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FRANK HUBER
Editors

CONJOINT MEASUREMENT

Methods and Applications

Fourth Edition

Springer

Conjoint Measurement

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Frank Huber
(Editors)

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With 39 Figures and 68 Tables

Springer

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Foreword

by
Paul E. Green

I am honored and pleased to respond to authors request to write a Foreword for this excellent collection of essays on conjoint analysis and related topics. While a number of survey articles and sporadic book chapters have appeared on the subject, to the best of my knowledge this book represents the first volume of contributed essays on conjoint analysis. The book reflects not only the geographical diversity of its contributors but also the variety and depth of their topics.

The development of conjoint analysis and its application to marketing and business research is noteworthy, both in its eclectic roots (psychometrics, statistics, operations research, economics) and the fact that its development reflects the efforts of a large variety of professionals - academics, marketing research consultants, industry practitioners, and software developers.

Reasons for the early success and diffusion of conjoint analysis are not hard to find. First, by the early sixties, precursory psychometric techniques (e.g., multidimensional scaling and correspondence analysis, cluster analysis, and general multivariate techniques) had already shown their value in practical business research and application. Second, conjoint analysis provided a new and powerful array of methods for tackling the important problem of representing and predicting buyer preference judgments and choice behavior - clearly a major problem area in marketing.

In addition, the fortuitous confluence of academic research, practictioner application, and easy-to-use software (distributed by Sawtooth Software and Bretton-Clark) provided the necessary mix for conjoint's rapid acceptance by both the private and public sectors. The rest (as they say) is history.

Recent Trends

Conjoint analysis continues to expand in terms of models, techniques, and applications. Examples include:

Prescriptive modeling: the development of normative models for finding the product/service or line of products/services that maximize the firm's return.

- Dynamic modeling: the development of normative conjoint models for representing competitive actions and reactions, based on game theoretic concepts.
- Extension of earlier models to choice-based conjoint situations, incorporating multinomial logit and probit modeling.
- Latent class, hierarchical Bayes modeling, and constrained choice modeling.
- Other new models, such as individual-level hybrid modeling, Sawtooth's ICE model, and empirical Bayes applications.
- Applications in diverse areas, including the design of lottery games, employee benefits packages, public works (such as the New Jersey E-Z Pass toll road

system), hotel and time share amenities, gasoline station layouts, and legal issues dealing with misleading advertising, antitrust violations, etc.
- New choice simulators that include sensitivity analysis, composing and evaluating selected segments, computation of monetary equivalents of part worths, share/return optimization, including Pareto frontier analysis.
- New developments in full-profile experimental designs, including d-optimal designs, randomized balance designs, and Plackett-Burman design extensions.
- The coupling of conjoint analysis with virtual-reality electronic displays that simulate product arrays, store interiors, house, and furniture layouts, etc.
- The coupling of conjoint analysis with the perceptual and preference mapping of choice simulator results.

The preceding points are only illustrative of the diversity and ingenuity of conjoint researchers/practitioners. And, clearly, more is yet to come.

The Validation Problem

Researchers and practitioners should have (and generally do have) a healthy skepticism about the "latest developments" in conjoint modeling. Fortunately, this book of essays contains a number of model comparisons and cross validation studies. New models and application areas have proliferated over the past 30 years; it is still highly important to evaluate the host of new "whizzbangs" that invariably accompany a rapidly growing research area.

Our Indebtedness

This new book of essays, Conjoint Measurement - Methods and Applications, is a welcome addition to the conjoint literature. Its publication attests to the international character associated with the growth and diffusion of interest and research in conjoint analysis. While conjoint has reached a level of popularity and maturity that few of us in its early stages would have imagined, the methodology is still far from becoming moribund. This book is a fitting testimonial to the sustained interest in conjoint methods and the vigor and acuity of this international gathering of researchers.

In closing, it seems to me that we should all express our gratitude to those early scholars -- Thurstone, Luce, Tukey, McFadden, Addelman, Kempthorne, Lazarsfeld, to name only a few -- who planted the seeds that have led to such a bountiful harvest for marketing researchers. And to go back even further, let's not forget the good reverend, Thomas Bayes. Were he here today, I'm confident that this book would merit his blessings.

Paul E. Green
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1 Conjoint Analysis as an Instrument of Market Research Practice

Anders Gustafsson, Andreas Herrmann and Frank Huber

1.1 Introduction

The essay by the psychologist Luce and the statistician Tukey (1964) can be viewed as the origin of conjoint analysis (Green and Srinivasan 1978; Carroll and Green 1995). Since its introduction into marketing literature by Green and Rao (1971) as well as by Johnson (1974) in the beginning of the 1970s, conjoint analysis has developed into a method of preference studies that receives much attention from both theoreticians and those who carry out field studies. For example, Cattin and Wittink (1982) report 698 conjoint projects that were carried out by 17 companies in their survey of the period from 1971 to 1980. For the period from 1981 to 1985, Wittink and Cattin (1989) found 66 companies in the United States that were in charge of a total of 1062 conjoint projects. Wittink, Vriens, and Burhenne counted a total of 956 projects in Europe carried out by 59 companies in the period from 1986 to 1991 (Wittink, Vriens, and Burhenne 1994; Baier and Gaul 1999). Based on a 2004 Sawtooth Software customer survey, the leading company in Conjoint Software, between 5,000 and 8,000 conjoint analysis projects were conducted by Sawtooth Software users during 2003. The validation of the conjoint method can be measured not only by the companies today that utilize conjoint methods for decision-making, but also by the 989,000 hits on www.google.com. The increasing acceptance of conjoint applications in market research relates to the many possible uses of this method in various fields of application such as the following:

- new product planning for determining the preference effect of innovations (for example Bauer, Huber, and Keller 1997; DeSarbo, Huff, Rolandelli, and Choi 1994; Green and Krieger 1987; 1992; 1993; Herrmann, Huber, and Braunstein 1997; Johnson, Herrmann, and Huber 1998; Kohli and Sukumar 1990; Page and Rosenbaum 1987; Sands and Warwick 1981; Yoo and Ohta 1995; Zufryden 1988) or to
- improve existing achievements (Green and Wind 1975; Green and Srinivasan 1978; Dellaert et al., 1995), the method can also be applied in the field of
- pricing policies (Bauer, Huber, and Adam 1998; Currim, Weinberg, and Wittink 1981; DeSarbo, Ramaswamy, and Cohen 1995; Goldberg, Green, and Wind 1984; Green and Krieger 1990; Kohli and Mahajan 1991; Mahajan, Green, and Goldberg 1982; Moore, Gray-Lee, and Louviere 1994; Pinnell 1994; Simon 1992; Wuebker and Mahajan 1998; Wyner, Benedetti, and Trapp 1984),

- advertising (Bekmeier 1989; Levy, Webster, and Kerin 1983; Darmon 1979; Louviere 1984; Perreault and Russ 1977; Stanton and Reese 1983; Neale and Bath 1997; Tscheulin and Helmig 1998; Huber and Fischer 1999), and
- distribution (Green and Savitz 1994; Herrmann and Huber 1997; Oppewal and Timmermans 1991; Oppewal 1995; Verhallen and DeNooij 1982).

In addition, this method is increasingly used as an instrument of
- controlling (Green and Srinivasan 1978; Herrmann et al., 1999).

Another field of application using basic strategic decisions such as
- Market segmentation (Hagerty 1985; Akaah 1988; De Soete and Winsberg 1994; DeSarbo, Olivier, and Rangaswamy 1989; DeSarbo, Ramaswamy, and Chaterjee 1992; DeSarbo, Wedel, Vriens, and Ramaswamy 1992; Diamantopoulos, Schlegelmilch, and DePreez 1995; Gaul and Aust 1994; Gaul, Lutz, and Aust 1994; Green and Helsen 1989; Green and Krieger 1991; Kamakura 1988; Ogawa 1987; Steenkamp and Wedel 1991; Steenkamp and Wedel 1993; Wedel and Kistemaker 1989; Wedel and Steenkamp 1989; Wedel and Steenkamp 1991). A good overview for the different segmentation approaches provides Vriens (1995) and Vriens, Wedel, and Wilms (1996). Conjoint analysis can be of great use here.
- The method is further applied to simulate purchasing decisions with a focus on competitors' responses (Mohn 1991).

This brief overview may give the impression that the success of this method comes from the application to new areas, in the sense of a broadening of the concept. But this is only one side of the coin. Simultaneously, research has been initiated to deepen the knowledge in certain areas. We have particularly seen many contributions for finding the optimal price for a certain product. In this context, an important distinction in analyzing the price attribute is made by Rao and Sattler in Chapter 2. They differentiate between two functions of the price. Consumers use the price of a product both as a signal of product quality (informational role) and as a monetary constraint in choosing it (allocative role). In their paper, Rao and Sattler implement a conjoint based research approach to separately estimate these two effects of price. While in practice only the net effect of the two roles of price are usually estimated in any conjoint measurement approach or brand choice model, our methodology is able to separate the two price effects.

It is the goal of conjoint analysis to explain and predict preferences that result in an assessment of achievements. Various achievement profiles are created (both real as well as hypothetical ones) by varying specific attributes, and these profiles are to be evaluated by the test persons. The contributions (partial benefits) that the various attributes make to overall preference (overall benefit) are estimated on the basis of overall preference judgments as expressed by the test persons. Accordingly each product concept is assigned with a specific overall benefit value. Thus no attribute-specific single judgments are summarized to yield an overall judgment (compositional approach) but vice versa; the contributions of the various attributes or their manifestations are filtered out of the overall judgments (decompositional approach).

Although many people speak of 'the conjoint analysis', the number of methods understood by this term and their variants is considerable. What all these approaches have in common, however, is a flow diagram developed by Green and Srinivasan (1978) which is shown in an updated form in Figure 1; the order of typical variants has been approximately selected based on their decreasing importance for practical applications (Cattin and Wittink 1982; Wittink and Cattin 1989; Wittink, Vriens, and Burhenne 1994).

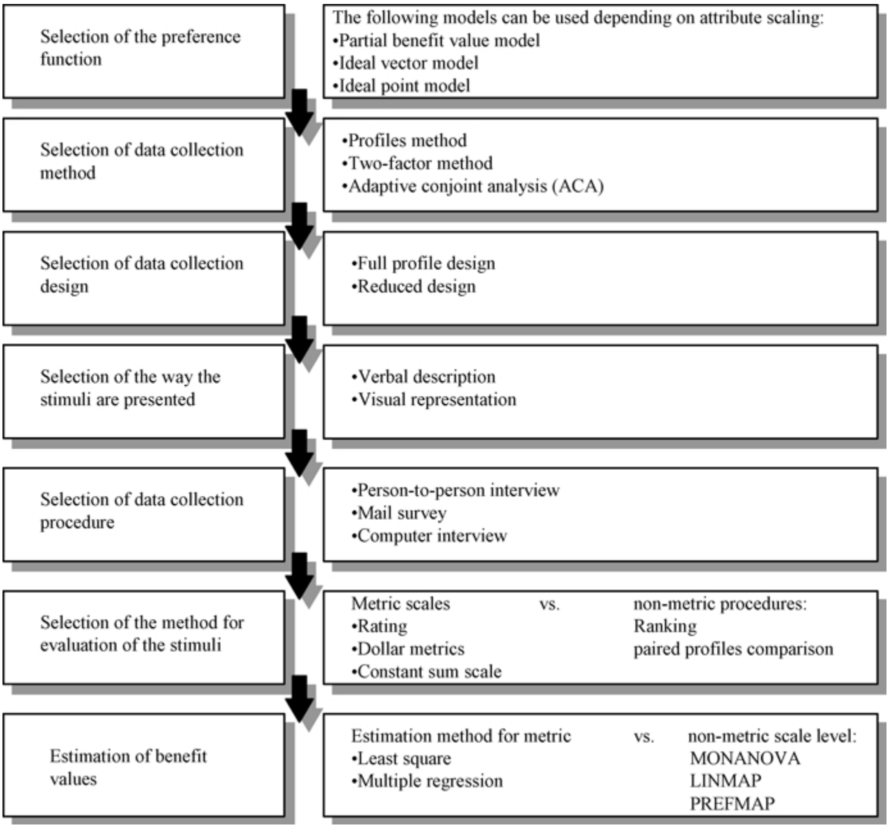


Figure 1: Flow diagram of conjoint analysis

1.2 Research areas and future development trends of conjoint analysis

1.2.1 A flow diagram of conjoint analysis

The various options regarding the flow diagram (see figure 1) of the process of analysis should be determined before carrying out a practical conjoint analysis (Green and Srinivasan 1978; Green and Srinivasan 1990; Vriens 1995). Although each step is suitable to reveal findings and future developments of the research areas, the individual steps are not carried out one after the other and decisions are not made independently. Furthermore, good conjoint research most likely occurs if the process is hypothesis driven. Each stage of the process should be used to approve or reject potential solutions to decision problems.

1.2.2 Data collection

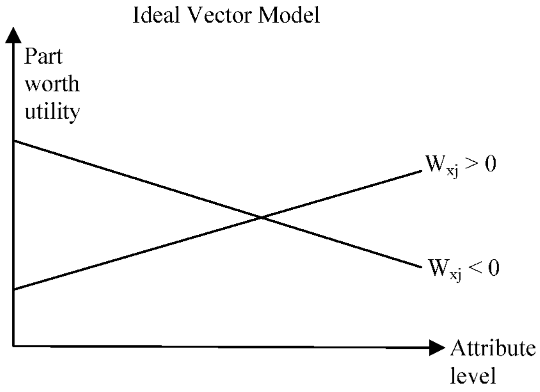
Selection of the preference function

The first step is the selection of the preference function based on which influence the defined attributes have on the respondents' preferences (other authors accentuate the relevance of the selection of the attributes and their levels in the first step, see Vriens 1995). This preference function therefore is the basis for determining partial benefit values for the respective attributes that reflect the preferences of the persons interviewed (Green and Srinivasan 1978; Schweikl 1985). The models that are most frequently used are the ideal vector model, the ideal point model, and the partial benefit model (See also Green and Srinivasan 1978; Vriens 1995).

When using the ideal vector model (see Figure 2) a proportional relationship is assumed between a partial benefit value and the manifestation of an attribute. This means that benefit increases ($w_{xj} > 0$) or decreases ($w_{xj} < 0$) with an increasing or decreasing manifestation of the attribute (Vriens 1995; Srinivasan, Jain and Malhotra 1983; Kamakura and Srivastava 1986; Allenby, Arora, and Ginter 1995).

If the ideal point model (see Figure 3) is used, the researcher assumes the existence of an ideal manifestation. The benefit value of a manifestation drops as soon as it falls below or exceeds the ideal point (Green and Tull 1982).

The partial benefit model (see Figure 4) is the most flexible of all three models and includes the ideal vector and the ideal point models as special cases (Green and Srinivasan 1978; Cattin and Wittink 1982; Louviere 1984; Wittink and Cattin 1989; Krishnamurthi and Wittink 1991; Green and Srinivasan 1990). This model does not assume a specific functional process and manifestations of attributes can only be interpolated if the scale level is metric.



Wxj: individual weighting of attribute x by respondent j

Figure 2: Preference value for various manifestations of attribute x while keeping the values of the other attributes constant

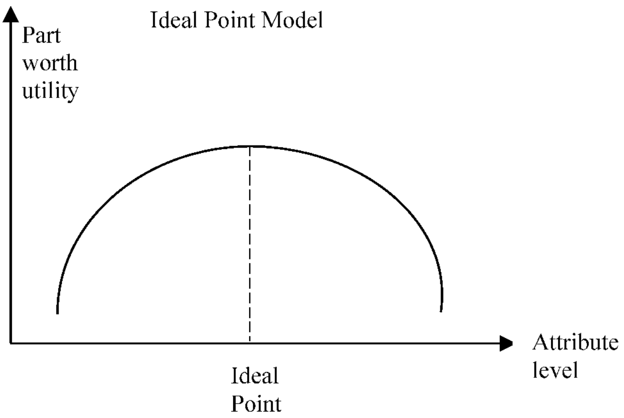


Figure 3: Preference value for various manifestations of attribute x while keeping the values of the other attributes constant

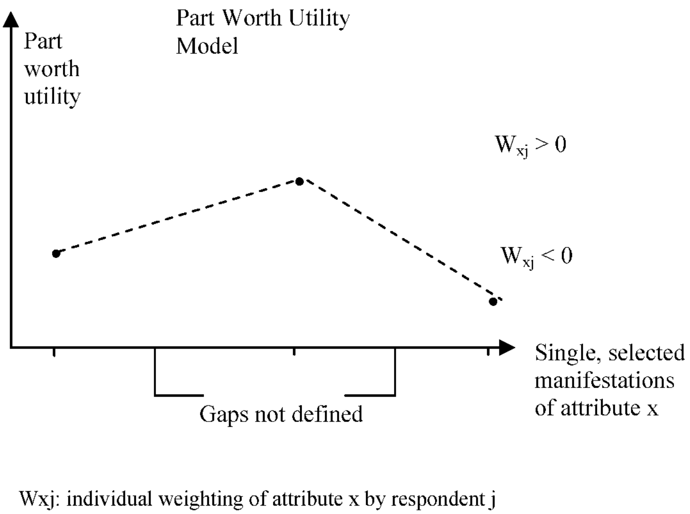


Figure 4: Preference value for various manifestations of attribute x while keeping the values of the other attributes constant

The partial benefit model is mainly used as a preference model for conjoint analysis (Green and Srinivasan 1978; Wittink and Cattin 1989; Cattin and Wittink 1982). A linking rule is required to distinguish between the overall benefit of the product alternative and the partial benefit values obtained using the preference function. In principle, two types of combinations can be distinguished. Unlike non-compensatory models, compensatory models evaluate all existing attributes in such a way that the low partial benefit of one attribute is compensated by an accordingly greater contribution to the overall benefit made by another attribute.

If the various manifestations of attributes are interpreted as independent (dummy) variables, the partial benefit model is formally identical to the ideal vector model (Acito and Hustad 1981; Mahajan, Green, and Goldberg 1982; Srinivasan 1979). The partial benefit model, however, provides greater flexibility for designing the attribute evaluation function. But this greater flexibility has a major setback that is not always properly taken into account in practical studies: the number of parameters to be estimated increases for a given number of test values. In contrast, the ideal vector model yields the smallest number of parameters to be estimated. The ideal point model ranges somewhere in between.

The studies by Cattin and Punj (1984), Srinivasan, Jain, and Malhorta (1983), Green and Srinivasan (1990), Krishnamurthi and Wittink (1991), and Hagerty (1986), for example, focus on the preference function to be able to make statements about the benefits of each model. Cattin and Punj state in their Monte Carlo study that a limited, special model (such as the ideal vector model) yields better predictions of preference values than a more general and flexible model (such as the partial benefit model). Here they agree in general with the recommendations given by Srinivasan, Jain, and Malhorta (1983). Krishnamurthi and Wittink (1991) compare the partial benefit model with three other model specifications. As a result of their study in the automobile sector, they advocate the assignment of a 'continuous function' (such as the ideal vector model) to attributes for which continuous progress is expected. In this context, it appears useful to pay increased attention to the ideal vector model (viewed critically Pekelman and Sen 1979). Baier and Gaul address this in their studies presented in Chapter 3. Their essay is based on the well-known probabilistic ideal vector model (De Soete and Carroll 1983; Gaul 1989; Baier and Gaul 1996). Deterministic points for alternatives and random ideal vectors for consumer segments are used for explaining and predicting individual choice behavior in a low-dimensional attribute space where the same model formulation is employed for parameter estimation and for market simulation. Moreover, it can be used to analyze data collected via the wide-spread ACA system. To compare the new approach with traditional counterparts they conducted a Monte Carlo study. Additionally, an application for the German mobile phone market is used to illustrate further advantages.

Selection of the data collection method

After a preference model has been selected, the next step is to determine the way in which the incentives are presented to the respondents for evaluation. Among the classic data collection methods of conjoint analysis are the profile (Green and Rao 1971) and the two-factor methods (Johnson 1974; for the paired comparison approach see Srinivasan, Shocker, and Weinstein 1973), which both have repeatedly been compared to the one-factor evaluation (for some critical comments about the one-factor-method, see Vriens 1995). Although the one-factor evaluation of the self-explicated approach (Huber 1974; Srinivasan and Wyer 1989) basically conflicts with the principle of conjoint analysis to trade-off factors of combinations of factors, conjoint researchers have dedicated numerous studies to this data collection strategy. One reason for this research is that one-factor evaluation has become an integral part of the frequently used adaptive conjoint analysis. Moreover, Huber points out that one-factor evaluation is superior to data collection methods traditionally used in conjoint analysis whenever multiple attributes influence the decision, when the demanders' expectations regarding attributes and manifestations of attributes of the objects selected are stable, and when alternative choices do not exert a major influence on the decision (Huber 1997). These statements were corroborated by the study of Srinivasan and Park (1997). Another proof that the self-explication approach should be considered in conjoint analysis is provided by Sattler and Hensel-Börner in Chapter 4. In their article they give a comprehensive overview of studies comparing the self-explicated approach and conjoint measurement. On the basis of a valuable comparison of several advantages as well as disadvantages of conjoint measurement and self-explication approaches, they discuss these two approaches in great detail. After this, a broad overview of empirical studies comparing the two approaches under consideration in terms of reliability as well as predictive validity shows the reader the state-of-the-art in that research area. Finally, they draw useful conclusions from their findings.

If the researcher decides in favor of the conjoint measurement and not the self-explicated approach he may choose between two methods of data collection. The **profile method** (synonyms are "full profile approach" or "multiple factor evaluation" (MFE), Green and Srinivasan 1978; Green and Tull 1982) describes the incentives to be evaluated by all K attributes considered. A full-profile description thus comes closer to a real buying situation (Green and Srinivasan 1978). Charts have proved their worth for representing incentives. The critical remarks by Wittink (1989) that this method was limited to approximately eight attributes requires qualification (e.g., Page and Rosenbaum 1989) as innovative forms of presenting incentives make it much easier for the individuals interviewed to carry out a preference evaluation.

The **two-factor method** (or "trade-off-analysis" or "two factor evaluation" (TFE) see Green and Tull 1982) reveals preferences for incentives only that are partially described by 2<K attributes (Mohn 1989). A typical feature of two-factor evaluations are trade-off matrices in which preferences have to be indicated in the associated matrix elements for all combinations of vertically or horizontally laid off manifestations of the two attributes considered. This approach has been criticized for being limited to ranking data (Wittink, Vriens, and Bruhenne 1994). This criticism must be qualified as well. It is true that Johnson (1974) introduced the two-factor evaluation explicitly for ranking data. However, it can easily be generalized for nearly any other evaluation scale that is common in conjoint analysis. It is a serious restriction of use, at least when using a polynomial linking function, that higher-order interaction effects cannot be taken into account (see Figure 5; Johnson 1974; Green and Tull 1982).

Two improvements of the traditional data collection methods have been used from the mid-1980s. An improvement of the profile method is called **hybrid conjoint analysis** (Green, Goldberg, and Montemayor 1981; Green 1984). It combines a direct (compositional) part of the survey in which the respondents have to give direct judgments about the importance of individual attributes, and an indirect (decompositional) part of the survey that represents the actual conjoint interview with selected combinations of attributes.

Adaptive conjoint analysis (ACA) is viewed as a modern form of the two-factor method (Johnson 1987). This method can provide a detailed analysis of the individual benefit structure of each respondent because the questions asked are adapted to previous answers in a computer-aided data collection process (Green and Srinivasan 1990).

Johnson (1974) initiated busy research activities focused on data collection methods (for a comparison of the approaches see Akaah and Korgaonkar 1983; Vriens and Wittink 1992). For example, Alpert, Betak, and Golden (1978; quoted from Green and Srinivasan 1978) and Montgomery, Witting, and Glaze (1977; quoted from Green and Srinivasan 1978) found that the two-factor evaluation had greater prediction validity. Segal (1982), however, agrees with Oppedijk van vee and Beazley (1977), Jain et al., (1979) and Rosko and McKenna (1983) that two-

The two attributes 'price' and 'warranty' are given. Please look at the manifestations of these properties and enter the number 1 into the combination you prefer most. Enter the number 2 for your second choice into one of the remaining fields. Enter the number 3 etc. for your next choices until all figures from1 to 9 have been used.

Evaluate all other pairs of attributes in this way.

			Warranty	
		6 months	12 months	18 months
	high			
Price	medium			
	low			

Figure 5: Example of a two-factor matrix

and multiple-factor evaluations are equal while profile evaluation had a slight advantage

According to a study by Safizadeh, the increasing popularity of the profile approach is due to the fact that multiple-factor evaluations have less problems resulting from overvaluation of single major attributes taken out of context than the other two approaches (Safizadeh 1989; Slovic, Fleissner, and Bauman 1972). Wittink, Vriens, and Burhenne (1994), however, have shown that since Adaptive Conjoint Analysis is gaining ground, a comparison of multiple-factor and ACA approaches would be of great interest. Finkbeiner and Platz (1986) as well as Agarwal (1988) found that the results in terms of precision of prediction are alike in these two approaches. This conflicts with the findings of studies by Huber et al., (1993).

As the number of attributes that could be integrated into a conjoint design increases with the development of the ACA or hybrid procedure, it makes sense to notice studies where these attributes are the object of interest (Pullman, Dodson, and Moore 1999). The studies recently initiated by Orme, Alpert, and Chistensen (1997) and Huber, Ariely, and Fischer (1997) that focus on semantic peculiarities of the attributes used in the profile method should particularly be noted here. Their findings indicate that an affirmative or negative presentation of items may influence the evaluation of alternatives. The loss aversion effect as known from descriptive decision theory could be proved (Kahneman and Tversky 1979; Tversky and Kahneman 1991).

Selection of the data collection design

In addition to the way in which the respondents are supposed to evaluate incentives, the number of incentives is of relevance. If the objective is to have all theoretically conceivable incentives evaluated, i.e., all combinations of attribute manifestations included in the study, this will be a **complete** (factorial) **design**. In view of data collection expenses (Pearson and Boruch 1986) and the risk of wearing out the respondents, it is important to keep the number of incentives to be evaluated to a minimum, though the number of incentives, i.e., the number of observations, should at least equal the number of parameters to be estimated. From an empirical point of view, S=30 incentives seem to represent an upper limit (Green and Srinivasan 1978).

It is also desirable to have the validation of preference models supported by significance tests for the parameters and ways of cross-validation. This, however, can result in technical data collection problems. Therefore, a **reduced design** is often preferred which attempts to represent the complete design based on a smaller number of incentives (Addelman 1962a; Addelmann 1962b; Green 1974; Green and Srinivasan 1978). There are basically two ways in conjoint analysis to reduce the number of incentives, which means to fractionate the complete factorial design. The easiest way called 'random sampling' consists of taking as many incentives out of the design by random selection as is required to reach the desired scope (Green and Srinivasan 1978). This approach, however, is not used in marketing research and practice. It is common to reduce the design systematically in such a way that orthogonality, i.e., the independence of the factors (attributes) is retained (Green, Helsen, and Shandler 1988; 1989; Moore and Holbrook 1990; and Steckel, DeSarbo, and Mahjan 1990 discuss the relative advantages of the orthogonal and non-orthogonalen Design). Depending on whether the manifestations of attributes are all equal in number or whether the number of manifestations varies between attributes, we distinguish symmetrical and asymmetrical types of fractionated factorial designs (for a brief introduction see Kuhnfeld 1997). The 7 base plans provided by Addelmann (1962a) have proved to be particularly helpful for constructing asymmetrical and symmetrical main effect designs.

As there is no independence of attributes in many applications of conjoint analysis, greater attention has been recently paid to data collection design that takes into account interaction effects. Hints regarding the construction of fractionated factorial orthogonal designs with as small a number of incentives as possible were given by Cochran and Cox (1957), Winer (1973), Shah and Sinha (1989), and Assmus and Key (1992). A further contribution in this research area is made by Blomkvist, Ekdahl, and Gustafsson in Chapter 5. In their paper they use a non-geometric design to generate the concepts. Non-geometric designs represent a class of orthogonal designs that when the assumption of effect scarcity is valid, i.e., that only a few of the attributes actually influence the respondents' preferences, provide an opportunity to analyze interactions between attributes as well as the attributes themselves. In this article the use of non-geometric Plackett-Burman designs for conjoint analysis is advocated. Also, a procedure based on restricted all subsets regression for taking advantage of the special characteristics of the non-geometric designs is proposed and demonstrated using data from a conjoint study performed on cellular telephone antennas in Sweden. Blomkvist, Ekdahl, and Gustafsson also conducted a Monte Carlo simulation to further illustrate the properties of the proposed procedure and the use of non-geometric Plackett-Burman designs for conjoint analysis.

Selection of the way in which incentives are presented

There are two ways to present the incentives defined in the previous steps (Vriens 1995; Green and Srinivasan 1978). When the presentation is verbal, the incentives can be presented on product information sheets using key words, descriptive sentences, or a combination of key words and explanatory sentences.

When the presentation is visual, graphic representation using drawings or photographs has to be distinguished from physical presentation (Wedel and Steenkamp 1991; Steenkamp and Wedel 1993) where real products or prototypes are used (Aust and Gaul 1995; Vriens et al., 1998; Page and Rosenbaum 1987; 1989). Each of these three ways has its advantages and disadvantages which Green and Srinivasan (1978 and 1990) describe in some detail (Vriens 1995). The extent to which the presentation of incentives determines the responses of the test persons is the focus of a study by Holbrook and Moore (1981). The object of study of these two authors is pullovers. Pullovers most certainly are products that must be visually experienced. They are appreciated for aesthetic elements rather than objective, rational ones. The verbal description caused the respondents to attach greater importance to the interaction of attributes. When they were presented as images, the main effect was dominant. Louviere et al. 1987, however, found no differences between the two ways of presenting incentives. A survey of other studies dealing with this highly interesting, though so far virtually unexamined, area can be found in Vriens (1995).

Selection of the data collection procedure

Respondents who take part in a survey make their statements depending on the way in which the incentives are presented - either in person-to-person interviews, in writing by mail, or using a computer (Vriens 1995). According to Wittink and Cattin (1989), surveys by telephone or mail are mainly used to ensure geographic representativeness. The telephone may even be helpful in improving the usually low return rates found with written polls in market research.

Levy, Webster, and Kerin (1983) combined both ways. They first contacted the respondents by telephone. If respondents were willing to take part in the survey, they would receive the survey documents by mail. Stahl (1988) reports a commercial use of conjoint analysis via ‘phone-mail-phone’ and proceeds like the two authors previously mentioned. After contacting the respondents by phone, the documents would be sent to them. Eventually, the interview and data collection would again be carried out by telephone. The results of this study are encouraging and indicate that conjoint analysis by telephone is an appropriate procedure for collecting preference judgments. Still, what the respondents are asked to do should not be too straining or take too long (Stahl 1988). Based on his years of experience with conjoint analyses, Cerro (1988) lists a number of items that determine the success of a written non-personal survey used for conjoint measurement. It includes elements such as a high training level of the respondents (Tscheulin and Blaimont 1993), a call in advance to ask for their cooperation, prompt delivery of the documents, giving a telephone number where to call for advice at any time, and one to three reminder calls.

In terms of computer-aided procedures Zandan and Frost (1989), report that the respondents have a distorted perception of the duration of the interview. When asked how much time they needed to answer the questions, the participants in the survey stated clearly shorter times than would be required.

Conjoint analyses, with the help of computers, require greater attention with a view to the growing popularity of the Internet. Not only financial reasons but also new ways of designing surveys, call for a more extensive use of this survey method. Although first results of conjoint analyses carried out on the Internet are now available, this field has been sparsely examined according to Witt (1997).

Selection of the preference rating scale

The scales to be used by respondents for evaluating the existing incentives can be divided into metric (Green and Krieger 1993; for the constant-sum-rating see Mahjan, Green, and Goldberg 1982; DeSarbo et al., 1982; DeSarbo, Ramaswamy, and Chaterjee 1992) and non-metric variants. Thus a metric scale level is assumed for rating scales, a non-metric scale level for rankings, and paired profiles comparisons.

When using a **rating scale** (the so-called rating method), respondents are supposed to grade the (subjectively) perceived benefit on a numbered scale. This scale, in principle, just allows the collection of ordinal, i.e., non-metric, data. It is assumed, however, that the respondents will perceive scale spacings as being similar given appropriate graphic representation, so that preference statements are used as metric data. It is considered a benefit, compared to **ranking scales** (the so-called ranking method), that the rating scale expresses the intensity of the preference (Stegmüller 1995). This cannot be determined using the ranking method; here as well, respondents are to evaluate the incentives based on their (subjectively) perceived benefit but the outcome is just an order of preferences. Such order may express the preference-worthiness of an incentive but does not result in metric (ordinal) preference data (Green and Srinivasan 1990).

In a **paired profiles comparison**, the interviewer confronts the respondent with two incentives (product profiles) at the same time, and the respondent has to decide which of the two (s)he prefers. It is a benefit of ordinal paired comparisons that intransitiveness in the preferences collected from the respondents can be detected. For example, a respondent who knows his or her preferences and is willing and capable to express them without making mistakes would say in a graded paired comparison using a rating scale of 11 that he or she prefers incentive A to incentive B by seven units, and incentive B to incentive C by eight units. Furthermore, incentive A is superior to incentive C by 15 units but this number of units is not available to the respondent on the scale. This difficulty of a limited scale is circumvented by so-called dollar metrics. The respondent would be asked after making his or her choice in a graded paired comparison: “How much more would you be willing to pay for this product compared to the one you did not choose?“

Many researchers have dealt with selecting a scale for recording preferences since conjoint research began. What was of major interest in this context was the question of which one of the various methods was most beneficial. Cattin and Bliemel (1978) compared rating and ranking surveys in a simulation analysis. But as they processed rating data using a metric estimation method (OLS) and ranking data using a non-metric method (MONANOVA), it is impossible to tell whether the results were influenced by the way in which the data was collected or by the estimation method.

The design by Carmone, Green, and Jain (1978) is more transparent. The authors found in their studies that rating scales will provide more accurate results than ranking scales if a great error variance can be expected. Scott and Keiser (1984) state the opposite after evaluating their own data from the field of capital investment goods. When the respondents evaluated the profiles based on a ranking, the predictive validity was greater compared to rating.

In Chapter 6, Huber, Herrmann, and Gustafsson also deal with a scale for recording preferences. As a result of studies carried out so far, they found that results obtained using the rating method do not significantly deviate from those obtained using ranking. The test designs chosen by the various authors do not allow a clear statement as to whether or not the two measuring approaches yield different conjoint results. Avoiding the mistakes in the research design that some of the studies made in this area, they analyzed a potential connection between the rating and ranking methods, as well as a new hybrid approach (consisting of rating and ranking).

An interesting aspect in recording preferences comes from Teichert and Shehu in Chapter 7. They have generated the evolutionary conjoint analysis. Evolutionary conjoint develops individualized, flexible designs with an especially high degree of consumer integration. Consumer evaluations directly influence the experimental design. They continuously influence the levels of each attribute in each of the successive generations. This is in contrast to adaptive design techniques, where the design input of respondents is restricted to the first step of the self-explicated tasks. The new model-free method of Teichert and Shehu is based on interactive evolutionary algorithms. Algorithms are based on the principle of "survival of the fittest" and provide robust solutions for large dimensioned optimization problems.

In Chapter 8, Elrod and Chrzan also focused their research efforts on the question of the best way for respondents to evaluate the profiles. Their method is to avoid the lack of information in choice data by supplementing these data with information about the extent to which the chosen alternative is preferred. Following this idea, Elrod and Chrzan consider two types of choice-based conjoint designs for two alternatives: one using ordinary full profiles and the other using partial profiles. Having indicated which of two alternatives they prefer, consumers then also indicate the extent of their preference for their chosen alternative. The authors provide answers to five research questions, where they focus on the question only if the extent-of-preference information increases the efficiency of choice designs.

1.2.3 Data analysis

Estimation of partial benefit values

To analyze the preference data collected in the previous steps, the partial benefit values will have to be estimated for all manifestations of attributes. The methods that are available for analysis will depend on decisions made to date in conjoint analysis (Vriens 1995). The type of preference model and the scale level of the preference data collected, in particular, provide the framework within which the market researcher can analyze data.

Conjoint analysis was originally limited to an ordinal scale level. Estimation algorithms had to take this standard into account. In recent years, however, the metric approach has increasingly replaced the traditional ordinal data level both in marketing research and practice. Therefore, the importance of non-metric algorithms declined. Non-metric algorithms include (Mazanec, Porzer, and Wiegele 1976) PREFMAP as developed by Carroll (1972), LINMAP as programmed by Srinivasan and Shocker (1973; 1977), and POLYCON by Young (1972). In contrast to these algorithms taken from multidimensional scaling, Kruskal (1965) developed a non-metric MONANOVA approach especially for conjoint analysis. Johnson (1975) designed his program with calculating partial benefit values in mind. With a metric scale level, however, the method used most frequently is a regular dummy regression analysis (Kruskal 1964a; Kruskal 1964b). The most important estimation techniques are MONANOVA, LINMAP, and OLS. In Europe, over 80% of all conjoint-studies used these estimators (see Wittink, Vriens, and Burhenne 1994).

The most important studies on the use of the various estimation algorithms were carried out by Cattin and Wittink (1976), Cattin and Bliemel (1978), Colberg (1977), Jain et al. (1979), Carmone, Green, and Jain (1978), Wittink and Cattin (1981), and Mishra, Umesh, and Stem (1989). Cattin and Wittink (1976) compared metric and non-metric procedures. As a result they found that metric approaches can be superior to non-metric ones. These results by Cattin and Wittink are confirmed in the study by Cattin and Bliemel (1978). More precisely, the two researchers prove the superiority of MONANOVA over OLS estimation for determinist data. The opposite, however, applies to stochastic data. Carmone, Green, and Jain (1978) varied five environmental conditions for each respondent that could influence the outcome of conjoint analysis. One such factor that varies is the estimation algorithm. The Kendall's tau measure of quality is nearly identical for a MONANOVA and a modified (metric) variance analysis. The study by Wittink and Catin (1981) yields a similar result. Mishra, Umesh, and Stem (1989) analyzed precision and the dispersion of parameter estimates in a simulation study with more than 2000 respondents. They compared the algorithms LINMAP, MONANOVA, and OLS while changing the preference function, the error variance of simulated respondents, and the research design. Their conclusion is as follows: if precision and parameter dispersion are equivalent for a researcher, the LINMAP method should be preferred. If precision is decisive and the variance of estimates is of lesser interest, however, the OLS method should be used. Jain et al., (1979) compared the algorithms MONANOVA, JOHNSON, LINMAP, and OLS based on empirical data. The authors found nearly similar results for all estimation procedures.

If partial benefit values are available, the immediate question is about the quality of the results. One measurement here is reliability and the other is validity. Reliability, for example, is in focus in studies by Acito, (1977; 1979) Cattin, and Weinberger (1980) Jain, Malhtra, and Pinson (1980) McCullough, and Best (1979) Parker and Srinivasan (1976), and Segal (1982) (further studies can be found in Vriens 1995). The external validity of the conjoint results was proved, for example, by Bateson, Reibstein, and Boulding (1987), and Green and Srinivasan (1990). The studies by Robinson (1980), Benbenisty (1983), and Srinivasan et al., (1981) should be noted as well. While Robinson identified the factors that are relevant for passengers when choosing an airline, Srinivasan et al., were interested in the selection of the means of transport for getting to work. In both cases the behavior predicted by the researchers is largely congruent with real behavior. Wittink and Montgomery (1979), and Montgomery and Wittink (1980) correctly predicted the selection of a university or high school, or the career decision of a university graduate, at a predictive probability of 63%. Srinivasan (1988) even arrived at a value of 69% while Krishnamurthi (1988) correctly predicted selections at 56-61% for various preference models based on the study by Montgomery and Wittink (1980). Wright and Kriewall (1980), however, only achieved 14% and 21% of correct predictions as to which university would be chosen.

Validity is also in the center of interest for Kamakura and Ozer (Chapter 9). The way Kamakura and Ozer generate knowledge in this field of research is to compare various conjoint models across their part-worth estimates based on actual behavior. Because they are comparing those methods across their part-worth estimates, they use a Multitrait-Multimehod (MTMM) framework to assess the relationships among the methods and the part-worth estimates. To test the relationships, the authors use both the traditional MTMM analysis and a direct product methodology.

Also highly valuable in this context is the work conducted by Louviere, Hensher, and Swait presented in Chapter 10. In their article they expand the domain of conjoint analysis techniques by placing them within the more general framework of random utility theory (RUT). Based on this theoretical playground, the analyst is now able to compare and test the models and model results more rigorously. The authors illustrated these ideas in three case studies that show that even simple RUT-based stated preferences (SP) experiments can yield quite complex models; complex SP experiments can also provide new and different insights into the behavior of the random component of utility.

Different approaches to analyzing such complex models are presented by Haaijer and Wedel in Chapter 11. In a brief but detailed way they first describe the general elements in conjoint analysis and the "classic" conjoint analysis approaches. Then the conjoint choice approach is discussed more extensively and an overview is given of recent conjoint choice applications in the marketing literature. Finally they suggest approaches that can be used to estimate a conjoint choice experiment, including the MNL, the Latent Class MNL, and MNP models.

These various models will be illustrated using an application to a conjoint choice experiment on coffee makers.

To minimize remaining uncertainty in parameter estimation, new methods for conjoint designs have been proposed (Arora and Huber 2001). The most spectacular are the polyhedral and the machine-learning approaches. They are presented in Chapter 12 and 13 by Toubia, Evgeniou, and Hauser and Giesen and Schuberth. Fast polyhedral methods use a special "fast" algorithm that constructs profiles / choice sets depending on a-priori information of previous judgment tasks. Polyhedral methods can be used for both metric-paired comparison questions in ACA and CBC. Machine-learning and fast polyhedral algorithms have made it feasible to adapt both metric paired-comparison and choice-based conjoint questions to each respondent. Such questions promise to be more accurate and customized to focus precision where it is most needed. The basic concept is that each conjoint question constrains the set of feasible part-worths. A researcher's goal is to find the questions that impose the most efficient constraints where efficiency is defined as maximally decreasing the uncertainty in the estimated part-worths.

In Chapter 14 Dellaert, Borger, Louviere, and Timmermans present a new kind of estimating model. In their paper the four authors develop an experimental design heuristic to permit the estimation and testing of a proposed heteroscedastic extreme value model of modularized and traditional consumer choices. With this new way to design conjoint choice experiments the marketing researcher will be able to give an answer to the question of how consumer choices to package or bundle separate components differ (if at all) from choices among traditional fixed product options. To calculate the model parameters, separate MNL models were estimated from the choices in three experimental sub-designs. After this a heteroscedastic extreme value model was estimated by pooling data across all three sub-designs, and allowing for different random components in each. With this approach, differences in random components among the three conditions can be estimated independently.

Aggregation of utilities and market simulation

The estimation of the partial benefit values which takes place within the framework of the conjoint analysis serves to determine the individual attributes that contribute towards a preference. Usually, however, the attention of theoreticians and those who carry out field studies is focused on gaining an insight into the typical reactive behavior of a large group of consumers, rather than the specific behavior of individuals.

The hierarchical cluster methods (Green and Srinivasan 1978; Green and Krieger 1991) are used most frequently to classify respondents on the basis of normalized, individual, and partial benefits. The sequential use of a hierarchical and a partitioning technique is proposed by Punj and Stewart (1983) (for an application of overlapping partitioning methods see Hruschka 1986 and for an overview of different approaches see Vriens 1995). Problems are often encountered, however, when this technique is used. In our opinion, the fact that the different methods for determining the partial benefit values produce divergent results makes it more difficult to classify demanders. The objective function of the widespread OLS method, for example, minimizes the squared deviations of the estimated, metric stimulus benefits from the observed stimulus ranks. Conversely, LINMAP, another technique for measuring the partial benefits, minimizes the degree to which the observed and estimated rank orders are violated by means of linear programming. This objective criterion does not measure the benefit differences between pairs of ranks, providing the estimated benefit values coincide with the observed order. The calculated estimate, and thus also the clusters that are formed, is consequently dependent on the applied solution method.

The estimated partial benefits are moreover characterized by their relative unreliability. This characteristic can be attributed to the reduced factorial design that is normally applied for conjoint analyses. The limited number of degrees of freedom that are available for calculating the parameters on the level of individuals in turn affects the reliability of the estimates. Poor data reliability may lead to classification errors (Vriens, Wedel, and Wilms 1996).

Another disadvantage is the possibility of "linking", i.e., if the variables that are taken into account in the study fail to differentiate clearly among the classes, the outcome is one large cluster containing the complete set of study objects (Everitt 1980). The large number of cluster methods that must be applied also proves problematic when it comes to forming classes. Hierarchical cluster techniques, such as single linkage, complete linkage, centroid cluster analysis, Ward's method, McQuitty's method, and the approach developed by Lance and William, tend to produce different results (Hartigan 1975). In addition, there are various ways of standardizing the data prior to the actual respondent classification procedure. The classification result is also influenced by the choice of method.

A further argument against the use of two-step classification methods is that two different objective criteria are optimized during the course of the calculations they entail. For example, whereas the objective of the first step is to minimize the squared deviations of the estimated metric stimulus benefits from the observed stimulus ranks by means of an OLS regression, Ward's algorithm maximizes the ratio between the inter-group variances and the intra-group variances of the individual coefficients.

In recent conjoint analysis applications designed to facilitate benefit segmentation, the segment-specific partial benefit values and the segmentation are estimated simultaneously rather than sequentially (DeSarbo et al., 1989; De Soete and DeSarbo 1991; Ogawa 1987; Wedel and Kistemaker 1989; Wedel and Steenkamp 1989). Baier and Gaul (1995) propose a modified best-approximation method for estimating the model parameters - the segmentation and the segment-specific partial benefit values.

Ramaswamy and Cohen in their article (see Chapter 15) reviewed and presented applications of the basic framework of latent class conjoint analysis, for both metric conjoint and choice-based conjoint situations. They noticed that given the problems with the tandem approach to segmentation in traditional metric conjoint and the difficulty of obtaining individual-level coefficients in the choice-based conjoint context, LSMs have proved to be a boon to market researchers. To show the strength of LSM, the authors have focused in their applications on simultaneous segmentation and prediction. Their outlook on further research areas is also remarkable.

A substantial improvement in clustering is the flexible approach to the segmentation of markets involving conjoint analysis called NORMCLUS employing various methods in combinatorial optimization, developed by DeSarbo/DeSarbo (Chapter 16). Their general approach accommodates multi-criterion objective functions, alternative types of clustering respondents, model or profile based segmentation schemes, constraints on coefficients, and constraints on segment memberships, etc. to adapt to the specific needs of the particular segmentation application being addressed. A variety of combinatorial algorithms are accommodated including genetic algorithms, simulated annealing, and various heuristics which are selected according to their efficiency in dealing with the structure and goals of the application at hand. The authors demonstrate the flexibility and practicability of their approach to develop a new industrial cleaner.

Knowledge of the benefit segments, however, is not the only important aspect in management decision-making processes. The extent to which changes in market shares can be brought about by modifying products or by altering the added values, for example, is also relevant. Depending on the object of the study various models could be used such as the first choice model, the Bradley-Terry-Luce model, the logit model, or the simulated probit model to transform the acquired partial benefits into choice decisions and thus to determine market shares (Vriens 1995). As the study conducted by Finkbeiner (1988) demonstrated, the first choice approach is the most suitable of all the previously mentioned choice models for predicting market share estimates. The findings obtained were refined on the basis of the study by Elrod and Krishnakumar (1989), and Davey and Elrod (1991). The studies revealed the advantages of first choice modeling when high-involvement products are the object of an investigation.

In Chapter 17, Huber, Orme, and Miller focus on choice simulators. They propose that effective choice simulators need three properties to effectively mirror market behavior. First, they need to display differential impact so that a marketing action at the individual or homogeneous segment level has maximal impact near a threshold but has minimal impact otherwise. Second, simulators need to reflect differential substitution, assuring that alternatives take proportionately more share from similar than dissimilar competitors. Finally, they need to exhibit differential enhancement, a property whereby a small value difference has a large impact on highly similar competitors but almost no impact on dissimilar ones. A new method that Huber, Orme, and Miller call Randomized First Choice enables simulators to closely match these properties in market behavior.

In the last Chapter (18), Whitlark and Smith focus on simulating and forecasting data on the basis of part-worth utilities. To be accurate, sales forecasts based on conjoint data should take into account possible competitive reactions, changes in product awareness and availability, and other marketplace realities such as varying usage rates and repurchase rates that unfold over time. The purpose of the article is to outline how sequential game theory and the macro-flow model can be applied to more accurately fit these assumptions when estimating market share and forecasting product sales.

1.3 Further Research

Despite many developments which have already taken place in conjoint analysis, many issues and new approaches to data collection or data analysis could be investigated. It is beyond the scope of this introduction to summarize all of them. In brief, we would only like to highlight some avenues which seem underdeveloped.

With regard to the process of data collection, one research topic is the further investigation of the use of photo-realistic pictorial representations for certain product categories. This field is becoming more relevant because new media, computer technology, and software packages in the meantime allow the use of visual stimuli. Furthermore, another fundamental message is that context still matters. The context within which judgments are made affects the utility structure that results from the analysis of those judgments, regardless of the conjoint method being used. Developing this area in more detail has the advantage that with the results, one should be able to match the context with the method used to estimate outcomes for the real world. In conjunction with the context, there is another interesting field of research. The area of conjoint analysis would benefit from research that can identify if and when bias actually occurs in model parameters, as well as if and when error variability is sufficiently large enough to offset gains from additional information per person. That is, in the absence of bias, more observations per person lead to higher statistical efficiency. In the case of choice experiments, evidence suggests that humans interact with experiments in such a way that more observations per person decreases choice consistency, which in turn decreases statistical efficiency.

In terms of the process of data analysis, more research is needed to investigate the relative capability of the various conjoint segmentation methods to recover the true segment structure (Vriens 1995). Research in this area is important, because on the one hand one-to-one marketing is too expansive and on the other hand the demand side is becoming more heterogeneous.

Little has been published in the way of formal tests to determine whether or not conjoint works in predicting significant real-world actions (Orme, Alpert, and Christensen 1997). As ancillary cases, there are interesting questions of whether or not one method works better than another, and under what circumstances each method should be preferred. Pioneering work in that area comes from Joel Huber (1997), but more meta-analysis is required.

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2 Measurement of Price Effects with Conjoint Analysis: Separating Informational and Allocative Effects of Price

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2.1 Introduction

One of the most frequent purpose of conjoint analysis is the measurement of price effects (Wittink and Cattin 1989; Wittink, Vriens, and Burhenne 1994). Usually this is be done by describing a number of product alternatives on a small number of attributes, including price, and collecting some kind of preference data for these product alternatives. From the estimated part-worth function for price one can infer price effects (Srinivasan 1979).

A particular problem of this approach is that the role of price often is restricted to its function as a monetary constraint in brand choice. However, it is well known that prospective buyers use price of a brand both as a signal of quality as well as a monetary constraint in the brand choice (Erickson and Johansson 1985). These two distinct roles of price in the consumers' evaluation of alternative offerings in the marketplace can be labeled as the informational (signal) role of price and the allocative (constraint) role of price. While these roles are conceptually distinct, their measurement using conjoint analysis becomes confounded owing to the difficulties of distinctly modeling the two effects of price. In practice, only the net effect of price is estimated.

In a meta-analysis study of price elasticity covering 367 products Tellis (1988) uncovered about 50 products where the estimated price elasticity is greater than zero; given the fact that effect of price on sales (or aggregation of individual choices) is the net result of both informational and allocative effects, it is conceivable that for these 50 products, the informational effect may have dominated the allocative effect. Further, the price elasticity was between 0 and –1 for an additional 40 products possibly indicating that the magnitude of the allocative effect exceeded that of the informational effect.

The lack of a distinction between these two price effects can be seen in the different views of price in the literature. The economic theory of consumer behavior (Nagle 1984) and the research on hedonic prices (Rosen 1974) focuses on the allocative role of price, whereas the stream of marketing research investigating the relationship between price and quality (Olsen 1977; Monroe and Dodds 1988; Dodds, Monroe, and Grewal 1991) largely focus on the informational effects of price.

The fact that price may convey some information on quality had been already acknowledged by Scitovsky (1945). Since then, more than 90 studies examined the relationship between price and perceived quality (see Gardner 1977; Rao 1984