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Commercial Use of Conjoint Analysis: A Survey

Conjoint analysis has been used extensively in marketing research to estimate the impact of selected product (service) characteristics on customer preferences for products (services). In this paper we discuss findings obtained from a survey of commercial users of the methodology. We project that around 1,000 commercial applications have been carried out during the last decade. We discuss the manner in which the methodology is used commercially, remaining issues that deserve further exploration, and recent advances or insights obtained by researchers working in this area.

Introduction

MARKETING researchers have made considerable use of conjoint analysis to estimate the impact of selected product (or service) characteristics on consumer preferences. Commercial use of the methodology appears to be widespread, although it is not universally accepted. In designing a conjoint analysis study, a researcher has many alternative approaches to choose from. To gain insight into the extent of usage and the manner in which the methodology is applied, a mail questionnaire was developed and sent to all research firms in the U.S. that were known to the authors to offer conjoint analysis commercially. Seventeen (all but three) of these firms cooperated with the survey before the end of 1980. In this paper we discuss the survey findings, and we elaborate on some of the remaining issues associated with the application of conjoint analysis. The 17 research firms[1] taken together have carried out approximately 700 research projects with conjoint analysis. Of these projects, 160 had been carried out during the most recent 12 months. The survey questions pertained to:

- the frequency of usage of the methodology by product/service category;
- the specific purpose of the research study;
- the method used for generating (defining) product attributes or characteristics;
- the model (e.g., a main effects, part worth model);
- the number of attributes;
- the method of data collection (i.e., full profiles, trade-off matrices);

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[1]Actually, two of the respondents represent advertising agencies, and one response was obtained from a large corporation. We did not contact other large corporations because the number of projects carried out for any one corporation is likely to be small. Furthermore, most institutions employ outside agencies to conduct a study involving conjoint analysis. However, we contacted all research and consulting companies and advertising agencies known to us to offer conjoint analysis commercially, as defined by Green and Srinivasan (1978, p. 104).

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- the mode of presenting objects (stimuli) to respondents;
- the response mode for collecting preference judgments (e.g., rank order preferences);
- the usage of alternative parameter estimation procedures;
- reliability and validity of the results;
- the method employed to summarize the results for presentation to management;
- issues associated with the implementation of results; and
- remaining issues and unsolved problems.

We have also attempted to relate the survey findings to the latest developments in conjoint analysis, and we make recommendations regarding issues that warrant further study.

Survey Results

Frequency of Usage by Product Category

Based on the responses, the first commercial project involving conjoint analysis was completed in 1971. The number of projects carried out per respondent at the time the survey was conducted (during the latter half of 1980) varies from 2 to 200. Taken together, the respondents have completed 698 projects during this decade, or approximately 70 projects per year.[2] During the most recent 12 months, however, a total of 160 projects have reportedly been carried out by the respondents.

The commercial applications of conjoint analysis have been broken down by product category to determine for which types of products and services the methodology has been employed by the survey respondents. Based on the results in Table 1, it appears that the majority of commercial applications involved consumer goods.[3] Also, consumer and industrial goods together account for more than 80% of the applications. There are no trends apparent in the category breakdown, as shown by the similarity between the percentages for the period since a company started using conjoint analysis and the figures reported for the most recent 12 months.

[2]This is a conservative estimate of the total number of projects. Considering nonrespondents and companies not contacted (including those in foreign countries), we project that around 1,000 projects have been completed as of 1981.

[3]Although the consumer goods category figures prominently in the frequency of usage of the methodology, this does not imply that conjoint analysis is more appropriate for such goods compared with other goods.

TABLE 1
Frequency of Usage of Conjoint Analysis by Product/Service Category

Category	Since Company Started	During Most Recent 12 Months
Consumer goods	429 (61%)	96 (60%)
Industrial goods	138 (20%)	33 (21%)
Transportation	25 (4%)	5 (3%)
Financial services	53 (8%)	6 (4%)
Government	18 (3%)	7 (4%)
Other services	35 (5%)	13 (8%)
Total	698	160

Project Purpose

In a given commercial application of the conjoint methodology, multiple objectives may be served. Green and Srinivasan (1978) mention the evaluation of new product or service concepts, consideration of alternative communication campaigns, and market segmentation among the objectives for applications in the private sector. From the survey we find that new product/concept identification was the purpose or one of the purposes in 72% of the projects (see Table 2). Perhaps somewhat surprisingly, pricing was mentioned second most frequently as an objective in 61% of the projects. Based on the survey responses, market segmentation was one of the objectives in 48% of the projects, and advertising was identified 39% of the time. The results were virtually identical if the responses for the most recent 12 months were used instead.

It should be noted that other procedures are available as well for the purposes discussed here. Specifically, several survey respondents mentioned that conjoint analysis is *not* used when the attributes used to define objects tend to be "soft." Thus, if the preference for an item is determined by perceptual dimensions and the perceptions are difficult or impossible to relate to physical attributes, conjoint analysis

TABLE 2
Percentage of Applications Involving Specified Purpose

Purpose	Percentage of Applications
New product/concept identification	72%
Pricing	61%
Market segmentation	48%
Advertising	39%
Distribution	7%

may not be a suitable methodology. Some respondents indicated that they do not use conjoint analysis when the number of attributes is large or when attributes tend to be highly correlated.[4]

Attribute Generation

One of the key assumptions underlying the methodology is that an individual's preference for an object can be decomposed into preference scores for components or characteristics of the object. If a main effects model is used, the preference score for a given attribute level does not depend on any other attribute. In order to gain insight into how preferences are determined and how the preferences for actual objects in the marketplace can be influenced, it is essential that considerable effort be expended on generating attributes. In a typical application (excluding applications involving computer interactive techniques), a set of attributes is defined prior to the collection of preference judgments.

In some applications, management may exclusively decide the set of relevant attributes. For example, in one study not covered by this survey, management was primarily interested in the influence of certain price variables relative to other dimensions, on the preference for subscription series of arts programs (Currim, Weinberg and Wittink 1981). In other cases, the set of attributes may be based more heavily on direct consumer input. In general, input from the target market as well as from management should be used. Thus the attributes should include those most relevant to potential customers and those which satisfy the managerial constraint (variables to be manipulated either in product design, pricing, communication campaigns or distribution efforts).

Every survey respondent mentioned that the client (i.e., management) was involved in the generation of attributes, as shown by the number of respondents indicating usage of "Expert judgment of client's personnel" in Table 3. Input from the target market is obtained through a variety of procedures, including group interviews and direct questioning of individual subjects. Only five respondents indicated that they used "protocols." However, these respondents tend to favor this procedure quite strongly, as indicated by the median rank value for this procedure.

Other procedures mentioned include the examination of alternative products/services available in the marketplace and in-depth interviews of individual subjects. The examination of existing items in the marketplace should not be relied upon exclusively, however. An advantage of conjoint analysis is the possibility of obtaining information about the influence of an attribute on preference, even when the existing items available in the marketplace do not vary on the attribute. For example, the available brands may be offered at identical prices. Yet this does not mean that price should be excluded as an attribute in the conjoint analysis project. It should be noted, however, that the other procedures may also be limiting in the sense that the attributes generated may reflect the variation in existing items rather than the potential impact an attribute has on consumer choice. In general, the generation of attributes and the amount of variation on a given attribute allowed for in the definition of hypothetical stimuli, should allow for the discovery of opportunities in the marketplace not otherwise evident. In addition, conjoint analysis can be used to obtain quantitative assessments of the market potential for new or modified products.

TABLE 3
Frequency of Usage of Alternative Attribute Generation Methods

Method	Number of Respondents Indicating Usage	Median Rank*
Expert judgment of client's personnel	17	2
Group interviews	15	2
Direct questioning of individual subjects	10	3
Kelly's repertory grid	7	3
Protocols	5	1
Other	3	3

*Based on "used most often" (1) to "used least often" and tabulated only for respondents who indicated that they used the method in question.

Model Specification

The most common model used by the survey respondents is the part worth model. In this model preference for an object is assumed to be an additive function of the values (worths) of its components (attribute levels). Companies that carry out only a limited number of conjoint analysis studies per year tend to rely exclusively on this model. In the vector model a continuous function is used to represent the influences of attributes on preference. For continuous functions an attribute should be measured on at least an interval scale. For example, price was mentioned by respondents as an attribute for which a continuous and often nonlinear function would be used to estimate the effect on preference. A quadratic function (Green and Srinivasan 1978, pp. 105–6; Pekelman and Sen,

[4]Some respondents have used conjoint analysis with a large number of attributes. The methodology can also accommodate correlated attributes. Such problems have been handled successfully in commercial and other applications.

1979a, 1979b) is an example of a continuous nonlinear function. Such a function can be used to approximate cases where preference is assumed to be monotone decreasing (increasing), such as for automobile preference as a function of miles per gallon. This specification can also be used for attributes that are of the ideal point type, such as the amount of sugar in a dessert.

Three of the survey respondents, one being a heavy user of the methodology, indicated that they use noncompensatory as well as compensatory models. A noncompensatory model may, for example, include a cutoff rule indicating that an object will not be considered at all if its specification on a given attribute is below a minimum level. Specifically, an individual may consider only medium sized automobiles no matter how attractive a compact might be on other characteristics. One survey respondent indicated that the specification of the (noncompensatory or compensatory) model would depend on the decision making structure, as identified in qualitative market research conducted prior to the collection of preference judgments. Of course, such a decision making structure may change as the nature of the available alternatives changes.

Another survey respondent uses a hierarchy of noncompensatory (threshold, disjunctive and lexicographic) and compensatory rules to approximate an individual's approach to determining preferences for alternative objects. One respondent indicated that the goodness of fit is usually higher for noncompensatory models compared with compensatory models. However, in a recent study Olshavsky and Acito (1980) found no significant difference in either internal or external validity between selected compensatory and noncompensatory models.

Some respondents are using recently developed modeling procedures that may be especially useful when the number of attributes is relatively large, such as componential segmentation (Green and DeSarbo 1979) and hybrid models (Green, Goldberg and Montemayor 1981). The hybrid modeling procedure includes direct ratings of attribute levels and of attribute importances.

Number of Attributes

Clients of the survey respondents appear to identify many attributes as being potentially relevant (up to as many as 50 attributes). However, there may be substantial overlap between the attributes initially identified. Thus a smaller set of attributes can be defined to capture much, if not all, of the initial set. Across all respondents the median number of attributes varies from 3 to 15, but for most respondents the median number of attributes actually used in conjoint analysis is 6 or 7. The number is kept relatively small, especially if the preference judgments are collected by means of the full profile approach. Individuals have difficulty evaluating objects defined on more than six attributes at a time because of information overload (Green and Srinivasan 1978).

Data Collection Procedures

The two main alternative procedures are the full profile or concept evaluation approach and the trade-off matrix or two factors at a time approach. Extensions or variations of these procedures (and issues related to data collection) are discussed by Green and Srinivasan (1978, pp. 107–9). We have summarized in Table 4 the relative frequency with which commercial applications completed by the survey respondents have involved alternative approaches. From this table it can be seen that a majority of the conjoint analysis applications has involved the full profile approach. The relative popularity of the full profile approach is especially pronounced if only the most recent 12 months are considered (69% of all applications) compared with the time since a company started using conjoint analysis (56% of the applications).

Eight survey respondents stated that they favor the full profile approach because it is more realistic, as exemplified by the statement, "It is the most realistic reflection of the choice environment." Other but less frequent reasons given in favor of this approach include speed, ease of administration, validity, interviewee convenience, flexibility in analysis and less respondent fatigue. The reasons given for the use of the two factors at a time approach include the ability to use many attributes, the speed with which the interview is completed, and the clarity of understanding of the task by respondents as well as by management.

It should be noted that the task of evaluating concepts becomes more complex as the number of attributes used to define the concepts increases. For this reason many researchers do not vary more than ap-

TABLE 4
Relative Frequency of Usage of Alternative Data Collection Methods

Method	Since Company Started	During Most Recent 12 Months
Full profile (concept evaluation)	56%	69%
Two factors at a time (trade-off matrices)	27%	13%
Combination of full profile and two factors at a time	14%	15%
Other	3%	3%

proximately six attributes in the set of profiles presented to an individual. Nevertheless, some survey respondents have used the full profile approach for applications involving substantially more than six attributes. However, usually special designs are used in such cases. For instance, a variation of the full profile approach can be used on two or more subsets of profiles defined on, say, six attributes, where some attributes are used in more than one subset (Green 1974). Moreover, as indicated earlier, some survey respondents have begun to use recently developed methods that involve alternative data collection approaches (e.g., Green, Goldberg and Montemayor 1981).

Interactive data collection procedures (Johnson 1980) are used by three of the survey respondents. Reasons given for the use of interactive approaches include speed of data collection, management interest, respondent interest, data quality and breadth of coverage. With interactive techniques the researcher has flexibility in varying the number and nature of the attributes as well as the specification of attribute levels across interviewees. Additional flexibility is obtained when the preference judgments requested at any particular stage in the data collection process depend on the preference judgments already provided by the individual. The consistency of an individual's judgments can be tested, and the interviewee can receive immediate feedback on his/her preferences. Furthermore, the arduous task of processing information from questionnaires is avoided.

Such interactive procedures are likely to become more popular as the technology required becomes more widely available, although the choice of interviewees is constrained unless the equipment needed to collect the information is portable and can be set up quickly in alternative locations. Respondent reaction to the use of computer interactive techniques appears to be favorable as indicated by the results of a study conducted for Xerox (MacBride and Johnson 1980). In this study, responses obtained through the electronic approach had higher predictive validity than a paper and pencil interview.

Methods of Presenting Stimuli to Interviewees

Verbal and paragraph descriptions of hypothetical objects are the most commonly used methods, as shown in Table 5. The survey respondents mentioned that these procedures are convenient, inexpensive and straightforward. Pictorial representations are also used, but typically in combination with verbal descriptions. Only on rare occasions does the set of objects involve actual products, presumably because the development of prototypes is frequently not feasible.

It should not be surprising that the method of presentation may affect the responses. Verbal and paragraph descriptions are subject to response biases resulting from the order in which attributes are presented (Johnson 1981). There is also some evidence that pictorial representations are more likely to produce configural processing of the information presented (Holbrook and Moore 1981).

TABLE 5
Relative Frequency of Usage of Alternative Methods of Presenting Stimuli to Respondents

Method	Since Company Started	During Most Recent 12 Months
Verbal descriptions	50%	46%
Paragraph descriptions	20%	23%
Pictorial descriptions	19%	17%
Actual products	7%	9%
Other*	4%	5%

*Other includes models or pseudoproducts.

Response Mode for Preference Judgments

Based on the answers provided for the period since a company started, a preference rank order of hypothetical objects was elicited more frequently compared with the use of rating scales. However, the difference in relative frequency of usage between these two response modes is minimal for the most recent 12-month period (see Table 6). Reasons provided by the survey respondents for using rank order judgments include ease of use, ease of administration, and a desire to keep the judgment task as close as possible to

TABLE 6
Relative Frequency of Usage of Alternative Response Modes for Preference Judgments

Response Mode	Since Company Started	During Most Recent 12 Months
Rank Order	45%	41%
Paired comparison	11%	5%
Rating scale	34%	39%
Other*	10%	15%
Variable Definition		
Preference	33%	44%
Liking	10%	8%
Intention to buy	54%	46%
Other**	3%	2%

*Other consists primarily of graded paired comparisons.
**Other includes actual purchase or order placement by respondents.

a consumer's usual shopping behavior. Rating scales are favored by some survey respondents because, it is claimed, the rating scales are less time-consuming for an interviewee and also because of interviewee convenience and ease of analysis.

Rating scales may not be practical when trade-off matrices are used to collect preference judgments. However, graded paired comparison judgments indicating the strength of preference for one object over another can be used instead, as shown by Johnson (1980). If rank order preference judgments are used, researchers should consider the possibility that the number of levels used for the attributes may have a systematic influence on the substantive results. Adjustments may be necessary before the results can be compared across attributes with varying numbers of levels (Wittink, Krishnamurthi and Nutter 1982).

The remainder of the results in Table 6 shows the relative usage of alternative definitions for the dependent (criterion) variable. "Intention to buy" is most frequently used, with "Preference" a close second choice, particularly if measured during the most recent 12-month period.

Alternative Estimation Procedures

The results in Table 7 suggest that regression analysis (and analysis of variance) is now the most commonly used estimation procedure, based on the survey responses for the most recent 12 months. This contrasts with the result that MONANOVA is the single most popular method during the period since the companies started using conjoint analysis. Note, however, that the "Other" category has the largest relative frequency. This category includes the PERMUTE algorithm and procedures consisting of a repertoire of methods (involving the identification of noncompensatory rules and the specification of decision-tree structures). None of the respondents indicated usage of LINMAP (Srinivasan and Shocker 1973) for parameter estimation, even though this technique was listed in the questionnaire as one of the possible procedures. We do, however, know that LINMAP has been applied commercially. Approximately 70 orders (half to the commercial sector) have been filled for this program (Shocker 1981). Based on the survey responses, there is a definite trend toward increasing use of techniques such as LOGIT and regression analysis. This trend may be related to the increasing usage of rating scales for the collection of preference judgments.

TABLE 7
Relative Frequency of Usage of Alternative Estimation Procedures*

	Since Company Started	During Most Recent 12 Months
MONANOVA	24%	22%
PREFMAP	3%	3%
LINMAP	—	—
Monotone regression	4%	5%
Regression/ANOVA	16%	28%
LOGIT analysis	10%	15%
Other**	48%	36%

*The percentages do not add up to 100 because some respondents often use more than one method for "convergence."
**Other includes the PERMUTE algorithm (an algorithm similar to MONONOVA) and a repertoire of methods that includes most of the above.

The substantive results obtained from conjoint analysis do not seem to depend very much on the specific estimation procedure. MONANOVA and regression analysis tend to provide similar results in terms of parameter estimates for both rank orders and rating scales (Carmone, Green and Jain 1978). This is probably due to the fact that MONANOVA suffers from local optimum solutions (Wittink and Cattin 1981, pp. 104–5). LINMAP is guaranteed to provide a global optimum. With simulated data, LINMAP outperformed MONANOVA, regression analysis and LOGIT, in terms of external validity, when rank order preference data were obtained from a dominant attribute model. On the other hand, for compensatory models with approximately normally distributed part worths for the attribute levels, the external validity was highest for regression analysis (Wittink and Cattin 1981). The comparisons are based on analytical procedures which in some cases have been updated. For example, Srinivasan has extended the linear programming procedure to include a "strict paired comparison" approach. He obtained higher predictive validity, in terms of the percentage of first choices predicted correctly, with this extension (Srinivasan 1981) than was obtained with the earlier version of LINMAP used in the study by Jain et al. (1979).

Other factors that may dictate or influence the choice of estimation procedure include the availability of software and the ability to constrain parameter estimates. For example, with functions that are expected to be monotone increasing (decreasing), simulation results indicate that predictive validity is improved if a quadratic or part worth function is constrained to be monotone over the range of attribute levels (Cattin 1981). With LINMAP such constraints can be introduced quite readily. Least squares procedures can also be adapted to accommodate such constraints.

Hybrid models have been introduced (Green, Goldberg and Montemayor 1981) to reduce the data required from an individual respondent. Interviewees

are first clustered based on self-explicated data. The preference judgments are used to estimate main effects and selected interactions at the segment (or aggregate) level. Ultimately, each interviewee's model is a weighted sum of the person's (individual) self-explicated model and a segment or aggregate conjoint model. Cattin, Gelfand and Danes (1981) recently proposed a simple Bayesian regression procedure to combine self-explicated data with an individualized conjoint model. Their analytical results indicate that the Bayesian procedure should outperform a procedure based on the individual preference judgments only. In either case, the idea behind the hybrid models is to augment, not to replace, the conjoint data. Self-explicated models by themselves appear to have lower external validity compared with the conjoint models (Cattin, Gelfand and Danes 1981; Green, Goldberg and Wiley 1981).

Reliability and Validity

The survey respondents indicated that they frequently obtain measures of reliability. The measures used include replications (i.e., asking interviewees to evaluate one or more stimuli twice, at different times), consistency checks and split half reliability measures.

With respect to validity, most of the survey respondents (11) indicated that they do obtain measures of validity, at least sometimes. Holdout stimuli or validation samples are used to compare actual and predicted preference judgments or to compute a cross-validated correlation (external validity). A few respondents check only the internal validity to eliminate data from interviewees "... whose data are not explainable by a model." The predictive validity is assessed occasionally through a comparison of an interviewee's preference ranking of brands available in the marketplace with the predicted ranking obtained from the individual's preference model.

The reliability of the results in an aggregate sense is influenced by the number of interviewees included in a study. This sample size is determined partly by the purpose of the study and the allocated budget. The summary results in Table 8 show that the sample size varies considerably across the survey respondents. The median sample size varies across the respondents from 100 to 1,000, although the median is in the 300 to 550 range for most respondents.

TABLE 8
Sample Size Used by Survey Respondents

	Mean (across respondents)	Median (across respondents)
High	2107	1200
Low	138	100–150
Median	466	500

Analysis of Conjoint Analysis Results

To summarize results to management and to identify promising marketing actions, the survey respondents carry out at least one of the following procedures:

- a market simulation, based on preference models estimated at the individual level, to predict market shares under various scenarios involving the introduction of a new product or modifications of an existing product (including changes in marketing mix variables);
- aggregation of preference judgments, and estimation of preference model parameters, at the segment level, or aggregation of individual level parameter estimates at the segment level;
- full aggregation of preference data across all interviewees.

To make market share predictions it seems advisable to use individualized preference models. Wittink and Montgomery (1979) obtained higher predictive validity for preference models estimated at the individual level than for segment based preference models. The segment based models, in turn, were more predictive of actual choice behavior, subsequent to the collection of data for conjoint analysis, than models estimated across all individuals. With respect to market simulation, special optimization procedures are available, such as POSSE (Green, Carroll and Goldberg 1981). Some survey respondents indicated they use such procedures.

However, it is not straightforward to make market share predictions based on conjoint analysis, for several reasons. (1) The conjoint models are based on preference or intent-to-purchase behavior, not on actual behavior. (2) There are likely to be attributes excluded from the models that may affect behavior in the marketplace. (3) The models should be extended to include the effect of mass communication, distribution effort and competitive reactions. (4) Perceptions of a product and its attributes may have to be modeled to incorporate the differences (links) between perceptions and objective or physical features included in the conjoint study. (5) New products may take several years to be developed and marketed, after which the nature of the competition may be different, and systematic changes in customer preferences may have taken place. Therefore, it is important to update the models or to determine how economic and other conditions influence the models' parameters.

It should be noted that even if market share predictions are made based on individualized models, the

results may also be summarized at some aggregate (i.e., segment) level to provide insight to management about the part worths of attribute levels for selected subgroups of potential customers. In this regard, Currim and Wittink (1980) have shown the equivalence of several alternative aggregation schemes when least squares analysis is used to estimate parameters. In a strict sense, however, the parameter estimates may not be comparable across individuals. At a more practical level, this difficulty is perhaps not severe. Researchers may, however, want to standardize the parameter estimates for each interviewee before making interpersonal comparisons.

A common way of summarizing results is to compute attribute importance weights, based on the conjoint analysis results, at the individual level and average these weights across individuals within a market segment. Usually, such derived importance weights are based on taking the difference between the parameter estimates of the most preferred and least preferred levels of a given attribute. In this manner, the importances reflect the amount of variation used for a given attribute in creating hypothetical objects. Furthermore, the importance of one attribute is measured relative to the importance of the other attributes used in the study.

Recent research results suggest, however, that the derived attribute importances may also reflect the number of attribute levels used in a study if rank order preference judgments are collected, even when the most and least preferred levels are held constant (Wittink, Krishnamurthi and Nutter 1982). Thus, if price is an attribute and a decision has been made to use as maximum and minimum levels $20 and $15, respectively, then the derived importance of price may be influenced by the number of intermediate price levels used to define hypothetical objects. This implies that the parameter estimates (e.g., part worths) may not be comparable across attributes. Hence, market share estimates may also be influenced systematically by the number of attribute levels (Wittink and Krishnamurthi 1981). We emphasize that this potential problem has been observed only for rank order preference judgments and not for cases when rating or other scales are used.

Implementation of Results

The survey respondents reported that the conjoint analysis results have had impact on concept (product) design, the selection of features for a new product, modification of existing products and pricing. A number of survey respondents expressed reservations about the extent of impact because ". . . it is difficult to assess the role of research in the final execution and implementation."

Unsolved Problems

The survey respondents mentioned the following aspects as problems that may require attention:

- the validity of the results (especially with respect to estimated market shares based on preference judgments for hypothetical objects);
- the number of observations needed for reliable estimation of parameters;
- how to handle a large number (i.e., more than eight) of attributes;
- how to deal with problems involving multiple decision makers, for example, industrial buying centers and family decision making;
- how to detect and incorporate interactions and nonlinearities in preference models; and
- the lack of "good software."

With respect to these points we note that the hybrid utility estimation approach advocated by Green, Goldberg and Montemayor (1981) is designed to incorporate selected interactions, estimated at the segment level. This approach can also accommodate a large number of attributes. A recent study by Krishnamurthi (1980) addresses the modeling of joint decision making situations.

Concluding Comments

Finally, we want to address a few other issues associated with conjoint analysis. Although the survey respondents did not specifically mention these issues, we feel that these points deserve additional thought. In informal discussions with other researchers, some of these points have been raised.

Of general concern is the question about the realism of the task required from interviewees. The trade-offs involved in comparing alternative hypothetical objects may seem quite unreal to individuals cooperating with a conjoint analysis study. If the preference judgments involve hypothetical objects representative of what is available in the marketplace, the interviewee may not have any difficulty providing realistic evaluations. If, on the other hand, the hypothetical objects differ dramatically from the actual objects (products) available, the task will be more demanding and the judgments may not be as representative of what an individual would actually do in a marketplace setting. If the quality of the preference judgments declines as the task for the interviewee becomes more artificial (i.e., less representative of choices available in the marketplace), then the applicability of the methodology may be severely limited. Conceivably then the results from conjoint analysis

if performed at some aggregate level may not differ dramatically from results that could be obtained through quantal choice models.[5] The main advantage of conjoint analysis would then consist of the opportunity to estimate models at the individual level based on an experimentally controlled set of objects.

Related to this issue is the ability and/or willingness of interviewees to provide accurate preference judgments. This problem is unique to conjoint analysis (and other survey research), as opposed to research such as quantal choice models which are based on revealed preferences. Interviewees who have agreed to cooperate with a study will differ on the degree to which they are devoted to providing accurate answers. If the preference judgment task is perceived to be an interesting one by an interviewee, we would expect greater accuracy compared with a task that is perceived to be uninteresting. For example, if an automobile manufacturer wants to select individuals to react to hypothetical automobiles, the manufacturer should take a sample from the target market. Individuals currently considering the purchase of a new car should be motivated and equipped to provide accurate preference judgments. However, such individuals may be reluctant to cooperate with a research study if they cannot distinguish the research from a sales pitch. Recent automobile purchasers do not have to worry about a possible sales pitch. Nevertheless, their motivation to provide accurate preference judgments is likely to be considerably lower. Researchers should pay careful attention to the problem of motivating interviewees.

[5]In quantal choice, the marketplace choice of an object is explained as a function of the object's characteristics across a set of customers, with limited opportunity to allow for individual heterogeneity in the parameter estimates. See Madansky (1980), Plott (1980) and Srinivasan (1980a) for comparisons of conjoint analysis and quantal choice models.

Consumer choice in the marketplace usually involves various perceptual dimensions as well as physical characteristics of alternative brands. The insight provided by the research results may be improved by explicitly incorporating perceptual dimensions. For an example of recent research involving the estimation of relationships between preferences, perceptions and physical features, see Hauser and Simmie (1981) and Holbrook (1981).

With respect to the selection of attributes, the use of brand name and price are somewhat controversial. Brand names may capture a number of aspects that may be covered separately by other attributes. As a consequence, conjoint analysis results for brand may be very difficult to interpret. Nevertheless, actual or perceived advantages associated with the brand name are relevant to the questions addressed in a conjoint analysis study. Similarly, price is controversial because interviewees may view price as an indication of product quality. For a discussion of issues associated with the use of price as an attribute, see Rao and Gautschi (1980) and Srinivasan (1980b).

Apart from these issues, we speculate that computer interactive techniques will receive increasing attention. This and other developments have been motivated, at least in part, by a desire to increase respondent motivation and to minimize respondent fatigue. There is also potential to integrate the effects of marketing mix and other (e.g., economic) variables with the results obtained from conjoint analysis. We also project increasing applications in industrial goods, although such applications require acceptable procedures for developing group preference models. We encourage commercial users to share their experiences with the marketing community so that the procedures can be adapted further and the effectiveness and efficiency of marketing research can be increased.

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