AN EXPLORATORY APPROACH TO THE INTEGRATION OF A CONJOINT ANALYSIS WITH A FISHBEIN ATTITUDE ANALYSIS

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ABSTRACT

AN EXPLORATORY APPROACH TO THE
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By

Terry C. Wilson

The Fishbein attitude models, included in the group of models frequently referred to as compensatory multiattribute models, are specified as multiplicative functions of belief about an outcome (B_i) and desirability of the outcome (a_i). The desirability component has elluded precise measurement and has been referred to many times as a suppressor variable in spite of the fact that the models are believed to be misspecified without it.

The purpose of the present study was to explore whether the integration of a conjoint analysis estimate of the desirability component with the traditional Fishbein model would improve the predictive validity of the Fishbein model.

Three subcompact automobiles and the relevant attributes for their purchase were chosen as they provide a setting conducive to use of both conjoint analysis and the regression methodology usually associated with the Fishbein model. Data for both the conjoint analysis and the Fishbein model were collected from an undergraduate marketing class during Spring quarter 1976 at Michigan State University. This provided a final sample size of 218 which is considered an adequate base for analysis with both of the methodologies utilized.

The limitations of the study were: 1) it was essentially exploratory, 2) sample is not generalizable, 3) the Fishbein model is considered

representative of the class of attitude models referred to as compensatory multiattribute attitude models, and 4) conjoint is a relatively unexplored technique with only meager evidence as to its proper and efficient use.

The conclusions of the present study were: 1) no statistically significant difference between the predictive validity of the traditional measurement techniques associated with the Fishbein model and the Fishbein model with the conjoint analysis integration, 2) the desirability component has very different distributional characteristics with the different estimates of that component, yet the predictive validity is unchanged which points to the danger of multiplying non-ratio component measures, and 3) the continued use of the traditional measurement methods of desirability is preferred on the grounds of simplicity with the reservation that a construct validity study of the desirability component should be conducted and replication of the present study made for final judgment to be valid.

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This guy is an Incredible Dicknose

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CHAPTER I

INTRODUCTION

Research Objectives

The past two decades have witnessed a vast expansion of research literature on the topic of consumer behavior as applied to marketing situations. Within this arena of study much research, discussion, and controversy have focused on the various aspects of attitudes. The preponderance of this research on attitudes has been published since 1970. Within the attitude research sector two general topics have been of the greatest interest to researchers (Wilkie and Pessemier, 1973). These are 1) model conceptualization and 2) methodology and component measurement.

Component measurement is the primary concern in the present research, the purpose of which is to explore whether the integration of a conjoint analysis model with the traditional Fishbein analysis would improve the predictive validity of the latter. Specifically, this research will attempt to integrate the utility weights from the conjoint analysis with the Fishbein model as objective weights for the predictor variables. Although the use of both conjoint analysis and the Fishbein model has been advocated for predicting brand preference (Wilkie and Pessemier, 1973), there has been no previously known attempt to integrate the two models.

When confronted with more than one model for possible use, a researcher or decision maker must weigh the situational specific advantages and disadvantages of each as well as reviewing their unique assumptions and implications. The model, or combination of models, to be chosen is the one which offers the best prediction or explanation depending on the research purpose. The results of this research do not obviate the necessity for such careful observation and judgment, but rather facilitate a more objective decision as to the appropriateness of the models.

Model Merits and Limitations

In order to promote an effective discussion of the two models under consideration here, it is necessary to briefly discuss why these models have provided fruitful ground for research. As models evolve to the stage of algebraic specification, a number of advantages are available to the researcher. First, algebraic models provide for explicit variable definition of the essential components. For example, the components of the Fishbein expectancy/value model can be specifically defined as opposed to a simple verbal description of diagrammatic representation. Second, the algebraic model allows a specific statement of assumptions. This includes assumptions inherent in the theory plus the assumptions inherent in the methodology used in representing a theoretical model. Third, these models allow the researcher to simplify complex arrangements of variables that otherwise elude precise measurement and sometimes even approximation. And finally, because the models abstractly measure a "real" situation, they provide a potentially useful method for the evaluation of explanatory and predictive power. In fact, attitude models have been justified and evaluated on both explanatory and predictive criteria.

While the benefits are substantial, however, there is a major shortcoming in algebraic models that is especially noticeable in the behavioral sciences. This drawback is the lack of normative measures. Such a lack of a clear-cut standardization point or benchmark makes it difficult to evaluate the meaningfulness of the results, a problem which has forced the behavioral scientist to rely on less explicit methods of evaluation. For example, a model of attitude structure has no norm referencing point. Whereas in the physical sciences the total absence of heat is a reference point for temperature, there is no such counterpart in the behavioral sciences that would establish a reference point for something like the degree of desirability of carbonation in soft drinks. A model must then be chosen that is as consistent as possible with available theory and provides a relative measure. The problem of defining such a model is not so much that it fails by omitting some vital detail, but rather that it proves useful in consideration of its purpose, either explanation or prediction or both. Only after this step will the validity and reliability of a particular model warrant further research.

By definition, then, a model is an abstract representation and not the exact duplication of some system or process. Indeed, models do not attempt to incorporate all restrictions and complexities of a process. Both the merits and limits of the model lie in its ability to isolate some essential factors with rigorous logical underpinnings. By focusing attention on a few aspects at a time, a model can bring into perspective the implications of the underlying assumptions and relationships. It is, however, all too easy to lose the implications in the enthusiasm of a research project, and it is always good procedure to outline them in advance.

Research Model Applicability

There are two models under scrutiny here, the Fishbein attitude model and a conjoint analysis model of utility. Of the two, a considerable amount of attention has been devoted to the Fishbein model which is also referred to as the expectancy/value attitude model in the marketing literature (Wilkie and Pessemier, 1973). Chapter II is devoted to the historical evolution and the advantages and disadvantages of using this model. By way of contrast, the conjoint analysis model, a recent addition to research methodology, has had little exposure in the marketing literature. Chapter III discusses the technique, its assumptions, and the advantages and disadvantages inherent in its use.

These models have been chosen for examination for several reasons. First, conjoint analysis is a relatively new methodology and needs clarification and explication as it relates to marketing if it is to be utilized properly. Second, although there are several alternative attitude models reported in the marketing literature, the Fishbein model is one of the most widely utilized. Many of the models contain similar, if not identical, advantages and limitations. Third, the Fishbein and conjoint models have been advocated for comparison notwithstanding the different advantages, limitations, conceptualization, and results of each (Day, 1972; Wilkie and Pessemier, 1973; Schmidt and Wilson, 1975). Fourth, the present project is within a framework that enables marketing to advance as a scientific discipline. For instance, the methodology yields results that are readily replicated, while, at the same time, it specifies the degree to which the two models under consideration can be integrated. Such specification provides greater reliability in future research efforts since it sensitizes researchers to the advantages and limitations of the models and thus facilitates more valid interpretation of the results. It will be helpful to specify the advantages and limitations of each of the models so that it is possible to gain a perspective of the project's scope.

Research Areas

A discussion of the respective advantages and limitations of each model under consideration can be clearly focused by utilizing the three areas of research outlined earlier. Recall that these were 1) model conceptualization, 2) methodology, and 3) component measurement. Recent research in these areas is discussed in Chapter II, while the aim of this section is clarification of the framework of the models.

Model Conceptualization

In terms of model conceptualization, a substantial difference between the models is that the attitude models are compositional while the conjoint approach is essentially a decompositional approach. Basically, the compositional approach attempts to build up the component parts to produce an attitude toward an act or object, while the decomposition approach attempts to break down an attitude into its component parts. This difference is further discussed in Chapter IV.

An advantage enjoyed by the attitude models is the compiled evidence from many research endeavors as to predictive and construct validity. This research addresses the issue of the comparative predictive validity as there is yet no evidence of superiority for either model. In terms of construct validity, at this time the Fishbein model is more highly rated. It has been shown to include the relevant variables as well as representing the actual cognitive map of individual respondents. On the other hand, conjoint analysis is a kind of 'black box' approach. There is very little evidence at this time to support the contentions of decomposition (Sheth, 1976). Conjoint analysis enjoys only the intuitively appealing prospects of face validity.

The conjoint analysis model does, however, have advantages inherent in its use. For instance, it does not require interindividual utility comparisons whereas the empirical use of the attitude models has such a requirement. A method of analyzing data intraindividually has been introduced to the attitude literature and is frequently used to avoid this problem (Bass and Wilkie, 1973).

The attitude models are for the most part compensatory. This means that a low rating on one attribute can be counterbalanced by a high rating on another attribute. The interpretation of conjoint analysis in published studies has also implicitly assumed a compensatory framework, although such a framework is not inherent to the technique. The disadvantage of assuming a compensatory model is, of course, that the object or act toward which the attitude is directed may fall below a consumer's qualifying level. That is to say, a brand may not rate high enough on some criteria to be included in the consumer's evoked set. The evoked set is that collection of brands which is considered for purchase.

Several other considerations are shared by both models. Both assume that the attributes under consideration are relevant and non-redundant. Both admit to the theoretical realization of the possible effects of intervening variables which poses a problem in that the models may evaluate the attributes quite precisely but other factors may intervene before actual behavior occurs. Both models assume a rational, i.e., consistent, consumer and both are essentially cross-sectional.

Methodology and Measurement

The second area for consideration is the methodology of each of the techniques. Any separation of methodology from component measurement becomes arbitrary at some point. The following discussions classify each of the advantages and limitations under one area or the other, but the classifications are not irrevocable, although it would hardly be a crucial distinction.

Again, under methodological considerations the Fishbein model requires only a short interview period compared to one that is typically quite long for conjoint. The reason the Fishbein model enjoys this advantage is that attitude questions are much more easily comprehended by respondents than the conjoint questions. Another advantage of the Fishbein model in this area is that it requires a minimum sample of about fifty while the conjoint model requires at least 200. This advantage, in part, stems from the fact that regression analysis is utilized in most of the attitude model procedures, while conjoint analysis typically estimates through use of a distance function. Regression is a thoroughly investigated technique through its constant use and is subject to the rigorous underpinnings of probability theory. On the other hand, conjoint analysis enjoys no such advantage of possessing an error theory and is subject to many rules of thumb. It essentially involves a heuristically derived solution with little assurance that the results are statistically significant. Conjoint analysis, however, is not restricted by the scale assumption of the regression technique. For example, it can be used with only nominal data, whereas regression requires at least intervally scaled input. Both models rely on data from survey techniques and neither purports proof of causality.

Extrapolation of utility weights to combinations other than those under study appears more valid with conjoint analysis since the regression technique used in the Fishbein analysis is constrained to only those combinations of attributes which are specifically outlined in the study. In fact, mixes of attributes other than those used for original input are beyond the relevant range of consideration for regression analysis. Both models can be adjusted to both consumer and industrial settings and both have the potential to consider curvilinearity.

The third and final area of consideration is that of component measurement. Conjoint analysis enjoys the advantage of not being subject to some of the possible bias and constraints of attitude scales, but at the same time suffers from a complex questionnaire format. This leads to the subject of measurement constraint. As noted above, any scale level is acceptable for conjoint analysis whereas regression generally requires at least interval data. This latter constraint has surfaced as an area of concern with several researchers in that the attitude models, such as Fishbein, are assumed to be subject to a multiplicative combination rule. Legitimate multiplication requires that all variables being multiplied have attained a ratio level of measure. Typically, however, attitude models measure their components with bipolar or Likert type scales which attain interval level of measure at best. The multiplication of two variables measured only on an interval scale can easily produce spurious results, a problem which presents a potentially significant limitation in use of the attitude models.

Design Outline

The differences between the two models being considered provide the thrust of this research project. Any evaluation must be based on the purpose for which a model is employed. Moreover, the situation chosen in which the models can be evaluated must be consistent with the assumptions and purposes of both. In order to approximate an acceptable setting for both models, then, American subcompact cars are used. A consumer durable is appropriate for both the conjoint and Fishbein models.

Since the purpose of this research is examination of alternative models, it is not necessary to select a random sample. The empirical results are being used for evaluation purposes and not for generalization. As previously indicated, Chapters II and III will discuss the Fishbein attitude model and conjoint analysis, respectively, while the scope and methodology are further detailed in Chapter IV, the results of the models are presented in Chapter V, and the final chapter is a discussion of those results.

CHAPTER II

THE FISHBEIN ATTITUDE MODELS

Research Background

Attitude theory and measurement, the topic of a great deal of marketing research in recent years, has proven useful for both understanding and prediction. The various theories of attitudes generally have their roots in psychology and social psychology and have been refined and adapted to marketing situations. Much of the work in marketing has taken place since 1970 with more than forty studies being reported between 1970 and 1973 (Wilkie and Pessemier, 1973). An equal number have been published since then. Research in the area has become quite sophisticated and refined as a result of such a vast amount of study. And this high degree of sophistication has spawned considerable debate as to the superiority of the many alternative models.

Compositional Compensatory Multiattribute Models

Much of the debate on attitude models concerns a class of models that have become known as compositional compensatory multiattribute models. As this class of models is rather specialized, it requires some further explication. The three words describing this class of models, compositional, compensatory, multiattribute, are important in understanding the general framework of recent research.

The Compositional and Decompositional Approaches

The compositional approach in essence specifies the model components and functional form of a cognitive map. Further, such an approach assumes that the components are separately specified a priori, according to theoretical considerations, and that consumers consider the components separately. A technique utilized for compositional models is regression analysis. The Fishbein attitude models are examples of compositional models.

The counterpart to the compositional approach is the decompositional approach which attempts to dissolve a cognitive map into its component parts. It assumes that the consumer thinks of a process or system in wholistic terms and does not weigh each component explicitly. Multidimensional scaling and conjoint analysis are essentially decompositional techniques. Proposals advocating both compositional and decompositional approaches, separately and in combination, can be found but neither approach has been shown to be superior in all situations (Day, 1972; Wilkie and Pessemier, 1973).

The Compensatory and Multiple Criteria Approaches

The term compensatory, as used in the phrase compositional compensatory multiattribute models, refers to the manner in which the attributes are combined. Specifically, it infers that a low rating on one attribute can be balanced out by a high rating on another attribute. For example, a brand of automobile may rate low on comfort and high on economy. The high rating on economy compensates for the low comfort rating. This compensatory approach assumes that the consumer gives an overall rating to an object or action because such a rating is required to compare and decide about that object or action. All attribute scores are collapsed to one dimension for decision making.

The alternative to the compensatory model is the multiple criteria or multiple cutoff model, a model, similar to the disaggregated model to be discussed later, which contends that the measures of different variables should not be combined. Combining positive and negative elements, say advocates of this model, renders a composite score uninterpretable and, hence, such elements require separate measurement. The superiority of compensatory vs. multiple criteria models has a long, involved evolution which is peripheral to this study but has been well documented (Schmidt and Kaplan, 1971). It is sufficient here to point out that the disaggregated attitude models are generally, but not always, preferred in consumer attitude studies (Wilkie and Pessemier, 1973).

The Multiattribute Approach

The final term under scrutiny, multiattribute, simply refers to the consideration of more than one attribute. Indeed, there is general consensus that attitudes are formed by reflection on more than one attribute. The object or act is viewed as a bundle of attributes leading to costs and benefits which are differentially desirable to individuals or total market segments. A significant advantage to the multiattribute approach is that it incorporates both understanding and prediction. Again, if the automobile is used as an illustration, attitudes are not formed by one attribute such as economy, but by several attributes such as economy, comfort, warranty, etc. Given that attitudes are formed through consideration of several attributes, it is of paramount importance that a methodology be employed that produces a relevant but nonredundant attribute list. The usual procedure for generating such attribute lists relies on methods for attribute generation. Exhaustive lists of attributes are gained from expert judgment, group depth interviews, or previous research. A technique such as factor analysis is then appropriate for the selection of the relevant and nonredundant list for inclusion in the attitude model (Wilkie and Pessemier, 1973).

The Models

Fishbein has suggested two separate models of attitude structure and from these a third model has been developed in the marketing literature.

The A_o Model

The A_o model involves an attitude toward an object and is algebraically formulated as (Fishbein, 1963):

$$A_o = \sum_{i=1}^{n} B_i a_i$$

where:

A_o = attitude toward an object

B_i = the individual's belief about the probability that the object is related to an outcome, i

a_i = the individual's evaluation of outcome i

n = number of beliefs

Note that this model has two components. The first is the cognitive component of belief that the object under consideration possesses some attribute (B_i); for example, belief that a Pinto is economical. Typically, consumers have been asked to respond to a bipolar scale such as the following:

Very Improbable						Very Probable
-3	-2	-1	0	+1	+2	+3

The second component is the affective component (a_i) measuring the desirability of the outcome. For example, the desirability of economy in a subcompact automobile would require a consumer response to a scale such as:

Very Undesirable						Very Desirable
-3	-2	-1	0	+1	+2	+3

These two components, B_i and a_i, are the reason the Fishbein model is often referred to as an expectancy/value model. The cognitive component is a measure of expectancy and the affective component is a measure of value. The scales of measurement noted above have been used for all models mentioned in this chapter (Bettman, Capon, Lutz, 1975; Wilkie and Pessemier, 1973).

The A_{act} Model

A second model, which was later developed by Fishbein and focused more directly on behavior, was intended to have greater validity because of such a focus. For example, an individual's attitude could very well be different for an object that is purchased as a gift as opposed to one purchased for personal use. This second model, sometimes referred to as the individual's attitude toward an act, requires a highly specific situation. In other words, the act of purchasing a specific brand is necessary if the model is not to be confounded by situational specific intervening variables. The model is referred to as the A_{act} model and is specified in algebraic form as follows (Fishbein, 1967):

$$B \simeq BI \simeq A_{act} = \sum_{i=1}^{n} (B_i a_i) w_o + (NB \cdot M_c) w_1$$

where:

B = behavior regarding a specific brand

BI = behavioral intention regarding a specific brand in a specific situation

A_{act} = attitude toward an action

B_i = beliefs about the outcome of performing the behavior

a_i = the evaluative aspects of the consequences

NB = normative (peer group) beliefs

M_c = motivation to comply with the norms

w_i = regression derived beta weights

n = number of relevant consequences of the behavioral act

The A_{act} is based on Dulaney's theory of propositional control (Dulaney, 1967), a theory which states that behavioral intent is a function of the attitude toward performing a specific behavior and the norms relevant in that situation together with the motivation to comply with the norms. The first application in a marketing setting of Fishbein's A_{act} model and its theoretical underpinnings appeared in a study of physicians prescribing behavior (Harrell and Bennett, 1974). The physician's attitude toward drug prescription for antidiabetic drugs was investigated, and specific brands of drugs were matched with specific patient descriptions. Normative beliefs and motivation to comply were also measured. This additional construct has since been suggested as a measure of social compliance rather than a part of attitude (Ryan and Bonfield, 1975). It is therefore believed that it is unnecessary for attitude measurement.

The Disaggregated Attitude Model

A third attitude model has evolved in the marketing literature based on empirical considerations of the two models already noted. The model, usually referred to as the disaggregated attitude model, is algebraically noted as:

$$A = f(B_i, a_i)$$

The A can represent the attitude toward an object or an act, depending on the researcher's objective, while B_i and a_i are the same as previously defined. Note that the difference between this model and the previous models is that the summation sign (Σ) has been replaced by a function sign (f). The function sign is meant to imply that each attribute, rather than being summed, now acquires a beta weight of its own.[1] The model might also be expressed more explicitly as:

$$A = (B_1a_1)w_o + (B_2a_2)w_1 \; . \; . \; . \; . \; . \; (B_ia_i)w_i$$

where w_i is the beta weight value corresponding to each attribute.

Recent Research Advancement

Given this discussion of the formulation of the attitude models relevant to this research, it is appropriate to note recent advancements

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[1]Note that the term beta weight is used in its technical sense. That is, beta weight is a standardized coefficient rather than a simple regression coefficient (Kerlinger and Pedhazur, 1973).

within this class of multiattribute attitude models. Two areas have been of general interest to researchers: 1) model conceptualization and description, and 2) methodological and measurement issues within the models. Both of these are discussed in an excellent review article by Wilkie and Pessemier (1973).

Model Conceptualization and Description

In the area of conceptualization and description there have been relatively few studies since that review article. The attitude toward an act model was thoroughly examined by Harrell and Bennett (1974) who are believed to have conducted the first test of this model in a marketing environment. A cross-validated sample held up well with an attribute list generated through factor analysis.

Another model, noted as the vector model which is very similar to the Fishbein models, has been proposed and briefly tested (Ahtola, 1975). This model may be expressed as:

$$A_k = \sum_{i=1}^{n} B_{ik} a_i$$

where:

A_k = an individual's attitude toward alternative k

B_{ik} = vector of probabilities of k's association with categories of i

a_i = vector of evaluations of categories of i

n = number of salient dimensions

Although obviously very similar to the Fishbein models, the vector model has an objective which leans more toward predictive than construct validity. It purports to possess the advantages of more clearly measuring B_i as only probabilities, and thereby gains more discriminatory power and more precisely measures the cognitive mapping dimensions of an individual. A brief test was conducted using a sample of fifty-two students' attitudes toward soft drinks. The results confirm that the vector model predicts preferences substantially better than Fishbein (Ahtola, 1975). Recall, however, that it also trades off some construct validity for this increase in predictive power. The most highly prized model should yield understanding and suggest feasible procedures for favorable control.

Various formulations of Fishbein's models and Dulaney's theory of propositional control have also been tested (Bonfield, 1974). Although the action model as well as the empirical evidence indicate that intention explains more variation in behavior than do attitudes, the model does not view behavior as essentially stochastic. Some people are of the opinion that social psychological influences, which vary according to the situation, outweigh the importance of the deterministic components of the attitude models. This would account for the typically low coefficients of determination, usually between .2 and .5, found in attitude studies. It does appear, however, that brand choice is less random, i.e., more deterministic, for segments of high income, education, and medium brand experience as well as low brand loyalty and high product importance. The more predictable results in situations with these characteristics are most likely the result of a more cognitive buying approach relative to other situations. And the more cognitive a purchase decision, the less likely it will be influenced by environmental factors, a conclusion also supported by research in the predominantly cognitive purchase of industrial capital equipment (Wildt and Bruno, 1975).

The relationships among the components of beliefs, knowledge, intentions, and behavior have also been investigated (Olshavsky and Summers, 1974). Beliefs appear to be consistent with intentions, behavior, and knowledge, although intentions were not consistent with behavior or knowledge, nor was behavior consistent with knowledge. The obvious intransitivity of these findings is attributed to factual and reasoning distortions on the part of the respondents. These findings are difficult to generalize, however, because of the situational specifics involved in the psychology of cigarette smoking which was the topic of investigation.

Experiments have also been conducted for purposes of model comparison (Mazis, Ahtola, Klippel, 1975). These comparisons, in spite of several multivariate statistical problems, conclude that predictive superiority is much clearer than the understanding of cognitive structure when alternative attitude models are dealt with. Again, the results indicate that the importance of the cognitive components is greatly affected by the situation specifics. Other research indicates parallel findings (Beckwith and Lehmann, 1975). For instance, the greater the ambiguity of a belief statement the less importance will be attached to that belief.

Model Methodology and Measurement

The second area of inquiry, methodology and measurement, has received considerable attention from researchers. One problem in this area is a direct descendant of utility theory in economics, that being interindividual utility comparisons. Such comparisons cannot be given rigorous meaning since utility measures vary from individual to individual (Nicholson, 1972; Scott, 1973; Wilkie and Pessemier, 1973). This problem of interindividual utility measurement is circumvented by using within individual estimates as opposed to across individual analysis utilized by some early studies.

Another issue here is the topic of scaling which in turn poses certain other problems. First, Fishbein advocates bipolar scales with plus and minus poles as exemplified earlier in this chapter. This position is important when the form of each individual's cognitive map is considered (Bettman, Capon, Lutz, 1975). Scale coding makes no difference, however, in the use of regression techniques (Kerlinger and Pedhazur, 1973). The fact that such bipolar scales yield no better than intervally scaled data does make a difference. Note that the Fishbein models propose the multiplication of the B_i and a_i components. Given only interval data, such an operation is illegitimate since all components entering into a multiplicative function must be of ratio scale. With non-ratio data it can be shown that any resultant correlations are often times spurious (Schmidt and Wilson, 1975).

The complication of non-ratio data can be avoided by use of an analysis of variance paradigm. And the first legitimate attempt at specifying a correct combinatorial rule for the Fishbein model utilized such a paradigm. The specification of functional form on the basis of construct validity is much more difficult and less common than specification on the grounds of predictive validity (Bettman, Capon, Lutz, 1975). Studies of functional form have reached several important conclusions.

First, lack of involvement in the task by the respondent may lead to simple additive combination rules. Second, respondents may use different combinatorial rules for different subsets of attributes. Finally, there is ample evidence that the multiplicative rule proposed by Fishbein reflects the true cognitive algebra of a majority of consumers.

The second conclusion proposing different combination rules for different sets of attributes poses some interesting possibilities. Attribute list generation, as previously noted, is an important task if the results of the attitude models are to be interpreted as reliable. The number of attributes employed is situation specific and generally depends on diagnosis of attitude structure, predictive efficiency, saliency assessment, and parsimony (Wilkie and Pessemier, 1973). As with many situation specific problems, a great deal of judgment is obviously required on the part of the researcher. One consideration omitted from the above list is the requirement of determinance. Different choice criteria play different roles in the behavioral process (Myers and Alpert, 1968). Those criteria which are equal for all brands or are relatively unimportant could be termed qualifying attributes without which a brand would not be considered part of the evoke set. Once the evoke set is established, however, the choice criteria related to intention or actual purchase could be termed determining attributes. For example, subcompacts could easily be viewed as equivalent when judged on safety factors, while electric cars may not qualify for inclusion within the evoke set because they do not meet a minimum safety requirement. However, given that a car has qualified on the relevant criteria, price may determine which product will actually be purchased. It is quite probable that many product purchase decisions would involve trade-offs of several determining attributes. It would be necessary to use only determinant attributes when behavioral intention is predicted. Qualifying attributes may confound results by violating the assumption of relevance and nonredundance.

This discussion of attribute types also has implications for the methodology. Regression analysis is many times utilized as the analytical technique for the Fishbein model. Given that regression will be used, one consideration is the variable selection procedure. Two possibilities are logically valid: 1) forward stepwise, or 2) multiple regression. Forward stepwise is a procedure developed for cost efficiency which adds one regressor at a time according to which regressor explains the most variance in the dependent variable. The alternative, multiple regression, estimates all coefficients simultaneously. According to Wonnacott and Wonnacott (1970), "...if there are clear prior guidelines indicating that a few specific regressors are appropriate, then they should all be used right away in a multiple regression, rather than tested one at a time with any sort of stepwise approach." The reason, of course, is that the regressors are very likely to be biased with a stepwise approach. The multiple regression approach is therefore the appropriate alternative and, although no specific discussion has appeared in the literature, it has been correctly applied in marketing studies (Bass and Wilkie, 1973; Wilkie and Pessemier, 1973). There are situations with many variables, however, in which forward stepwise is the appropriate choice (Harrell and Bennett, 1974).

Several studies have appeared examining different types of attitude scales. Statement polarity, for example, has been shown to be misleading in some instances (Falthzik and Jolson, 1974). Most marketing studies have used positively posed statements, and the intensity of agreement for positive statements is higher than the intensity of disagreement for negative statements. Also, respondents with relatively lower levels of education are most likely to be affected by statement direction, while those with very strong convictions are least likely to be affected.

In another project the similarities and differences of the stapel and semantic differential were examined (Hawkins, Albaum, and Best, 1974). Both scales produced similar results and both were shown to be quite reliable. Constant sum and semantic differentials have also infrequently been employed for situationally specific problems (Wilkie and Pessemier, 1973).

Another measurement problem that has been encountered with the attitude models is presence of a halo effect. The halo effect which is the extent to which belief ratings vary across attributes for a given brand, poses the threat of potentially suppressing important variation (Wilkie and Pessemier, 1973). However, it has been shown to be less confounding for major consumer durables and industrial goods than for other goods categories which can be substantially affected (Beckwith and Lehmann, 1975). A variation of the Fishbein models, the single attribute model, has been shown to be misspecified due to halo effects, misspecification referring to the fact that the a_i element is eliminated from the attitude model and, hence, the estimate of B_i becomes biased (Wonnacott and Wonnacott, 1970).

The weighting of predictor variables by both subjective and objective schemes has also been a topic of research interest (Harrell and Anderson, 1976). The independent (predictor) variables in models being considered here have the two components of belief and desirability. The desirability component, which has been intensively investigated and reported in the literature (Mazis, Klippel, Ahtola, 1975), has been defined as performance vector, force, behavioral potential, aroused motivation, subjective expected utility, attitude, affect, importance, reinforcement value, and valence by various researchers. Given the large number of descriptions of this component, it becomes obvious that opinions abound with respect to exactly what the component is and how it should be measured. In several projects the operationalized version of the desirability component has been shown to cause negative beta weights (Bass and Wilkie, 1973; Sheth and Talarzyk, 1972; Wilkie and Pessemier, 1973). There appears to be substantial agreement that this is a result of unreliable measurement of the desirability component. The specific goal of the present research project is to employ the utility weights derived from a conjoint analysis in lieu of the desirability component based on the contention that this component will provide greater predictive validity through more reliable measurement.

Due to the measurement problems explained above, several researchers have proposed alternative methodologies (Wilkie and Pessemier, 1973). One possibility that is frequently alluded to is conjoint analysis, a technique explained in the following chapter.

CHAPTER III

THE CONJOINT APPROACH

Research Background

The first published composition on conjoint measurement is attributed to Luce and Tukey (1964), although bits and pieces of the background were developed by Fisher in the 1930s. After the initial conceptualization of the technique, the literature in the field of mathematical psychology was then extended by Tversky (1967), Lingoes (1967), Krantz and Tversky (1971), Young (1972), Krantz (1972), and Johnson (1973, 1975). These references provide the theoretical underpinnings of the technique.

Conjoint Measurement and Conjoint Analysis: A Clarification

Before a discussion of the literature and the technique in detail, it will be useful at this point to definitionally clarify some of the terminology. There is much interchanging in the literature of certain terms which provides an ideal setting for confusion and ambiguity.

The definition of conjoint measurement in its originally used context applies to the measurement models of conjoint variables (Luce and Tukey, 1964). The terms conjoint analysis and conjoint scaling also appear in the literature. In this paper conjoint analysis refers to the measurement of the values of jointly occurring variables through quantification of respondent value systems. An example of jointly occurring variables can be taken from the expectancy/value type models, one of which is the Fishbein model of attitudes explained in the previous chapter. The jointly occurring variables are a_i (desirability) and B_i (belief), the measurement of which has traditionally been separated in the marketing literature. In other words, they are measured separately with different scales. Conjoint measurement is a method of measuring a_iB_i as one unit and then searching for a combination rule that best fits a_iB_i when they are decomposed into separate entities; that is to say, conjoint measurement provides a systematic search procedure to test whether a_i and B_i are best predicted by a multiplicative, additive, or quadratic function. Berner (1976) has performed such an analysis for the expectancy theory in work motivation which is a closely analogous case.

Conjoint analysis, in contrast to conjoint measurement, heuristically searches for an intervally scaled utility function that best fits the rank ordered responses on a specified list of attributes. The utility function can thus be examined for rank order of attribute levels for each respondent. Alternative methods of obtaining the rank ordered responses are presented in the section entitled Data Collection. Conjoint scaling is an anomaly referring to the similarity between conjoint and non-metric multidimensional scaling algorithms. Two major similarities exist between the two methods. First, both require non-metric, i.e., nominal or ordinal, input yet produce output that is metric, i.e., interval or ratio. Second, there is no error theory for either method.

Neither can test the significance of the solutions, a limitation suffered by all of the multivariate interdependence algorithms (Kinnear and Taylor, 1971). Other examples of these methods are cluster and factor analysis.

The first reference to conjoint measurement in the consumer research literature was made by Green and Rao (1971) whose article noted that the original work of Luce and Tukey was the foundation for the type of analysis employed. Conjoint analysis is also referred to in some literature as trade-off analysis (Johnson, 1974). The reason for the latter designation is that both methods were being developed simultaneously but independent of each other. The trade-off terminology simply refers to a specific method of obtaining respondent data. There is, however, no other difference between the two terms. More explication of this method is found later in this chapter under Data Collection. There is no evidence that any method of data collection is more valid than any other or gives rise to different results (Johnson, 1973).

With the above definitional clarifications, then, the remainder of this chapter deals with specifying the important aspects of conjoint analysis required to gain a working perspective of the technique. The general conjoint analysis model, including the inherent assumptions, is explained. Following that explanation is a general discussion of the computer algorithms, alternative data collection procedures, and finally a review of the published literature which utilizes this methodology.

The Model Assumptions

The assumptions of conjoint analysis have been previously specified in bits and pieces in the theoretical literature, although they have not been outlined specifically for application of the technique. Nevertheless, it is important that they be so outlined as the technique has undergone relatively minor investigations thus far with respect to its robustness.

First, in order to delimit a workable scope, the basic model of interest in this paper is assumed to be additive. The major use of the additive model is the measurement of the joint effects of a set of independent variables on the ordering of a dependent variable, analogous to the main effects model in analysis of variance. The general model can be expressed as:

$$U(X) = U_1x_1 + U_2x_2 + \ldots \ldots U_nx_n$$

where:

$U(X)$ = the overall worth (utility) of a set of attributes

U_1x_1 thru U_nx_n = the part worths (utilities) for each level

Second, the respondent is assumed to have completely ordered all of the orthogonal combinations of attribute levels. Orthogonal (nonredundant) combinations imply that the efficient use of fractional factorials can be appropriate. Fractional factorials are especially important when there are many attributes with many levels which would induce respondent fatigue and non-involvement (Green, 1974). The assumption of complete ordering is a more restrictive assumption than need be made for conjoint measurement, but it is applicable to this study. In their original conceptualization Luce and Tukey assumed only nominally measured data, but the more restrictive case of ordered data is much easier to handle as a measurement model than the nominal case (Coombs, et. al., 1970).

In the event of obtaining ordered data, there is a third assumption called cancellation axiom which must be satisfied (Luce and Tukey, 1964; Coombs, et. al., 1970). This axiom, coming from mathematical psychology, has a simple counterpart in the economics literature which is more familiar to marketers. This assumption states that indifference curves do not cross unless a consumer has inconsistent tastes, which is an inadmissable contradiction (Scott, 1973). Researchers have developed methods of dealing with this predicament.

One method of evaluating respondent consistency, i.e., the cancellation axiom, in a conjoint analysis context is by Kendall's tau statistic (Conover, 1971). This statistic, proposed by Kendall in 1938, is of the form:

$$\tau = \frac{Nc - Nd}{n(n-1)/2}$$

where:

τ = tau coefficient from sample data

Nc = number of concordant pairs

Nd = number of discordant pairs

n = total number of rankings

Pairs are concordant if the rank order by the respondent agrees with the rank order of the utilities produced by the conjoint algorithm. A pair is discordant if the rank orders disagree. The above formula is sometimes referred to as indicating "badness of fit" or "stress." A value of 1.0 would indicate perfect agreement of the rank order of the algorithm with the rank order of the respondent, a -1.0, a perfect negative rank order, and a value of zero, an unrelated ordering. As a rule of thumb, a tau value of less than .70 would denote too great an inconsistency on the part of the respondent to be included in the analysis (AT & T, 1974). Admittedly, this is not a scientifically derived number, but it does indicate a reasonably close fit and therefore will be utilized in this study.

A fourth implicit assumption is noted in mathematical psychology as solvability which is analogous to the assumption in economics which states that indifference curves are everywhere dense. In other words, an indifference curve passes through each point in a commodity space, an assumption which is, of course, not technically true, especially in the case of indivisible goods (Nicholson, 1972). However, given that a consumer develops a relevant range of utilities for a commodity space, and that the commodity space is a function of product attributes rather than separate and individual products, this assumption will be met to such a sufficiently high degree of approximation that it will be unlikely to develop as an empirical problem.

A fifth and final assumption is that the product attributes are independent; that is to say, the model precludes any interaction effects among attributes being present. Implicitly included in this assumption is an underlying measurement model which reflects the utility of each attribute to the respondent. From the literature on attitudes the elements of the model are combined multiplicatively. Multiplicative here means that a utility value can be derived for each attribute level so that, when multiplied, the pairwise products have the same rank order as the original data. It is interesting to note at this point that the multiplicative model is a trivial derivation of the additive model. The reason for this derivation is that numbers have the same rank order as their logarithms and logarithms (antilogs) are taken of multiplicative (additive) utilities they become additive (multiplicative) (Johnson, 1974).

Desirable Dimensions of a Market Situation

Given the above assumptions, it is useful to outline the desirable characteristics of a market situation whereby conjoint analysis becomes an appropriate technique. Following is a list of such desirable dimensions.

1. Product (or service) is realistically decomposable into a set of basic attributes leading to the decision process. This is primarily a reductionist viewpoint. For example, the purchase of a durable good such as an automobile would be decomposable. People use explicit criteria to purchase such an item such as price, seating capacity, and warranty. On the other hand, an impulse or fad purchase would most likely not be required to meet such explicit criteria. A chunk of bubble gum is probably bought without consideration of attribute levels.

2. Product (or service) choice tends to be an economically rational, high stake decision process. It generally follows that the choice tends to be high cost and high individual involvement, and that there is substantial time devoted to making the decision. Again, the above example of a durable good would fit these criteria.

3. There is one decision maker. Although this statement needs no explanation, it can pose difficulties. In an industrial setting it can usually be determined whether the decision is made by an individual or a committee. But it also is possible, as it is with consumer purchase decisions, that one person may make the decision but only after considerable external influence. A case in point is the purchase of a consumer durable. The family unit may not make the decision, but it is reasonable to conclude that the decision maker was influenced by family

members. Specifically, then, the problem is that a respondent may be able to provide attribute rank orders, but these rank orders may not be the ones actually used in the final decision process. One possibility is for husband and wife to respond to the measurement instrument together. Another possibility is that each individual may revise the rank order after input by other family members. Rank order revision, however, has no empirical evidence presently and would be a fertile topic for further investigation.

4. Product (or service) is chosen according to highly specific, non-subjective attributes. In other words, attribute level specification is perceptively homogeneous across consumers. Specificity and objectivity are factors to be considered in the choice of attribute levels, but it is flexible almost to the point of being arbitrary. For example, attribute levels that mean totally different things to different people are unacceptable. Seating capacity in an automobile might be denoted as four. To some people, this may mean four adults; to others it may mean two adults and two children. The solution is to state the levels more specifically, such as adult seating capacity. In many instances it is possible to argue either way concerning the homogeneous meaning of words. The solution is an <u>a priori</u> consideration, but not to the point of laborious proof.

5. In the event of many attribute level combinations the factorial combinations of the basic attribute levels must be believable. The alternatives must be realistic or non-involvement by the respondents confounds any research results. For instance, an automobile with a seating capacity of six adults that gets forty mpg, and costs $2,000 is ludicrous in today's marketplace. The attribute levels must be within a range considered relevant for present consumers.

As is true with most methodologies, it is difficult to imagine a product that would fit exactly all of the model assumptions detailed above. Recall, that conjoint analysis is still highly experimental, and the above market characteristics are based on the statistical assumptions and meager empirical work now available. It is desirable to satisfy as many of the above dimensions as possible and note the limitations of the research with respect to the others.

Just as with the assumptions, a definitive list of publicly available computer algorithms is not to be found. The following section outlines such algorithms.

Computer Algorithms

It is not within the scope of this paper to delineate all of the technical aspects of the available algorithms, but rather to describe their general characteristics and origin. All algorithms noted here are non-metric decomposition methods similar to the techniques of non-metric scaling (Green, Carmone, and Wind, 1972). They all attempt to do the same thing in slightly different ways; that is, they convert respondent rank orders into utility estimates. This conversion is usually accomplished by an heuristic iteration procedure which searches for a set of utility values for each respondent that will minimize a badness of fit or stress measure. or equivalently maximize a phi or tau value such as the one explained earlier. Arithmetically, a phi or tau value could be visualized as an attempt to minimize the difference between the original rank orders (Y) and the computed utility values ($\hat{Y}$). Thus, with the difference $(Y - \hat{Y}) = d$, the algorithm is in search of a configuration of utilities to minimize the d value or badness of fit. It becomes obvious at this point that the procedure thus far is very analogous to the least squares method of regression analysis, the major difference between the two being that least squares is a metric procedure while conjoint is a non-metric procedure. The conjoint programs seek a unique configuration in that the configuration is subject only to similarity transforms. A similarity transform is invariant only with respect to operations that will not change the observed rank orders, which is the constraint under which all of the non-metric programs operate. Permissable operations are addition or subtraction of a constant and rotation of a configuration about the origin (Green and Tull, 1975). Through operation with similarity transform constraint, the iterations of the algorithm continue in an attempt to find perfect monotonicity, that is to say, perfect agreement between observed rank orders and computed utilities.

As is the case with many statistical multivariate algorithms, each of the programs listed below has its own special technical peculiarities. These unique properties may be important for mathematical purposes, but tend not to be revealed in empirical work (Green and Tull, 1975).

1. MONANOVA - J. B. Kruskal
2. CCM - Frank Carmone
3. POLYCON
ADDALS - Forest Young
MORALS
4. CM-I - James Lingoes
5. LINMAP - Allan Shocker and V. Srinivasan
6. NMRG - Richard Johnson
7. ORDMET - Gary McClelland and Clyde Coombs
8. PREFMAP, Phase IV - Douglas Carroll and J. J. Chang

As with other statistical algorithms, there is presently no evidence regarding the choice of one of the above algorithms rather than another for empirical work. The program utilized for this study is

Richard Johnson's NMRG program, which was selected simply on the basis of its availability and the opportunity for technical advice on its use and which has been employed in many other instances, as is noted in a later section entitled Applications in the literature. Appendix B contains Johnson's program and the method of deriving the solution.

Given this background on the computer algorithms, the next step is a delineation of alternative data collection procedures. These procedures are outlined in the following section.

Data Collection

Thus far, the data collection procedures for conjoint analysis in market settings have generally involved one of two methods. The first is referred to as the trade-off method and the second as the full profile or concept evaluation method. Under similar conditions similar results will be obtained using either method (Johnson, 1973).

The Trade-Off Method

The trade-off method requires rank ordering by a respondent of preferences in all levels of two attributes. An example will clarify exactly what a trade-off matrix attempts to do. A respondent might be shown a matrix like the following pertaining to automobiles

	Purchase Price		
	$3,000	$3,500	$4,000
U.S. Manufacturer			
Foreign Manufacturer			

and be asked to fill in the respective alternatives by rank ordering each. Note that one axis is a ratio scale (price) and the other is a nominal (origin). These axes could be any combination of levels of measure because the respondent is able to rank order any combination of levels. The attributes can be determined from a comprehensive list by use of a technique such as factor analysis, or from previous research (Harrell and Bennett, 1974).

With respect to attribute levels, there is a need for believability, i.e., levels within a relevant range for consumers, as noted in the previous section. Each combination of levels must be realistic, but there is no other specific criterion for establishing the levels. They must not, as also was previously noted, be ambiguous, but this is hardly a strict criterion.

Now, let us suppose that given the above matrix the respondent has hypothetically rank ordered the alternatives as follows:

	Purchase Price		
	$3,000	$3,500	$4,000
U.S. Manufacturer	1	2	4
Foreign Manufacturer	3	5	6

By simple inspection, it can be ascertained that this respondent prefers an auto that is manufactured in the U.S. as opposed to a foreign manufacturer and lower prices to higher prices, other things being equal. By a joint examination of the attributes in the above matrix, more information can be obtained. For instance, while this consumer's second choice is a $3,500 auto manufactured in the U.S., it would be more desirable to switch to a foreign manufacturer than pay another increment in price. This conclusion assumes that the consumer trade-off is with only these two attributes with the ceteris paribus assumption holding. Thus, the relative influence of the factor level can be ascertained, and, through investigation of other attributes such as warranty, seating capacity, etc., the respondent's value system for an automobile purchase can be reconstructed. Such reconstruction would be done by allowing an algorithm such as NMRG to restructure as closely as possible all combinations of rank ordered factor levels and by assigning appropriate utility values to each level. Through knowledge of the utilities of each level, the rank order of preference of a given combination of levels for that respondent could be made.

The Full Profile Method

The above data collection procedure is quite different from the procedure described initially by Green and Rao (1971) whose approach has been referred to as the full profile or concept evaluation method which is closer to the functional form investigations in psychology (Berner, 1976). With this procedure respondents are asked to rank order product concepts which differ simultaneously with respect to several attributes. An example might be:

> An automobile manufactured in the U.S., for a price of $3,500, with a 2 year warranty, and a dealer that is a 20-minute drive from your home.

The above statement would be in an array of statements that varied with respect to the relevant attributes, i.e., country of origin, price, length of warranty, and dealer location. The assortment of choices can be written, verbal, or pictorial. In the event of a totally new product concept, such a concept could even take the form of the actual experimental product. When the number of options requiring rank order is large a sort board can be efficiently utilized.

Differences Between The Two Methods

An examination of the two methods described above reveals differences which would concern researchers under varying circumstances. The trade-off method is laborious for the respondent and requires the respondent to abstract each comparison due to the *ceteris paribus* assumption. On the other hand, the full profile method specifies a concept fully and thus promotes a higher probability of commonality of perception. Still, the greater inherent realism in the full profile method is limited by the fact that respondents cannot easily interpret profiles including more than five to seven attributes (Johnson, 1974). A drawback in this method is the cost, especially for the more reliable pictorial method where scale drawings are a necessity and where mock models are often needed. Both methods call for a great deal of respondent training with each requiring an interview of approximately 1½ hours. The problem of too many factor level combinations for rank ordering by respondents is solved through various orthogonal designs, e.g., Latin square, fractional factorials (Green, 1974).

Applications in the Literature

A limited number of examples of conjoint analysis have made their way into the literature. Although such diverse applications as consumer non-durables, financial services, industrial goods, automobiles, and transportation have been noted they are generally unavailable for academic perusal (Green and Rao, 1971). Major attempts at the use of the technique which have been published are noted below.

From the beginning the published marketing research applications have contained the detail to make the technique plausible under varying circumstances. The original marketing publication specifically outlined possible applications in media planning, discount pricing, and opinion research (Green and Rao, 1971). Much of the groundwork was also developed in terms of general use of the technique including the model, the assumptions, and the available algorithms. Also outlined were possible applications of the model in physical distribution, new product evaluation, packaging and branding, attitude measurement, and cost benefit analysis.

Implementing some of these ideas was the initial step taken in the literature. Applications in consumer menu preference and condominium design and pricing appeared first (Green, Wind, and Jain, 1972; Fiedler, 1972). Both were applications of the additive conjoint model, although one difference was that the MONANOVA algorithm was utilized in the menu preference study while NMRG was used for the condominium study.

Another published study investigated worth of discount cards to housewives (Green, Carmone, and Wind, 1972). This study introduced the possibility of combining the use of multidimensional scaling and conjoint analysis. The complementarity of the two techniques is natural as the criteria (axis) must be subjectively evaluated for the scaling procedures while conjoint prespecifies the axes. The ideal, of course, is a matching of the subjective and prespecified criteria, a matching which depends largely on the care taken to prespecify the correct attributes. MONANOVA was the algorithm utilized for the conjoint analysis.

The first publication in the area of physical distribution was conducted for Air Canada (J. D. Davidson, 1973). After a random telephone survey of 20,000 households for the relevant geographical area, 1055 respondents were selected for personal interviews. It was determined from initial group depth interviews that people could describe their preferences for mode of travel, i.e., car, bus, train, conventional air, and STOL (short take off and landing), in terms of thirteen independent attributes. The objective of the study was to build a model that would forecast and evaluate the different modes of transportation and the effect of different marketing strategies on the STOL market share. Respondents were asked to complete twenty-one trade-off matrices to determine their utility function for each of the transportation modes. The NMRG program was utilized in the analysis.

Trade-offs in automobile brand choice was the topic of yet another investigation (Johnson, 1974), the bulk of which was devoted to the explication of the practical considerations when conjoint analysis is implemented. For instance, the assumptions, the computations, and the validity of the technique were addressed. It was also noted that to date there were not enough data available to validate the procedure through a comparison of the results with actual variables in the marketplace, another point which emphasized the pioneering nature of the technique. The NMRG algorithm was used for the analysis.

Still another applied example of conjoint analysis is in the area of consumer non-durables (Green and Wind, 1975). Together with many other examples is a detailed one examining the market for a new spot remover for carpets and upholstery. As the article was exemplary in content, many of the technical details were omitted, but five attributes were used in a 3 x 3 x 3 x 2 x 2 design (indicating the number of levels for each attribute). This design would involve 108 alternatives to be tested in a full factorial design. Due to considerations such as cost and respondent endurance, however, an orthogonal array of combinations was utilized and the number of combinations was thus limited to 18. Further consideration in the use of orthogonal designs is given by Green (1974). In the above analysis of non-durables, MONANOVA was used for the analysis.

A final example of conjoint analysis, in the context of a location problem (Parker and Srinivasan, 1976), involved the location of rural health care facilities according to consumer preferences combined with community considerations and in terms of cost/benefit constraints. Several elements of reliability and validity factors were noted as being favorable to the conjoint procedure. A subprogram of the LINMAP procedure was utilized to analyze the data base (Shocker and Srinivasan, 1974).

Limitations and Advantages of Conjoint Analysis

Clearly, the above examples indicate the initial spectrum of possibilities using conjoint analysis, although, admittedly, there are limitations. For instance, it is difficult to obtain an interview of 1½ hours with industry personnel. Because the technique is cross sectional in nature, it would be desirable to repeat such interviews at selected intervals and this would again be difficult to do. It is also obvious that utilities change over time and at different rates for different situations. In general, it is believed that a sufficient sample size would be from 200 to 500 and this too could present problems.[1] It is also possible that in industrial settings, where the product specifications are explicit but numerous (greater than ten or twelve), the technique would not be efficient. And it is worthy to note that no error theory is available for conjoint analysis; that is to say, there are no significance tests as such for the utilities or the general models. Another problem that is difficult to overcome is that of non-involvement by respondents. The mental task of explicitly comparing multidimensional statements is quite rigorous. Many respondents find the task involves too much thinking and they therefore require a substantial incentive to participate.[2]

The distinct and unique advantage of the technique is, of course, its potential ability to construct consumers' value systems given the satisfaction of the assumptions. People are generally unable to explicate utility values either because they do not know them or they feel they must adhere to socially acceptable norms. Conjoint analysis implicitly constructs the utilities within each respondent's system.

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[1]This has not been scientifically validated but it has been proven empirically true according to a discussion by David K. Hardin at a University of Chicago sponsored seminar, March 16, 1976. Seminar entitled, "Marketing Trade-Offs Using Conjoint Analysis."

[2]Discussion by Joe Murphy, Research Director at General Foods at seminar entitled, "Marketing Trade-Offs Using Conjoint Analysis," March 16, 1976.

Given the above discussion of conjoint analysis and the previously outlined discussion of relevant attitude literature, the next section details the methodology of this research project.

CHAPTER IV

SCOPE AND GENERAL METHODOLOGY

Estimated Models

The background and underpinnings of this study were given in Chapters I, II, and III, while this chapter explicates the specific methodology for integrating a conjoint analysis model and the Fishbein attitude models. Theoretical considerations were listed in Chapter I. There are no criteria that points to one model as superior to the other but instead each yields a rather different interpretation. Given the purpose of integrating two models, then, there are three estimation procedures involved.

The first estimation procedure involves the Fishbein models of attitude. The more recent model of attitude toward an action, A_{act}, is estimated here. Recall from Chapter II that this model takes the validated algebraic form:

$$BI = \sum_{i=1}^{n} B_i a_i$$

The model in its disaggregated form is also estimated in the form:

$$BI = f(B_i a_i)$$

Second, a utility based estimate of each respondent's value system is obtained from a conjoint analysis which produces an intervally scaled utility weight for each attribute level.

The third and final estimate is for a combined model which substitutes the utility estimates of the conjoint analysis for the desirability component of the Fishbein models. This is a legitimate substitution based on previous research discussed in Chapter II. The combined models would be expressed algebraically as:

$$A_o = \Sigma B_i U_i$$

$$BI = \Sigma B_i U_i$$

$$BI = f(B_i U_i)$$

where the U_i is the utility estimate from the conjoint analysis. Chapter V also contains an analysis of the distributional characteristics of the desirability and utility components. The assumptions of the Fishbein and conjoint models are discussed below.

Attribute Determination

Subcompact automobiles were chosen as the consumer non-durable category to be investigated. Three major American brands were selected for evaluation since consumers are likely to be more familiar with these than with non-American cars. The relevant determinant attributes used for this study, attributes obtained from previous research (Mazis, Ahtola, Klippel, 1975) and confirmed as currently relevant for subcompact cars,[1] were: 1) Brand, 2) Price, 3) Style, and 4) Dependability. Although it is interesting to note that only these four attributes rate as highly important to consumers, it is generally believed that consumers use no more than three criteria for any purchase. This has been found to be the case in multidimensional scaling and factor analytic studies

[1]From communication with Robert Bierley, Research Department at General Motors.

of determinant attributes. If other than determinant attributes were specified for inclusion in the models used here, the results could well be spurious. For instance, it is a well known fact that if a non-determinant attribute is included in a regression equation it is likely to increase explained variance and have a biased beta weight. This is especially likely to occur if the non-determinant variable is collinear with a determinant attribute. For this reason, then, only important determining attributes should be included in the model. It is, of course, quite possible that consumers would like to have other attributes determinant but they are without a variation in choice. For example, automobile warranty may be very important to some consumers, but it is relegated to the status of a qualifying factor if it is equal for all brands, which is, in fact, the present state of affairs.

For use in both the Fishbein and the conjoint models the levels of each attribute were specified as follows:

1. Brand
   a. Chevette
   b. Pinto
   c. Vega
2. Style
   a. Modern Style and Lines
   b. Average Styling
   c. Constant Style that is Functional
3. Dependability
   a. Sturdy, Quality Workmanship
   b. Average Workmanship
   c. Minimum Workmanship
4. Price
   a. $3,000
   b. $3,500
   c. $4,000

The definitions and implications of these levels for both models are discussed below.

Research Sample

The sample consisted of 238 undergraduate business students enrolled in MTA 317 at Michigan State University for Spring quarter, 1976. Before this number was arrived at, six questionnaires were determined not usable because they were incomplete. This sampling procedure, of course, does not constitute a random sample. Randomness, however, is only an issue in the discussion of external validity, and the issues under examination in this study involve only internal validity. Since generalization to the sampled population is not a concern, a random selection of respondents is unnecessarily cumbersome and time consuming. Another concern relevant only to external validity is the elimination of order bias within the questionnaire which can be achieved by switching the order of the questions. But there was no attempt to generalize to a sampled population and, therefore, order bias became irrelevant. The sample size was sufficient to reliably employ both techniques used in this study.

Each individual in the sample was requested to complete the questionnaire that appears in Appendix A. Note that the questionnaire obtains data for both the Fishbein and conjoint models.

Model Considerations

Given this research scenario, it is necessary to explain the implications for each of the models under consideration.

The Fishbein Models

The Fishbein model has received considerable attention by researchers, and, hence, the implications specific to this setting can easily be established. Empirical considerations for the Fishbein model are 1) attribute determinance, 2) a brand specific setting, and 3) attribute independence. Attribute determinance is discussed above and requires no further explanation. The setting is brand specific, i.e., Pinto, Vega, and Chevette; hence, this criterion is satisfied. The independence of the attributes, which is a requirement common to both Fishbein and conjoint, is established by examining the correlation matrix of all attributes included in Chapter V. As noted in Chapter II, the usual method of determining attribute independence is through a technique such as factor analysis which is most appropriate when the attributes cannot be specified a priori. Factor analysis also assists the researcher in establishing factors that are independent and avoids subsequent attribute redundancy. Although the attributes for this study were suggested from previous research, as was noted above. For the present study it is necessary to check factor independence. Factor analysis then becomes an unnecessarily arduous procedure.

A totally valid alternative to factor analysis in this situation is borrowed from econometrics (Farrar and Glauber, 1967). The procedure is quite simple and straight-forward. The criterion for attribute collinearity is established from the comparison of the first order correlations with the multiple correlations for each set of attributes used in a regression equation. If the first order correlation, i.e., the simple correlation between two attributes, is less than the multiple correlation from the total regression equation, then the factors are considered sufficiently uncorrelated so as not to bias the regression weights. This procedure is carried out in Chapter V in order to insure that the attributes are indeed independent for this study. As a cross-check on the stability of the beta weights, a cross-validation is performed. The sample is cross-validated by estimating the beta weights for a 50-50 sample split. With this procedure, the confidence levels of the beta weights should overlap if the sample is stable, i.e., collinearity is not present (Kane, 1968). This completes the empirical considerations for the Fishbein models.

Conjoint Analysis: Implications

With only a meager amount of empirical evidence available on conjoint analysis, it is necessary to consider the implications in more detail. First, a choice must be made between the full profile and trade-off data collection methods as explained in Chapter III. The full implications of each of these methods are of current interest to researchers, but the choice must be made on a subjective basis. The trade-off method was used in this study as it has several inherent advantages not available with the full profile method. First, given four factors with three levels each, there is a total of 12 factor levels. When these are taken two at a time, there are only six possible unique combinations of factor levels. In the alternative full profile method, however, the number of possible factor level combinations would be $3^4 = 81$. In order that respondent fatigue and non-involvement be avoided, the full profile method would require a fractional factorial design. Hence, the trade-off method is more efficient. It is also worthwhile to note that there is no research indicating superior accuracy in the use of either technique.

The major problems encountered with the trade-off approach are the ceteris paribus condition and lack of respondent task comprehension. Using the trade-off method requires the respondent to vary levels of two factors while giving no consideration to variant conditions of other factors. With little experience or training in this task, it is to be expected that the average consumer will find it difficult to abstract a problem into a ceteris paribus setting. This first problem is mostly avoided by using a student sample since students understand the assumption from their economics courses and, because of their academic experience, are more likely to be able to abstract a situation than other randomly selected respondents. As for the second problem of lack of respondent task comprehension, it has been noted that an average interview length for a conjoint questionnaire has historically been 1½ hours. Much of this time is spent explaining to respondents the task at hand. The administration time for students was substantially less, however, approximately 25 minutes or one-third the usual requirement, again because of their greater ability to abstract and follow directions with only minimal instructional effort.

Conjoint Analysis: Assumptions

The previous chapter stated the applied assumptions of the type of conjoint analysis used here. First, it is assumed that the general model is additive. It seems reasonable, although again there are no strict criteria, that no interaction exists in the choice of subcompact cars. For instance, it is assumed that a respondent is equally as likely to require a given level of dependability regardless of the style of the car; that is to say, dependability does not vary across levels of style. If, in fact, the model for subcompacts is non-additive, polynomial (non linear) conjoint would be appropriate. Unfortunately, there are presently no studies which apply polynomial conjoint analysis. Of course, the attitude models suffer a like disadvantage in their linearity assumption.

Second, the respondent is assumed to have ordered all relevant combinations of factor levels. This criterion has been met which leads to the assumption of the cancellation axiom. In order that this assumption be met, any respondent with a tau value of less than 0.70 is removed before the analysis is completed. Recall that tau reflects the consistency of each respondent's answers with the computed utility values. A cut-off of 0.70 seems to reasonably exclude any inconsistent respondent, although, again, no specific cut-off point has been established as being best.

A fourth assumption, that of solvability, appears well grounded as the levels of each factor provide a total range from high to low. By virtue of using this total range, it is likely that a respondent is sufficiently free to locate the position of his indifference curve for that attribute. The final assumption of attribute independence is examined with the same procedure discussed under the Fishbein model.

Conjoint Analysis: Consideration of Desirable Characteristics

Given the above assumptions, it is now desirable to examine whether this study meets the practical characteristics outlined for conjoint analysis. First, there is no reason to believe that subcompact automobiles are not decomposable into a set of basic attributes which lead to a decision process. In fact, it seems reasonable that such a decision is decomposable given that such a substantial expenditure will not be taken lightly by the buyer. Decomposable attributes then lead to the second characteristic, that the decision process tends to be rational in an economic sense. Since subcompacts fit into the consumer durables category, the decision is most likely to have a high involvement as it is a high stake, high cost decision. It is also quite likely that such an important decision would involve more than one decision maker. For example, the purchase of consumer durables is usually influenced by family members or at least reference groups.

In most instances the perceptions of a single individual decision maker are necessary or the computed utility values will not reflect the total decision process. If others' attitudes are a significant influence in a purchase, they may or may not be incorporated into the respondent's utilities. In any event, this again becomes an external validity issue. The sample results are not generalizeable if the criteria of a single decision maker are not met. However, the intention here is not generalization but rather model comparison. And model comparison, in which internal validity becomes the important issue, is not affected.

The final assumptions of believability and perceptive homogeneity of factor levels are much more difficult to validate than the preceding assumptions. They are subjective formulations at best and are difficult to evaluate except in a logical framework. Because the brands chosen hold substantial market shares in the United States, they should be among the most familiar alternatives. Students, especially business majors, are more aware of alternative auto purchases than would be consumers who are more isolated and less educated.

The attribute of dependability is probably composed of several components including workmanship, maintenance, and reputation. Workmanship seems to be a core issue here. If quality workmanship goes into a car, it is quite probable that it will require less maintenance and over a period of time establish a reputation as being dependable. Workmanship, then, seems a logical proxy for that attribute referred to by consumers as dependability. Style is another attribute that is only justifiable with logic. Style has been specified from constant (low) to modern (high). It would seem that the phrase "modern style and lines" would provoke the respondent to think about how the car looks. The other end of the spectrum permits the respondent a choice opposite of modern. A constant style, such as Volkswagen uses, represents a full range of choice. It is also noteworthy that both models suffer from an ambiguity in attribute level specification, but probably the Fishbein model is less disadvantaged as it provides a zero point on the bipolar scale which, in essence, permits the respondent to ignore the attribute. The attribute must be ranked, however, in the conjoint model.

The specification of price levels, \$3,000 to \$4,000, is within the current price range of the subcompact brands. But, again, the intervals are \$500 between levels, whereas the interval could have been virtually any amount. The \$500 seemed to represent an interval that would require the respondent to consider it rather than ignore it before going up or down one level.

This concludes the discussion of the methodology. The following section addresses the limitations of the present study.

Limitations of the Present Study

This research must be viewed as essentially of an exploratory nature. The objective of integrating the models has been accomplished but not without limitations. First, the Fishbein model is considered representative of the group of compensatory multiattribute models in that it shares with them many of the same advantages and disadvantages. Other models in this group could conceivably perform differently under the conditions outlined in this study, however. This study does not attempt to speak for those models.

Second, the sample for this research was not generalizeable in that it does not represent a random selection of respondents. The random selection process was not necessary to accomplish the objective of this study, but the possibility exists that it could affect the results. As discussed previously, such an effect is intuitively unlikely but it still should not be overlooked.

The technique of conjoint analysis is relatively new and future research will most likely uncover theoretical limits presently unknown to researchers. With any such new technique, it is, of course, advisable to view the results cautiously. Other than simple logic, there is relatively little evidence as to the best data collection methods. The trade-off method was used for this study but the implications of it, or the full profile method, are, for purposes of reliability and validity, virtually unknown. Conjoint analysis faces the additional limitation of a complex respondent task. It requires an arduous mental exercise on the part of the respondent which, of course, defrays participation by many respondents. There is also the serious limitation of no error theory. Again, this problem is inherent to heuristic solutions and must be considered as an *a priori* limitation. Preclusion of the use of common tests of statistical significance severely limits the substantive conclusions that can be drawn from an analysis.

Conjoint is, like any methodological technique, prone to misuse by abuse. It presently has only been published in the marketing literature as an additive model, though it is very possible that some utility functions or decision rules do not adhere to this assumption of additivity. It is likely that future efforts will attempt to deal with interactive models. Again, there is little indication of the presence of a particular model in a particular situation or how well the simpler models estimate the more complex ones. These limitations are not immaterial but neither are they formidable.

This completes the examination of the assumptions underlying each of the models under consideration and the inherent limitations in the present research. The following chapter presents the analysis of both models.

CHAPTER V

ANALYSIS AND RESULTS

Respondent Consistency

This chapter includes the results of both the Fishbein model and the conjoint model, along with an attempt to integrate the models. The underpinnings of the models and the general methodology have been discussed in the previous chapters.

The questionnaire used to obtain the data and the instructions for the questionnaire are included in Appendix A. Recall that the time required for completion of the entire instrument, i.e., the questions pertaining to both the conjoint and Fishbein models, was approximately twenty five minutes. As this time span is substantially less than the time usually required for completion, it was especially crucial that the respondents understand and complete the task according to instructions. As noted in the previous chapter, an *a priori* decision was made to eliminate respondents with a tau value of less than 0.70. By use of this criterion, twenty respondents were eliminated from the analysis, a number which constituted 8.4 percent of the usable responses. Since previous research with conjoint analysis is so scarce, it is difficult to say whether this is an inordinate deletion rate. Discussions with industry sources, however, have revealed that discards varies from six to fifteen percent.[1] If this range is in fact correct, then the 8.4 percent is quite acceptable. After consideration of these discards, 218 usable and valid responses remain for analysis which is also an acceptable number for the two techniques being utilized.

Results from Fishbein Analysis

The analysis in this section is consistent with previously published analysis of the Fishbein models. As discussed earlier, it is important to determine attribute independence. Again, the criterion is relevant to assure stabilization of the beta weights. And the criteria for stabilization in any given regression equation is that the simple correlations between the independent variables be less than the multiple correlation coefficient. Table 1 presents the correlation matrix for all variables in the A_{act} and disaggregated models. Table 1B is the correlation matrix for the A_o model. Of course, the summated models of A_o and A_{act} are not hindered by collinearity as there is only one independent variable. The disaggregated model for each brand, however, has three independent variables which could present the problems inherent to collinearity. The problem does not arise in this study as can be seen in Table 1A.

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[1]From a discussion with David K. Hardin of Market Facts, Inc., Joe Murphy of General Foods, and Paul E. Green of University of Pennsylvania at a seminar, "Marketing Trade-Offs Using Conjoint Analysis," March 16 and 17, 1976 at University of Chicago.

TABLE 1

CORRELATION MATRIX

	Behavioral Intent Toward: Chevette	Pinto	Vega	Summated Attributes For: Chevette	Pinto	Vega	Chevette: Style	Dependability	Economy	Pinto: Style	Dependability	Economy	Vega: Style	Dependability
Behavioral Intent														
Toward:														
Pinto	.262													
Vega	.225	.363												
Summated Attributes														
For:														
Chevette	.484	-.018	.012											
Pinto	.030	.529	.091	.334										
Vega	.025	.089	.541	.248	.221									
Chevette:														
Style	.450	-.056	-.089	.737	.104	-.053								
Dependability	.416	-.009	.072	.763	.285	.219	.317							
Economy	.084	.046	.067	.561	.352	.436	.060	.274						
Pinto:														
Style	-.030	.418	.090	.192	.779	.128	.137	.161	.098					
Dependability	.039	.495	.059	.201	.829	.111	.007	.314	.118	.472				
Economy	.070	.251	.059	.395	.628	.288	.093	.159	.672	.200	.342			
Vega:														
Style	.067	.142	.382	.124	.152	.700	.069	.044	.161	.254	.017	.066		
Dependability	.026	.040	.534	.198	.121	.783	.096	.341	.226	.024	.171	.077	.265	
Economy	.046	.009	.274	.239	.229	.750	.099	.094	.628	-.003	.055	.553	.268	.466

TABLE 1A

SELECTED RESULTS FROM TESTS OF COLLINEARITY

	Multiple R	Style and Dependability	Economy and Dependability	Style and Economy
Chevette	.535	.317	.274	.060
Pinto	.543	.472	.342	.200
Vega	.590	.265	.466	.268

Note that there is no multiple R (from Table 4) that is less than the simple correlation between any two of the variables for each brand equation, which leads to the conclusion that the problem of collinearity will not bias the respective beta weights for any of the equations.

TABLE 1B

CORRELATION MATRIX FOR A_o MODEL

	Attitude Toward: Chevette	Pinto	Vega	Summated Attributes For: Chevette	Pinto
Attitude Toward:					
Pinto	-.025				
Vega	.050	.127			
Summated Attributes For:					
Chevette	.617	-.006	-.016		
Pinto	.001	.692	.056	.334	
Vega	.014	.053	.651	.248	.221

As a cross-check, each of the reported regression equations was subjected to a cross validation which involved splitting the total sample of 218 into two equal parts of 109 each. The regression equations were run for each half and then compared to the regression equation for the total sample. In each case a Fisher r to z transformation confirmed the stability of the equations.[2] The confidence intervals for the beta weights also overlapped between equations (Kane, 1968). Therefore, all three checks on the stability of the estimates confirmed the total sample estimates.

The first model estimated was the original Fishbein model (Fishbein, 1963). Again, this model is expressed algebraically as:

$$A_o = \sum_{i=1}^{n} B_i a_i$$

The brand specific estimation of this model is presented in Table 2, and the computer program utilized for all regression models presented here is the Statistical Package For The Social Sciences (Nie, et. al., 1975).

The second model estimated was the summated model of behavioral intent (Fishbein, 1967). Recall that this model can be expressed as:

$$BI = \sum_{i=1}^{n} (B_i a_i) w_o$$

The brand specific estimation of this model is presented in Table 3. It is interesting to note, when Tables 2 and 3 are compared, that the original Fishbein model of attitude toward an object produced higher correlation coefficients than does the behavioral intent model, a

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[2] The Fisher r to z transformation is computed as:

$$\frac{(Z_{r_1} - Z_{r_2})}{\frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}}$$

and compared to the Normal distribution. See Slakter, Malcom J. Statistical Inference For Educational Researchers. Reading, Massachusetts: Addison-Wesley, 1972, Chapter 19. Note that this transformation assumes the coefficients are computed from samples.

TABLE 2

A_o MODEL ESTIMATES

	Multiple R	R^2	F	p
Chevette	.617	.380	132.0	.001
Pinto	.692	.479	197.4	.001
Vega	.651	.424	158.3	.001

TABLE 3

A_{act} MODEL ESTIMATES

	Multiple R	R^2	F	p
Chevette	.484	.235	65.9	.001
Pinto	.529	.280	83.5	.001
Vega	.541	.293	89.0	.001

finding which is atypical of past studies (Wilkie and Pessemier, 1973). A possible reason for such an occurrence is the sample used for analysis in that the behavioral intent of students simply may not be a reliable indication of attitudes. In any event, it does not hinder the model integration in this study as all variations of the Fishbein model are combined with the conjoint analysis.

The third model estimated was that previously referred to as the disaggregated model. Disaggregated, of course, refers to attributes and not individuals. Recall this model can be expressed as:

$$BI = \beta_o + \beta_1 B_1 a_1 + \beta_2 B_2 a_2 + \beta_3 B_3 a_3 + \beta_4 B_4 a_4$$

with a beta weight being attached to each of the four attributes under consideration. The results of this model are presented in Tables 4 and 5. Table 4 considers the correlation analysis of each brand, while Table 5 gives the beta weights for each attribute of each brand. Although the correlations are slightly higher than the summated model of behavior intent, they are still lower than the correlations in Fishbein's original attitude toward an object model. Note also that the three beta weights for economy are not significant at the .10 significance level. This non-significance does not necessarily indicate that economy lacks importance, but possibly that since the automobiles under consideration are perceived as relatively equal on this attribute, economy becomes a qualifying rather than a determining factor.

Conjoint Analysis

The results of a conjoint analysis are quite straight-forward

TABLE 4

DISAGGREGATED FISHBEIN MODELS OF BEHAVIORAL INTENT

	Multiple R	R^2	F	p
Chevette	.535	.286	28.5	.001
Pinto	.543	.295	29.7	.001
Vega	.590	.348	37.8	.001

TABLE 5

BETA WEIGHTS FOR EACH PRODUCT ATTRIBUTE
BY BRAND FOR DISAGGREGATED MODELS OF BEHAVIORAL INTENT

	Style	Dependability	Economy
Chevette	.353	.310	-.022
	(.001)	(.001)	(.712)
Pinto	.233	.357	.082
	(.001)	(.001)	(.182)
Vega	.261	.472	-.015
	(.001)	(.001)	(.808)

() indicates significance level.

An empirically verifiable assumption of conjoint analysis is the cancellation axiom discussed in Chapter III which assumes that the respondents are consistent in their answers and this consistency is reflected in the previously discussed tau value.

The conjoint analysis for this study was completed using Richard Johnson's Non-Metric Regression (NMRG) program. Recall that the result of the conjoint analysis program is the determination of utility values for each attribute level. The algorithm performs this task for each respondent since inter-individual utility comparison is not considered a valid methodology

The conjoint algorithm computes both additive and multiplicative utilities. Additive utilities were used in this study simply because they are more easily manipulated, although the use of multiplicative utilities in the proper context would produce identical results. For example, the additive utilities obtained for respondent number 001 are as shown below. Similar results were obtained for each respondent.

Attribute level	Utility
Chevette	0.07630
Pinto	0.07630
Vega	0.07631
Modern Style and Lines	0.03265
Average Styling	0.10768
Constant Style that is Functional	0.08850
Sturdy, Quality Workmanship	0.70302
Average Workmanship	0.07630
Minimum Quality Workmanship	-0.55041
Price of $3,000	0.31607
Price of $3,500	0.17931
Price of $4,000	0.26647

The utilities are, of course, intervally scaled, which thereby makes subtraction and division by a constant legitimate operations. With these scale considerations in mind, the next step is the computing of a utility range for each individual on each attribute. An example using a single attribute best clarifies the procedure for such a computation.

If the attribute of brand is used, there are six possible ways of computing the range:

1. Chevette $<$ Pinto $<$ Vega
2. Chevette $<$ Pinto $\geq$ Vega
3. Chevette $>$ Pinto $\leq$ Vega
4. Chevette $>$ Pinto $>$ Vega
5. Chevette $=$ Pinto $<$ Vega
6. Chevette $=$ Pinto $\geq$ Vega

All other possible combinations are redundant with one of the above combinations. Each respondent will fulfill the criterion for only one of the six possibilities listed above. For respondent 001, the category would be number 6 as that individual has rated all brands equal. By use of the same procedure, ranges for all four attributes can be computed for each respondent.

Again, in reference to respondent 001, the ranges for each attribute would be as follows:

Brand	0.0000
Style	0.0750
Dependability	1.2534
Price	0.0496

In order that the importance of each attribute be expressed in relation to the other attributes, it is possible to sum the above utility ranges and compute the percent of total utility attributable to each attribute.

For example, the sum of the utility ranges listed above is 1.3780. When each range is divided by this sum, the following percentages are obtained:

Brand	0.0
Style	5.4
Dependability	89.6
Price	3.6

These percentages will, of course, sum to 100, except for rounding errors. It can easily be seen from these figures, then, that dependability is by far the most important attribute to this respondent. Style and price combined account for less than ten percent of the total utility, and there is no differentiation with respect to brand.

It must be noted, however, that a factor's relative importance is dependent on the factor levels included in the design. For instance, had the price range been $2,000 to $6,000, that range's relative importance could have easily exceeded style and dependability. The range of $3,000 to $4,000 used in this study is quite likely to include those values of the relevant range which are close to the extreme. In other words, it is difficult to buy even a subcompact car for less than $3,000, and those small cars above $4,000 are usually not direct competitors with the less expensive models because of the price factor. Although this discussion is rather peripheral to this study, since the objective was the integration of two models and not generalization of the results, it is quite easy to conceive of studies in a commercial setting which would require generalizability and the issue would become critical.

Results from Integrating the Models

Now that the conjoint analysis and the Fishbein models have been estimated, it is appropriate to examine how they might be integrated. There is no direct comparison of the two because one is a construct model of attitudes, while the other is an analytical technique. Both conjoint analysis and the Fishbein model do, however, ultimately attach weights to the attributes under consideration, although these weights are not directly comparable, primarily because the Fishbein model estimates are anchored to an object (automobile) while the conjoint weights are not so attached. In other words, the weights estimated in the Fishbein analysis are for the attributes of style, dependability, and economy as they are related to a specific brand, while, the conjoint analysis assigns weights to each attribute including brand. Moreover, the conjoint weights are separate estimates which are not anchored to a specific brand, but rather are independent estimates.

One possibility exists for integrating the two models and that is the substitution of the utility weights from the conjoint analysis for the desirability ratings in the Fishbein model. This substitution would produce a model, analogous to the original Fishbein model, specified as:

$$A_o = \sum_{i=1}^{n} B_i U_i$$

where:

A_o = attitude toward an object

B_i = the individual's belief about the probability that an object is related to an outcome, i

U_i = the individual's utility for outcome i

Another estimation, also possible for the model of behavioral intent, would be expressed as:

$$BI = \sum_{i=1}^{n} B_i U_i$$

where the components are the same as above, except for the dependent variable which would be behavioral intent (BI) rather than attitude toward an object (A_o).

This disaggregated model of attitudes would then be estimated as:

$$BI = f(B_i U_i)$$

The variables are again defined the same as above, with the exception that the summation sign (Σ) is replaced by a function notation (f) to indicate that the attributes will not be summed but rather will each be associated with a separate beta weight.

Tables 6 through 8 present the respective regression estimations of the above models. When Table 6 and Table 2 are compared, the use of U_i in place of a_i produces slightly different multiple R's. The use of U_i in the attitude models produces a slightly lower multiple R for two brands (Chevette and Pinto), while the third brand (Vega) has a slightly higher multiple R. The same results occur for the summated model of behavioral intent (comparisons of Tables 3 and 7). Estimation of a_i with the traditional bipolar scales again appears to contribute to a slightly higher multiple R for two of the three brands. In all comparisons an r to Z transformation shows no statistically significant difference between the multiple R's.

The disaggregated model of behavioral intent produces some interesting results also. An examination of Table 4 versus Table 8 shows

TABLE 6

A_o MODEL WITH UTILITY SUBSTITUTED FOR DESIRABILITY

	Multiple R	R^2	F	p
Chevette	.557	.310	95.7	.001
Pinto	.619	.383	132.5	.001
Vega	.661	.437	165.4	.001

TABLE 7

A_{act} MODEL WITH UTILITY SUBSTITUTED FOR DESIRABILITY

	Multiple R	R^2	F	p
Chevette	.452	.205	54.8	.001
Pinto	.484	.234	65.1	.001
Vega	.567	.321	100.9	.001

TABLE 8

DISAGGREGATED MODEL WITH UTILITY SUBSTITUTED FOR DESIRABILITY

	Multiple R	R^2	F	p
Chevette	.479	.229	20.9	.001
Pinto	.500	.250	23.5	.001
Vega	.578	.331	34.9	.001

the multiple R's to be consistently higher for the model employing a_i as the measure of desirability versus the model using U_i.

To illustrate an indication of the differences in the distributions of a_i and U_i, Table 9 is presented. In terms of kurtosis, the distributions have like signs but different magnitudes, the most substantial difference being for the attribute style. Skewness differs less drastically with respect to magnitude but changes from negative to positive for style, with the other attributes again being consistent. The range and median are presented for more completeness in examining the distributions but are meaningless for comparative purposes as they are not in standardized units.

In summary, then, the integrated model has not produced significantly different results than the Fishbein as the latter has traditionally been used in marketing. There are, however, considerations which would indicate continued use of the traditional Fishbein model and these are presented in the following chapter.

TABLE 9

DISTRIBUTIONAL CHARACTERISTICS OF UTILITY* AND DESIRABILITY**

	Style		Dependability		Economy	
	a_i**	U_i*	a_i	U_i	a_i	U_i
Kurtosis[1]	3.538	.344	4.024	1.075	-.191	-.443
Skewness[2]	-.931	.849	-.348	-.906	.349	.611
Range	0-21	0-1.552	0-18	.111-1.720	7-18	.006-1.43
Median	14.32	.347	11.709	1.262	12.293	.457

*Utility estimates from the conjoint analysis.

**Desirability estimates from a seven point bipolar scale.

[1]Kurtosis is a measure of the peakedness or flatness of a distribution relative to the normal distribution. A normal (mesokurtic) distribution has a kurtosis coefficient of zero, a peaked (leptokurtic) distribution has a positive coefficient, and a flat (platykurtic) distribution has a negative coefficient.

[2]Skewness is a measure of the deviation from symmetry in a distribution. A positive coefficient indicates that the cases cluster more to the left of the mean while a negative coefficient indicates a cluster of cases to the right of the mean. As the skewness (and the kurtosis) is a standardized coefficient, the mean of any distribution is located at zero. (Nie, et. al., 1975).

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this chapter is to discuss the conclusions from this project and outline the implications of those conclusions for future research efforts. In the first section the analysis is integrated to reach conclusions on the basis of the combined Fishbein and conjoint models, while the second section offers ideas for future research.

Conclusions from Synthesis of the Two Models

The purpose of this study was the integration of a conjoint analysis model with the Fishbein attitude model, an integration which was accomplished by substituting the conjoint utility weights for the desirability component of the Fishbein model. As discussed in Chapter V, this integrating procedure produced a model with a multiple R that was not significantly different than the estimate obtained when the original desirability component was used. This result is interesting in view of the quite different distributional characteristics of the utility and desirability components found in this study, a difference which again points to the danger of multiplying non-ratio scales. This research presents clear empirical evidence that quite different distributions can lead to statistically equal correlation analysis. The theoretical implications of the multiplication of non-ratio scales have previously been outlined by Schmidt and Wilson (1975) who also point out the theoretical possibility of obtaining spurious correlation analysis.

With both empirical and theoretical evidence of spurious correlations, then, the verdict as to which weight has greater construct validity is uncertain. Either or both measures could be valid or invalid, and further study of construct validity would be required to be certain.

The results of this study, however, do give several indications as to which measure should be used until such time as the validity of one or the other is shown to be superior. First, the original Fishbein desirability component is to be preferred on the grounds of simplicity. The tedious mental task involved in obtaining conjoint data is definitely a drawback compared to the simpler bipolar scales required for measurement of the desirability component. In fact, substantial incentive is required for most respondents to complete a conjoint questionnaire as the task is quite a rigorous mental exercise in multidimensional comparison. The bipolar scale, on the other hand, is familiar to most respondents and requires relatively little thought.

A second issue where the continued use of the desirability component is the more prudent course evolves from the mathematical derivation of the conjoint utility weights. Although the marketing literature refers to these weights as utilities, they can be interpreted quite differently. Mathematically, they are a non-metric counterpart of least squares beta weights (Appendix B). Both regression and conjoint analysis can be expressed as:

$$X\,b = Y$$

where:

X is a matrix

b is a vector of weights

Y is the dependent variable

The primary difference between conjoint and regression, when both are expressed in terms of the above model, is that the regression model specifies a metric scale for the X matrix, while conjoint specifies a matrix of dummy variables, i.e., zeroes and ones, for the X matrix. The b term is estimated by a least squares solution for regression, while conjoint solutions are produced by a gradient vector. Although the vector of b weights for conjoint analysis has been loosely termed utilities, this vector might or might not in fact be utilities by the accepted economic definition. Heuristically derived solutions, such as conjoint, are useful for generation of weights, but they are not to be relied on to produce dimensions which are interpreted as constructs (Sheth, 1976).

The solution to this interpretation problem for the conjoint weights is the use of simple non-metric regression. Thus, rather than specify the X matrix as a dummy matrix of zeroes and ones, the matrix could be specified exactly as it is for least squares. Then, by the use of a non-metric procedure rather than least squares, the stringent assumptions of the normal regression procedure could be avoided. This procedure, however, again suffers from the lack of probabilistic underpinnings that provide an error theory. In any event, it should be recognized that the weights produced by conjoint analysis are not necessarily utility weights. It must also be acknowledged that the use of non-metric regression does not avoid the multiplication of non-ratio scales.

In summary, then, the use of the Fishbein model for the prediction of brand preference, except for the possibility of spurious correlations, is more desirable than the integrated model tested in this study. Moreover, the primary limitations of component measurement for the Fishbein model are not overcome by the integrated model. Nevertheless, the measurement of the desirability component should continue as a research topic with the aim of overcoming the measurement limitations. The following section points out other areas that would provide fertile grounds for future study.

Recommendations for Future Research

In the context of the present research it would be useful to test alternative composition rules rather than seek scale values that are in best agreement with a prespecified, e.g., additive, composition rule. For instance, the functional form, i.e., combinatorial rule, of the Fishbein model is generally thought to be multiplicative. Conjoint measurement would be the appropriate technique for investigating this issue (Berner, 1976).

It is also interesting to note that the better performance of the A_o model compared to the A_{act} model differs from the results of other research projects (Harrell and Bennett, 1974). This discrepancy could be due to the fact that this project used a student sample, but it could also be due to the consumer durable being investigated. Thus, a future project might investigate the hypothesis that brand preference for consumer durables is better predicted with the A_o model than with the A_{act} model and just the reverse for consumer non-durables. Better prediction with A_o would assume that durables, with the higher risk and greater economic investment, may well be the target of an attitude rather than the attitude being formed toward the act of purchase. The A_{act} model could, with the same logic, be more appropriate for predicting brand preference for consumer non-durables. A research project to investigate these possibilities could enhance the usefulness of the models by indicating the proper setting for their use.

Again, the limitations noted in Chapter IV are relatively undeveloped areas which provide grounds for methodological research. One aspect that would be especially applicable for marketers in their frequent sample survey analyses would be the investigation of the differences and similarities between the trade-off and full profile methods of data collection. An explicit delineation of these differences and similarities would eventually lead to more accurate and efficient analysis. In such an investigation the possibility of differing combinations of the two methods could also be considered. In other words, it is possible that there are uses for alternative schemes between the specification of factors two at a time versus the specification of single levels of each factor in a single combination.

As noted earlier, the effects of qualifying versus determining factors is also a topic for study. Such study could then lead to evidence of second choice theories and other, more complex types of interaction models. In any event, it is clear that there are many uses, both managerial and theoretical, for both conjoint analysis and the Fishbein attitude models.

APPENDICES

APPENDIX A

QUESTIONNAIRE AND INSTRUCTIONS

INSTRUCTIONS FOR CONJOINT QUESTIONNAIRE

As you will note, the first two pages of the questionnaire you have just received are composed of six 3 x 3 matrices. The task at hand is to rank order each of the alternatives in each matrix from (1) most desirable to (9) least desirable. An example will help clarify the procedure.

Suppose we are concerned with two attributes (1) top speed of a car, and (2) price of the car. Our matrix would then appear as follows (on overhead transparency):

	130 mph	100 mph	70 mph
$2,500	(1) 5	(2) 3	(5) 1
$4,000	(3) 6	(4) 4	(6) 2
$6,000	(7) 7	(8) 8	(9) 9

The average response of consumers in an actual study (Johnson, 1974) appear in parenthesis above. Your conception may differ from the average respondent, however. For example, you might feel that 70 mph is fast enough (for safety reasons) and your ranking might appear like that of the second numbers in each cell. This would be a perfectly legitimate response as long as it reflects how you would trade off these factors. Of course, trading off only two factors assumes that all other factors remain constant. For instance, in the example matrix attributes such as warranty, seating capacity, miles per gallon, etc. would be assumed constant with only mph and price varying.

Now, please begin filling in each of the matrices on your questionnaire.

T. Wilson
MTA 317
May 20, 1976

QUESTIONNAIRE ON SUBCOMPACT AUTOS

PLEASE WAIT FOR INSTRUCTIONS!

	Chevette	Pinto	Vega
Modern Style and Lines			
Average Styling			
Constant Style that is functional			

	Chevette	Pinto	Vega
$3,000			
$3,500			
$4,000			

	Chevette	Pinto	Vega
Sturdy, Quality Workmanship			
Average Workmanship			
Minimum Quality Workmanship			

	$3,000	$3,500	$4,000
Modern Style and Lines			
Average Styling			
Constant Style that is Functional			

	Modern Style and Lines	Average Styling	Constant Style that is Functional
Sturdy, Quality Workmanship			
Average Workmanship			
Minimum Quality Workmanship			

	$3,000	$3,500	$4,000
Sturdy, Quality Workmanship			
Average Workmanship			
Minimum Quality Workmanship			

In general, we would like to know your opinion about several characteristics of small cars. Please tell me the rating you would give to each of the characteristics using the following scale.

Very Undesirable			Neutral			Very Desirable
______	______	______	______	______	______	______
-3	-2	-1	0	+1	+2	+3

Brand:
- Chevette______
- Pinto ______
- Vega ______

Dependability:
- Sturdy, quality workmanship______
- Average workmanship ______
- Minimum quality workmanship______

Style:
- Modern style and lines______
- Average styling ______
- Constant style that is functional ______

Price:
- Low ______
- Medium ______
- High ______

Please rank the following automobiles as your first choice, second choice, and third choice.

- Chevette______
- Pinto ______
- Vega ______

Please use the following scale to indicate the probability of your purchasing each of the three brands listed below:

Very Improbable					Very Probable	
______	______	______	______	______	______	______
-3	-2	-1	0	+1	+2	+3

- Chevette______
- Pinto ______
- Vega ______

Now indicate the probability that you would buy <u>any</u> compact or subcompact car. ________

It is also important to know your evaluation of the characteristics of different brands. Please use the following scale in rating each sentence below.

Strongly Disagree			Neutral			Strongly Agree
______	______	______	______	______	______	______
-3	-2	-1	0	+1	+2	+3

The Chevette would be:		The Pinto would be:		The Vega would be:	
Dependable	______	Dependable	______	Dependable	______
Economical	______	Economical	______	Economical	______
Stylish	______	Stylish	______	Stylish	______

Demographic Information:

G.P.A.	College Status	
______less than 2.00	______Freshman	______Single
______2.01 to 2.40	______Sophomore	______Married
______2.41 to 2.80	______Junior	
______2.81 to 3.00	______Senior	______Male
______3.01 to 3.40	______Graduate	______Female
______3.41 to 4.00		

Have you bought a new car within the last 6 months?

______No ______Yes

If yes, was it a compact or subcompact?

______No ______Yes

Do you plan to buy a new car within the next 6 months?

______No ______Yes

APPENDIX B

CONJOINT PROCEDURE AND ALGORITHM

This appendix technically describes the computational operations of Richard Johnson's NMRG computer program (Johnson, 1975). It is included for technical completeness, although for most readers Chapter III is probably sufficient for purposes of understanding conjoint analysis. The program is written in FORTRAN IV with less than 200 statements. It is available from Richard M. Johnson, Vice President, Market Facts, Inc., 100 S. Wacker Drive, Chicago, IL, 60606. All material in this appendix is from Johnson, 1973 and 1975 or easily derivable from those sources.

Initializing the conjoint analysis procedure is accomplished through specification of a coefficient matrix of dummy variables consisting of zeroes and ones to indicate the presence or absence in an object of each level of each attribute. The matrix would have a row (n) for each object and a column (p) for each attribute level. A unit element in cell position ij would indicate that object i possessed the jth attribute level. "A set of weights for each column is sought such that the weighted row sums of the coefficient matrix would be monotonic with the individual's rank order of preference among the objects described by that matrix."

Consider a coefficient matrix X of order n x p, and an unknown vector b of length p to contain part weights. Let the vector y of length n contain an individual's preference ratings. Let $X\, b = \hat{y}$. The problem then becomes finding a vector b such that the elements of the $\hat{y}$ vector are as nearly monotonic to the given vector y as possible.

As a measure of monotonicity, consider the measure θ^2 (Johnson, 1973):

$$(1)\quad \theta^2 = \frac{\sum_{i,j} \delta_{ij} \; (\hat{y}_i-\hat{y}_j)^2}{\sum_{ij} \; (\hat{y}_i-\hat{y}_j)^2}$$

where:

$$(2)\quad \delta_{ij} = \begin{cases} 1 \text{ if sign } (\hat{y}_i-\hat{y}_j) = \text{sign } (y_i-y_j) \\ 0 \text{ otherwise} \end{cases}$$

Note that this definition of δ forces the θ^2 statistic to zero for a perfect fit, and to one for a perfectly inverse relationship. The interpretation of θ^2 as the proportion of variation in the $\hat{y}$'s which is discordant with the y's is more easily seen through examination of the formula. The numerator is the sum of squared differences between all pairs of $\hat{y}$'s that are discordant with the y's. The denominator is simply a normalizing constant which constrains the range of θ^2 to the unit interval.

The iterative procedure for the minimization of θ^2 consists of starting with an arbitrary vector b of the form 1 x p and modifying this vector successively. The direction of the modification indicated by gradient vectors.

The gradient vector g corresponding to an iterative form of b is derived by differentiating θ^2 partially with respect to b' (an iterative form of b). To indicate the form of the gradient, we set

$$(3)\quad \theta^2 = \frac{u}{v}$$

for scalars u and v, then

$$(4)\quad \frac{d\theta^2}{db'} = \frac{1}{v^2} \left(v \frac{du}{db'} - u \frac{dv}{db'}\right)$$

using equations (1) and (3) and the transitive property:

$$(5) \quad \frac{u}{v} = \frac{\sum_{ij} \delta_{ij} \, (\hat{y}_i - \hat{y}_j)^2}{\sum_{ij} (\hat{y}_i - \hat{y}_j)^2}$$

then

$$(6) \quad \frac{du}{db'} = 2\sum_{ij} \delta_{ij} \, (\hat{y}_i - \hat{y}_j)$$

Using x_i and x_j as the ith and jth rows of X and $\hat{y}_i$ and $\hat{y}_j$ as scalars

$$(7) \quad \frac{du}{db'} = 2\sum_{ij} \delta_{ij} \, (x_i - x_j)(\hat{y}_i - \hat{y}_j)$$

With the same procedure:

$$(8) \quad \frac{dv}{db'} = 2\sum_{ij} \delta_{ij} \, (x_i - x_j)(\hat{y}_i - \hat{y}_j)$$

By substituting (7) and (8) into (4) we get,

$$(9) \quad \frac{d\theta^2}{db'} = \frac{1}{v^2} \, (2v \sum_{ij} \delta_{ij} \, (x_i - x_j)(\hat{y}_i - \hat{y}_j) - 2u \sum_{ij} \delta_{ij} \, (x_i - x_j)(\hat{y}_i - \hat{y}_j))$$

and simplifying

$$(10) \quad = \frac{2}{v} \sum_{ij} \delta_{ij} \, (x_i - x_j)(\hat{y}_i - \hat{y}_j) - \frac{2u}{v^2} \sum_{ij} \delta_{ij} \, (x_i - x_j)(\hat{y}_i - \hat{y}_j)$$

$$(11) \quad = \frac{2}{v} \sum_{ij} (x_i - x_j)(\hat{y}_i - \hat{y}_j)(\delta_{ij} - \frac{u}{v})$$

So, the gradient vector

$$(12) \quad g = \frac{2}{v} \sum_{ij} (x_i - x_j)(\hat{y}_i - \hat{y}_j)(\delta_{ij} - \theta^2)$$

The program normalizes both b and g to have unit sums of squares at each stage and uses the current value of θ as the "step size" with the recursive equation.

$$b_{m+1} = b_m - \theta_m g_m$$

where m is the iteration number. This process can be terminated after a limiting number of iterations. For example, when Θ fails to decrease, or the default option is reached. The default option for stabilization of Θ is thirty iterations. Fifteen iterations were utilized for this project with the average number of iterations required for Θ stabilization being eight with a range of one to fourteen. This is to be expected because the successively smaller modifications of X are based on the Θ value.

In brief summary, the procedure for one iteration is as follows:

1. For a given X, compute all pairs of distance values $(\hat{y}_i - \hat{y}_j)$
2. Evaluate the sign of $(\hat{y}_i - \hat{y}_j)$ and cumulate the δ_{ij}'s
3. Calculate Θ^2 and g as shown above
4. Normalize X and g to have equal sums of squares
5. Replace X by $X - \Theta_g$

There are also procedures for considering ties and missing data, neither of which posed a problem for this research. The respective procedures are presented by Johnson (1975).

The following page is an example of the input for each individual. The example shown is for respondent number 001 from this sample.

An Example

To further clarify the mathematics shown above, the following example is included. In the present study there are four attributes with three levels each (see Chapter IV). The grand input matrix for each respondent could then be viewed as:

			B			S			D			P	
		1	2	3	4	5	6	7	8	9	10	11	12
	1												
B	2												
	3												
	4												
S	5												
	6												
	7												
D	8												
	9												
	10												
P	11												
	12												

The letters B, S, D, and P stand for brand, style, dependability, and price respectively. Each of the 3 x 3 cells above represents a single trade off matrix. Note that a trade off matrix with the same attribute on both axes is illegitimate. That is to say, the levels of an attribute cannot be traded off against itself. This eliminates the diagonal of the above matrix. Note also that the top and bottom sides of the matrix are redundant. In other words, style and brand are the same as brand and style. The trade off matrices used as input can be from either the top or bottom but not both. In other words, the input must be consistently from the top half or the bottom half. Noting the questionnaire in Appendix A, the bottom half is used for this study.

The program is designed to accept row-wise or column-wise data, but again all cases must be consistent. Row-wise input was used for this data base.

Specification of the X matrix simply involves specifying the location of the respondent's rank ordering in the overall matrix. For example, the first respondent filled in the first trade off matrix for style and brand as shown below.

	Chevette	Pinto	Vega
Modern Style and Lines	3	2	1
Average Styling	6	5	4
Constant Style that is Functional	9	8	7

This translates to a column vector (y) as follows:

$$\begin{bmatrix} 3 \\ 2 \\ 1 \\ 6 \\ 5 \\ 4 \\ 9 \\ 8 \\ 7 \end{bmatrix}$$

The X matrix, with dimensions of 9 x 12, would appear as follows:

$$\begin{bmatrix} 100 & 100 & 000 & 000 \\ 010 & 100 & 000 & 000 \\ 001 & 100 & 000 & 000 \\ 100 & 010 & 000 & 000 \\ 010 & 010 & 000 & 000 \\ 001 & 010 & 000 & 000 \\ 100 & 001 & 000 & 000 \\ 010 & 001 & 000 & 000 \\ 001 & 001 & 000 & 000 \end{bmatrix}$$

To illustrate, the first row of the X matrix:

100 100 000 000

would be interpreted as identifying the first number in the y vector (3) as being located in the first column and the fourth row of the grand matrix. Referring back to the grand matrix, the first column and fourth row is the intersection Brand 1 and the first level of the attribute style. Each number in the y vector can be located in the grand matrix by using the above procedure.

The scheme outlined above for specifying the X matrix would require nine cards for each trade-off matrix, which for this study would total 54 cards for all six trade-off matrices. Constant use of the program is more efficient if the cards are simply accessed from tape rather than separately punched for each project.

The following page is an example of the output for each respondent. The example shown is for respondent number 001 from this sample. To clarify the interpretation of the sample output, Iteration simply refers to the number of the iteration and the corresponding theta and tau values. Recall that theta has an inverse relationship to tau. A lower theta value (or a higher tau value), indicates more consistent responses to the trade-off matrix. The iterative procedure seeks a best fitting function using theta as a criterion, and in the case of respondent 001, after 15 iterations settles at a value of 0.04706 for theta and 0.73148 for tau.

The variable number refers to the attribute level as specified in the grand matrix. Again referring back to the grand matrix, it can be seen that variable numbers 1, 2, and 3 correspond to the brands Chevette, Pinto and Vega respectively. Variables 4, 5, and 6 correspond to the three levels of style, 7, 8, and 9 correspond to the levels of dependability, and 10, 11, and 12 correspond to the levels of price. The Additive and Multiplicative columns on the printout are the utility values for each of the variables (attribute levels). For example, the additive utility for variable 1 (Chevette) is 0.07630, the additive

SAMPLE OUTPUT FROM NON-METRIC REGRESSION PROGRAM

ID = 001

ITERATION	THETA	TAU
1	0.93953	-0.60185
2	0.52517	0.49074
3	0.17703	0.75926
4	0.10039	0.92593
5	0.06111	0.79630
6	0.05985	0.94444
7	0.04620	0.71296
8	0.04998	0.69444
9	0.05036	0.71296
10	0.04971	0.69444
11	0.04841	0.73148
12	0.04846	0.69444
13	0.04776	0.73148
14	0.04769	0.69444
15	0.04706	0.73148

VARIABLE	ADDITIVE	MULTIPLICATIVE
1	0.07630	1.07928
2	0.07630	1.07929
3	0.07631	1.07930
4	0.03265	1.03319
5	0.10768	1.11369
6	0.08850	1.09262
7	0.70302	2.01984
8	0.07630	1.07929
9	-0.55041	0.57671
10	0.31607	1.37173
11	0.17931	1.19639
12	0.26647	0.76608

utility of variable 4 (constant style that is functional) is 0.03265, and so forth. Recall from Chapter III that the multiplicative utilities are simply the logarithms of the additive utilities.

Computer Algorithm

The following algorithm is the NMRG program as set up on the IBM computer at Xavier University.

```
     R. M. JOHNSON/ MARKET FACTS / AUGUST,1973
THIS PROGRAM PERFORMS NONMETRIC REGRESSION TO MINIMIZE THE THETA
CRITERION.  IT HAS A SPECIAL FEATURE WHICH ALLOWS IT TO COMPUTE A
SINGLE SET OF WEIGHTS WHICH PROVIDE THE BEST FIT TO SEVERAL BLOCKS
OF DATA SIMULTANEOUSLY.  EACH BLOCK MUST CONTAIN N OBSERVATIONS.
ORDER COMPARISONS ARE ONLY MADE WITHIN BLOCKS.  A SECOND FEATURE
ALLOWS WEIGHTING SO AS TO PAY GREATER ATTENTION TO FITTING
INPUT VALUES WITH SMALLER MAGNITUDES ( SUCH AS FIRST,SECOND,
ETC.  RANK ORDERS WHEN USING PREFERENCE INPUT DATA).
CURRENT RESTRICTIONS ARE 10 BLOCKS,50 OBSERVATIONS PER BLOCK.
AND 20 INDEPENDENT VARIABLES.
INPUT ORDER:
  1) CONTROL CARD(1615)
    A) NUMBER OF OBSERVATIONS PER BLOCK (N)
    B) NUMBER OF INDEPENDENT VARIABLES (M)
    C) NUMBER OF BLOCKS ( NBLKS   DEFAULT=1)
    D) ITERATION LIMIT ( DEFAULT=30)
    E) WEIGHTING OPTION(1 IF WEIGHTING DESIRED, 0 OTHERWISE)
    F) TIES OPTION (NORMALLY 0, 1 IF TIES NOT TO BE FORCED)
    G) CARD OUTPUT OPTION (ADDITIVE) 1=  CARD OUTPUT
    H) SUPPRESS PRINT OPTION AFTER WEIGHTS 1=  SUPPRESS
  2) INITIAL WEIGHTS( ONE CARD, 40F2.1)
  3) DATA CARDS IN FORMAT(40F2.0), EACH CARD CONTAINING ALL DATA
  FOR A SINGLE OBSERVATION:  M INDEPENDENT VARIABLES FOLLOWED BY
  A DEPENDENT VARIABLE.  ALL CARDS FOR A BLOCK MUST BE
  TOGETHER IN THE DECK.  A ZERO VALUE FOR THE DEPENDENT VARIABLE
  RESULTS IN THAT OBSERVATION NOT BEING USED IN THE COMPUTATION.
```

```
 SHORT BLOCKS CAN BE FILLED OUT WITH BLANK DATA CARDS.
OUTPUT CONSISTS OF THE VALUE OF THETA ACHIEVED BY EACH ITERATION, A
A SET OF WEIGHTS APPROPRIATE FOR AN ADDITIVE MODEL, AND A SET
OF WEIGHTS APPROPRIATE FOR A MULTIPLICATIVE MODEL OBTAINED BY
TAKING ANTILOGS OF THE FIRST SET.
      DIMENSION X(10,36),IY(10),YHAT(10),W(12),G(36),D(36),GNUM(36)
      DIMENSION GDEN(36),S1(12)
      INTEGER*2 DATA(66,10,37)
      READ(5,901) N,M,NBLKS,ITRLIM,IWT,ITIES,ICARD,ISUP
      IF(NBLKS .LT. 1) NBLKS=1
      IF(ITRLIM.LT.1) ITRLIM=30
      IF(IWT .LT. 0) IWT=0
      WRITE(6,914)
      WRITE(6,901)N,M,NBLKS,ITRLIM,IWT     ,ITIES,ICARD,ISUP
      NM1=N-1
      MP1=M+1
      MM1=M-1
      WEIGHT=1
      READ(5,905)(W(J),J=1,M)
      WRITE(6,903) (W(J),J=1,M)
    1 DO 10  I=1,NBLKS
      DO 10  J=1,N
   10 READ(11,912,END=999) ID,(DATA(I,J,K),K=1,MP1)
      WRITE(6,914)
      WRITE(6,998)ID
  998 FORMAT(5X,'ID =  ',A5)
      WRITE(6,900)
      DO 1000  ITER=1,ITRLIM
      DO 20  I=1,M
      GNUM(I)=0.
   20 GDEN(I)=0.
      SNUM=0.
      SDEN=0.
      TAUNUM=0
      TAUDEN=0
```

```
      DO  105  IBLOCK=1,NBLKS
      DO  24  I=1,N
      IY(I)=DATA(IBLOCK,I,MP1)
      DO  24  J=1,M
   24 X(I,J)=DATA(IBLOCK,I,J)
      DO  30  I=1,N
      YHAT(I)=0.
      DO  30  J=1,M
   30 YHAT(I)=YHAT(I)+X(I,J*W(J)
      DO  103  I=1,NM1
      IF(IY(I).EQ.0)  GO  TO  103
      IP1=I+1
      DO  100  J=IP1,N
      IF(IY(J).EQ.0)  GO  TO  100
      IDIF=IY(I)-IY(J)
      DIF=YHAT(I)-YHAT(J)
      PROD=IDIF*DIF
      PROD=-1.*PROD
      IF(IDIF .EQ.  0  .AND. ITIES .EQ. 1)  GO  TO  100
      DIF2=DIF*DIF
      DO  40  L=1,M
   40 D(L)=X(I,L)-X(J,L)
      IF(IWT.EQ.0)  GO  TO  43
      FI=FLOAT(IY(I))
      FJ=FLOAT(IY(J))
      WEIGHT=1./FI/FJ
   43 CONTINUE
      IF(PROD .GT. 0.)  GO  TO  50
      SNUM=SNUM+WEIGHT*DIF2
      TAUNUM=TAUNUM+1
      DO  45 L=1,M
   45 GNUM(L)=GNUM(L)+DIF*D(L)
     +*WEIGHT
      GO  TO  100
   50 SDEN=SDEN+WEIGHT*DIF2
```

```
      TAUDEN=TAUDEN+1
      DO  55 L=1,M
   55 GDEN(L)=GDEN(L)+DIF*D(L)
    +*WEIGHT
  100 CONTINUE
  103 CONTINUE
  105 CONTINUE
      THETA2=SNUM/(SNUM+SDEN)
      THETA=SQRT(THETA2)
      TAU=(TAUDEN-TAUNUM)/(TAUDEN+TAUNUM)
      WRITE(6,902)  ITER,THETA
    + ,TAU
      DO  110  L=1,M
  110 G(L)=GNUM(L)-THETA2*(GNUM(L)+GDEN(L))
      SUMW2=1.0E-20
      SUMG2=1.0E-20
      DO  125  I=1,M
      SUMW2=SUMW2+W(I)*W(I)
  125 SUMG2=SUMG2+G(I)*G(I)
      SUMW2=SQRT(SUMW2)
      SUMG2=SQRT(SUMG2)
      DO  130  I=1,M
  130 W(I)=W(I)/SUMW2-(SQRT(THETA))*G(I)/SUMG2
 1000 CONTINUE
 1001 CONTINUE
      WRITE(6,914)
      WRITE(6,904)
      DO  205 J=1,M
      S1(J)=EXP(W(J))
  205 WRITE(6,902) J,W(J),S1(J)
      IF(ICARD.NE.0) WRITE(7,913) ID,W
      IF(ICARD.NE.0) WRITE(7,913) ID,S1
      IF (ISUP.NE.0)  GO  TO  1
      DO  200  IBLOCK=1,NBLKS
      DO  124  I=1,N
```

```
      IY(I)=DATA(IBLOCK,I,MP1)
      DO  124  J=1,M
  124 X(I,J)=DATA(IBLOCK,I,J)
      WRITE(6,907)
      WRITE(6,901) (IY(I),I=1,N)
      DO 150 I=1,N
      YHAT(I)=0.
      DO  150 J=1,M
  150 YHAT(I)=YHAT(I)+X(I,J)*W(J)
      DO  160  J=IP1,N
      IP1=I+1
      DO  160  J=IP1,N
      IF(IY(I)  .GT.  IY(J))  GO  TO  160
      S=YHAT(I)
      YHAT(I)=YHAT(J)
      YHAT(J)=S
      IJ=IY(I)
      IY(I)=IY(J)
      IY(J)=IJ
  160 CONTINUE
      WRITE(6,906)
      DO  399  I=1,N
  399 WRITE(6,902)   IY(I),YHAT(I)
  200 CONTINUE
 5000 CONTINUE
      GO  TO  1
  900 FORMAT(///,'  ITERATION    THETA')
  901 FORMAT(1615)
  902 FORMAT(110,7F10.5)
  903 FORMAT(10F12.6)
  904 FORMAT(///,'   VARIABLE  ADDITIVE  MULTIP')
  905 FORMAT(40F2.1)
  906 FORMAT(///,' DEPENDENT & PREDICTIONS SORTED BY DEPENDENT')
  907 FORMAT(///' INPUT DATA')
  910 FORMAT(10F1.0,F2.0)
```

```
911 FORMAT(16F5.0)
912 FORMAT(A3,2X,37I1)
913 FORMAT(A3,2X,12F6.3)
914 FORMAT('1')
999 CALL EXIT
    END
```

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