagen	233	F
20	11250	1	0	0	1	3	1	2	0	Vega	238	F
19	08750	1	0	0	1	5	0	1	0	Dutsun	244	F

Note : Variable

1. Age
2. Income
3. Sex : Male=1, Female=0
4. Marital status : Married=1, Single=0
5. Number of children
6. Place of residence : City=1, Town or suburbs=0
7. Frequency of car used per week
8. Degree of usage at weekend : Heavy=1, Otherwise=0
9. Number of cars owned
10. Possibility of increase in income : Yes=1, No=0

Table IX-4

Supporting output for 6-way discriminant analysis,
 perception-preference segments versus background
 characteristics.

Summary table

Step number	Variable*		F value to enter or remove	Number of variables included	U- statistic
	Entered	Removed			
1	1		29.5247	1	0.2714
2	9		11.7742	2	0.1299
3	10		5.0254	3	0.0881
4	7		2.4994	4	0.0710
5	8		1.4068	5	0.0624
6	4		1.2029	6	0.0557
7	5		1.4738	7	0.0484
8	2		1.0749	8	0.0436
9	6		0.6879	9	0.0406
10	3		0.2759	10	0.0394

Eigenvalues					
4.82808	1.50073	0.30052	0.20248	0.11346	
0.00000	0.00000	-0.00000	-0.00000	-0.00000	

Cumulative proportion of total dispersion					
0.69516	0.91124	0.95451	0.98366	1.00000	
1.00000	1.00000	1.00000	1.00000	1.00000	

Canonical correlations					
0.91017	0.77467	0.48071	0.41035	0.31922	
0.00099	0.00019	0.00086	0.00096	0.00119	

* See the note on Page 271.

Table IX-5

The method for calculation of
market shares of brands

(1) If monotone ascending (the negative-ideal point case)

$$MS_1 = \frac{d_{I1}^2}{\sum_{i=1}^n d_{Ii}^2} \times 100 \quad i = 1, 2, \dots, 8$$

(2) If monotone descending (the positive-ideal point case)

$$MS_1 = \frac{\frac{1}{d_{I1}^2}}{\sum_{i=1}^n \frac{1}{d_{Ii}^2}} \times 100 \quad i = 1, 2, \dots, 8$$

BIBLIOGRAPHY

1. J.S.Armstrong and T.Overton, "Brief vs. Comprehensive Descriptions in Measuring Intentions to Purchase," Journal of Marketing Research, Vol. VIII (February 1971), pp.114-117.
2. H.Assael and G.S.Day, "Attitude and Awareness as Predictors of Market Share," Journal of Advertising Research, Vol. 8, No. 4, 1968, pp.3-10.
3. Automotive News, January 1, 1972 - March 12, 1973 and 1972 Almanac Issue, Marketing Services Inc.
4. J.N.Axelrod, "Attitude Measures that Predict Purchase," Journal of Advertising Research, Vol. 8 (march 1968), pp.3-17.
5. F.M.Bass and W.W.Talarzyk, "An Attitude Model for the Study of Brand Preference," Journal of Market Research, Vol. IX (February 1972), pp.93-96.
6. N.E.Beckwith, "Multivariate Analysis of Sales Responses of Competing Brands to Advertising," Journal of Marketing Research, Vol. IX (May 1972), pp.168-176.
7. J.F.Bennett and W.L.Hays, "Multidimensional Unfolding : Determining the Dimensionality of Ranked Preference Data," Psychometrika, Vol. 25, 1960, pp.27-43.
8. N.H.Borden, Advertising in Our Economy, Richard D.Irwin, Inc., Chicago, Illinois, 1949, 301p.
9. Ibid., p.174.
10. J.M.Brion, Corporate Marketing Planning, John Wiley & Sons, Inc., New York, 1967, 577p.
11. F.E.Brown, "Price Image versus Price Reality," Journal of Marketing Research, Vol. VI (May 1969), pp.185-191.
12. F.E.Brown, "Who perceives Supermarket Prices Most Validly ?" Journal of Marketing Research, Vol. VIII (February 1971), pp. 110-113.
13. M.C.Burk, "Survey of Interpretations of Consumer Behavior," in H.H.Kassarjian and T.S.Robertson ed., Perspectives in Consumer Behavior, Scott, Foresman and Company, Glenview, Illinois, 1968, pp.30-40.

14. R.D.Buzzell and M.J.Baker, "Sales Effectiveness of Automobile Advertising," Journal of Advertising Research, Vol. 12 (June 1972), pp.3-8.
15. J.D.Carroll, Individual Differences and Multidimensional Scaling, Bell Telephone Laboratories, Murray Hill, N.J., 1969 (Mimeographed).
16. J.D.Carroll, Individual Differences and Multidimensional Scaling, Bell Telephone Laboratories, Murray Hill, N.J., 1972 (Mimeographed), pp.107-111.
17. J.D.Carroll and J.J.Chang, "A General Index of Nonlinear Correlation and its Application to the Program of Relating Physical and Psychological Dimensions," American Psychologist, Vol. 19, 1964, p.540.
18. J.D.Carroll and J.J.Chang, "Analysis of Individual Differences in Multidimensional Scaling via An N-way Generalization of "Eckart-Young" Decomposition," Psychometrika, Vol. 35, No. 3, September 1970.
19. J.D.Carroll and J.J.Chang, How to Use PROFIT, A Computer Program for Property Fitting by Optimizing Nonlinear or Linear Correlation, The Bell Telephone Laboratories, Murray Hill, N.J., 1970 (Mimeographed).
20. J.D.Carroll and J.J.Chang, Relating Preference Data to Multidimensional Scaling Solutions via A Generalization of Coombs' Unfolding Model, The Bell Telephone Laboratories, Murray Hill, N.J., 1967.
21. J.J.Chang and J.D.Carroll, How to Use MDPREF, A Computer Program for Multidimensional Analysis of Preference Data, The Bell Telephone Laboratories, Murray Hill, N.J., 1969 (Mimeographed).
22. N.Cliff, R.Pennell, and F.W.Young, "Multidimensional Scaling and Cognition I - Relations among Judgments Obtained under Varying Conditions," Technical Report No. 1, University of Southern California, Los Angeles, California, February 1967.
23. C.H.Coombs, "Psychological Scaling without a Unit of Measurement," Psychological Review, Vol. 57, 1950, pp.145-158.
24. W.H.Cunningham and W.J.E.Crissy, "Market Segmentation by Motivation and Attitude," Journal of Marketing Research, Vol. IX (February 1972), pp.100-102.

25. W.L.Davidson, Political Thought in England, the Utilitarians, from Bentham to J.S.Mill, H.Holt and Company, New York, N.Y., 1916, 256p.
26. G.Day, "Evaluating Models of Attitude Structure," Journal of Marketing Research, Vol. IX (August 1972), pp.279-286.
27. G.S.Day and R.W.Prett, Jr., "Stability of Appliance Brand Awareness," Journal of Marketing Research, Vol. VIII (February 1971), pp.85-89.
28. R.Dorfman and P.O.Steiner, "Optimal Advertising and Optimal Quality," American Economic Review, Vol. 44 (December 1954), pp. 826-836.
29. C.Eckart and G.Young, "The Approximation of One Matrix by Another of Lower Rank," Psychometrika, Vol. 1, 1936, pp.211-218.
30. F.Emery, "Some Psychological Aspects of Price," in B.Taylor and G.Wills, ed., Pricing Strategy, Brandon Systems Press, Princeton, N.J., 1970, pp.98-111.
31. G.T.Fechner, Elements der Psychophysik (Reprint), Leipzig, Breitkopf and Hartel, Germany, 1889.
32. R.Gatty, "Multivariate Analysis for Marketing Research : An Evaluation," Applied Statistics, Vol. 15, No. 3 (1966), pp.157-172.
33. P.E.Green and F.J.Carmone, Multidimensional Scaling and Related Techniques in Marketing Analysis, Allyn and Bacon, Inc., Boston, Mass., 1970, 203p.
34. P.E.Green and S.M.Jolly, TRICON II : An IBM 360/65 FORTRAN IV Program for Computing Slaters 1 in the Triangularization of Conjoint Similarities Data, Marketing Science Institute, Boston, Mass., (Mimeographed).
35. P.E.Green and V.R.Rao, Applied Multidimensional Scaling : A Comparison of Approaches and Algorithms, Holt, Reinhardt and Winston, Inc., New York, 1972, 292p.
36. P.E.Green and P.J.Robinson, "TRICON : An IBM 360/65 FORTRAN IV Program for the Triangularization of Conjoint Similarities Data," Journal of Marketing Research, Vol. 5 (May 1968), pp.219-220.
37. P.E.Green and D.S.Tull, Research for Marketing Decisions, Prentice-Hall N.J., 1966, 532p.

38. L.Guttman, "A New Approach to Factor Analysis : The Radex," in P.E.Lazarsfeld ed., Mathematical Thinking in the Social Sciences, Glencoe, Illinois, Free Press, 1954, pp.258-345.
39. R.I.Haley and R.Gatty, "Adapting Attitude Scale Data to Computer Processing," Computer Operations, Vol. 2, No. 2 (April - May, 1968).
40. J.Harp, "Socioeconomic Correlates of Consumer Behavior," American Journal of Economics & Sociology, Vol. 20 (1961), pp.265-270.
41. J.A.Howard and J.N.Sheth, "A Theory of Buyer Behavior," in H.H. Kassarian and T.S.Robertson ed., Perspectives in Consumer Behavior, Scott, Foresman and Company, Glenview, Illinois, 1968, pp. 467-487.
42. H.S.Houthakker, "The Present State of Consumption Theory," Econometrica, Vol. 29 (October 1961), pp.708-713.
43. S.C.Johnson, "Hierarchical Clustering Schemes," Psychometrika, Vol. 32 (September 1967), pp.241-254.
44. R.M.Johnson, Multiple Discriminant Analysis : Applications to Marketing Research, Market Facts, Inc., Chicago, Illinois, 1970.
45. H.H.Kassarjian, "Field Theory in Consumer Behavior," in S.Ward and T.S.Robertson ed., Consumer Behavior : Theoretical Sources, Prentice-Hall, Inc., Englewood Cliffs, N.J., 1973, 576p.
46. Ibid., p.127.
47. G. Katona, "Rational Behavior and Economic Behavior," Psychological Review, September 1953, pp.307-318.
48. J.M.Keynes, The General Theory of Employment, Interest and Money, London, MacMillan and Co., Ltd, 1936, 403p.
49. A.Y.C.Koo, "An Empirical Test of Revealed Preference Theory," Econometrica, Vol. 31 (October 1963), pp.646-663.
50. J.B.Kruskal, "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis," Psychometrika, Vol. 29, 1964, pp.1-27.
51. J.B.Kruskal, "Nonmetric Multidimensional Scaling : A Numerical Method," Psychometrika, Vol. 29, 1964, pp.115-129.
52. J.B.Kruskal, Version SMS of M-D-SCAL, A More Portable Equivalent of Version SM, The Bell Telephone Laboratories, Murray Hill, N.J., November 17, 1971 (Mimeographed).

53. J.B.Kruskal and F.Carmone, How to Use MDSCAL, A Program to Do Multidimensional Scaling and Multidimensional Unfolding (Versions 5M of MDSCAL, All in FORTRAN IV), Bell Telephone Laboratories, Murray Hill, N.J., October 1969 (Mimeographed).
54. Z.V.Lambert, "Price and Choice Behavior," Journal of Marketing Research, Vol. IX (February 1972), pp.35-40.
55. H.J.Leavitt, "A Note on Some Experimental Findings about the Meanings of Price," Journal of Business, Vol. 27 (July 1954), pp.205-210.
56. R.M.Lienert, "Car of Future to be Smaller and Safer," Advertising Age, June 19, 1972, p.29.
57. B.Lipstein, "The Dynamics of Brand Loyalty and Brand Switching," Proceedings of 5th Annual Conference, Advertising Research Foundation, New York, 1959, pp.101-108.
58. D.B.Lucas and S.H.Britt, Measuring Advertising Effectiveness, McGraw-Hill Book Company, New York, 1963, 399p.
59. D.L.MacLachlan, "A Model of Intermediate Market Response," Journal of Marketing Research, Vol. IX (November 1972), pp. 378-384.
60. R.B.Maffei, "Planning Advertising Expenditures by Dynamic Programming Methods," Management Technology, Vol. 1 (December 1960), pp.94-100.
61. W.F.Massy, "Discriminant Analysis of Audience Characteristics," Journal of Advertising Research, Vol. 5, No. 1 (March 1965), pp.39-48.
62. F.E.May, "Adaptive Behavior in Automotive Brand Choices," Journal of Marketing Research, Vol. 6 (February 1969), pp62-65.
63. J.D.McConnell, "An Experimental Examination of the Price-Quality Relationship," Journal of Business, Vol. 41 (October 1968), pp. 439-444.
64. D.B.Montgomery and G.L.Urban, Management Science in Marketing, Prentice-Hall, Inc., Englewood Cliffs, N.J., 1969, 376p.
65. H.L.Munn, "Brand Perception as Related to Age Income, and Education," Journal of Marketing, Vol. 24 (January 1960), pp.29-34.
66. F.M.Nicosia, "Brand Choice : Toward Behavioral-Behavioristic Models," in H.L.Davis and A.J.Silk, ed., Behavioral and Management Sciences in Marketing, Ronald Press, New York, 1972.

67. F.M.Nicosia, Consumer Decision Processes : Marketing and Advertising Implications, Prentice-Hall, N.J., 1966, 284p.
68. K.S.Palda, "The Hypothesis of a Hierarchy of Effects : A Partial Evaluation," Journal of Marketing Research, Vol. 3 (February 1966), pp.13-24.
69. V.R.Rao, The Salience of Price in the Perception and Evaluation of Product Quality : A Multidimensional Measurement Model and Experimental Test, Ph.D. dissertation, University of Pennsylvania, May, 1970, 342p.
70. K.H.Schaffir and E.W.Orr, Jr., "The Determination of Advertising Budgets for Brands," Journal of Advertising Research, Vol. 3 (March 1963), pp.7-11.
71. R.L.Schultz, "Market Measurement and Planning with a Simultaneous-Equation Model," Journal of Marketing Research, Vol. VIII (May 1971), pp.153-164.
72. B.P.Shapiro, "Price Reliance : Existence and Sources," Journal of Marketing Research, Vol. X (August 1973), pp.286-294.
73. R.N.Shepard, "The Analysis of Proximities : Multidimensional Scaling with an Unknown Distance Function," Part One, Psychometrika, Vol. 27, 1962, pp.125-140.
74. R.N.Shepard and J.B.Kruskal, "Nonmetric Methods for Scaling and for Factor Analysis," American Psychologist, Vol. 19, 1964, pp. 557-558.
75. R.N.Shepard, A.K.Romney, and S.B.Nerlove, Multidimensional Scaling - Theory and Applications in the Behavioral Sciences, Vol. 1, 261p., Vol. 2, 323p., Seminar Press, New York, N.Y., 1972.
76. H.A.Simon, "Theories of Decision-Making in Economics and Behavioral Science," American Economic Review, Vol. 49 (June 1959) pp.253-283.
77. J.L.Simon, "A Simple Model for Determining Advertising Appropriations," Journal of Marketing Research, Vol. II (August 1965), pp.285-292.
78. Patrik Slater, "Inconsistencies in a Schedule of Paired Comparisons," Biometrika, Vol. 48, 1961, pp.303-312.
79. R.Stone, The Measurement of Consumers' Expenditure and Behavior in the United Kingdom, Vol. 1, Cambridge University Press, 1954, 180p.

80. W.S.Torgerson, "Multidimensional Scaling : Theory and Method," Psychometrika, Vol. 17, 1952, pp.401-419.
81. W.S.Torgerson, Theory and Methods of Scaling, John Wiley & Sons, Inc., New York, 1958, 460p.
82. W.S.Torgerson, Theory and Methods of Scaling, John Wiley & Sons, Inc., New York, 1960, pp.268-276.
83. D.Yankelovich, "New Criteria for Market Segmentation," Harvard Business Review, Vol. 42 (March-April 1964), pp.83-90.