Vithala R. Rao

Applied Conjoint Analysis

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To the memory of esteemed Professor Paul E. Green, founder of conjoint analysis methods, a revered scholar, a wise advisor, and a dear friend.

Preface

I started this project some 10 years back; Professor Paul Green assisted me in the early phase of this work.

During the last 5 years or so, there have been several interesting developments in the conjoint analysis methods and models, notably incentive-aligned methods. I attempted to incorporate these yet keeping the basic thrust of the applied nature of this work. New methods appear on an almost daily basis. It is rather difficult to keep the coverage current. But, I tried to be up to date as much as feasible.

My intent is to bring various conjoint analysis methods to a level understandable to students and practitioners without losing rigor. As I ventured on this book, I soon realized how vast this field had become. Selection of topics and illustrations has become a difficult task. Nevertheless, I hope that this book presents an array of applications in marketing in a reasonably comprehensive manner. The edited book by Anders Gustafsson, Andreas Herrmann, and Frank Huber, *Conjoint Measurement: Methods and Applications*, Fourth Edition, Springer, 2007, in particular will be a good complement to this work. I wish that I was able to devote space to various behavioral aspects of choice.

I am grateful to several people in helping me make sure that this work is of a high caliber. These include two anonymous reviewers of my early versions and several colleagues such as Olivier Toubia and Oded Netzer of Columbia. My thanks are due to Abba Krieger of the Wharton School whose encouragement provided the necessary impetus to complete this work. Seenu Srinivasan of Stanford gave me early access to his paper on adaptive self-explicated method. Young-Hoon Park of Cornell gave me early access to his paper on barter conjoint, which is covered in Chap. 9; he also was a sounding board for ideas on organizing materials in Chap. 3. Sundar Balakrishnan of the University of Washington, Bothell, kindly reviewed the material on genetic algorithms for product design. Steve Gaskin graciously reviewed the material on legal applications covered in Chap. 8. Wes Hutchinson of the Wharton School kindly shared his working paper on self-designed products. Carolyne Saunders, a doctoral student in marketing at Cornell University, carefully read this volume and made several suggestions to enhance clarity. Yu Yu of Georgia State University helped with the analysis reported in Chap. 4. Chang Hee

Park of Binghamton University assisted me with the WinBUGS analysis reported in Chap. 4.

I am grateful to Brian Orme of Sawtooth Software for giving me access to their versatile software, which now includes several newer methods, not all of which are discussed here.

I appreciate *Marketing Letters* for allowing me to reproduce a paper written based on the 2008 Choice Symposium as a supplement. This paper, published in this journal (Vol. 19, December 2008 issue), gives a contemporary view of where conjoint methods stood a short while back.

I thank Christian Rauscher, editor from Springer, for his patience with the completion of this volume. Finally, I thank Saroj Rao for her help and patience throughout this project.

December 2013 Vithala R. Rao
Ithaca, NY

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Problem Setting

1.1 Introduction

1.1.1 Marketing Decisions and Role of Consumer Choice

Several interdependent decisions are involved in the formulation of a marketing strategy for a brand (of a product or service). These include not only decisions about the product's characteristics but also its positioning, communication, distribution, and pricing to chosen sets of targeted customers. The decisions will need to be made in the wake of uncertain competitive reactions and a changing (and often unpredictable) environment. For a business to be successful, the decision process must include a clear understanding of how customers will choose among (and react to) various competing alternatives. It is well accepted in marketing that choice alternatives can be described as profiles on multiple attributes and that individuals consider various attributes while making a choice. While choosing, consumers typically make trade-offs among the attributes of a product or service. Conjoint analysis is a set of techniques ideally suited to studying customers' choice processes and determining tradeoffs.

Conjoint analysis is probably the most significant development in marketing research over the last 30 years or so. Since its introduction to marketing research in 1971 (Green and Rao 1971), it has been applied in several thousand applied marketing research projects. The method has been applied successfully for tackling several marketing decisions such as optimal design of new products, target market selection, pricing a new product, and competitive reactions. A significant advantage of the method has been its ability to answer various "what if" questions using market simulators; these simulators are based on the results of an analysis of conjoint data collected on hypothetical and real choice alternatives.

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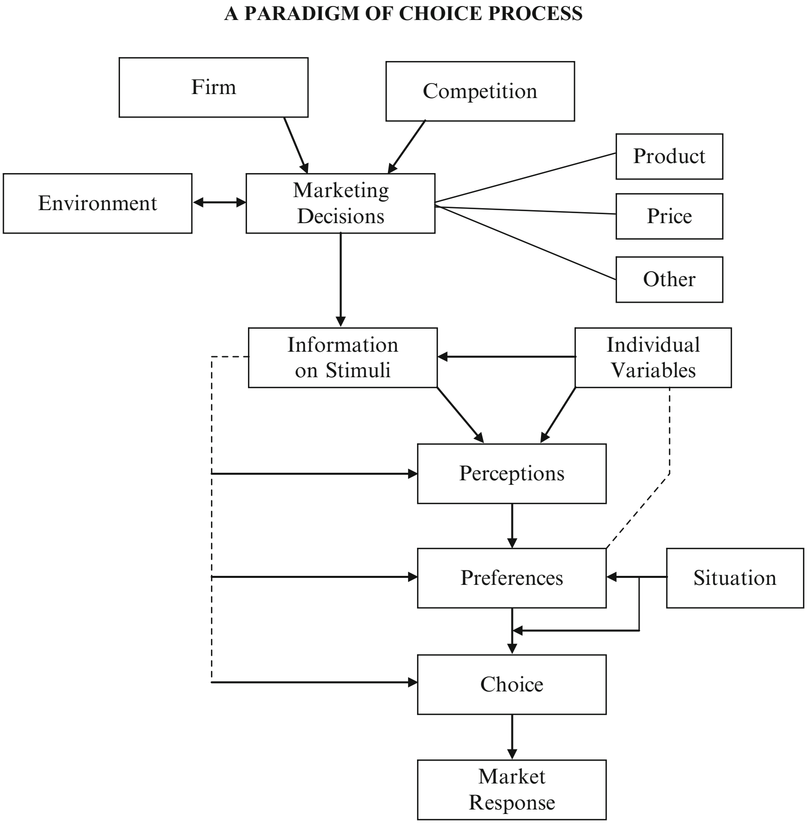

Fig. 1.1 A paradigm of choice process

1.1.2 A Framework for Understanding Consumer Choice

Established methods of marketing research are often used in developing an understanding of consumers' choice processes. A marketing research study involves the study of consumer perceptions, preferences, and choices in a set of choice situations. A streamlined view of how various consumer behavior constructs are related is shown in Fig. 1.1. Beginning at the top of the figure, a marketing manager makes decisions about her brand in light of the information gathered from the environment. According to this view, a consumer assimilates the information across all (considered) alternatives and forms perceptions about the choice set. These perceptions form the basis for preferences toward the alternatives; one should note that both the perceptions and preferences can be idiosyncratic to the individual. Stated differently, this paradigm incorporates individual heterogeneity in the way information on alternatives is assimilated by the individuals. The next stage in this process is the way preferences get translated into choices; it is an individual's preferences which form the basis for choices in the marketplace. An individual's preferences will naturally be modified by characteristics of the choice situation (e.g. choices made for one's own consumption or for a gift, changes in one's income and so on). Finally, aggregation of the choices by all potential consumers will lead to a prediction of the overall market response (e.g., sales of an item).

1.2 Origins of Conjoint Analysis

While the foundations of conjoint analysis go back to at least the 1920s, it is generally agreed that the seminal paper by Luce and Tukey (1964) on the theory of conjoint measurement formed the basis for the applied field of conjoint analysis. The development of the field was aided considerably by the proliferation of algorithms for the computations involved.

Conjoint measurement is concerned with determining the joint effect of levels of two or more attributes of stimuli on the total evaluative judgments of a set of stimuli (see Rao 1977 for a review of conjoint measurement in marketing analysis). The objective is to decompose the total evaluation into component scores, imputable to each attribute level or combination of attribute levels. The theory is concerned with the conditions under which there exist measurement scales for both the evaluative score (dependent variable) and each attribute level (independent variables), and a pre-specified composition rule. All are based on formal axiomatic system formulated by Krantz et al. (1971), including the axioms of consistency, transitivity, and attribute independence. The evaluative score can be categorical, ordinal or interval-scaled. For example, consider an individual's evaluation of a pair of running sneakers described on two attributes of price and quality (e.g., $70 per pair and medium quality); these responses can be categorical (e.g. suitable for serious young runners, for casual young runners, or for retirees), ordinal (e.g., very good, good, bad or very bad value for money), or interval-scaled (e.g., a rating on a 10 point scale on value for money). With such evaluation scores of price and quality on a number of profiles, an analyst can develop a utility function for the individual. Calling the functions for price and quality v_p, and v_q respectively (called partworth functions), the composite specification for the evaluation can be additive as $a*v_p + b*v_q$ or polynomial as $a*v_p + b*v_q + c*v_p*v_q$ or some other formulation. The axioms enable the analyst to choose the appropriate specification.

In the course of implementing conjoint measurement methods to applied business problems, such as those encountered in marketing, the emphasis on theoretical aspects of measurement has given way to the more pragmatic issues of design of studies and analysis of data. This is due to various intricacies in testing[1] whether the axioms are satisfied in the data collected. The testing procedures require extensive data and are highly complicated even for a small number of respondents. This process became frustrating for applied researchers.

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[1] See Corstjens and Gautschi (1983) for detailed methods for testing these axioms.

The methodology that has evolved to handle these problems is popularly called "conjoint analysis" to reflect the stated distinction. Conjoint analysis refers to any decompositional method that estimates the structure of a consumer's preferences[2] in terms of the levels of attributes of the alternatives. The methodology quite heavily uses statistical experimental design and parameter estimation methods.

Conjoint analysis is quite closely related to other developments in Information Integration Theory and its associated method of Functional Measurement (Anderson 1970). The functional measurement approach involves the use of analysis of variance (ANOVA) methods for problems of information integration. These methods have been applied in a variety of contexts dealing with understanding and modeling the process of judgment and groups including Social Judgment Theory and its related method of Policy Capturing.[3] Early applications in psychology were concerned with the modeling of clinical judgments (Dawes and Corrigan 1974), which basically involved estimating a multiple regression model between the overall judgments of an object and its characteristics (for example, relating the characteristics of a job candidate to a job in a company).

Thus, the conjoint analysis approach is decompositional in nature as contrasted with the approaches of Fishbein (1967) and Rosenberg (1956) which are compositional or buildup methods. The compositional approaches were popular in marketing research in the 1970s and 1980s. In these methods,[4] the overall attitude (or preference) towards an object is expressed as a weighted sum of the importance of attributes and the scores of the object on various attributes. This formulation is utilized in the self-explicated methods of conjoint analysis (described in Chaps. 2 and 5). Further, the self-explicated methods can be integrated in some of the models by which conjoint analysis is implemented in practice (e.g., the hybrid modeling approach); we will describe these in Chaps. 2 and 3.

The methods of conjoint analysis are quite distinct from those of multiattribute utility estimation developed by Keeney and Raiffa (1976). This approach derives the utility function deductively from a set of assumptions and the parameters of the function are obtained from tradeoff judgments and from preferences for alternative gambles. The theory is normative as opposed to that in conjoint analysis which is descriptive (or paramorphic). Further, the data collection procedures needed for estimating these multiattribute utility functions are quite complicated and tedious. Accordingly, these methods are not used much in marketing studies.

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[2] This method is quite similar to preference analysis in multidimensional scaling which focuses on estimating the ideal points for or weights on perceptual dimensions. These functions will be described in Chap. 2.

[3] A computer software called Policy-PC offered by the Executive Decision Services, Albany, NY allows for a menu of utility functions.

[4] See Wilkie and Pessemier (1973) for a comprehensive review.

1.3 Some Terminology

It will be useful to differentiate between two terms that are encountered in conjoint analysis. These are: product characteristics and product attributes. In general, "characteristics" are objectively measured descriptors of a product while "attributes" are subjective assessments of a product. For example, with respect to a chocolate, the amount of sugar in a chocolate of a given size is an objectively measured characteristic while the judgment of how sweet the chocolate is the attribute of "sweetness". Conjoint studies can be conducted using either product characteristics or attributes. But, the term "attribute" has been in vogue to represent either case and we will not make this distinction further in this book.

It is well accepted in marketing that choice alternatives can be described as profiles on multiple attributes. The methods of conjoint analysis are based on the premise that individuals consider various aspects of a choice alternative. The methods then permit a decomposition of an individual's overall preference judgments about a set of choice alternatives into separate and compatible utility values corresponding to each attribute. These separate functions are called attribute-specific partworth functions.

Historically, the methods of conjoint analysis have been used for new product design decisions. In this situation, an analyst necessarily has to rely upon judgments of new product ideas (long before they are developed). Usually, preferences about these new product concepts are elicited from potential consumers (see Rao and Soutar 1975 for an example). Thus, conjoint analysis of preferences has historically been the mainstay for new product decisions. Further, preferences are later mapped into predicted choices using various choice rules.

More recently, data on simulated or intended choices have been used in marketing research. These data have eliminated the need to translate preferences into choices because the analysis focuses directly on choices. The designs of choice-based conjoint studies to elicit such data are quite similar although some major differences exist in the analytical models employed.

1.4 Principal Types of Conjoint Analysis

Over the past several years, various researchers have contributed to the general methodology of conjoint analysis. The reader is referred to Green and Srinivasan (1978, 1990) for excellent reviews of the field of conjoint analysis. Essentially, there are four types of conjoint methods: the traditional method (CA) that uses stated preference ratings; choice-based conjoint analysis (CBCA) that uses stated choices; adaptive conjoint analysis (ACA) developed in part to handle the issue of large numbers of attributes, and self-explicated conjoint analysis, which is a bottom-up method. The first three of these can be called decompositional methods because the stated preference or stated choice data are decomposed to obtain partworth functions. The fourth one is called a compositional method because it composes a preference score from ratings of scores on attribute levels and relative importances of attributes. We will briefly describe each of these.

The traditional conjoint analysis (CA) collects preferences (judgments) for profiles of hypothetical products each described on the entire set of attributes selected for the conjoint study (e.g. Green and Wind 1975). These profiles are called full profiles. However, when one concatenates levels of all attributes, the complete set of full profiles (or full factorial design) will in general be very large. A respondent will be unduly burdened when asked to provide preference judgments on all profiles. Typically, a smaller set of full profiles (selected according to an experimental design) are used in a conjoint study. An individual's overall stated preferences are decomposed into separate and compatible utility values corresponding to each attribute typically using regression-based methods. These separate functions are called attribute-specific partworth functions. In most cases, the preference functions can be estimated at the individual level. This estimated preference function can be deemed as an indirect utility function.

While the traditional decompositional conjoint approach involves full profiles of product concepts described on multiple attributes, several new data collection formats have emerged over the years (see Johnson 1974). A significant development is the use of data on stated choices elicited under hypothetical scenarios that mimic the marketplace and estimating partworth functions from such data using primarily multinomial logit methods; these methods are labeled choice-based conjoint (or choice-conjoint) methods (CBCA or CBC) and became popular in the early 1990s and are probably the most widely used methods currently.

Researchers also have developed adaptive conjoint methods which are called adaptive conjoint analysis (ACA) (Johnson 1987). The method involves first a self-explicated task (i.e., eliciting data on attribute importances and attribute level desirabilities using ranking and subsequent rating) followed by preference ratings for a set of partial profile descriptions, two at a time, using a graded, paired comparison scale. The partial profile descriptions are tailored to each respondent based on the data collected in the self-explicated task. Both the tasks are administered on a computer. This method is a type of hybrid[5] model approach.

In contrast, the compositional approach based on the multi-attribute attitude models (mentioned above) estimates preferences from judged values of the components (importances and desirabilities) that contribute to preference. In the compositional approach, individuals are asked to evaluate the desirability of each level of all the attributes as well as the relative importances assigned to the attributes. Then, the preference for any product concept is estimated as a weighted sum of the desirabilities for the specific levels of attributes describing that concept; the weights are the relative importances. This approach is called the "self-explicated" method (see Green and Srinivasan 1978 for more details). Studies have shown that the self-explicated method is surprisingly quite robust (Srinivasan and Park 1997).

[5] Hybrid models involve a combination of several tasks aimed to increase the "efficiency" of data collection in conjoint studies usually for products with a large number of attributes. We will discuss these in Chaps. 2 and 3.

Theoretical Foundations: As noted earlier, the traditional conjoint analysis (ratings-based stated preferences) has its foundations in the measurement theory. The choice-based conjoint methods (for stated choices) are based on the behavioral theory of random utility maximization (McFadden 1974); the origin of this approach is the law of comparative judgment developed by Thurstone (1927). This approach decomposes an individual's random utility for an object into two parts: deterministic utility and a random component. Depending on the distributional assumptions for the random component, a number of alternative models are developed to describe the probability of choice of an object. The most popular one is the multinomial logit model that uses the extreme value distribution for the random term. These methods belong to the family of discrete choice analysis methods. A comprehensive volume by Louviere, Hensher, and Swait (2000) elaborates on these stated choice methods; see also Ben-Akiva and Lerman (1991) for foundations of these methods. The self-explicated methods (e.g. Srinivasan and Wyner 1989) draw their theoretical basis for the Fishbein-Rosenberg models of attitude formation and attitude structure (Fishbein 1967). The adaptive conjoint methods are based on a mixture of these theories and are more pragmatic to tackle problems in data collection and analysis in conjoint analysis.

1.5 Focus of this Book

This book is oriented toward methods and applications of conjoint analysis in marketing. But, it would not be appropriate to ignore the range of applications of these general methods (notably discrete choice analysis or CBCA) in other areas. The choice-based conjoint studies are widely applied in many areas of the social and business sciences, including but not limited to agricultural economics, energy economics, environmental and resource economics, health economics, human resource management, pharmacy, psychology, travel and transportation, tourism and many other areas. We provide a flavor of the extensive applications in other areas in the Appendix to this chapter by summarizing 29 published articles. These studies may offer insights to marketing researchers on the extensive potential of this methodology.

1.6 Industry Uses of Conjoint Analysis

Since its introduction, conjoint methods have been applied in a large number of applied marketing research projects. There is no recent estimate of the number of applied studies[6] but its use is increasing tremendously. The conjoint methodology

[6] Three surveys were conducted among firms that provide marketing research services by Wittink and his colleagues on the commercial use of conjoint analysis in Europe (1986–91) and USA (1981–85 and 1971–80). While the estimates of actual numbers of projects varied greatly, the authors documented that 698 projects were conducted by 17 firms in the US during the 5 years 1976–80 as compared to 1,062 projects by 66 firms in the US during the 5 years 1981–85.

Table 1.1 Sample list of conjoint applications

Consumer nondurables	Industrial goods	Other products
1. Bar soaps	1. Copying machines	1. Automotive styling
2. Hair shampoos	2. Printing equipment	2. Automobile and truck tires
3. Carpet cleaners	3. Facsimile transmissions	3. Car batteries
4. Synthetic-fiber garments	4. Data transmission	4. Ethical drugs
5. Gasoline pricing	5. Portable computer terminals	5. Toaster/ovens
6. Panty hose	6. Personal computer design	6. Cameras
7. Lawn chemicals		7. Apartment design
Financial services	**Transportation**	**Other services**
1. Branch bank services	1. Domestic airlines	1. Car rental agencies
2. Auto insurance policies	2. Transcontinental airlines	2. Telephone services and pricing
3. Health insurance policies	3. Passenger train operations	3. Employment agencies
4. Credit card features	4. Freight train operations	4. Information-retrieval services
5. Consumer discount cards	5. International Air Transportation Association	5. Medical laboratories
6. Auto retailing facilities	6. Electric car design	6. Hotel design
7. High-tech maintenance service		

has been applied in several areas; these include consumer nondurable products (bar soaps, carpet cleaners, lawn chemicals etc.), industrial goods (copying machines, portable computer terminals, personal computer design etc.), other products (car batteries, ethical drugs, pesticides, etc.), financial services (branch bank services, auto insurance policies, credit card features etc.), transportation (domestic airlines, electric car design etc.), and other services (Hotel design, car rental agencies, telephone pricing etc.). Table 1.1 lists some product categories where these methods were applied in marketing. The method has been applied successfully for tackling several marketing decisions such as optimal design of new products, target market selection, pricing a new product, and studying competitive reactions. Some high profile applications of these techniques include the development of Courtyard Hotels by Marriott (Wind et al. 1989) and the design of the E-Z Pass Electronic Toll Collection System in New Jersey and neighboring States in the US (Green et al. 1997). We will describe some of these studies in Chaps. 6, 7, 8, and 9 on applications. A significant advantage of the conjoint method has been the ability to answer various "what if" questions using market simulators; these simulators are based on the results of an analysis of conjoint data collected on hypothetical and real choice alternatives.

In Europe, 956 projects were conducted by 59 firms during the 5 years, 1986–91. These numbers show extensive diffusion of the methodology on both sides of the Atlantic. Table 1.11 summarizes the results on the utilization of various methods of data collection, analysis, and specific purpose of the conjoint studies in the three surveys

1.7 An Illustration of Conjoint Method

Setting: The basic ideas of conjoint analysis will be illustrated with an example[7] of the design of a public transportation system for a small city such as Ithaca, New York. We will initially use the traditional conjoint method. Assume that you are in charge of a research project to determine the best attributes (characteristics) of such a system. Assume also that you have determined that two attributes of the system—fare per trip and average waiting time—are the most salient for the potential users (residents of the community) of the system. (You know that such a determination would normally be based on extensive discussion with, and marketing research among, various relevant groups in the community.) The implications of these two system attributes are quite clear; the fare will have an immediate impact on the demand and revenues (and, therefore, profits of the system) while the average waiting time of the system will have an impact on the size of the fleet and frequency of schedules (and, therefore, costs as well as demand). Our interest is not to delve into these relationships but to show how evaluative judgments from potential users can be analyzed using conjoint analysis.

Data: Let us assume that you have decided upon the different levels for the two attributes of the system. Assume that three values are chosen for each attribute. These are 55¢, 85¢ and $1.15 for the fare, and 10, 20, and 30 min for the average waiting time. Given our simplified view, then each transportation system is a combination of these two sets of values. We have a total of 9 (= 3 × 3) combinations of these systems. For the sake of simplicity, we will deal with the valuations by one potential user, Jim. We will ask Jim to consider the nine combinations and rate them on a zero to 100 point scale, where a "0" rating means that he will never consider riding the system and "100" rating means that he will certainly consider riding the system. Assume that Jim gave the following ratings for the nine bus systems.

		Average waiting time		
		10 min	20 min	30 min
Fare per trip	$1.55	100	95	80
	$1.85	92	85	60
	$2.15	75	70	50

As one could expect, Jim's ratings show that he would most prefer the system with the lowest fare ($1.55) and lowest waiting time (10 min). Continuing with other ratings, we see that he would rather wait longer (20 min) than pay more ($1.85); compare systems ($1.55, 20 min) and ($1.85, 10 min) with that of ($1.55,

[7] While we are describing an example of product design here, the method of conjoint analysis is versatile in tackling various managerial problems such as product line decisions, competitive decisions, product/service pricing and the like. Several chapters in the book are devoted to these applications.

10 min). The system with 20 min waiting time and \$1.85 fare comes next (in the rating of 85); at this point, he would wait an even longer period (30 min) at lower price (\$1.55) rather than paying more for less waiting time, and so on. Thus, the data collected from Jim give us an idea on how he trades off one attribute off against the other.

Analysis: Methods of conjoint analysis yield estimates of attribute trade-offs using a formal model for analysis. Various analytical procedures exist for estimating these trade-offs. (We will discuss these in a later chapter.) Continuing with this example, we can use the well-known method of dummy variable regression for decomposing Jim's evaluations into partworth functions specific to fare and waiting time. More formally stated, the method estimates two functions, $U_1(X_1)$ and $U_2(X_2)$ respectively for the two attributes X_1 (fare) and X_2 (waiting time) in such a way that the sum of various realizations of U_1 and U_2 best represent the judged evaluations (Y's) for the nine systems.

Model: We may write this model as:

$$\begin{aligned} Y_i &= U_1(x_{i1}) + U_2(x_{i2}) + \text{Error} \\ i &= 1, 2, \ldots, 9 \end{aligned} \tag{1.1}$$

where

x_{i1} = level of the fare for the ith system,
x_{i2} = level of the waiting time for the ith system,
Y_I = preference rating given to the ith system,
$U_1(\bullet)$ = partworth function for attribute 1 (fare), and
$U_2(\bullet)$ = partworth function for attribute 2 (waiting time).

The error term is essentially the same as the random part of the utility function described earlier. For this analysis, we will define dummy variables XF_1, XF_2, XW_1 and XW_2 for fare and waiting time as follows:

$$XF_1 = \begin{cases} 1 \text{ if fare is } \$1.55 \\ 0 \text{ otherwise} \end{cases}$$

$$XF_2 = \begin{cases} 1 \text{ if fare is } \$1.85 \\ 0 \text{ otherwise} \end{cases}$$

$$XW_1 = \begin{cases} 1 \text{ if waiting time is 10 minutes} \\ 0 \text{ otherwise} \end{cases}$$

$$XW_2 = \begin{cases} 1 \text{ if waiting time is 20 minutes} \\ 0 \text{ otherwise.} \end{cases}$$

The reader may note that we defined two dummy variables for the three-level attribute because the third level is automatically determined when the dummy variables are zero for the third level. The analysis simply consists of performing

Table 1.2 Illustration of conjoint analysis using dummy variable regression. *Panel A*: *Preference ratings for combinations of fare and waiting time*

	Waiting time		
Fare ($)	10 minutes	20 minutes	30 minutes
1.55	100	95	80
1.85	92	85	60
2.15	75	70	50

Table 1.3 Illustration of conjoint analysis using dummy variable regression. *Panel B*: *Setup for dummy variables*

Fare	Waiting time	Rating of preference	XF_1	XF_2	XW_1	XW_2
1.55	10	100	1	0	1	0
1.55	20	95	1	0	0	1
1.55	30	80	1	0	0	0
1.85	10	92	0	1	1	0
1.85	20	85	0	1	0	1
1.85	30	60	0	1	0	0
2.15	10	75	0	0	1	0
2.15	20	70	0	0	0	1
2.15	30	50	0	0	0	0

Table 1.4 Illustration of conjoint analysis using dummy variable regression. *Panel C*: *Regression results*

Regression statistics	
Multiple R	0.990
R-square	0.981
Adjusted R-square	0.962
Standard deviation of error	3.23
Observations	9

an ordinary least squares regression of the ratings on the nine systems on these four dummy variables. The set up of the data for regression and the results are shown in Tables 1.2, 1.3, 1.4, and 1.5.

Fit of the Model: The regression model fits extremely well to Jim's data, with an R-square value[8] of 0.99. The fitted model is:

$$Y = 49.8 + 26.7\ XF_1 + 14.0\ XF_2 + 25.7\ XW_1 + 20.0\ XW_2. \qquad (1.2)$$

[8] This high value of R-square is due to the hypothetical data. In general, the fits of the model to data at the individual level will not be this high (and average around 0.7 or so). The fits for some individuals will be poor for a variety of reasons such as unreliable responses and complexity of the task involved. We will discuss later incentive-compatible methods of data collection which ensure more reliable responses.

Table 1.5 Illustration of conjoint analysis using dummy variable regression

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	2158.444	539.6111	51.66489	0.001068
Residual	4	41.77778	10.44444		
Total	8	2200.222			

	Coefficient	Standard Error	t-Stat	*P*-value
Intercept	49.8	2.41	20.66	3.24E-05
XF_1	26.7	2.64	10.11	0.00054
XF_2	14	2.64	5.31	0.006064
XW_1	25.7	2.64	9.73	0.000626
XW_2	20	2.64	7.58	0.001625

The least squares estimates of the nine ratings from this regression are very close to the actual ratings as shown below.

	Waiting time		
Fare	10 min	20 min	30 min
\$1.55	102.2 (100)	96.5 (95)	76.5 (80)
\$1.85	89.5 (92)	83.8 (85)	63.8 (60)
\$2.15	75.5 (75)	69.8 (70)	49.8 (50)

Actual ratings are shown in parentheses

Partworth Functions: Leaving out the intercept for the moment, the regression model shown in (1.2) is separable into functions specific to fare and waiting time. These two separable functions are called partworth functions. Thus, the partworth functions are:

For fare:

$$U_1(x_1) = 26.7\ XF_1 + 14.0\ XF_2$$

For waiting time:

$$U_2(x_2) = 25.7\ XW_1 + 20.0\ XW_2.$$

These are piece-wise linear functions with three points (corresponding to the levels of the attributes). A plot of these functions is shown in Fig. 1.2. We note from these functions that Jim experiences a small loss of utility for an increase of waiting time from 10 min to 20 min and a large loss for increase from 20 min to 30 min. Further, the loss in utility for increase in fare is quite uniform over the interval (\$1.55–\$2.15) covered in the evaluation.

PARTWORTH FUNCTIONS (P-W) FOR THE BUS SYSTEM EXAMPLE

a Numerical Values

Fare	P-W	Waiting Time	P-W
$1.55	26.7	10 minutes	25.7
$1.85	14.0	20 minutes	20.0
$1.15	0	30 minutes	0

b Plots of Partworth Functions

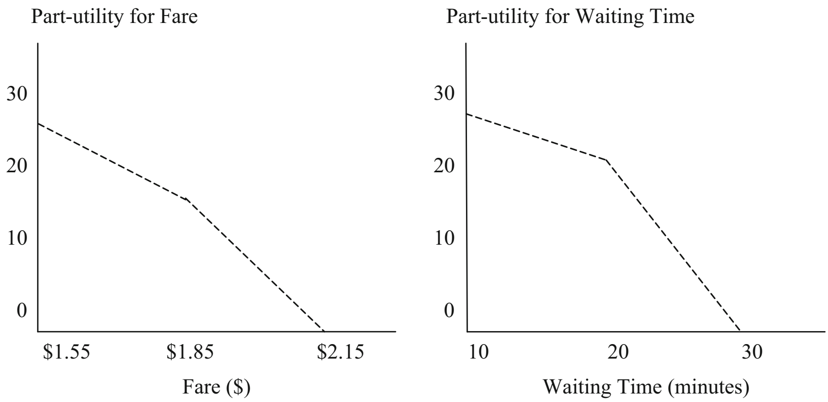


Fig. 1.2 Partworth functions (P-W) for the bus system example

Trade-offs: We may use the partworth functions to measure the trade-offs between the two attributes. Suppose that a system exists with the attribute levels of 20 min of waiting time and $1.85 of fare. We note that a change (reduction) in waiting time to 10 min will increase the utility of the system by 5.7 (= 25.7–20.0) units; this increase translates to a decrease in fare of $\frac{5.7}{(26.7 - 14.0)} * 30¢ = \frac{5.7}{12.7} * 30¢ = 13.5¢$ or a fare of $1.85–$0.135 = $1.715. These computations imply that the two systems (10 min, $1.715) and (20 min, $1.85) yield approximately the same utility to Jim. Thus, the trade-off between waiting time and fare has been established as roughly 13.5¢ for 10 min at the point (10 min, $1.85). This relationship is not necessarily constant; it varies from point to point, depending on the shape of the utility functions, U_1 and U_2. [Appendix 1 describes computing trade-offs for three types of functions.]

Normalization: To enable easy comparison, it is useful to normalize the estimated partworth functions. One conventional way to normalize is to set the smallest and largest values across all of the component functions at 0.0 and 1.0 respectively. Shown below are utility functions in this example with such normalization. The equation for this normalization for any partworth is

Partworth function		Values before normalization	Values after normalization
U_1:	\$1.55	26.7	1.0
	\$1.85	14.0	0.524
	\$2.15	0	0.0
U_2:	10 min	25.7	0.963
	20 min	20.0	0.749
	30 min	0	0.0

v = (u−a)/(b−a) where a and b are the smallest and largest values respectively in the partworth function before normalization, and u and v are the corresponding values in the partworth function after normalization. For example, the normalized value of 0.524 for the fare of \$1.85 is computed as: (14.0−0)/(26.7−0). Note that this normalization enables one to deal with smaller numbers without altering the internal relationships among the functions and makes it easy to compare partworth values within a partworth function and across partworth functions.

Importances of Attributes: A convenient measure of the importance of the attributes in the total utility function is the range of the partworth functions.[9] A relative measure can be obtained by rescaling these measures such that they all add to 100%. Using this procedure, we compute the relative importance for fare as: $\frac{26.7}{26.7+25.7} = 51\%$ and that for waiting time as 49 %. This result is generally consistent with Jim's ratings of the nine alternative bus systems. This importance measure is called RIMP (or relative importance measure).

Prediction: The estimated functions can be employed (interpolated if necessary) to predict the utility score for a new system not used in data collection. For example, the estimate for a system with \$1.70 fare (midway between \$1.55 and \$1.85) and 15 min waiting time will be:

$$49.8 + \frac{(26.7 + 140)}{2} + \frac{(25.7 + 20.0)}{2} = 93.$$

(In this prediction, we linearly interpolated the values of partworth functions for fare and waiting time.) The predicted value is quite consistent with the original ratings. Such estimates can be made for a number of proposed new systems; one could make a prediction of Jim's choice behavior using such estimates.

[9] Other measures such as partial R-squared exist for this purpose; we will discuss them in Chap. 2

Interpolation of partworth functions for intermediate values of attribute scores assumes that the function is linear between two contiguous attribute levels. Such interpolation may be reasonable. But, extrapolation of a partworth function outside the range of an attribute can yield misleading results and should generally be avoided. The problem can be solved by an appropriate selection of values for an attribute while designing the hypothetical stimuli. (We will discuss this issue in the next chapter.)

Validation: In general, the estimated utility functions should be validated. The relevant methods include predictive validation for a holdout sample of systems and validation of future market behavior, intended or actual (e.g., first choices, sales or market share).

Alternative Models: We have implicitly treated the levels of the two attributes as nominal-scaled, although they have continuous values. We could reformulate the model of equation (1.1) as:

$$Z = M(y) = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \text{Error} \tag{1.3}$$

where X_1 and X_2 are the variables measuring waiting time and fare and γ_0, γ_1, and γ_2 are parameters. This model can be estimated using regression analysis. We would expect the estimates of γ_1 and γ_2 to be negative. Incidentally, we may note that Model (2) assumes linearity of the partworth functions while no such assumption was made in Model (1); in fact, Model (1) assumes piece-wise linear partworth functions. Also, both the models assume no interaction between waiting time and fare. This is because the effect of any one variable, say X_1 does not depend on the value of the second variable, X_2. If this were to be the case, we can specify the effete of X_1 as a function of X_2 and reformulate the model. For example we can use a linear specification as: $\gamma_{1,}$ the effect of X_1 as $\gamma_{10} + \gamma_{11}X_2$. In that case, the reformulated model will be:

$$Z = \gamma_0 + \gamma_{10} X_1 + \gamma_2 X_2 + \gamma_{11} X_1 X_2 + \text{Error}. \tag{1.4}$$

In this formulation, the additional term is the product of X_1 and X_2 to represent the interaction between these two variables. This idea can be extended to a model with several X- variables. We will return to this question in Chap. 3.

This small, but comprehensive, illustration describes the essence of conjoint analysis. Its salient features include identification of attributes, design of hypothetical alternatives, data collection, analysis and interpretation of results. As the reader may surmise, the procedure is simple and straightforward for the case of two attributes. Various complexities arise when we deal with practical problems which typically have three or more attributes, each at several levels. For example, the total number of alternative products will explode and the problem will be to select a subset of profiles that can be administered to respondents in a survey. We turn to these larger issues in the subsequent chapters.

1.7.1 Application of Choice-Based Conjoint Analysis

We will now illustrate the use of choice-based conjoint analysis with the same transportation example. For this purpose, assume that choice sets of size three were designed and an individual respondent was asked to indicate which of the options his/her (stated) choice is. The OPTEX procedure[10] of the SAS system was used to generate 42 choice sets each with three options and no choice option included and a partial list of choice sets is shown in Table 1.6. One can note that these choice sets contain some dominated options and some where the individual has to make trade-offs.

The 42 choice sets were evaluated by a small sample of three respondents and their choice data were analyzed using a conditional logit model; the method of maximum likelihood was employed in the estimation (details of which are described in Chap. 4). The model fit was very good[11] and the estimated utility function is: $3.35XF_1 + 1.65XF_2 + 3.35\ XW_1 + 1.02XW_2$, where XF1 etc. are dummy variables as defined earlier. The partworth functions also show a similar pattern discussed earlier. We will describe several details of this choice-based conjoint method in Chap. 4.

1.7.2 Implementation of a Conjoint Study

The above two examples for the public transportation system illustrate the basic ideas. While several types of conjoint methods exist, the two main alternatives are the ratings-based and choice-based conjoint analysis. In Fig. 1.3 shows the various decisions that an applied researcher needs to make for implementing a conjoint study with the focus on these main alternatives. The steps are quite self-explanatory. Several technical details will be described in Chaps. 2, 3, and 4. These details will involve selection of attributes, design of profiles or choice sets and analysis methods and utilization of results.

[10] The SAS Optex Code for the Transportation Example is as follows:

data ab; n = 1; do time = 10 to 30 by 10; do fare = 55 to 115 by 30; output; n = n + 1; end; end; run;

proc optex data = ab seed = 73462 coding = orth; class time fare; model time fare; blocks structure = (42)3; run;

output out = try number = 1 blockname = blk; proc print data = try; run.

[11] The number of observations was 126 (=3 × 42). The likelihood ratio for the model was 144.5 with 4 degrees of freedom.

Table 1.6 Partial list of choice sets for the transportation problem

Choice set	Description	Option 1	Option 2	Option 3
1	Waiting time	30	20	10
	Fare	1.55	1.85	2.15
2	Waiting time	20	10	30
	Fare	1.55	1.85	2.15
3	Waiting time	20	30	10
	Fare	2.15	1.85	1.55
4	Waiting time	20	30	10
	Fare	2.15	1.55	1.85
5	Waiting time	10	30	20
	Fare	1.55	2.15	85
6	Waiting time	20	30	10
	Fare	1.85	1.55	2.15
7	Waiting Time	20	10	30
	Fare	2.15	1.85	1.55
8	Waiting Time	30	20	10
	Fare	1.85	1.55	2.15
9	Waiting time	10	30	20
	Fare	1.55	1.85	2.15
10	Waiting time	20	30	10
	Fare	1.55	1.85	2.15
11	Waiting time	10	30	20
	Fare	1.55	1.85	2.15
12	Waiting time	20	10	30
	Fare	2.15	1.85	1.55
13	Waiting time	10	30	20
	Fare	2.15	1.85	1.55
14	Waiting Time	10	30	20
	Fare	1.55	2.15	1.85
15	Waiting time	20	30	10
	Fare	1.55	1.85	2.15
16	Waiting time	10	30	20
	Fare	2.15	1.55	1.85

1.7.3 Another Illustration

As another illustration of the ratings-based conjoint method,[12] assume that a wireless provider firm interested in determining trade-offs among various features of a smart phone (a technologically advanced product with a number of features). In order to simplify the data collection, assume that the firm is interested in the trade-offs among five attributes, namely, style of the phone, brand name, talk-time, weight, and camera quality (having predetermined a number of standard features). Price attribute was not included because it was part of a contract with the wireless

[12] Readers may also be interested in the classic paper, Green and Wind (1975), for a comprehensive application of the ratings-based conjoint method.

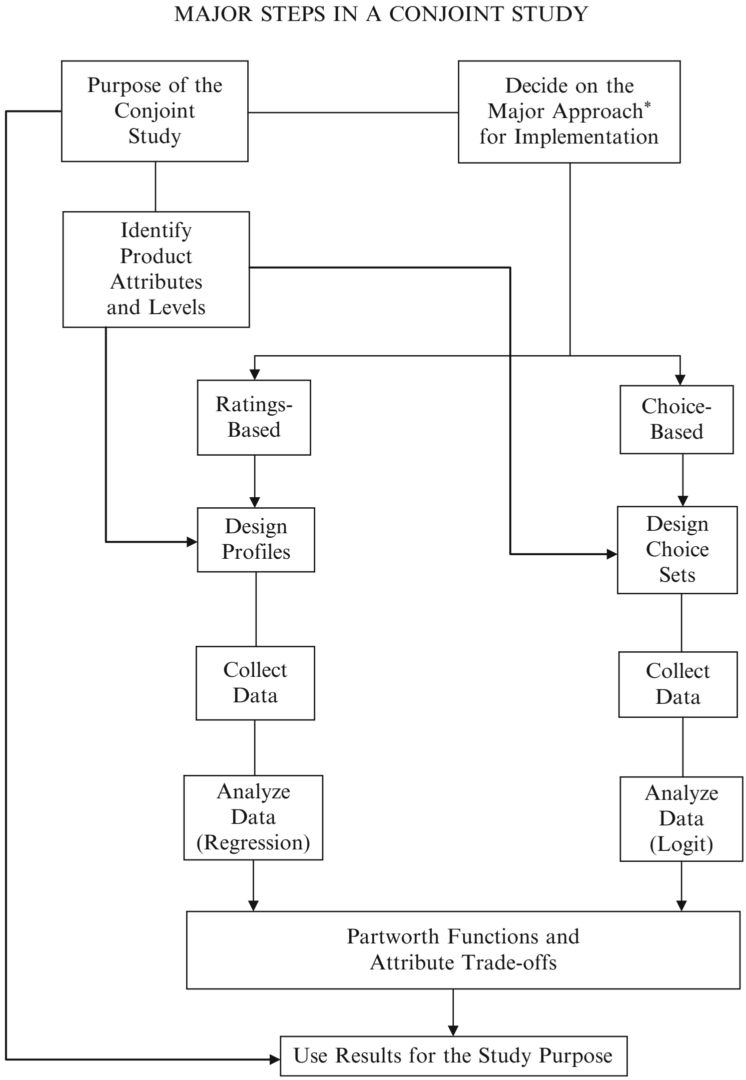


Fig. 1.3 Major steps in a conjoint study. Several alternatives exist here; two are highlighted (Source: Reprinted with permission from Rao (2009) published by Springer)

provider and was about the same for all brands. Each of these five attributes is varied around 4 levels. Table 1.7 shows the features that are pre-decided and the levels of the five features varied in the study.

The total number of possible hypothetical profiles are 1,028 (= 4 × 4 × 4 × 4 × 4), which are combinations of the levels of the five attributes. Given that it is almost impossible to have a respondent judge all these profiles, the study designer has selected 32 of these profiles using a fractional factorial design. In the study, respondents were shown the complete list of standard features and were asked to provide preferences on a zero to 100 point scale for the 32 profiles. These profile descriptions were provided using a computerized questionnaire.

We will show the results from analysis of one respondent's evaluations as shown in Table 1.8. These data are analyzed using dummy variable regression after converting each attribute into three dummy variables as shown in Table 1.9 to obtain partworth functions for the five attributes. The resulting regression and partworth values are also shown in Table 1.9. The measures of relative importance (RIMP) of attributes based on range of each partworth function are also shown in Table 1.9. Figure 1.4 shows the plots of partworth functions for the five attributes.

Although not shown, the fit of the partworth model to the individual's preference ratings is quite good with an adjusted R-square of 0.88. Based on this analysis, one can conclude that this respondent has strong preference for a flip style Blackberry smart phone that is lightest in weight with a talk time of 9 h and a camera quality of 6 Mega pixels. From the graphs of the partworths one can see that the decline in utility from these levels of the attributes to other levels is not uniform. Further, there is nonlinearity in the partworth function for the attribute of camera quality. Looking at the relative importances, this individual places most importance for the style attribute followed by talk time, weight, brand, and camera quality in that order. The partworth functions can be used to predict the individual's preference rating for a profile not covered in the 32 profiles. Further, one can estimate preferences for items in any choice set; these estimates can be used to predict the individual's first choice and other choices. Also, if the study is conducted for a sample of respondents, the vector of estimated relative importances can be used to form clusters of individuals whose importances are quite similar; these clusters are akin to market segments. Focusing on one brand (e.g. LG), one can make predictions of first and other choices for the sample for various scenarios (e.g., anticipated changes in the product designs of competing brands); such a process is the simulation aspect of conjoint analysis, which is highly useful for managers. We will discuss this aspect in a later chapter.

1.7.4 Features of Conjoint Analysis

Five different features of conjoint analysis should be pointed out. These are:

1. It is a measurement technique for quantifying buyer tradeoffs and values;
2. It is an analytical technique for predicting buyers' likely reactions to new products/services;

Table 1.7 Your basic smart phone

Attribute	Levels 1	2	3	4
Style	Candy bar 	Slide phone 	Flip phone 	Touch screen 
Brand	Blackberry	Nokia	LG	Samsung
Talk-time	3 h	5 h	7 h	9 h
Weight	100 g	115 g	130 g	145 g
Camera quality	2 Mega pixels	3 Mega pixels	6 Mega pixels	8 Mega pixels

Below is a description of the fixed specifications of your Smart Phone:

Telecom: **Data services** WAP, E-Mail, WWW, SMS, MSN Messenger, MMS; **Modem** Integrated Wireless cellular modem; and **Cellular enhancement protocol** EDGE, GPRS, GSM

Operating System/Software: **OS provided** Microsoft Windows Mobile 6.0 Professional; **Software included** GPS Catcher, Alarm, ASUS Zip, Contacts, Location Courier, Windows Live, Business Card Recognition, Backup, ActiveSync, Microsoft Word Mobile, Microsoft PowerPoint Mobile, Notes, Windows Media Player, Travelog, Auto Cleaner, Meeting Time Planner Newstation, Calendar, Microsoft Excel Mobile, Calculator, Microsoft Internet Explorer Mobile, ASUS Remote Presenter, MSN Messenger, File Explorer

Memory: **Installed RAM** 64 MB; **RAM technology** SDRAM; **Installed ROM** 128 MB Flash Phone: **Call features** Call hold, Call history, Call forwarding

Processor: **Processor** Texas Instruments 200 MHzOMAP1.850

Input Device: **Input device type** Jog Dial, Keypad, Stylus, 5-way navigation button

Digital Camera: **Features** Self timer, Landscape/portrait mode, Video recording
Audio: **Digital audio standards supported** WMA, MIDI, MP3, AAC; **Audio input type** FM tuner; **Audio output type** Speaker(s); and **Voice recording capability**
Display: **Display type** 2.6 in TFT active matrix; **Color support** 16-bit (64K colors); **Max resolution** 320 × 240
Power: **Battery installed (max)** 1 Lithium ion; **Power supply device** Power adapter; **Power device type** Power adapter
Expansion/Connectivity: **Wireless connectivity** IEEE 802.11b, IEEE 802.11g, Bluetooth 2.0 EDR; **Port/Connector Type: Interface** 1Audio, 1USB; **Connector Provided** Mini-USB Type B, Sub-mini phone 2.5 mm; **Expansion slot(s) total (free)** 1 MicroSD
Physical Characteristics: **Width** 2.3 in. **Depth** 0.6 in. **Height** 4.4 in
GPS: **GPS System/GPS Navigation** GPS receiver
General: **Dimensions (W × D × H)** 2.4 in × 0.5 in × 4.5 in. **Color** Black; **Packaged contents** Protection bag, Car holder, Cigarette lighter adapter; and **Vibrating Alert**
Phone: **Call features** Call hold, Call history, Call forwarding

Table 1.8 Saroj's preference ratings for smart phones

Profile number	Brand	Style	Talk time (hours)	Weight (grams)	Camera quality (MP)	Stated preference ratings
1	Blackberry	Touch screen	7	100	2	80
2	Blackberry	Flip	9	115	2	95
3	Blackberry	Candy bar	9	100	4	93
4	Blackberry	Slide	5	145	4	85
5	Blackberry	Candy bar	5	115	6	90
6	Blackberry	Slide	7	130	6	90
7	Blackberry	Touch screen	3	130	8	85
8	Blackberry	Flip	3	145	8	90
9	Nokia	Slide	3	115	2	85
10	Nokia	Touch screen	5	130	2	80
11	Nokia	Flip	7	100	4	92
12	Nokia	Slide	7	145	4	80
13	Nokia	Touch screen	9	100	6	90
14	Nokia	Flip	3	145	6	90
15	Nokia	Candy bar	9	115	8	90
16	Nokia	Candy bar	5	130	8	80
17	LG	Slide	5	100	2	88
18	LG	Candy bar	3	145	2	72
19	LG	Flip	5	115	4	90
20	LG	Touch screen	9	145	4	80
21	LG	Candy bar	3	100	6	85
22	LG	Flip	7	130	6	85
23	LG	Touch screen	7	115	8	80
24	LG	Slide	9	130	8	92
25	Samsung	Flip	9	130	2	90
26	Samsung	Candy bar	7	145	2	65
27	Samsung	Touch screen	7	115	4	75
28	Samsung	Candy bar	3	130	4	65
29	Samsung	slide	9	115	6	97
30	Samsung	Touch screen	5	145	6	75
31	Samsung	Slide	3	100	8	90
32	Samsung	Flip	5	100	8	93

3. It is a segmentation technique for identifying groups of buyers who share similar tradeoffs/values;
4. It is a simulation technique for assessing new product service ideas in a competitive environment; and
5. It is an optimization technique for seeking product/service profiles that maximize share/return.

These features will become clear in subsequent chapters of this book.

Table 1.9 Estimated partworth values for the illustrative data for smart phone study

Attribute	Level	Recoded dummy variables D1	D2	D3	Partworth value	Relative importance (%)
Brand	Blackberry	1	0	0	7.25	17.77
	Nokia	0	1	0	4.63	
	LG	0	0	1	2.87	
	Samsung	0	0	0	0.00	
Style	Candy bar	1	0	0	−0.97	26.76
	Flip	0	1	0	9.95	
	Touch screen	0	0	1	7.58	
	Slide	0	0	0	0.00	
Talk time	3 h	0	0	0	6.99	21.74
	5 h	0	0	1	−1.88	
	7 h	0	1	0	2.12	
	9 h	1	0	0	0.00	
Weight	100gr	1	0	0	7.88	19.31
	115 gr	0	1	0	6.01	
	130 gr	0	0	1	1.89	
	145 gr	0	0	0	0.00	
Camera quality	2 MP	0	0	0	0.00	14.41
	4 MP	1	0	0	1.22	
	6 MP	0	1	0	5.88	
	8 MP	0	0	1	5.15	

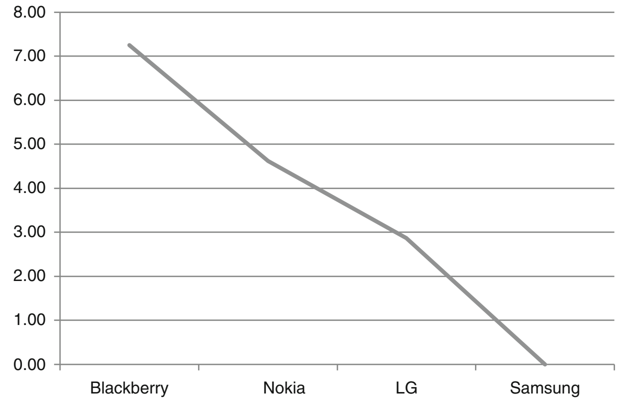
1.8 Taxonomy of Conjoint Methods

The two illustrations discussed so far illustrate various aspects of the methodology as applied to a single respondent. During the last 20 years or so, different researchers have applied different techniques to derive partworth functions of attributes in a variety of settings. Table 1.10 summarizes these extensions by contrasting them with the features of the two illustrations.

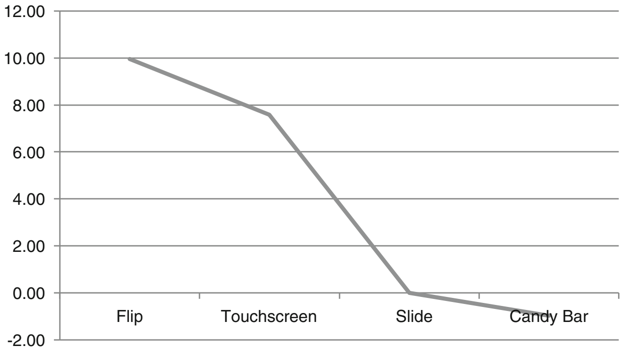
The variety of new models developed and the techniques for estimation of partworth functions is very impressive. Figure 1.5 shows a taxonomy of various approaches and a sampling of early contributions to the field. This taxonomy is based on three aspects in which current approaches of conjoint analysis differ. These are: (1) data collection process; (2) incorporation of prior constraints on attribute partworth functions; and (3) level of aggregation of analysis. Given the need for including large numbers of attributes (and levels) in any practical problem, data collection using full profiles, developed according to a statistical design, becomes quite difficult. To contend with this problem, methods of self-explication, combinations of self-explication and full profiles, and adaptive conjoint analysis have been developed. The Bayesian methods (e.g. Cattin et al. 1983) and incorporation of order constraints or monotonic constraints (e.g. Allenby et al. 1995) are relevant when the analyst wishes to incorporate prior knowledge. Finally,

PARTWORTH FUNCTIONS FOR THE SMART PHONES ILLUSTRATION

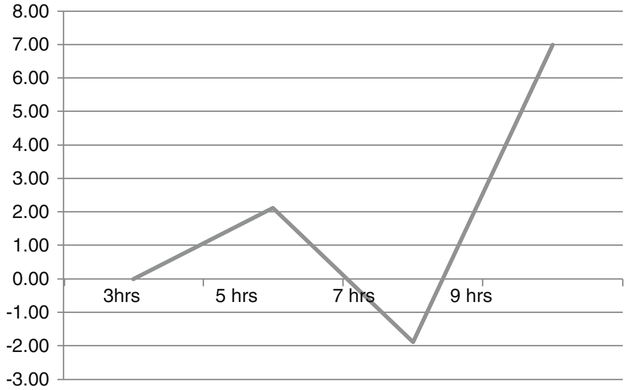
a Brand

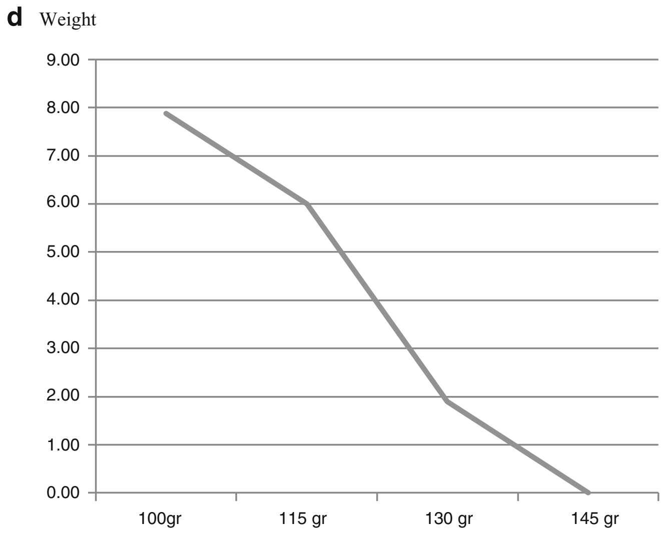


b Style



c Talk Time





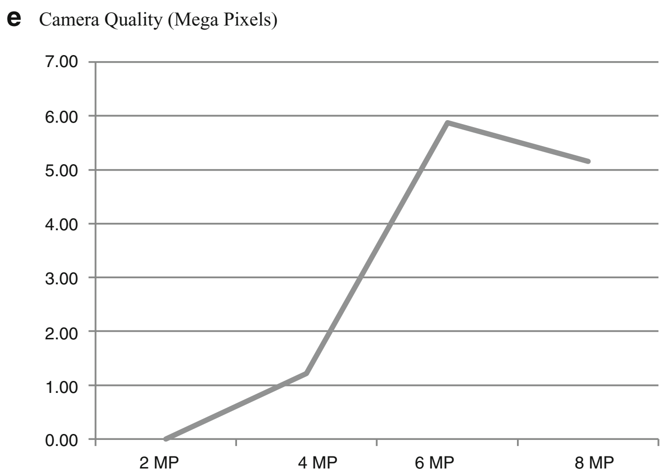


Fig. 1.4 Partworth functions for the smart phones illustration

while traditional analysis is done at the individual level, some approaches of data collection enable estimation of only aggregated models; the level at which such aggregation can be assessed by clustering or prior segmentation methods. We will delve into these differences in the second and subsequent chapters.

Table 1.10 Different features of a conjoint study

Feature	How used in the two illustrations?	Other possibilities	Some relevant methods
Use of external information to place constraints on the partworths of attributes	Not used in the illustrations	Prior information can be incorporated in the design of profiles and as constraints on the partworth functions in the estimation stage	Bayesian techniques
Type of data collected	Stated preferences in both the transportation and smart phone illustrations	Paired comparisons	
	Stated choices data in the transportation illustration	Ranking	
Level of analysis	Analysis conducted for each respondent separately in both the illustrations. In addition, analysis at the subgroup level in the transportation illustration	Respondents can be aggregated before analysis or aggregation incorporated into the analysis	Clustering; componential segmentation
Dependent variable	Stated preference ratings for each profile in both the illustrations	Paired comparisons of preferences for profiles	Linear programming methods (e.g., LINMAP)
	Stated choice variable in the transportation illustration	Ranking of preferences	Logit modeling of choices
Use of self-explication	Not used	Self-explication data can be combined with data on profiles	Hybrid models Adaptive conjoint methods CASEMAP Bayesian methods

Three surveys were conducted among firms that provide marketing research services by Wittink and his colleagues on the commercial use of conjoint analysis in Europe (1986–91), USA (1981–85 and 1971–80). While the estimates of actual number of projects varied greatly, the authors documented that 698 projects were conducted by 17 firms in the US during the 5 years 1976–80 as compared with 1,062 projects by 66 firms in the US during the 5 years 1981–85. In Europe, 956 projects were conducted by 59 firms during the 5 years, 1986–91. These numbers show extensive diffusion of the methodology on both sides of the Atlantic.

EARLY DEVELOPMENTS IN PARTWORTH ESTIMATION METHODS

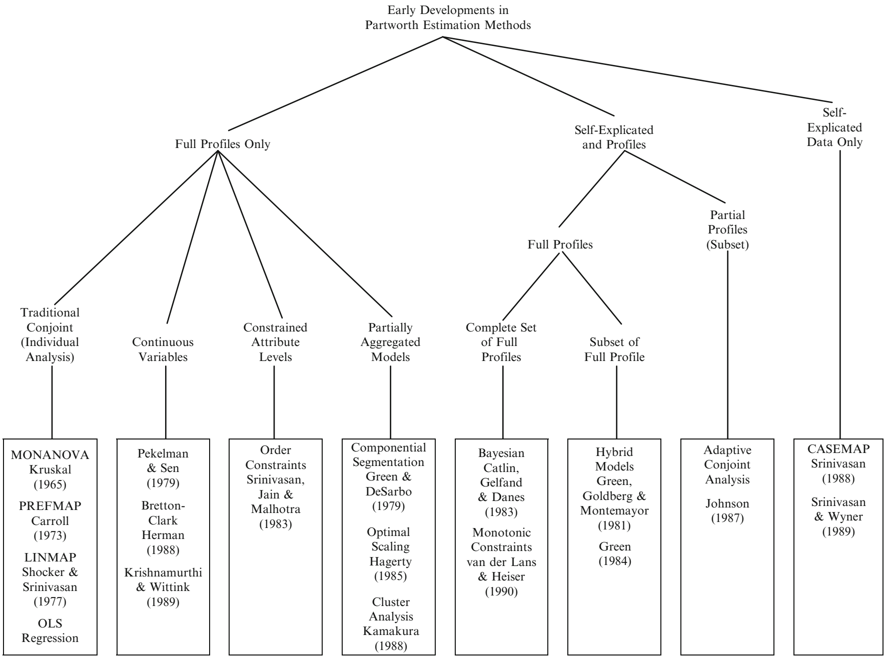


Fig. 1.5 Early Developments in partworth estimation methods (Source: Reprinted with permission from Carroll and Green (1995), published by the American Marketing Association)

Table 1.11 summarizes the results on the utilization of various methods of data collection, analysis and specific purpose of the conjoint studies in these three surveys.

1.9 Overview of Subsequent Chapters

This chapter has described the basic ideas of conjoint analysis, and commented on the wide range of possibilities and practice in industry. The remaining chapters of the book present extensive details of the methods and applications.

Chapter 2 describes the steps involved in designing a ratings-based conjoint study. These include issues of selection of attributes and levels, use of statistical experimental designs for determining profiles and methods of collection of data of preference ratings. In addition, the newly developed adaptive methods and hybrid methods designed to handle multiple attributes are discussed in this chapter.

Chapter 3 describes specification of different partworth functions and how attributes are coded for data analysis. This chapter covers various methods for

Table 1.11 Commercial use of conjoint analysis-Europe and USA

	Percentage of applications[a]		
	Europe July 86–June 91	USA Jan. 81–Dec. 85	USA 1971–1980
Product/service category			
Consumer goods	54	59	61
Industrial goods	17	18	20
Financial services	14	9	8
Other services	13	9	9
Other	2	5	3
Purpose[b]			
Pricing	46	38	61
New product/concept identification	36	47	72
Market segmentation	29	33	48
Competitive analysis	22	40	(c)
Repositioning	13	33	(c)
Advertising	2	18	39
Distribution	NA[c]	5	7
Means of data collection			
Personal interview	44	64	NA
Computer-interactive method (ACA)	42	12	
Telephone interview	7	8	
Mail questionnaire	3	9	
Combination	4	7	
Stimulus construction			
ACA-design	42	NA[c]	(c)
Full-profile	24	61	56
Tradeoff matrix	15	6	27
Paired comparison	4	10	(c)
Combination	5	10	14
Other (hybrid)	10	13	3
Stimulus presentation			
Verbal description	75	NA[c]	50
Pictorial representation	9	NA	19
Actual products or prototypes	6	NA	7
Paragraph description	3	NA	20
Combination	7	NA	(c)
Other	(c)	(c)	4
Response scale			
Rating scale (including ACA)	70	49	34
Rank order	22	36	45
Paired choice	5	9	11
Other	3	13	10
Variable definition			
Preference intensity (ACA)	42	NA[c]	(c)
Preference	26	NA	44
Intention to buy	18	NA	46

(continued)

Table 1.11 (continued)

	Percentage of applications[a]		
	Europe July 86–June 91	USA Jan. 81–Dec. 85	USA 1971–1980
Choice	7	NA	(c)
Liking	4	NA	8
Other	3	NA	2
Estimation procedure			
Ordinary Least Squares (OLS)	59	54	16
MONANOVA	15	11	24
Logit	7	11	10
LINMAP	7	6	-
Other	12	18	55

Source: Adapted from Cattin and Wittink (1982), Wittink and Cattin (1989), Wittink et al. (1994) with permission of the publisher.

[a]The results reported are weighted by the number of projects completed by each supplier.

[b]A given study may involve multiple purposes, such that the percentages reported add up to more than 100.

[c]This category or characteristic was not included in the survey instrument.

estimating attribute partworth functions from preference ratings data. These analyses can be implemented at various levels of individual, subgroup and aggregate sample. It also covers how the partworth estimates are integrated into conjoint simulators; in this process methods used for transforming a preference rating into a choice probability are described. In addition, the analysis methods for the hybrid conjoint model and adaptive methods are included in this chapter. The chapter also describes the use of hierarchical Bayesian methods in the estimation of individual-level partworth functions.

The objective of Chap. 4 is to focus on an alternate dependent variable, namely, choice. This chapter is devoted to methods of design and analysis of conjoint-based choice experiments where choice is measured directly. The random utility theory forms the basis for these experiments. Both binary choice and multinomial choice experiments are described as well as newer Bayesian methods for design of choice studies are covered in Chap. 4. Details of various analysis techniques, based on the multinomial logit are included in this chapter. This chapter also includes a discussion of the role of incentive compatibility in choice experiments to ensure that responses are truthful in choice experiments and a few applications of choice-based conjoint methods.

Chapter 5 describes several methods that are suitable for handling large number of attributes. These methods include partial and full profile methods; attribute simplification methods; information integration and meta-attributes approaches; classic and adaptive self-explicated methods; methods that combine several approaches; upgrading methods; and support vector machines method. The chapter shows how these methods are implemented with some examples. In addition, an attempt is made to provide a systematic and subjective comparison of these methods on a number of criteria to enable an applied researcher to make a selection for a particular problem.

Each of the three Chaps. 6, 7, and 8, is devoted to a discussion of how conjoint analysis has been used for specific applications. Chapter 6 focuses on product and service design and product line decisions; it includes several applications (some pioneering and some contemporary) and shows how the ratings and choice-based methods are implemented in practice. The use of genetic algorithms for product design is included in this chapter. Chapter 7 is devoted to conjoint applications to product positioning and market segmentation decisions; in addition it includes a succinct comparison of different segmentation approaches.

Chapter 8 deals with pricing decisions. The chapter also includes a discussion on how to separate the two distinct roles of price (allocative and informational) and how lack of such separation can create biases in the pricing decisions using conjoint methods. The chapter includes conjoint applications to bidding, pricing product lines, and multipart pricing.

Chapter 9 describes various miscellaneous applications of conjoint methods. The applications cover various aspects of marketing mix (other than product and price). Specifically, this chapter illustrates how conjoint methods are used in competitive marketing strategy decisions, marketing resource allocation, store location decisions, choice of a distribution channel, setting sales quotas, measuring damage due to patent infringement, in courtroom deliberations of legal issues, measuring brand equity and customer satisfaction. It also includes discussion of how this methodology is used in website design.

Chapter 10 reviews more recent developments in experimental design and data analysis. The new approaches of barter conjoint method, probabilistic polyhedral estimation and measurement of peer influence are described in this chapter. It also presents an assessment of future developments.

Finally, Chap. 11 reproduces an article, "Beyond Conjoint Analysis: Advances in Preference Measurement" to encapsulate this area.

Appendix

A Selection of Applications of Conjoint Analysis in Areas Other than Marketing

While this book deals with applications in the area of marketing, the methodology of conjoint analysis has been applied in several other disciplines. In this Appendix, we show a selection of applications in areas such as environmental economics, health economics, electric utilities, energy saving, transportation, and food safety. We provide brief details of the methods employed in the studies identified.

No.	Author(s) and date (s)	Area of application	Context	Theoretical concepts used	Conjoint approach	Analysis technique(s)
1.	Baarsma (2003)	Environmental economics	Valuation of IJmeer nature reserve in the Netherlands	Willingness to buy, random utility maximization	Ranking and rating alternatives in one choice set out of 30 sets, each set consisting of six profiles described on three attributes	Rank ordered Logit analysis
2.	Beenstock et al. (1998)	Electric utilities	Measuring resistance to change power outage	Willingness to accept; willingness to pay; asymmetric effect	Choice-based approach with set alternatives (prospects) each described on five attributes	Conditional logit and rank-ordered conditional logit analyses
3.	Haefele and Loomis (2001)	Forest health	Measurement of valuations of attributes of forest health considering the when panel nature of conjoint data	Random utility maximization; marginal value of an attribute	Ratings of descriptions of options to control pest under each of three scenarios described on the type of insect, including its area of impact, and effects of uncontrolled infestation	Random coefficient ordered probit regression
4.	Kienast et al. (1983)	Human resources benefit programs	Evaluation of utility/cost ratios for elements of compensation packages	Trade-offs among attributes	Participation of several benefit contributors	Metamap (a regression-based method)
5.	Maddala et al. (2003)	Health services	HIV testing preference measurement. Hypotheses on testing for effects of overlap in choice sets	Random utility maximization	Pair wise choices for a number of choice sets	Random-effects probit model
6.	Poortinga et al. (2003)	Energy saving	Preference measurement for energy-saving measures described on three characteristics of domain, strategy, and amount	Fractional factorial design for profile construction	Rating of acceptability of 23 energy-saving measures described as combinations of characteristics (domain, strategy and amount of energy saving)	Analysis of variance

(continued)

No.	Author(s) and date (s)	Area of application	Context	Theoretical concepts used	Conjoint approach	Analysis technique(s)
7.	Roe et al. (1996)	Environmental economics	Measurement of Hicksian compensating variation from conjoint ratings data	Random utilities framework; Hicksian compensating variation from commodity bundle preferences	Ratings of combinations of Atlantic salmon management schemes	Tobit, ranked logit, and binary logit
8.	Telser and Zweifel (2002)	Health care	Measuring marginal willingness to pay (MWTP) for the reduction of the risk of fracture of the femur	Random utility framework	Whether or not to purchase indications for 23 scenarios each described on four attributes	Random effects probit model. Computation of MWTP using author's own model
9.	Zinkham and Zinkham (1994)	Land management and capital budgeting	Assessment of attribute partworths in land-use/management	Trade-offs	Rank ordering of four land use/management systems, each described on seven attributes	Adaptive conjoint analysis
10.	Miguel et al. (2000)	Health care	Measurement of WTP for surgery versus hysterectomy	Random utility framework and discrete choice	Choices between scenarios for surgery and hysterectomy, each defined on six attributes	Random effects probit model and WTP calculations
11.	Skjoldborg and Gyrd-Hansen (2003)	Health economics	Measurement of WTP for health care attributes (including cost) in Denmark	Linear additive utility model	Binary choices among two descriptions of hospital services, each described on eight attributes	Random effects binary probit model
12.	Adamowicz et al. (1997)	Environmental economics	Role of perceptions in revealed and stated choice preference	Random utility framework	Stated choice data from choice based experiment	Multinomial logit model (variations)
13.	Gerardz et al. (2003)	Healthcare	Use of stated preferences for use in developing breast screening participation enhancement strategies	Random utility framework	Yes or no responses for one of two sets of 16 breast screening options, designed according to a fractural factual design using 10 attributes	Random effects probit model

14.	Hensher et al. (1999)	Transportation	Combining stated preference and revealed preference data in modeling choice	Random utility framework	Use of survey for SP choices to elicit binary choices for 16 scenarios and most recent choice actual and consideration sets for revealed choices	Several types of logit models multinomial separately for SP and RP data and for combinations
15.	Morrison et al. (2002)	Environmental economics	Measurement of differences in environmental quality and deviating of value estimates for benefit transfer in Australia	Discrete choice modeling	SC and choice responses for five choice sets, each set consisting of three options described on five attributes	Multinomial Logit modeling of choice data and a simulated procedure to compute implicit prices for benefit transfer
16.	Viney et al. (2005)	Health economics	Investigation of experimental design properties of choice-based conjoint experiments	Random utility max. framework using three different designs for comparison	Choices from 16 different choice sets, each with four options, described by four attributes of health states	Multinomial logit models
17.	Finn and Louviere (1992)	Food safety	Investigation of the appropriate response to issues of public concern	Best-Worst (B-W) scaling random errors	Sixteen scenarios (complete factorial of 3 attributes 4x2x2)	Multinomial logit model and B-W scaling
18.	Schroeder and Louviere (1999)	Recreation	Study of effects of user fees on the usage of public recreation sites in the Midwest using stated choice models	Random utility theory	Binary choices for each of 16 pairs of park descriptions, each described on 22 attributes (including user fees and choices for 8 choice sets consisting of 3 sites plus staying at home)	Multinomial logit model

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Chapter 2
Theory and Design of Conjoint Studies (Ratings Based Methods)

2.1 Introduction

The basic principles of designing a marketing research study will apply to any study that uses conjoint analysis. Differences arise in the conceptual foundations. The conceptual model of conjoint analysis is quite straightforward; it postulates that the utility of a multi-attributed item can be decomposed into specific contributions of each attribute and possibly their interactions. The approach is easy to implement if the number of attributes is small. But, problems arise in most practical problems because of the large number of possible hypothetical alternatives for a given problem. In general, only a subset of possible alternatives is chosen for the study. Experimental design methods exist for selecting such subsets.

Over the years, however, researchers have developed various alternative approaches for implementing a conjoint analysis project. Basically, these approaches differ in the way preferences are elicited from respondents for a set of hypothetical choice alternatives. (These include the use of self-explicated data, adaptive data collection, and componential segmentation.) Each data collection approach leads to a corresponding approach to analyzing the data collected. This chapter first reviews the so-called standard or traditional approach in which a subset of full profiles of choice alternatives are rated by a respondent and the data are analyzed for each individual using regression analysis. Extensions to ranked data will be briefly discussed.

This chapter then presents and compares an array of alternative parameter estimation approaches. In particular, these approaches have arisen to handle the problem of large numbers of attributes in an applied situation. Examples are provided to illustrate the different approaches.

This chapter also covers the issues of stimulus presentation for data collection, reliability and validity of data. Naturally, the issues of validity are linked to the specific conjoint model used and how it is estimated (the next chapter covers the corresponding analysis methods).

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Table 2.1 Steps in conducting a conjoint analysis

Step	Details
Problem definition	Problem definition and planned usage of results
	Selection of attributes and levels
Design of profiles and survey administration	Preparation of master orthogonal design
	Preparation of questionnaire and profile cards
	Administration of survey—personal or TMT interview
Analysis	Analysis—estimation of partworths and attribute importances
Use of results	Segmentation—relating partworth clusters to background data
	Preparation of files for simulator—partworths, product profiles, base cases, background variables
Simulation and optimization	Simulations and sensitivity analysis
	Further analyses, e.g., optimization of single products or product line
Report	Preparation of report, presentation, and leave-behind simulator/optimizer with appropriate input files

2.2 Designing a Conjoint Study

As with any marketing research study, designing a conjoint study involves various steps. These are shown in Table 2.1.

Naturally, a conjoint study design begins with a definition of the problem and planned usage of results. For example, imagine that the study is being conducted for helping a firm with the design of a new product; and assume further that the firm already has an entry in the product category. In this situation, the main problem for research is not only to determine the best characteristics of the new product but also the degree to which the new product may cannibalize the sales of the firm's current product. In addition to determining the optimal levels of product attributes that maximize sales of the new product, the conjoint study needs to pay attention to estimating the total sales of the two products of the firm (existing and proposed). The researcher needs to ensure that the study design will yield the necessary results.

The next step in the study design is to select the attributes and levels for constructing the hypothetical product profiles. Then, a questionnaire needs to be constructed and a survey needs to administered among a sample of the relevant target population. The survey can be administered by several methods including a personal interview, a telephone, mail and telephone (TMT) interview, or via computer in an interactive mode. The remaining steps are essentially analysis of the data according to certain conjoint models for estimating the partworth functions and using the results for various purposes of the study. Uses include segmentation of the market, product design, estimating cannibalization, determining optimal prices and the like. Almost invariably, a market simulation is developed with the results designed to answer various "what if" questions.

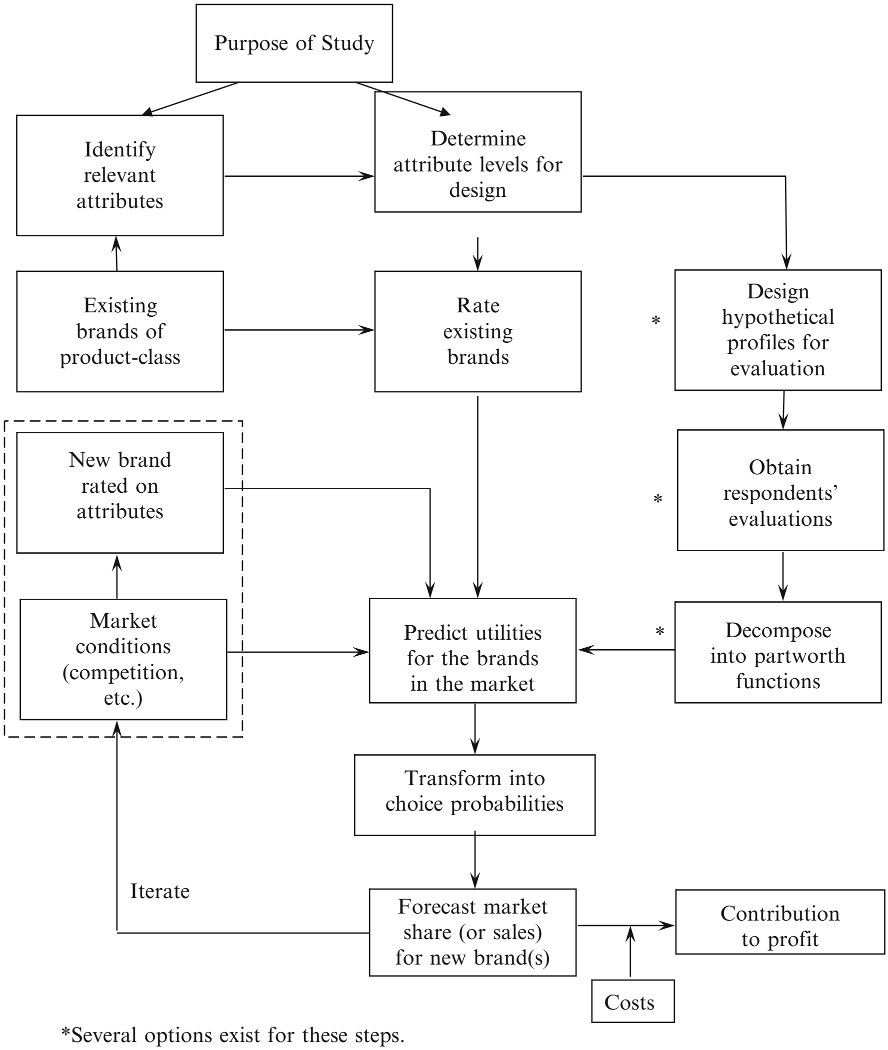


Fig. 2.1 A flowchart for applying conjoint analysis for product design and forecasting sales

A flow chart of the study design process as applicable to the problem of product design is presented in Fig. 2.1. The reader may note from the figure that an important aspect of the conjoint study design is the selection of attributes and levels. Further, several options exist for some steps such as design of hypothetical profiles, collection of data, estimating partworth functions, and converting predictions of utilities into choice probabilities. Finally, the estimate of sales of the new brand developed from market simulation will be used in estimating the revenue potential for the new brand. Relevant costs will need to be developed for arriving at an estimate of contribution to profit. These costs should include production, marketing and allocated costs. If appropriate, the simulation should be extended over several periods for determining the net present value[1] of the new product. We now return to a discussion of attribute selection, design of hypothetical profiles, and survey administration techniques. Analysis methods will be described in the next chapter.

2.3 Types of Attributes and Partworth Functions

As noted in Chap. 1, conjoint methods are intended to "uncover" the underlying preference function of a product in terms of its attributes. The specification of the function will depend upon the types of attributes chosen for the study. The attributes of a product can be divided broadly into two classes: categorical and quantitative. A nominal scale using either brand names or verbal descriptions such as high, medium or low describes a categorical attribute; here the levels of the attribute are described by words. A quantitative attribute is one measured by either an interval scale or ratio scale; numbers describe the "levels" of such an attribute. We have seen examples of these two classes of attributes in the two illustrations discussed in Chap. 1.

The levels of a categorical attribute can be recoded into a set of dummy variables (one less than the number of levels) as described in Chap. 1. A partworth function is then specified as a piecewise linear function in the dummy variables. Figure 2.2a portrays a partworth function for 4-level categorical attribute.

A quantitative attribute can be used in a manner similar to a categorical attribute by coding its values into categories or used directly in the specification of the partworth function for the attribute. Depending upon the analyst's operationalization of the attribute, the function can be linear or nonlinear. A linear function is appropriate for an attribute deemed to be desirable (e.g. speed of a laptop computer) or undesirable (e.g., weight of a laptop computer); such a function is called a vector model for which the utility increases (or decreases) linearly with the numerical value of the attribute. Figure 2.2b portrays the vector model for both desirable and undesirable attribute situations.

One particular form of nonlinear function is the ideal point model; there are two forms of the ideal point model: positive and negative ideal point models. A positive ideal point model posits an "ideal" value of the attribute to be the most desired and the partworth falls as the attribute values depart from this ideal value; an example of such an attribute is sweetness of a chocolate. For a negative ideal point model, the utility is lowest at the ideal value and it increases as the attribute departs from the ideal value; an example of such an attribute is the temperature of tea because

[1] We will not delve into the financial aspects of new product evaluations in this book but only wish to point out the connections between conjoint results and investment analysis.

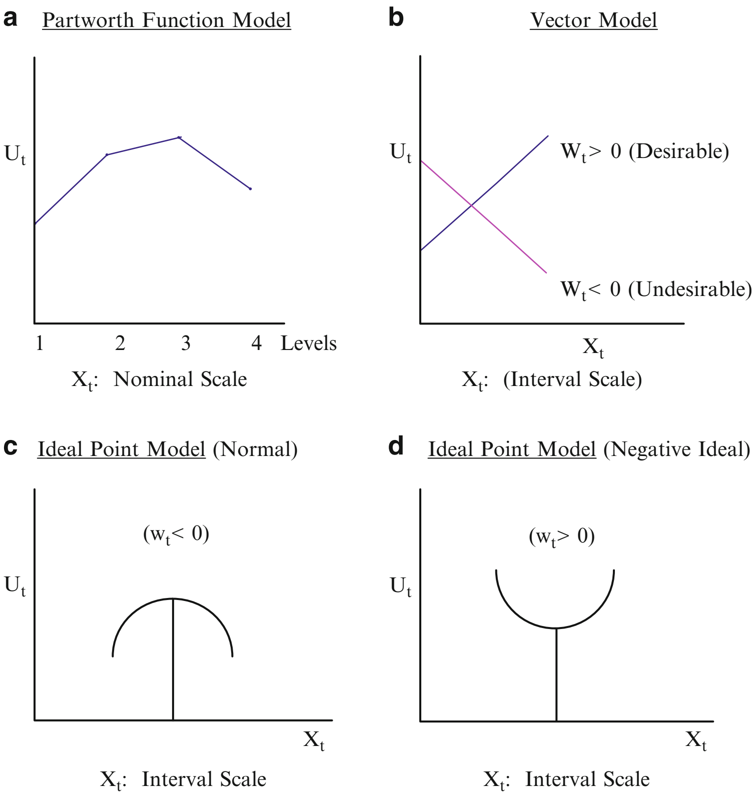


Fig. 2.2 Three forms of component utility functions

people like either an iced tea or hot tea but not tepid tea. These specifications are shown graphically in Fig. 2.2c, d.

Other nonlinear functions can be specified for the partworth functions of a quantitative attribute. One such possibility is a satiation model for which the utility increases with the attribute but never decreases as in the positive ideal point model; examples of such an attribute are the quantity of food in a combination meal, amount of space in a computer hard drive, number of minutes in cell phone contract, and the amount of news delivered by a television news program (except when one is not overwhelmed by information) We will not delve further into the mathematical specifications of such nonlinear functions.

The additive conjoint model is:

$$y_j = U_1(x_{j1}) + U_2(x_{j2}) + \ldots + U_r(x_{jr}) + \text{Error}$$

where $U_t(\bullet)$ is the component utility function specific to the t-th attribute and x_{jt} is the level for the j-th profile on the t-th attribute. No constant term is specified, but it could be included in any one of the component utility functions or assumed to be zero (without any loss of generality.) The form of these functions varies with respect to the scale used for the attributes, as discussed above.

Nominal Scaled Attributes: Partworth Function Model: The component utility function for the t-th attribute, which is nominally scaled, can be formally written as:

$$U_t\left(x_{jt}\right) = U_{t1}D_{t1} + U_{t2}D_{t2} + \ldots + U_{tr_t-1}D_{tr_t-1}$$

where

r_t is the number of discrete levels for the t-th attribute (resulting from the construction of the profiles or created ex post);

D_{tk} is a dummy variable taking the value 1 if the value x_{it} is equivalent to the k-th discrete level of x_t and 0 otherwise; and

U_{tk} is the component of the partworth function for the k-th discrete level of x_t.

In practice, only (r_t-1)—one less the number of discrete levels of the attribute—dummy variables are necessary for estimation; For example, if $r_t = 4$, the partworth model will be:

$$U_t\left(x_{jt}\right) = U_{t1}D_{t1} + U_{t2}D_{t2} + U_{t3}D_{t3}.$$

The unknowns in this function are U_{t1}, U_{t2}, . . ., which are estimated using dummy variable regression. We may note that this model fits a piece-wise linear approximation to the underlying utility function. See Fig. 2.2a for an illustration of this function for a 4-level nominal attribute and it also shows U_{t4}, the value for the 4th level as computed from the three estimated values of U_{t1}, U_{t2}, and U_{t3}. The magnitudes of U_{t1}, U_{t2}, etc. show the level and direction of the partworth function for various discrete levels of the attribute. The differences in these partworth values matter and not the absolute values.

Interval-Scaled Attribute: We consider two forms for the component utility function for the t-th attribute, which is an interval-scaled attribute. These are the vector model and the ideal point model. Mathematically,

$$\mathrm{U_t}\left(\mathrm{x_{jt}}\right) = \begin{cases} \mathrm{w_t x_{jt}} & \text{for the vector model; and} \\ \mathrm{w_t}\left(\mathrm{x_{jt}} - \mathrm{x_{0t}}\right)^2 & \text{for the ideal point model;} \end{cases}$$

where

w_t is a weight (positive or negative); and

x_{0t} is the ideal point on the t-th attribute.

We may note that the weight and/or the ideal point in this model (vector or ideal point) are estimated using regression analysis. A summary of the interpretation of these functions is given in Table 2.2.

Table 2.2 Functional forms and interpretations of the three component utility functions

Type of model	Functional form	Estimation method	Sign of U or w	Meaning
Partworth (Nominal x)	$\sum_{k=1}^{r_t} U_{tk} D_{tk}$	Dummy variable regression	+ve −ve	Changes in U's show the direction of the partworth function in relation to levels of the attributes
Vector (Interval x)	$w_t x_{jt}$	Multiple regression	+ve −ve	Attribute is more desirable Attribute is less desirable
Ideal points (Interval x)	$w_t \left(x_{jt} - x_{0t}\right)^2$	Multiple regression	+ve −ve	Negative ideal point Normal ideal point

2.4 Selection of Attributes and Levels

It should be quite clear from Fig. 2.1 and Table 2.1 that selection of attributes and levels is a very crucial step in the design of conjoint studies. This step is as much an art as a science. The scientific aspects arise from an understanding of the consumer's choice process, more specifically salient attributes involved in the choice of an alternative by a majority of target consumers. The art aspect of this process arises from relating one's understanding to potential managerial action. Given the numerical explosion of the total number of hypothetical alternatives, it is often prudent to opt for a "smaller" number of attributes and levels to include in the study.

Various methods are available to the researcher for determining the salient attributes of a product category. First, information available from a previous consumer survey can be used to identify a set of salient attributes. External sources such as *Consumer Reports* can provide a list of attributes used in their evaluations of the product category. Another source is a primary study among a small sample of consumers using such methods as direct questioning and Kelly's repertory grid method.[2] Armed with these sources of information, the researcher can conduct brainstorming with the relevant managers of the firm (e.g., R&D, marketing, sales, marketing research) to determine which attributes should be included in the study. Usually this last step is quite deliberate. It will usually bring out any constraints among the attributes that should be considered (e.g., inclusion of a particular feature in a product is not feasible with the existing technology and therefore it is not appropriate to add that feature in the study design). These discussions may also identify any

[2] This method involves the following steps. Select a random sample of three brands in the product category of interest and ask a respondent (or a small sample of respondents) to indicate the way in which two of the brands are similar and different from the third. The answer will reveal an attribute that is salient to the comparison; probe for additional ways. Change the pair and repeat the question. Select another triple and repeat the questions. Continue this process until no additional attributes are revealed. The final result will be a list of attributes that are likely to salient for the product category. See David Hughes *Attitude Measurement,* Scott Foresman, 1972.

conflicts that may exist among the management group and help identify special considerations that the study should pay attention to in the attribute selection.

In addition to ensuring the relevance of the included attributes to the individual choice process, the attributes should be actionable from a managerial point of view. Further, it should be simple to convey the attribute information to the respondents. It is also important to reduce any duplication or redundancy among the attributes; this can be accomplished by looking at the inter-correlations among the attributes and deleting redundant attributes.

Having selected the attributes, the researcher has to determine the levels and range of the attributes. This process is usually somewhat judgmental. A principal criterion here is that the attribute levels should be actionable from an R&D viewpoint. Further, the ranges of the attributes could be larger than reality but not so large as to be unbelievable. In general, it is useful to restrict the number of levels for any attribute to a relatively small number such as 2 to at most 5 or 6; this is partly due to the fact that published designs exist for these small numbers. (Appendix 1 shows several designs developed by Addelman (1962)). The general objective in restricting the number of levels to a relatively small number is to ensure fewer profiles to be generated for data collection. When quantitative attributes are used, it is important to pretest the levels to ensure that they are far enough apart to be realistically distinct.

In various studies, researchers have found an empirical regularity regarding the effect of differences in the number of attribute levels across attributes (See Wittink et al. 1982, 1989); the main result[3] is that attributes with more levels systematically achieved higher importances than those with fewer levels. Researchers need to keep this in mind while deciding on the number of attribute levels to use. One way to deal with this problem is to design studies with almost the same number of attribute levels for each attribute.

2.5 Stimulus Set Construction

2.5.1 General Considerations

Once the attributes and levels are chosen, the researcher is ready to generate the stimulus set of hypothetical profiles for evaluation by respondents. This is usually accomplished by the use of a statistical experimental design. The procedure for constructing stimulus profiles is intertwined with the particular conjoint approach used (e.g., full profiles, self-explicated method or others as shown in Fig. 1.5 of Chap. 1). For example, if the researcher is planning to use a full profile approach, it is automatically implied that the stimuli will be full profiles. Likewise, if the partial profile approach is used, the decision is in terms of which attributes are to be used in

[3] This effect is observed for various data collection methods such as full profile ratings and rankings and full profile paired comparisons. The magnitude was found to be smaller for adaptive conjoint analysis methods.

generating the partial profiles (one approach is to use the Sawtooth's Adaptive Conjoint Analysis Method).

Similarly, the determination of the stimulus set is also affected by the method of data collection (e.g., personal interview, mail survey or telephone, interactive or combinations) to be used in the study. For example, the number of profiles presented to a respondent cannot be very large if a telephone method or a computer interactive method is used. If a combination method such as TMT (telephone-mail-telephone) is used, one can generally use a large number of profiles in the study. Finally, the design chosen for stimulus construction also depends upon the need to estimate interactions among attributes; in such cases, the designs are much more complex.

It is important to point out that according to industry practice of conjoint analysis in the USA and Europe (see Table 1.5 of Chap. 1), adaptive conjoint designs are becoming popular partly due to the availability of software for implementing that approach.

The following practical considerations should be kept in mind when deciding upon the number of stimuli to be presented to the respondent:

1. There should be enough degrees of freedom for estimating the model at the individual level. The rule of thumb here is that the ratio of n/T should be as large as practical where n is the number of profiles (or stimuli) to be evaluated and T is the number of estimated parameters.
2. The prediction error should be as low as practical. The expected mean square error in predictions is $(1+ T/n)\sigma^2$ where σ^2 is the unexplained (error) variance of the model. For a given T, as n increases from $2T$ to $5T$ the prediction error decreases by 20 %. Therefore, a large number of profiles should be included to the extent feasible. A good target is to ensure that n is between $2T$ and $3T$.
3. The number of profiles to be evaluated should not be too large given the type of data collection procedure used. For example, in a self-administered survey, it is often difficult to maintain respondent interest when the number of profiles is much above 30.
4. The profiles presented should be believable (and should resemble existing products as much as possible). Pictorial and other realistic forms of presentation should be considered, to the extent feasible.

2.5.2 Statistical Designs for Generating Full Profiles

Against this background, we describe selected ways of generating full profiles of attributes for a conjoint study. The designs discussed are full factorial designs, fractional factorial designs, orthogonal arrays (symmetric and asymmetric), and incomplete block designs. We also discuss the method of random sampling as a way to generate full profiles when statistical designs are not feasible. Finally, we briefly describe a method developed for generating "acceptable" designs, which deals with the problem of presenting unrealistic profiles for respondent evaluation. For each design, we briefly illustrate the method along with a discussion of both advantages and disadvantages. See Green (1974) and Green et al. (1978) for a general discussion of design of experiments for conjoint studies.

In the following discussion, we describe designs with levels labeled as 1, 2, 3, etc. for the attributes (or 0, 1, 2, etc in the designs shown in the Appendix 3). In practice the researcher should assign the actual values of the attribute levels to levels 1, 2, 3, etc (or 0, 1, 2, etc). in a random manner. Also, the constructed profiles should be randomized before administering them to a respondent.

2.5.3 Full Factorial Designs

The profiles generated by a full factorial design include all combinations of the attribute levels. For example, in a conjoint project with three attributes respectively with 4, 3, and 2 levels, respectively, the full factorial design will consist of $4 \times 3 \times 2 = 24$ profiles to be evaluated by each respondent. One significant advantage of a full factorial design is its ability to estimate the main effects and interaction terms in the utility function. In such a design, the analyst may also set aside evaluations of 2 to 4 profiles for the purpose of holdout predictions.

As an example, consider a conjoint problem for evaluating credit cards, each of which is defined on three attributes at 2, 3 and 2 levels. The attributes are:

Attribute 1: Interest rate on outstanding loan with levels of 15 % and 12 %
Attribute 2: Credit limit with levels of $2,500, $5,000 and $10,000
Attribute 3: Ability to earn airline miles on any chosen airline with levels of yes or no.

Assume that all other attributes are kept constant at acceptable levels. For this problem, the researcher will have a total of $2 \times 3 \times 2 = 12$ profiles, which are concatenations of all levels of the attributes. These profiles are (15 %, $2,500, yes), (12 %, $10,000, no) and so on.

But, these (full factorial) designs are not practical when the total number of combinations is large (either due to large number of attributes or large number of levels for each attribute or both). Consider a design with three attributes each with five levels; the full factorial involves $5 \times 5 \times 5 = 125$ profiles, a number too large for any one respondent to evaluate. One way to deal with problem is to construct fractional factorial designs, which reduce the number of profiles to be administered to a respondent.

2.5.4 Fractional Factorial Designs

These designs, as the name implies, involve selecting a fraction of the profiles constructed in a full factorial design. For example, a one-half fractional factorial design of the $4 \times 3 \times 2$ full factorial will generate 12 profiles; these are selected in a systematic manner from the 24 profiles generated.

The advantages of a fractional design are obvious in terms of the demands placed on the respondent. Also, such a design will often enable estimation of some interactions among the attributes (the identification of which interactions can be estimated will depend upon the specific fraction chosen; details are beyond this introductory discussion). The specific fraction to be chosen will depend upon considerations such as interview time (and implicitly the research budget) and the nature of the interactions that are not confounded in the design.

A fractional factorial design was employed in an unpublished study on how managers evaluate marketing research proposals. Each proposal was described on four attributes. The attributes and levels were:

Cost: $55,000; $70,000; $85,000
Supplier reputation: established in the industry; new in the industry
Time to delivery results: 2 months; 4 months
Type of methodology to be used: “basic”; “state of the art”

In this study, the total number of possible profiles was $3 \times 2 \times 2 \times 2 = 24$. But, the study employed 12 profiles constructed according to a fractional factorial design (or a ½ factorial). These profiles (in random order) are shown in the first twelve rows in the table below; the last two profiles are used in the study for the purposes of validation. The actual questionnaire used in this study is shown in Appendix 1 to this chapter.

Proposal	Cost in $000s	Supplier reputation	Time to delivery	Methodology
1	55	New	4 months	Basic
2	70	New	2 months	Sophisticated
3	70	Established	4 months	Sophisticated
4	55	Established	2 months	Basic
5	70	Established	2 months	Basic
6	85	New	2 months	Sophisticated
7	85	Established	2 months	Basic
8	85	Established	4 months	Sophisticated
9	55	New	2 months	Sophisticated
10	70	New	4 months	Basic
11	85	New	4 months	Basic
12	55	Established	4 months	Sophisticated
13	85	New	4 months	Sophisticated
14	70	Established	2 months	Sophisticated

2.5.5 *Orthogonal Main Effects Plans*

Orthogonal main effects plans are one particular type of fractional factorial designs with some desirable properties. There are several advantages associated with orthogonal designs. First, these designs are parsimonious. Second, they enable estimation of all main effects of attributes in a conjoint study. These designs can be blocked so that each individual receives a balanced subset of profiles (as implemented in hybrid methods). Computer programs (e.g., SAS OPTEX[4]) exist for generating orthogonal main effects designs for different levels and numbers of attributes. Lastly, they were shown to yield good predictions even when some profile combinations are not fully realistic. The predictions made from these designs are not subject to predictive bias if the correlation pattern among the attributes changes from the calibration set to the prediction set.

Thus, the researcher has to consider the following factors while deciding to use an orthogonal main effect plan for a conjoint study:

1. Confidence that interactions can be neglected in a design;
2. Whether the most appropriate model of utility is additive in terms of the attribute effects; and
3. Availability of an orthogonal main effect plan for the particular problem on hand.

The last point is important because orthogonal main effect plans can be constructed for only certain numbers of levels and attributes in a conjoint study. If the researcher has no access to computer software for generating designs, she may consult published catalogs of possible designs (See Addelman (1962a and b)) and in some cases they can be adapted to one's problem. For example, an orthogonal design developed for a problem with 3 attributes each with 4 levels can easily be modified for a problem with 4 attributes in which two are at 4 levels and the other two are at 2 levels each. The same design can also be modified for a problem with three attributes in which one attribute is at 3 levels and the other two are at the original 4 levels each.

An orthogonal main effect plan is called symmetric if each attribute in the design has the same number of levels. Otherwise, it is called asymmetric. A condition for a design to be orthogonal (for both symmetric and asymmetric designs) is that each level of one factor should occur with each level of another factor with proportional frequencies. In a symmetric orthogonal design, each level of a factor occurs an equal number of times with each level of another factor. This condition is called the proportionality rule. It is useful to check whether a design is orthogonal using this rule.

For example, an orthogonal array in a conjoint study with 4 attributes each at 3 levels consists of 9 profiles. Labeling the attributes as A, B, C, and D and the levels as 1, 2, and 3 the profiles in this symmetric orthogonal array are shown in Table 2.3.

[4] Statistical Analysis System, Cary, N.C.

Table 2.3 Symmetric orthogonal array for 3^4 design

Profile	A	B	C	D
1	A1	B1	C1	D1
2	A1	B2	C2	D3
3	A1	B3	C3	D2
4	A2	B1	C2	D2
5	A2	B2	C3	D1
6	A2	B3	C1	D3
7	A3	B1	C3	D3
8	A3	B2	C1	D2
9	A3	B3	C2	D1

Table 2.4 Orthogonal arrays for selected situations. *Situation 1*: 3 Attributes (A, B and C) each at four levels

Profile	A	B	C
1	A_1	B_1	C_1
2	A_1	B_2	C_3
3	A_1	B_3	C_4
4	A_1	B_4	C_2
5	A_2	B_1	C_2
6	A_2	B_2	C_4
7	A_2	B_3	C_3
8	A_2	B_4	C_1
9	A_3	B_1	C_3
10	A_3	B_2	C_1
11	A_3	B_3	C_2
12	A_3	B_4	C_4
13	A_4	B_1	C_4
14	A_4	B_2	C_2
15	A_4	B_3	C_1
16	A_4	B_4	C_3

Note that this is an asymmetric orthogonal array

The profiles in this design are the combinations (A1, B1, C1, D1), (A1, B2, C2, D3) and so on. The reader may observe that every pair of attribute levels, i.e., A_i B_j, A_i C_k, A_i D_l, etc. appears once (and only once) in the design.

Orthogonal main effects plans for three situations are shown in (Tables 2.4, 2.5 and 2.6). These designs are for conjoint studies with 3 attributes with 4 levels each, (Situation 1 in Table 2.4) 4 attributes with 2 levels for two and 4 levels for the remaining 2 attributes (Situation 2 in Table 2.5), and 5 attributes with 2 levels for two and 3 levels for three attributes (Situation 3 in Table 2.6). These may be used for commonly occurring conjoint studies.

In a study with 9 attributes each at two levels, the orthogonal main effect plan consists of 16 profiles (shown in Table 2.7); this is a symmetric orthogonal design. An asymmetric orthogonal design in a study with 9 attributes, two of which are 4 and 3 levels respectively and the remaining seven are at 2 levels will also consist of 16 profiles (shown in Table 2.8).

Table 2.5 Orthogonal arrays for selected situations. *Situation 2*: 4 Attributes (A, B, C and D); A and B at four levels and C and D at two levels

Profile	A	B	C	D
1	A_1	B_1	C_1	D_1
2	A_1	B_2	C_1	D_2
3	A_1	B_3	C_2	D_1
4	A_1	B_4	C_2	D_2
5	A_2	B_1	C_1	D_2
6	A_2	B_2	C_1	D_1
7	A_2	B_3	C_2	D_2
8	A_2	B_4	C_2	D_1
9	A_3	B_1	C_2	D_1
10	A_3	B_2	C_2	D_2
11	A_3	B_3	C_1	D_1
12	A_3	B_4	C_1	D_2
13	A_4	B_1	C_2	D_2
14	A_4	B_2	C_2	D_1
15	A_4	B_3	C_1	D_2
16	A_4	B_4	C_1	D_1

Note that this is an asymmetric orthogonal array

Table 2.6 Orthogonal arrays for selected situations. *Situation 3*: 5 Attributes (A, B, C, D and E); A, B and C at three levels and D and E at two levels

Profile	A	B	C	D	E
1	A_1	B_1	C_1	D_1	E_1
2	A_1	B_2	C_2	D_2	E_1
3	A_1	B_3	C_3	D_2	E_2
4	A_1	B_1	C_2	D_1	E_2
5	A_2	B_1	C_2	D_1	E_2
6	A_2	B_2	C_1	D_2	E_2
7	A_2	B_3	C_2	D_2	E_1
8	A_2	B_1	C_3	D_1	E_1
9	A_3	B_1	C_3	D_2	E_1
10	A_3	B_2	C_2	D_1	E_1
11	A_3	B_3	C_1	D_1	E_2
12	A_3	B_1	C_2	D_2	E_2
13	A_1	B_1	C_2	D_2	E_2
14	A_1	B_2	C_3	D_1	E_2
15	A_1	B_3	C_2	D_1	E_1
16	A_2	B_1	C_1	D_2	E_1

Note that this is an asymmetric orthogonal array

An example of orthogonal design, as used in a project on the design of cargo vans, is given in Tables 2.9 and 2.10. The attributes and levels are shown in Table 2.9 and the design in Table 2.10.

Orthogonal arrays are categorized by their *resolution*. The resolution identifies which effects, possibly including interactions, are confounded and which ones are estimable. For example, resolution III designs enable the estimation of all main effects free of each other, but some of them are confounded with two-factor interactions. For resolution V designs, all main effects and two-factor interactions

Table 2.7 A symmetrical orthogonal array for the 2^9 factorial design

Combination	Attributes and levels								
	A	B	C	D	E	F	G	H	I
1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	1	2	2
3	1	1	1	2	1	2	2	1	2
4	1	1	1	2	2	1	2	2	1
5	1	2	2	1	1	1	1	2	2
6	1	2	2	1	2	2	1	1	1
7	1	2	2	2	1	2	2	2	1
8	1	2	2	2	2	1	2	1	2
9	2	1	2	1	1	1	2	1	2
10	2	1	2	1	2	2	2	2	1
11	2	1	2	2	1	2	1	1	1
12	2	1	2	2	2	1	1	2	2
13	2	2	1	1	1	1	2	2	1
14	2	2	1	1	2	2	2	1	2
15	2	2	1	2	1	2	1	2	2
16	2	2	1	2	2	1	1	1	1

Here all attributes have two levels each

Table 2.8 An asymmetric orthogonal array of the $4 \times 3 \times 2^7$ factorial design

Combination	Attributes and levels								
	A	B	C	D	E	F	G	H	I
1	1	1	1	1	1	1	1	1	1
2	1	2	1	2	2	2	1	2	2
3	1	3	2	1	2	2	2	1	1
4	1	2	2	2	1	1	2	2	2
5	2	1	1	2	2	1	2	2	1
6	2	2	1	1	1	2	2	1	2
7	2	3	2	2	1	2	1	2	1
8	2	2	2	1	2	1	1	1	2
9	3	1	2	1	2	2	1	2	2
10	3	2	2	2	1	1	1	1	1
11	3	3	1	1	1	1	2	2	2
12	3	2	1	2	2	2	2	1	1
13	4	1	2	2	1	2	2	1	2
14	4	2	2	1	2	1	2	2	1
15	4	3	1	2	2	1	1	1	2
16	4	2	1	1	1	2	1	2	1

are estimable free of each other. Higher resolution designs require larger designs and therefore a larger number of full profiles to be administered to respondents. Resolution III orthogonal arrays are most frequently used in marketing research

Table 2.9 Factors and levels–vans

A. Cargo area height	F. Payload capacity
1. 44 inches	1. 1,000 pounds
2. 47 inches	2. 1,500 pounds
3. 54 inches	3. 2,500 pounds
B. Cargo area length	4. 3,500 pounds
1. 88 inches	G. Engine size/price/MPG
2. 101 inches	1. 4-CYL gasoline ($150 less than standard), with 24 MPG
3. 112 inches	2. 6-CYL gasoline (standard engine), with 20 MPG
4. 126 inches	3. V-8 gasoline ($185 more than standard 6), with 14 MPG
C. Cargo area width	4. V-8 diesel ($750 more than standard 6), with 24 MPG
1. 59 inches	H. Price of standard van
2. 64 inches	1. $11,200
3. 66 inches	2. $11,400
4. 70 inches	3. $11,600
D. Width of side door opening	4. $12,000
1. 36 inches	
2. 44 inches	
3. 48 inches	
E. Flat floor preference	
1. Yes	
2. No	

There are over 18,000 combinations and the design covers $\approx$ 0.2 % of total

conjoint studies and there are very few studies with designs of a higher order resolution.

Orthogonal arrays can be either balanced or imbalanced in terms of levels of attributes. The property of level balance implies that each level occurs equal number of times within each attribute in the design. An imbalanced design gives larger standard errors for the parameter (partworth) estimates. An additional property of an orthogonal design is that of proportionality criterion; this implies that the joint occurrence of any two levels of different attributes is proportional to the product of their marginal frequencies. Designs can satisfy the proportionality criterion yet fail the level balance criterion.

2.5.6 Incomplete Block Designs

Incomplete block designs are useful when the researcher is unable to administer a large number of profiles to any respondent. Here, we consider only the balanced incomplete block designs for the ease of exposition.

While there exist several variations of these designs, the basic idea is to develop a set of orthogonal profiles and divide them up into subsets and administer them to

Table 2.10 Orthogonal main effects design–vans

	Factor							
Stimulus	A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1
2	2	1	2	2	1	2	3	4
3	3	1	3	3	2	3	4	2
4	2	1	4	2	2	4	2	3
5	2	2	1	1	2	2	2	2
6	1	2	2	2	2	1	4	3
7	2	2	3	3	1	4	3	1
8	3	2	4	2	1	3	1	4
9	2	3	1	2	1	3	3	3
10	3	3	2	1	1	4	1	2
11	2	3	3	2	2	1	2	4
12	1	3	4	3	2	2	4	1
13	3	4	1	2	2	4	4	4
14	2	4	2	1	2	3	2	1
15	1	4	3	2	1	2	1	3
16	2	4	4	3	1	1	3	2
17	1	1	1	3	1	3	2	4
18	2	1	2	2	1	4	4	1
19	3	1	3	1	2	1	3	3
20	2	1	4	2	2	2	1	2
21	2	2	1	3	2	4	1	3
22	1	2	2	2	2	3	3	2
23	2	2	3	1	1	2	4	4
24	3	2	4	2	1	1	2	1
25	2	3	1	2	1	1	4	2
26	3	3	2	3	1	2	2	3
27	2	3	3	2	2	3	1	1
28	1	3	4	1	2	4	3	4
29	3	4	1	2	2	2	3	1
30	2	4	2	3	2	1	1	4
31	1	4	3	2	1	4	2	2
32	2	4	4	1	1	3	4	3
33	3	4	4	2	1	4	3	4
34	1	1	1	3	2	1	1	1

Stimuli 33 and 34 are for validation and are not part of the orthogonal array

each subject in a subgroup of people. The overall administration yields the same number of replications for each profile.

Let n = number of profiles in the orthogonal design; r = replications for each profile; k = number of profiles administered to any one person; b = number of blocks of profiles (each block is administered to one respondent in the study). Then, in balanced incomplete block designs, the following conditions hold:

Table 2.11 Balanced incomplete design involving nine profiles and four profiles per block

Block	Profiles				Block	Profiles			
1	1	2	3	4	10	2	3	6	7
2	1	2	4	9	11	2	4	5	8
3	1	2	5	7	12	2	6	8	9
4	1	3	6	8	13	2	7	8	9
5	1	3	8	9	14	3	4	5	8
6	1	4	6	7	15	3	4	7	9
7	1	5	6	9	16	3	5	7	9
8	1	5	7	8	17	4	5	6	9
9	2	3	5	6	18	4	6	7	8

Table 2.12 The nine profiles for the three attributes (A, B, and C) each at three levels (1, 2, and 3)

Profile	A	B	C
1	A_1	B_1	C_1
2	A_1	B_2	C_3
3	A_1	B_3	C_2
4	A_2	B_1	C_2
5	A_2	B_2	C_1
6	A_2	B_3	C_3
7	A_3	B_1	C_3
8	A_3	B_2	C_2
9	A_3	B_3	C_1

1. Each profile appears at most once in a block;
2. Each profile appears exactly r times in the administration;
3. Each pair of profiles occurs exactly l times together.

Then the following conditions hold among the parameters of the design:

$$\mathrm{nr} = \mathrm{bk} \text{ and } l(\mathrm{n} - 1) = \mathrm{r}(\mathrm{k} - 1).$$

In light of the fact that n, r, k, b, and l are integers, balanced incomplete block designs exist for only certain combinations of these numbers.

As an example, consider a conjoint study with 3 attributes each at 3 levels. Using an orthogonal design, assume that 9 full profiles are developed for this study. Assume further that the study will be implemented by telephone and that four profiles will be administered to each respondent. There exists a balanced incomplete design for this situation and it will be ideal for implementing this study. Here, $n = 9$ and $k = 4$. The basic design calls for 18 blocks, each block representing a respondent and can be replicated across sets of 18 respondents in the sample. Each profile (out the nine) is replicated $r = 8$ times and each pair appears $l = 3$ times. The conditions stated above are satisfied here. The design is shown in Table 2.11. Table 2.12 shows the corresponding nine profiles of three attributes with three levels each.

Several plans for balanced incomplete designs are available in the classic text on experimental designs by Cochran and Cox (1957). Two plans for 9 and 16 profiles are shown in Tables 2.13 and 2.14; the block size is 5 in the plan for 9 profiles and it is 6 for the plan with 16 profiles.

Table 2.13 Balanced incomplete designs for nine profiles and sixteen profiles. Plan for nine profiles: n = 9, k = 5, r = 10, b = 18, ℓ = 5

Block	Profiles					Block	Profiles				
(1)	1	2	3	7	8	(10)	1	2	3	5	9
(2)	1	2	4	6	8	(11)	1	2	5	6	8
(3)	2	3	5	8	9	(12)	1	3	4	5	6
(4)	2	3	4	6	9	(13)	2	3	4	7	8
(5)	1	3	4	5	7	(14)	2	4	5	7	9
(6)	2	4	5	6	7	(15)	3	5	6	7	8
(7)	1	3	6	7	9	(16)	1	4	7	8	9
(8)	1	4	5	8	9	(17)	3	4	6	8	9
(9)	5	6	7	8	9	(18)	1	2	6	7	9

Table 2.14 Balanced incomplete designs for nine profiles and sixteen profiles. Plan for sixteen profiles: n = 16, k = 6, r = 9, b = 24, ℓ = 3

Block	Profiles						Block	Profiles						Block	Profiles					
(1)	1	2	5	6	11	12	(9)	1	3	6	8	13	15	(17)	1	4	5	8	10	11
(2)	3	4	7	8	9	10	(10)	2	4	5	7	14	16	(18)	2	3	6	7	9	12
(3)	5	6	9	10	13	14	(11)	5	7	9	11	13	15	(19)	5	8	9	12	13	16
(4)	7	8	11	12	15	16	(12)	6	8	10	12	14	16	(20)	1	4	6	7	13	16
(5)	1	2	9	10	15	16	(13)	2	4	6	8	9	11	(21)	1	4	9	12	14	15
(6)	3	4	11	12	13	14	(14)	1	3	5	7	10	12	(22)	6	7	10	11	14	15
(7)	1	2	7	8	13	14	(15)	2	4	10	12	13	15	(23)	2	3	10	11	13	16
(8)	3	4	5	6	15	16	(16)	1	3	9	11	14	16	(24)	2	3	5	8	14	15

2.5.7 *Random Sampling*

This procedure involves drawing a random sample of profiles from the total set of all possible profiles of attributes. For example, in a conjoint problem with 8 attributes each at 3 levels, there is a total of 3^8 (=6,561) possible profiles. The analyst draws a random sample of these profiles as suited to the study implementation. In general, one should draw a larger sample than the number to be used in the study so that one can delete dominated profiles from the sample. This method is quite attractive when there are no feasible designs for the problem on hand.

This method is rather easy to implement if the attributes are continuous. In this case, a multivariate distribution can be defined using the means, standard deviations, and interattribute correlations of the attribute scores. The stimulus descriptions could then be drawn from a multivariate normal (or other) distribution (Standard algorithms exist for this purpose). When the design includes some continuous and some categorical attributes, proxy continuous random variables and appropriate cut-offs could be defined for the categorical attributes; for example, one needs one cut-off value for a dichotomous attribute and two cut-off values for a three level attribute and so on. The random sampling procedure seems to be well suited to attributes that are of the ideal point type because it is possible to include many values for an attribute, thereby enabling one to identify the ideal values. This is not feasible when one uses a small number of values as in categorical attributes.

An illustration of random sampling is the study by Rao and Steckel (1995) to elicit managers' price responses to environmental changes. They asked managers from various countries to indicate price responses to their product for various situations described by external (their competitor's price change) and internal (their own cost change) factors. Each factor was described by two levels (increase and decrease). The values for the changes in the external and internal factors were drawn from a uniform distribution.

2.5.8 Generating "Acceptable" Designs

When orthogonal main effects plans are used, it is likely that some profiles will be meaningless (e.g. a product with more desirable levels of attributes is offered with a low price). A general problem is the environmental correlation among the attributes of the design. This issue is handled in several ad hoc ways such as ignoring the problem, searching for a different orthogonal design, perturbing the profiles that are either meaningless or infeasible, or selecting another profile instead of the meaningless profile, or deleting the infeasible profiles. In most cases, these ad hoc methods help solve the problem and make the profiles more realistic and acceptable to the respondent in the evaluation process. The consequence of such adjustments is that the resulting design will not be orthogonal.

Steckel et al. (1991) have developed a procedure based on combinatorial optimization to deal with this problem. Their method consists of generating the requisite number of profiles so as to maximize the orthogonality of the design (as defined by the determinant of the design matrix). While the resulting design according to their method is not orthogonal it comes very close. Unfortunately, there is no published computer program available for implementing this procedure.

2.6 Data Collection Methods

Several methods have been in used in practice to collect evaluative (or preferential) data[5] from respondents in a conjoint study. These methods are somewhat linked to the procedures employed for generating stimulus sets (or profiles). A respondent can evaluate a set of profiles or a specific profile in a number of ways. Methods used in practice include direct assessments of a profile, comparing one profile against another, comparing all the profiles and evaluating them one at a time, comparing each profile against an intended purchase and so on. Over the years, approaches such as the self-explicated methods, hybrid methods and adaptive methods have also been used in

[5] We will describe choice-based conjoint methods in Chap. 4. The data collected in that method is either yes or no scale or sometimes a ranking of options in a choice set.

practice. Also, some researchers have used only partial profiles (i.e., a product concept described by only a subset of attributes); in particular, two attributes have been historically used and the resulting method has been called the trade-off method.

As we saw in Chap. 1, the approach in which full profiles are evaluated (called the full profile approach) has been quite popular until recently. The trade-off method has been used with much lower frequency. More recently, however, adaptive methods have become more popular partly due to the advent of computer software called ACA (Adaptive Conjoint Analysis). We discuss below the details of with these approaches and some issues involved in applying them in practice.

In any of these methods, the scale used for evaluations can be categorical, ordinal or interval-scaled. For example, if the evaluation is in terms of "would buy the profile" or "would not buy the profile", the scale is categorical. If the profiles are ranked from high to low (with or without ties), the scale is ordinal. If each profile is rated on a zero to 10 point scale, the evaluation is interval-scaled.

Our focus here is on six approaches: the full profile approach, trade-off matrix method, paired comparison methods, self-explication methods, adaptive methods, and hybrid methods.

2.6.1 Full Profile Approach

In this method, each concept is described on all attributes selected for study and such descriptions are presented to the respondents. The profiles are constructed according to the methods described in the previous section. If the number of attributes (and the levels) is not too large, all combinations may be presented for evaluation. Otherwise, some form of reduction using orthogonal main effects plans or other designs is called for. In general, the profile is presented on a computer screen on paper. A sample stimulus card is shown in Fig. 2.3 for a conjoint study of automobile tires.

The mechanics of this approach are quite simple in terms of survey administration. Also, it is easy for a respondent to visualize the product concept before evaluation because all attributes are included. But, the number of combinations explodes as the numbers of attributes and levels increase.

2.6.2 Trade-off Matrix Method

In this approach, a respondent is asked to evaluate product concepts, which are combinations involving two attributes at a time. The attribute pair is changed so that the respondent will finally evaluate all possible pairs of attributes in the study. In studies with an extremely large number of attribute pairs, some experimental design methods may be used to select which pairs to include in the survey. At any rate, the respondent imagines that the other attributes are kept fixed in the product concept at some (unspecified) levels. An example of results from such a procedure is shown in Fig. 2.4 for a study on automobile tires. These responses show how the

Brand Sears Tread Life 50,000 miles Sidewall White Price $55

Fig. 2.3 Sample stimulus card for full profile approach

Tread Life

Tire Brand	30,000 Miles	40,000 Miles	50,000 Miles
Goodyear	8	2	1*
Goodrich	12	6	3
Firestone	11	7	5
Sears	10	6	4

*1 denotes the best-liked combination and 12 denotes the least-liked combination for a hypothetical respondent.

Fig. 2.4 Illustration of two-factor-at-a-time approach

respondent is trading off the levels of the two attributes; for example, this respondent prefers most Goodyear tire with 50,000 miles of tread life and she would rather stick with Goodyear brand with a lower tread life (40,000 miles) as the second preference and the Goodrich brand with 50,000 miles as the third preference etc. The responses do show that brand name is traded off for the tread life.

While this approach is easy for the respondent to provide responses, it is hard to know what assumptions the respondent is making about the attributes not specified in the matrix. Further, it is hard to aggregate the results from different respondents because of this limitation. Although this approach was popular at one time, it is no longer the case.

Question: Please indicate which profile you prefer? Choose a number below to indicate the degree to which you prefer one over the other.

-4	-3	-2	-1	0	1	2	3	4

Like the one on the left	Indifferent	Like the one on the right

Profile #5

A.	Time taken to ship order after receipt.	2 days
B.	Ratio of jewelry and fashion items to the rest.	65:35
C.	Frequency of publication.	4 times a year
D.	Sponsor of catalog.	Q

Profile #3

A.	Time taken to ship order after receipt.	1 day
B.	Ratio of jewelry and fashion items to the rest.	40:60
C.	Frequency of publication.	8 times a year
D.	Sponsor of catalog.	R

Attributes:

Fixed set: Type of paper, number of pages, mode of ordering and payment, Target audience

Variable set: (Design attributes)

A. Time taken to ship order after receipt (3 levels)	1. Within 1 day 2. Within 2 days 3. Within 4 days	C. Frequency of publication	1. 3 times a year 2. 4 times a year 3. 6 times a year 4. 8 times a year
B. Ratio of jewelry and fashion items to the rest (4 levels) (implied price levels)	1. 80:20 2. 65:35 3. 50:50 4. 40:60	D. Sponsor of catalog (4 levels)	1. P 2. Q 3. R 4. S

Fig. 2.5 Illustration of graded paired comparisons method for two full product profiles

2.6.3 Paired Comparison Methods

In this approach, the respondent is presented with a pair of profiles (either full or partial) and is asked for a judgment as to which of the two is more preferred. An example of the use of this method for full profiles is shown in Fig. 2.5 for a study on the design of catalogs for a direct mail company. Figure 2.6 shows an example of its use for partial profiles.

The advantage of this method is that the respondent is asked to focus on two product concepts and therefore the evaluations may be more meaningful. The disadvantage is that the number of pairs to be administered can be very large for any realistic conjoint study.

Question: Please indicate which profile you prefer? Choose a number below to indicate the degree to which you prefer one over the other.

-4	-3	-2	-1	0	1	2	3	4

Like the the one on on the left	Indifferent	Like one the right

Four times speed of IBM PC and six hour battery	OR	Twice the speed of IBM PC and twelve hour battery

Note: In this example, each profile shows two attribute levels.

Fig. 2.6 Illustration of graded paired comparison method for two partial product profiles

2.6.4 Self-explication Methods

This method is based on the expectancy-value model (a compositional method) that posits utility as the sum, across all attributes, of the product of attribute importance and desirability of the levels of an attribute (briefly described in Chap. 1). Rather than estimating the attribute importances, this method elicits the weights directly from the respondent. Experience indicates that this method yields predictive validity roughly comparable to that of the full profile approach.

The procedure is as follows. The respondent first evaluates desirability (or attractiveness) of each level of each attribute on a multi-point scale such as zero -10 with other attributes held constant where the most preferred level on the attribute may be assigned the highest value (10) and the least preferred level assigned the lowest value (zero). The respondent is then asked to allocate a sum of say 100 points across the attributes so as to reflect their relative importance. If there is a large number of attributes, the allocation procedure may be done for each pair and a constant sum scale derived for the attribute importances. The partworth values for each attribute are simply the product of the relative importance for the attribute and the attribute-level desirability ratings. Actual implementation with regard to the elicitation of desirability and importances often varies in practice.

The self-explicated method has several advantages. First, the method is simple to administer and easy to use even when the number of attributes is large. Second, it is a flexible way to use the full profile approach in different data collection environments such as telephone-mail-telephone methods. Finally, there is no need for any difficult estimation method to derive the partworth function.

However, the method has disadvantages, these are noted below along with possible solutions to deal with them.

(a) *Measurement of Attribute Level Ratings and Importances*. Respondents may find it difficult to provide ratings for attribute levels holding everything else constant if there is a substantial inter-correlation between attributes. [One solution is to eliminate redundant attributes in the design before data collection.] This procedure may also result in biases regarding the relative importances of attributes for socially sensitive attributes (e.g. salary in a job selection experiment). The question of relative importance is highly ambiguous because all respondents do not have a common basis for comparison, due to different experiences with the product category. One solution is to define importance as the increase in utility to the consumer by going from the least preferred level to the most preferred level of each attribute.
(b) *Nature of Utility Model Implied by the Procedure*. This procedure assumes that a utility model taking the form of an additive partworth model is the true model and is applicable to all respondents. This problem is most relevant for ratings-based conjoint methods rather than nonmetric (ranking) data because of the opportunity to transform ranked data to fit an additive model.
(c) *Attribute Redundancy*. The self-explication approach can lead to double counting if there are redundant attributes. The solution lies in eliminating redundant attributes before data collection. (This problem is not as serious with the full profile approach.)
(d) *Potential Linearity of the Desirability Scale for Quantitative Attributes*. The responses to the desirability ratings (on a 0–10 scale, say) for attribute levels with equal intervals follow a linear scale. Thus, this procedure does not permit any nonlinearity in the partworth function for a quantitative attribute.
(e) *Limitation of Exclusive Dependence on this Approach*. If no other data are collected from the respondent except that indicated above (desirability ratings and relative importances), one will not be able to assess the validity of any predictive results for new products from this approach (it is therefore important to collect additional data on purchase likelihoods for full profiles of attributes).

As an illustration, we show the questions used for an application of the self-explication method to a project on the design of cargo vans in Fig. 2.7.

2.6.5 Adaptive Methods

The methods described so far are essentially a one-shot approach to calibration of the utility functions; that is, a set of data are collected and analyzed to get the partworth functions. But, it is easy to argue that if one designs additional questions on the basis of some preliminary idea of the partworth functions, the final estimates of the partworth functions will be more indicative of the true underlying utility of the individual. The adaptive methods are essentially based on this premise. In one sense, the approach is quite consistent with Bayesian statistical analysis. The most popular implementation

1. Please consider the following attributes:

- Cargo area height
- Cargo area length
- Cargo area width
- Width of side door opening
- Flat floor preference
- Payload capacity
- Engine size/price/MPG
- Base price

2. Now that you have considered each of the eight attributes of the van individually, we'd like to know how important the attributes themselves are to you. Assume that you have 100 points available in terms of their relative importance. If you wish, you may allocate zero points to one or more attributes, but the total should sum to 100.

- Cargo area height ________________
- Cargo area length ________________
- Cargo area width ________________
- Width of side door opening ________________
- Flat floor preference ________________
- Payload capacity ________________
- Engine size/price/MPG ________________
- Base price ________________

Fig. 2.7 Interviewing procedure for the self-explicated part of a project on the design of cargo vans

of the adaptive conjoint methods is through the interactive computer software called Adaptive Conjoint Analysis (ACA) and we focus our discussion on this particular method. This discussion is based on Sawtooth Software's published materials (See Johnson 1987, 1991).

The ACA procedure consists of four phases (Version II of the software). In Phase I, each respondent ranks one's preferences for each level of each attribute of the study in turn. Phase II consists of having the respondent rate the attributes in terms of their importance on a 1 to 4 equal-interval rating scale where 4 denotes the highest importance. In the Phase III, the respondent receives a set of paired partial profiles (designed by the software using the information collected in the first two phases) and makes a preference judgment on a nine point equal interval scale. The objective is to get an assessment of which profile is preferred over the other and by how much; these are called graded paired comparisons. In the Phase IV, the respondent receives 2 to 9 profiles composed of at most 8 attributes. These calibration concepts are chosen by the software so as to progress from highly undesirable to highly desirable. The respondent rates these on a 0 to 100 likelihood of purchase scale.

The procedure in the third phase is at the heart of the ACA methodology. The procedure is adaptive in the sense that each paired comparison is constructed so as to take advantage of the information collected about the respondent's partworths in the previous steps.

The ACA approach clearly has several advantages. It is a highly visible way to elicit an individual's preference functions. It is quite versatile and can be adapted to almost any situation. From the respondent's perspective it is easy to learn and use and can even be fun. In an evaluative study of this technique, Green et al. (1991) found some weaknesses of the approach. First, they found a weakness in forcing equal subjective scales and ranges for all attributes in Phase I and they deemed the scale used in Phase II to be too coarse. Although the data collected in Phase III are the major component of the method, they found a lack of consistency between the way profiles are designed to be indifferent and the use of a 9 point scale for assessment. Finally, the software needs to utilize commensurate scales in all the four phases. The authors indicated ways to improve the ACA system such as providing of an option for including a partworth updating feature that does not require commensurate units between phases and a formal procedure for finding commensurate units between Phase I/II and Phase III. The Sawtooth software has been modified since to handle these problems (we return to the method of analysis used in this approach in the next Chap. 3). See also Mehta et al. (1992) for an examination of this method.

The paper by Huber and Klein (1991) deals with a related problem of how individuals adapt acceptable minimum attribute levels (cut offs) in a choice environment.

Recently, Toubia et al. (2003) developed a method for sequentially asking questions in adaptive conjoint analysis. These methods are called "polyhedral methods". Estimation based on this approach is covered in the next chapter with comparative results between ACA and the polyhedral method of estimation.

2.6.6 Hybrid Methods

Hybrid methods have been developed to deal with the problem of handling large number of attributes (and levels) in a conjoint study. It is obvious that no one respondent has the desire or time to evaluate a large number of profiles. This problem was tackled by combining the two approaches of the self-explicated method and the full profile approach. Essentially, the hybrid approach involves two phases. In Phase I, the respondent is asked to provide data on attribute desirabilities and attribute importances in a manner quite similar to the self-explicated approach. In Phase II, the respondent is given a limited number of profiles for evaluation rather than administering all profiles as done in a full profile approach. The limited number of profiles administered is drawn from a master design, constructed according to an orthogonal main effects plan or some other experimental design. The final estimation of partworth functions in this approach is at the level of a subgroup. The software need to be tailor-made specific to the situation on hand. We return to the details of the estimation method in Chap. 3. See Green (1984) for an exposition of hybrid methods.

The hybrid approach tackles the problem of large number of attributes or levels in an appealing manner. Also, the issue of being able to estimate the partworth functions at the level of an individual respondent has recently been resolved with the use of hierarchical Bayes methods (See Lenk et al. 1996). (We will discuss this method in Chap. 3.).

2.7 Stimulus Presentation

There are essentially three basic approaches for presenting stimuli in a conjoint study.

These are verbal descriptions, pictorial descriptions, and prototypes (or samples) of actual products designed according to the profiles developed for the study. Other methods such as the use of paragraph descriptions have also been used in studies. Traditionally, however, researchers have used terse verbal descriptions owing to the simplicity involved; verbal descriptions are still the more popular method (see Table 1.4 of Chap. 1). But, this approach may not truly convey the stimulus that is being evaluated. This issue is particularly relevant for food products where taste may be an important consideration. An additional issue with verbal descriptions is the possibility that different respondents interpret the words differently, thereby increasing the heterogeneity in the responses. See Vishwanathan & Narayan (1992) for a study on differences in processing of natural-value and scale-value numerical information.

Use of pictures or visual props is generally a good method for describing product concepts that involve larger numbers of attributes and levels within an attribute. Pictures make the evaluation task more interesting for the respondent and reduce information load in the verbal descriptions. Further, pictures increase the perceptual homogeneity across respondents. However, the use of pictures allows for interaction effects to become more prominent in the evaluation process; a consequence of this is that the model estimated may not be additive in main effects alone. Examples of attributes described as pictures are shown in Fig. 2.8.

The approach of using prototypes is perhaps the most appealing. But, it is not feasible in many situations. Also, it can increase the cost of a conjoint study immensely.

2.8 Reliability and Validity

Internal reliability and validity of conjoint results based on holdout samples is generally very high; the Pearson correlation of test/retest reliability is approximately 0.85 in some studies. However, in an extensive study, Reibstein et al. (1988) found that the type of data collection procedure does have a significant impact on the reliability of conjoint results; the paired comparisons method was shown to have highest reliability relative to the full profile method and the trade-off method. Further, they found that reliability scores were much higher for the attribute sets than the stimulus sets; but, these results need further testing for generalization. See also McCullough and Best (1979), Segal (1982) and McLachlan et al. (1988) for other studies on this subject.

The internal predictive validity on the basis of holdout samples was also shown to be quite high; the Pearson correlation was about 0.75, but, the external validity of conjoint studies is hard to measure. While methods such as BASES product concept testing or in-store experimentation are feasible options for checking external validity, the most frequently used method at this time seems to be managerial judgment. More studies are needed for testing the external validity of conjoint methods. See also

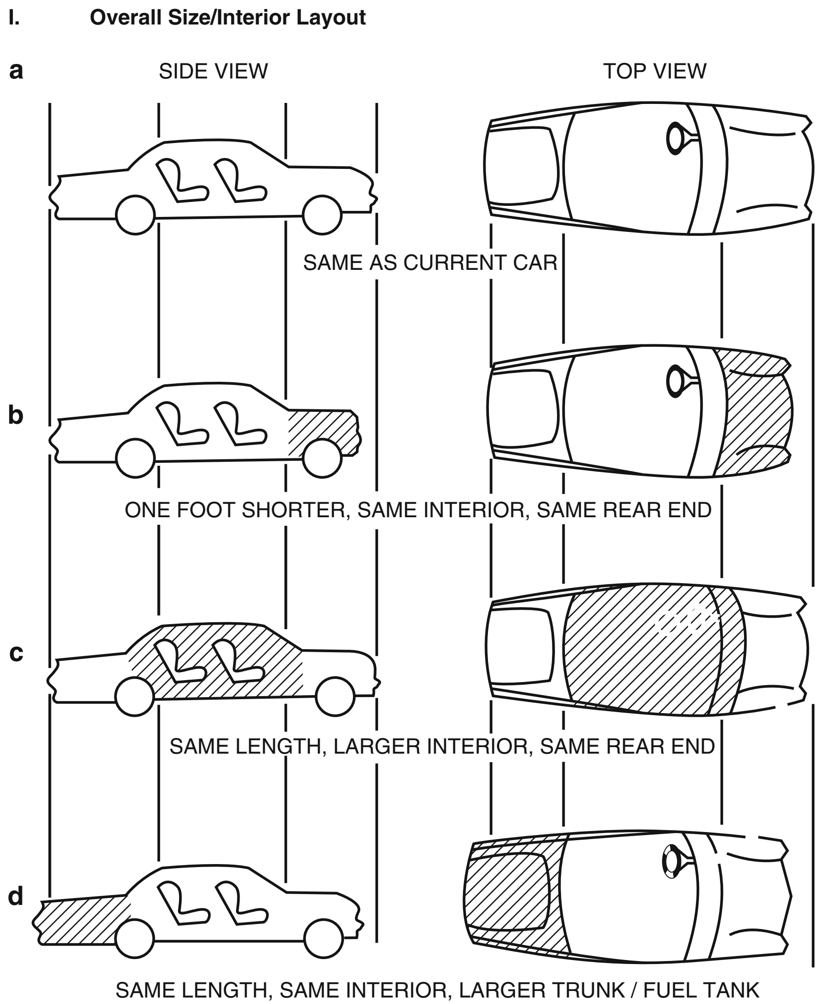


Fig. 2.8 Examples of use of visual props for attributes of a car

Akaah and Korgaonkar (1983) for a comparision of predictive validity of sevaral ratings-based conjoint methods and Acito and Jain (1980) for a discussion of the relationship of respondent's education level to the predictive accuracy of selected conjoint methods. The study by Huber et al. (1993) is quite comprehensive on this topic.

2.9 Summary

This chapter has described the principal steps involved in the design of a conjoint study. It elaborated on methods for constructing stimulus sets using experimental design procedures. Factorial designs, balanced incomplete block designs and

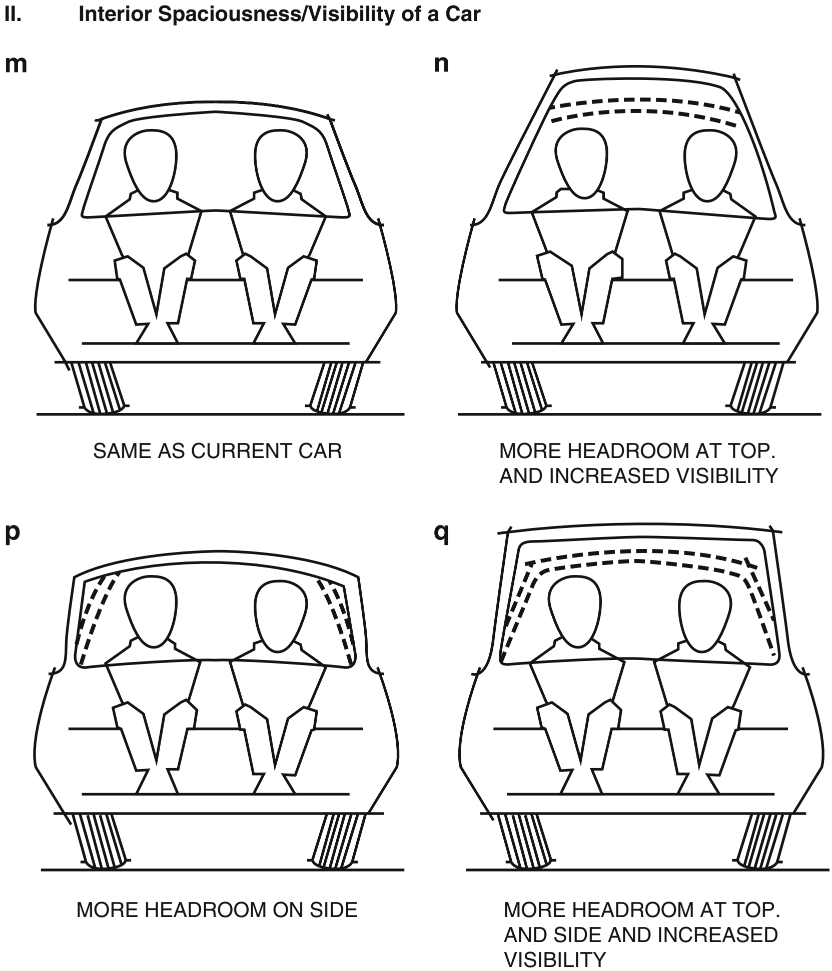
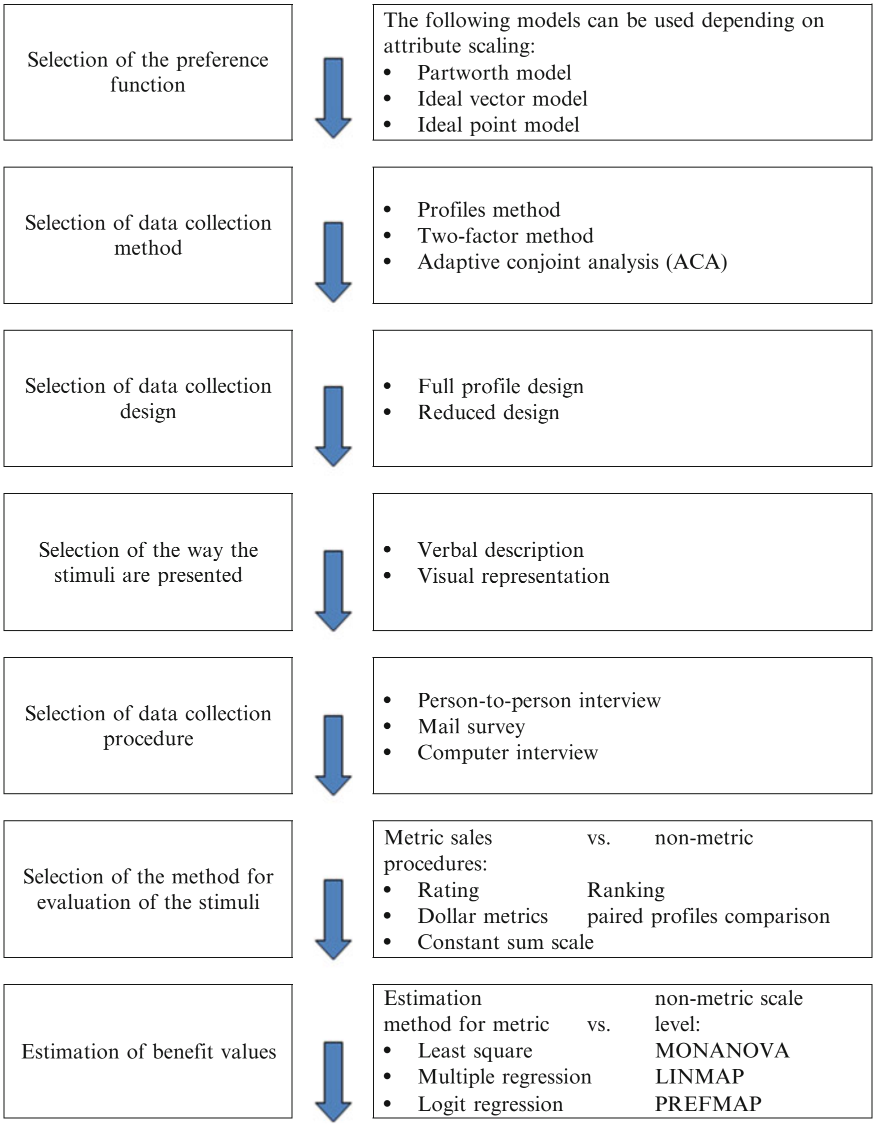


Fig. 2.8 (continued)

orthogonal main effects plans are suitable for generating stimulus sets of profiles of attributes. We also described different data collection methods such as the full profile method, the pair-wise trade-off matrix, the self-explicated method and graded paired comparisons. The approaches of adaptive conjoint and hybrid conjoint, which utilize the self-explicated approach, are more recent developments. The adaptive method is implemented in an interactive mode, using a computer software; this approach is becoming more popular. The hybrid conjoint method is particularly suited for dealing with the issues of large numbers of attributes and levels in a conjoint study. Further, the issue of inability to estimate partworth functions at the individual level has also been resolved.

The chapter also covered the issues of how stimuli should be presented in a conjoint design. While verbal descriptions have been traditional, pictures are now being used to a greater degree. In addition to some realism, they offer the flexibility of



Source: Reprinted with permission from Gustaffson, Anders, A. Herrmann and F. Huber (eds.) Conjoint Measurement, Third Edition, Chapter 1, page 9, Springer, 2003.

Fig. 2.9 Flow diagram of conjoint analysis (preference-based)

presenting information on a greater number of attributes and levels. Finally, we also discussed the issues of reliability and validity of conjoint methods.

While this chapter focused on a few of the steps in Fig. 2.1, which deals with the design of studies for collecting data, the next chapter covers the remaining steps. The focus of the next chapter is on analysis methods and models for estimating the partworth functions and using the results. The flow diagram shown in Fig. 2.9

provides a summary of various steps and alternatives available for the ratings-based conjoint analysis.

Appendix 1

Illustration of a Ratings-Based Conjoint Questionnaire

Conjoint Analysis of Research Proposals

I. The Good Gourmet Food Company has recently completed product development work on a new line of frozen pastries and pies. They intend to launch the new product line, Delectible Delights, in 6 months with a major introductory advertising and promotional campaign. Prior to that time, the brand manager, Margaret Malott, intends to have a market segmentation study conducted for the frozen dessert category. Ms. Malott hopes that such research will help her to identify the most appropriate market segments toward which to direct advertising and promotional expenditures for Delectible Delights. The lead time for translating research results into strategy is expected to be about two months.

Ms. Malott has received proposals from fourteen marketing research suppliers interested in designing and fielding such a study, and is now faced with the problem of deciding which supplier to choose.

* * * * *

Assume that you are in a position to evaluate the fourteen proposals submitted by these suppliers. Each proposed study can be defined along four attributes:

- *COST*: $55,000; $70,000; $85,000
- *SUPPLIER REPUTATION*: established in the industry; new in the industry
- *TIME TO DELIVERY OF RESULTS*: 2 months; 4 months
- *TYPE OF METHODOLOGY TO BE USED*: “basic”, (using standard research techniques); “state of the art”, (using sophisticated research techniques).

Profiles for each of the fourteen proposed studies are provided in the attached questionnaire. Assume that all of the proposals meet the minimum requirements on the issues of sampling, questionnaire construction, data collection, and report presentation.

For each proposed study, please indicate how likely *you* would be to accept such a proposal, on a scale from 0 (“Would definitely not accept this proposal”) to 100 (“Would definitely accept this proposal”). You may choose any number between 0 and 100. (For example, feel free to use numbers such as 37, 50, 92, etc.)

[Note: A few changes were in the last section for student respondents.]

Illustration of a Conjoint Questionnaire

0	10	20	30	40	50	60	70	80	90	100
Definitely not accept										Definitely accept

PROPOSAL #1

COST:	$55,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	4 months	
METHODOLOGY:	Basic	

PROPOSAL #2

COST:	$70,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	2 months	
METHODOLOGY:	Sophisticated	

PROPOSAL #3

COST:	$70,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	4 months	
METHODOLOGY:	Sophisticated	

PROPOSAL #4

COST:	$55,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	2 months	
METHODOLOGY:	Basic	

PROPOSAL #5

COST:	$70,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	2 months	
METHODOLOGY:	Basic	

PROPOSAL #6

COST:	$85,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	2 months	
METHODOLOGY:	Sophisticated	

Illustration of a Conjoint Questionnaire

0	10	20	30	40	50	60	70	80	90	100
Definitely not accept										Definitely accept

PROPOSAL #7

COST:	$85,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	2 months	
METHODOLOGY:	Basic	

PROPOSAL #8

COST:	$85,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	4 months	
METHODOLOGY:	Sophisticated	

PROPOSAL #9

COST:	$55,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	2 months	
METHODOLOGY:	Sophisticated	

PROPOSAL #10

COST:	$70,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	4 months	
METHODOLOGY:	Basic	

PROPOSAL #11

COST:	$85,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	4 months	
METHODOLOGY:	Basic	

PROPOSAL #12

COST:	$55,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	4 months	
METHODOLOGY:	Sophisticated	

Illustration of a Conjoint Questionnaire

0	10	20	30	40	50	60	70	80	90	100
Definitely not accept										Definitely accept

PROPOSAL #13

COST:	$85,000	Your Rating
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	4 months	
METHODOLOGY:	Sophisticated	

PROPOSAL #14

COST:	$70,000	Your Rating
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	2 months	
METHODOLOGY:	Sophisticated	

Illustration of a Conjoint Questionnaire

II. (a) Below is a list of ten factors clients use in selecting a marketing research supplier. Rank these from high ("1") to low ("10") in terms of importance from your point of view.

	Rank
Marketing Insight	____________
Research Design	____________
Sampling	____________
Data Collection	____________
Analysis Design	____________
Report Organization	____________
Presentation of Results	____________
Delivery Time	____________
Cost Estimate	____________
Experience in Research	____________

(b) Are there any other factors that you deem should be considered in supplier selection? If so, please list them.

____

____

____

III. A few questions about yourself:

(a) In what type of organization do you work?

- Research Supplier ☐
- Client ☐
- Other ☐

(b) Number of years of your experience in marketing research. ______________

(c) How many research projects were you responsible for? ____________ (Approximate)

(d) How many research projects did you participate in? ____________ (Approximate)

(e) Your highest academic degree: ______________
and field: ______________

Appendix 2

Measures of Efficiency of an Experimental Design

When an analyst selects a design for creating profiles or choice sets in conjoint studies, it is important to pay attention to the efficiency of the design. In general, the efficiency of a design is a measure of the standard error of the estimates made from such a design against the minimum possible standard error for the full profile design.

Various measures for discuss the efficiency of an experimental design can be described as follows for the linear model (Kuhfeld et al. 1994), $Y = X\beta + \varepsilon$; where β is a $p \times 1$ vector of parameters, X is an nxp design matrix, and ε is random error. With the usual assumption on errors, the least squares estimate of β is given by $(X'X)^{-1}X'Y$. The variance-covariance matrix of the parameter estimates (or partworths) of the attributes is proportional to $(X'X)^{-1}$. The efficiency of a design is based on the information matrix $X'X$. An efficient design will have a smaller variance matrix and the eigen values of $(X'X)^{-1}$ provide measures of the size of the matrix. Three efficiency measures (all based on the eigen values) are:

A-efficiency: 1/(n trace $((X'X)^{-1}$/p);
D-efficiency: 1/(n| $(X'X)^{-1}$ $|^{1/p}$); and
G-efficiency: $\sqrt{p/n}/\sigma_M$, where σ_M is the minimum standard error possible.

The minimum standard error is attained when a full factorial design is used and any fractional design will have efficiency less than 1. These three measures are useful for making comparisons of efficiency of designs used for a given situation.

Orthogonal designs for linear models are generally considered to be efficient because their efficiency measure is close to 1. (Three measures of efficiency of an experimental design are described in Appendix 2). Kuhfeld et al. (1994) show that the OPTEX procedure (SAS Institute 1995) can produce more efficient designs while achieving neither perfect level balance nor the proportionality criteria. An example of such a design is shown in Table 2.15 for a factional design for a study with 5 factors, 2 at 2 levels and 3 at 3 levels (or a $2 \times 2 \times 3 \times 3 \times 3$ design). The D-efficiency for the design in Table 2.15 is 99.86 % compared to the D-efficiency of 97.42 %. See also Kuhfeld (2003).

Table 2.15 Information-Efficient Fractional Design for an 18-run for a $2^2 3^3$ Design

No.	Factor 1 (2 levels)	Factor 2 (2 levels)	Factor 3 (3 levels)	Factor 4 (3 levels)	Factor 5 (3 levels)
1	**−1**	**−1**	**−1**	**0**	**−1**
2	−1	−1	0	−1	0
3	−1	−1	0	1	−1
4	−1	−1	1	0	1
5	−1	−1	1	1	1
6	−1	1	−1	−1	0
7	−1	**1**	−1	0	−1
8	−1	1	0	−1	1
9	−1	1	1	1	0
10	1	−1	−1	−1	1
11	1	**−1**	−1	1	0
12	1	−1	0	0	0
13	1	−1	1	−1	−1
14	1	1	−1	1	1
15	1	**1**	0	0	1
16	1	1	0	1	−1
17	1	1	1	−1	−1
18	1	1	1	0	0

Source: Reprinted with permission from Kuhfeld et al. (1994), published by the American Marketing Association

Appendix 3

Several Orthogonal Plans

Source: Addelman, Technometrics; Reproduced with permission

Basic Plan: 1; 4; 3; 2^7; 8 Trials

*	*	1234567
0	0	0000000
0	0	0001111
1	1	0110011
1	1	0111100
2	2	1010101
2	2	1011010
3	1	1100110
3	1	1101001
*-1, 2, 3		

Basic Plan: 2; 3^4; 2^4; 9 Trials

1234	1234
0000	0000
0112	0110
0221	0001
1011	1011
1120	1100
1202	1000
2022	0000
2101	0101
2210	0010

Basic Plan: 3; 4^5; 3^5; 2^{15}; 16 Trials

12345	12345	00000	00001	11111
*****	*****	12345	67890	12345
00000	00000	00000	00000	00000
01123	01121	00001	10111	01110
02231	02211	00010	11011	10011
03312	01112	00011	01100	11101
10111	10111	01100	00110	11011
11032	11012	01101	10001	10101
12320	12120	01110	11101	01000
13203	11201	01111	01010	00110
20222	20222	10100	01011	01101
21301	21101	10101	11100	00011
22013	22011	10110	10000	11110
23130	21110	10111	00111	10000
30333	10111	11000	01101	10110
31210	11210	11001	11010	11000
32102	12102	11010	10110	00101
33021	11021	11011	00001	01011
1-000	2-000	3-000	4-111	5-111
*-123	*-156	*-789	*-012	*-345

Basic Plan: 4; 3^7; 2^7; 18 Trials

1234567	1234567
0000000	0000000
0112111	0110111
0221222	0001000
1011120	1011100
1120201	1100001
1202012	1000010
2022102	0000100
2101210	0101010
2210021	0010001
0021011	0001011
0100122	0100100
0212200	0010000
1002221	1000001
1111002	1111000
1220110	1000110
2010212	0010010
2122020	0100000
2201101	0001101

Basic Plan: 5; 5^6; 4^6; 3^6; 2^6; 25 Trials

123456	123456	123456	123456
000000	000000	000000	000000
011234	011230	011220	011110
022413	022013	022012	011011
033142	033102	022102	011101
044321	000321	000221	000111
101111	101111	101111	101111
112340	112300	112200	111100
123024	123020	122020	111010
134203	130203	120202	110101
140432	100032	100022	100011
202222	202222	202222	101111
213401	213001	212001	111001
224130	220130	220120	110110
230314	230310	220210	110110
241043	201003	201002	101001
303333	303333	202222	101111
314012	310012	210012	110011
320241	320201	220201	110101
331420	331020	221020	111010

(continued)

342104	302100	202100	101100
404444	000000	000000	000000
410123	010123	010122	010111
421302	021302	021202	011101
432031	032031	022021	011011
443210	003210	002210	001110

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Chapter 3
Analysis and Utilization of Conjoint Data (Ratings Based Methods)

3.1 Introduction

We saw in the previous chapter various methods for designing and collecting data in ratings-based conjoint studies. The data collection procedure used almost invariably dictates the type of analytical method used in conjoint analysis. In addition, analysis methods depend on two major factors: the nature of the scale used for the dependent variable (preference) and the desired level of data aggregation.

When the responses are measured on an interval scale, ordinary least squares regression methods are quite suitable. But, when the responses are either ordinal (ranked) special methods such as monotone regression/linear programming are called for. For categorical data, relevant methods include the multinomial logit/probit; another method hardly ever used is the categorical conjoint measurement. Given the preponderance of the use of interval scales for collecting response data in conjoint projects, we will focus mainly on regression-related methods of analysis.

In general, ratings data are analyzed at the individual level. But, when the sample is very large, it can be unwieldy to deal with the individual-level results for a large sample of individuals. Thus, there is a need to do some kind of aggregation. Aggregation (i.e. creation of subgroups or treating the sample as a whole) can be done either at the analysis level or at the results level. It is preferable to aggregate at the results level because no specific assumptions are needed on the homogeneity of individuals while estimating a subgroup-level model; in general, one can fit different partworth models specific to each individual in the sample. Summarizing results from several individual level analyses is akin to tabulation of several outputs from individual level analyses (e.g. partworth values, degree of fit, relative importances of attributes etc.). It is also typical to cluster the individual level partworth functions or derived attribute importances. Clustering methods are also quite useful in forming subgroups of respondents for analysis at an aggregated level. In addition there exist analysis approaches that use prior information and these are also described in this chapter.

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While it is preferable to analyze data at the individual respondent level, the estimates of the partworth functions can be less reliable owing to the small number of observations relative to the number of parameters estimated. Thus, some kind of aggregation of the sample into subgroups is usually desirable. But, the average individual coefficient for a fixed design is equivalent to the pooled coefficient. Given this equivalence, one is almost always better off building individual level models and aggregating the results.

Assumptions of homogeneity need to be satisfied when performing aggregated analysis. Segmenting individuals on the basis of relevant characteristics is one way of identifying groups for which a common analysis can be done. These variables include background characteristics such as age, gender and occupation, usage of the product category, preferred/last chosen brand, etc. These variables do not include the preference scores for the profiles in the conjoint study. An alternative way is to group individuals based on their evaluative responses to the profiles; here, the variables will be preference scores for the profiles, profile preferred most, etc. In either case, the most relevant technique of analysis for aggregation is cluster analysis.

In some cases, the analyst may wish to estimate one function for the sample as a whole and yet wish to account for heterogeneity among individuals. The objective here then is to incorporate additional variables to account for heterogeneity among partworth functions and conduct one analysis for the sample as a whole. One such procedure is called componential segmentation; but it is no longer much used. This procedure is generally adopted when the data are collected by a hybrid conjoint design. A set of newer hybrid conjoint models were recently developed that enable estimation of individual-level partworths. We will describe relevant analysis methods and models for these cases.

An overriding objective in conjoint analysis is to make predictions of choice for new alternatives not considered in the design. In such tasks, it is better to predict choices at the individual level and aggregate the individual choice predictions to the market level (with appropriate weighting if needed). A choice simulation generally accomplishes this. Developing a choice simulation model from the conjoint results is common in practice. The issues of which choice rules to apply and how sensitive the choice predictions are to the use of different rules will be described in this chapter. Problems arise as how to incorporate brand-specific factors and make other adjustments in a choice simulator; we also will discuss these issues in this chapter.

Against this background, the focus of this chapter is on the various analytical methods for estimating the partworth functions and summarizing the results from a conjoint study. It will also cover techniques involved in using the results for a choice simulation and optimization. The simulation helps in answering various “what-if” questions that are extremely critical for managerial decisions based on conjoint data.

3.2 Analysis Models for Ratings Data

We will first consider the analysis models for ratings data or continuous responses (or interval-scaled evaluations). The basic method of analysis for ratings data is multiple regression. One simply has to set up the predictor variables in such a way to describe the partworth functions specified earlier and to regress the response data on the predictor variables. The models for other types of evaluation scales are quite similar; but analysis methods differ as pointed out earlier.

3.2.1 Notation

Consider a conjoint design with a number of attributes at different numbers of levels. Assume further that a subset of all possible profiles is evaluated by a sample of respondents. In order to specify the model for analysis, we will use the following notation.

Let

I = number of respondents;
R = number of attributes;
ℓ_r = number of levels for the r-th attribute; r = 1, 2, . . ., R
J = number of profiles evaluated by the respondent;
X_j = j-th profile $\left(x_{1j_1}, x_{2j_2}, \ldots, x_{Rj_R}\right)$, j = 1, 2, . . ., J; ($j_1$ is the level for the first attribute and so on)
N = number of respondents in the study;
Y_{ij} = evaluation of the j-th profile by the i-th respondent (i = 1, 2, . . ., I);
Z_i = vector of S background variables describing the i-th respondent; i = 1, 2, . . ., I
$Q_r = \ell_r - 1$ = number of dummy variables for the r-th attribute;
D_{rq} = the dummy variable for the q-th level of the r-th attribute (q = 1, 2, . . ., Q_r);
D_{rqj} = value of the dummy variable, D_{rq} for the profile;
Z_{is} = the score of the i-th respondent on the s-th background variable;s = 1, 2, . . ., S; i = 1, 2, . . ., N.
U_r (.) = partworth function for the r-th attribute; r = 1, 2, . . ., R
U (X_j) = utility of the j-th profile for a respondent; j = 1, 2, . . ., J and
DV = set of all D-variables; there will be $\sum_r Q_r = Q$ DV-variables in all.

Note that if any attribute is quantitatively described (e.g., miles per gallon) and used at a finite number of levels in the design, the analyst has the option to use it directly as one variable rather than using a set of dummy variables (because the attribute can also be treated as a categorical attribute). Categorical attributes will be converted into appropriate number of dummy variables (i.e. one less than the number of levels) of the attribute. We discussed in the previous chapter various ways in which partworth functions can be specified for different attributes. In general, the partworth function for a categorical attribute is specified as a piece-wise linear function with the use of dummy variables for the categories. The partworth function for a continuous attribute can be specified either as a linear function (a vector model) or as a quadratic function (an ideal point model). Appendix 1 describes how to compute trade-offs between two attributes for three cases of utility functions (linear, piece-wise linear and quadratic); these cases correspond to the vector model, the partworth model for categorical attributes, and the ideal point model.

3.2.2 Additive Utility Model

The additive utility model is applicable for data collected according to an orthogonal array or where interactions among attributes can be ignored. This model of utility will consist of parts corresponding to the three types of attributes. Letting the number of attributes of the three types (categorical, vector, and ideal point) be $(p_1 + p_2 + p_3 = p)$, the utility function can be specified as:

$$
\begin{aligned}
U = \beta_0 &+ \text{partworth functions for the } p_1 \text{ attributes which are categorical} \\
&+ \text{partworth functions for the } p_2 \text{ attributes which are vector -type} \\
&+ \text{partworth functions for the } p_3 \text{ attributes which are ideal point type.}
\end{aligned}
$$

Here β_0 is a constant term for the model as a whole. By suitable definition of the attributes, this model can be specified as an additive function which is linear in parameters.

As an illustration, consider a conjoint study conducted among teenagers for determining the optimal design of a chocolate candy bar. The study used the following attributes and levels and used an orthogonal design. Thirty-two profiles were presented to respondents for evaluation of the liking of each chocolate profile.

Attribute	Number of levels	Description of levels
1. Shape of chocolate	3	Square; rectangular; spherical
2. Type of nuts present	4	Almonds, peanuts, hazel nuts, or no nuts
3. Consistency of chocolate	3	Creamy, semi-hard, hard
4. Amount of sugar	5	Continuous variable drawn randomly from the range of 5–40 % sugar (in terms of weight of the chocolate bar)
5. Weight of chocolate	3	50, 75, 125 g

In this study $p = 5$. We may specify the partworth functions for the first three attributes as piece-wise linear functions because these attributes are categorical; a categorical attribute with k categories will require (k-1) variables to describe it; actual coding is discussed in the next section. Accordingly, these three attributes will require $2 + 3 + 2 = 7$ parameters. The function for the fourth attribute (amount of sugar) is perhaps best described by an ideal point model concave at the origin (with 2 parameters).[1] The fifth attribute, weight of chocolate is a continuous variable, but was specified at three levels. Therefore, it can be treated as a categorical attribute with 2 parameters (or 2 dummy variables) or as a continuous attribute. In the latter case, the partworth function for this attribute (weight of chocolate) can be specified either as a vector model (with 1 parameter) or as an ideal point model (with 2 parameters). With these three options, the values of p_1, p_2 and p_3 for this study and the number of estimated parameters will be as follows:

Option for the weight of chocolate attribute	Number of categorical attributes (p_1)	Number of attributes with vector specification (p_2)	Number of attributes with ideal point specification (p_3)	Number of parameters in addition to intercept
1. Categorical scale	4	0	1	11
2. Interval scale with a vector model	3	1	1	10
3. Interval scale with an ideal point model	3	0	2	11

For example for the option of categorical scale for weight, the number of parameters will be $2 + 3 + 2 + 2 + 2 = 11$ (in addition to the intercept)

3.2.3 *Utility Model with Interactions*

For modeling response data where interactions are important, one simply has to use product terms to specify pair-wise interactions. For a two-attribute case, the utility function ignoring the intercept term will be specified as:

$$U = aU_1 + bU_2 + cU_1U_2 + \text{error}$$

Here, U_1 and U_2 will be specified as before. If both attributes are continuous, the function will simply consist of linear terms and product terms. In the chocolate illustration, one can use a fractional factorial design that permits interaction between the attributes of amount of sugar and consistency of the chocolate. Let S represent the (continuous) attribute of sugar and C1 and C2 represent the dummy

[1] The specification will be $gx + hx^2$, where x is the amount of sugar. The resulting specification for the part-utility function will be linear in parameters. The ideal point will be positive ideal if h is negative and a negative ideal if h is positive.

variables for the consistency of chocolate attribute. Then, the interaction between these two attributes is captured by inclusion of the product terms, S*C1 and S*C2.

3.2.4 Coding for Categorical Attributes

The use of dummy variables is only one way to code a categorical attribute. Two other coding schemes are also used in practice; these are effects coding and orthogonal coding. The fit of the model will not change with any of these coding schemes.

For a three-level categorical attribute, the three coding schemes will be as follows:

	Dummy variables coding		Effects coding		Orthogonal coding	
Level	D_1	D_2	D_1	D_2	D_1	D_2
Level 1	1	0	1	0	−1	−1/2
Level 2	0	1	0	1	1	−1/2
Level 3	0	0	−1	−1	0	1

Dummy variable coding is quite common because of the ease of developing such codes. The partworths for the levels need to be derived with the dummy variable codes. With effects coding, the derived partworth values will sum to zero. The coefficients estimated from the orthogonal scheme will be uncorrelated while there is some correlation for the other two. Further, the partworth values for the three levels can be derived from the estimated coefficients. But, the orthogonal coding scheme is hardly ever used in practice possibly due to the difficulty of interpretation of the estimates for the recoded variables. The benefits of the orthogonal coding are the lack of correlation between the estimates for the orthogonal variables (or contrasts) and the interpretation. The coefficient of the first orthogonal variable measures the difference between the partworths of levels 2 and 1 of the attribute while the coefficient for the second orthogonal variable measures the difference between the partworth for the third level and the averages of the first two levels. The procedure for recovering the partworths from the estimates of the two recoded variables will be as follows. Assume that the estimates are B_1 and B_2 and the partworth values for the three levels are β_1, β_2, and β_3. The relationships are as follows:

Partworth value	Dummy variable coding	Effects coding	Orthogonal coding
β_1	B_1	B_1	$-B_1-B_2/2$
β_2	B_2	B_2	$B_1-B_2/2$
β_3	0	$-B_1-B_2$	B_2

An illustration of these coding schemes and the corresponding correlation matrices for the recoded variables for a 3-attribute conjoint study is shown in

Table 3.1 Illustration of coding categorical attributes

Example of an orthogonal design and coding attribute levels

					Scheme 1: dummy variable coding						Scheme 2: effects coding							Scheme 3: orthogonal contrasts coding						
ID	A	B	C	Int	DA1	DA2	DB1	DB2	DC1	DC2		D1	D2	D3	D4	D5	D6		D×1	D×2	D×3	D×4	D×5	D×6
1	1	1	1	1	1	0	1	0	1	0		1	0	1	0	1	0		−1	−1	−1	−1	−1	−1
2	1	2	2	1	1	0	0	1	0	1		1	0	0	1	0	1		−1	−1	1	−1	−1	−1
3	1	3	3	1	1	0	0	0	0	0		1	0	−1	−1	−1	−1		−1	−1	0	2	0	2
4	2	1	2	1	0	1	1	0	0	1		0	1	1	0	0	1		1	−1	−1	−1	1	−1
5	2	2	3	1	0	1	0	1	0	0		0	1	0	1	−1	−1		1	−1	1	−1	0	2
6	2	3	1	1	0	1	0	0	1	0		0	1	−1	−1	1	0		1	−1	0	2	−1	−1
7	3	1	3	1	0	0	1	0	0	0		−1	−1	1	0	−1	−1		0	2	−1	−1	0	2
8	3	2	1	1	0	0	0	1	1	0		−1	−1	0	1	1	0		0	2	1	−1	−1	−1
9	3	3	2	1	0	0	0	0	0	1		−1	−1	−1	−1	0	1		0	2	0	2	1	−1
					DA1	*DA2*	*DB1*	*DB2*	*DC1*	*DC2*		*D1*	*D2*	*D3*	*D4*	*D5*	*D6*		*D×1*	*D×2*	*D×3*	*D×4*	*D×5*	*D×6*
				DA1	1						D1	1						D×1	1					
				DA2	−0.5	1					D2	0.5	1					D×2	0	1				
				DB1	0	0	1				D3	0	0	1				D×3	0	0	1			
				DB2	0	0	−0.5	1			D4	0	0	0.5	1			D×4	0	0	0	1		
				DC1	0	−0	0	0	1		D5	0	0	0	0	1		D×5	0	0	0	0	1	
				DC2	0	0	0	0	−0.5	1	D6	0	0	0	0	0.5	1	D×6	0	0	0	0	0	1

Note: The dummy variables DA1, DA2 etc. in Schemes 1, 2 and 3 are defined in the above section on "coding for categorical attributes"

Table 3.1. In this study, each attribute had three levels. Evaluations were obtained on nine profiles constructed according to an orthogonal main-effects design.

3.2.5 Model Selection

It is important to choose an appropriate model for the data on hand. These models may actually differ from one respondent to another. Given that the purpose of conjoint analysis is to predict customer reactions to new products and services, a relevant criterion for model selection is to choose the model with highest predictive validity. This is accomplished by examining how well the estimated model will predict the highest preference rating for a set (usually 2 or so) of holdout profiles; for each respondent a hit will imply that the model correctly predicted the profile with highest stated preference. Then, the percentage of hits (called the hit rate) is computed for the model. The model with highest hit rate can be deemed as the better model. See Hagerty (1985) for some procedures to improve predictive power in conjoint analysis.

Another way to examine alternative models is via the prediction error. In this approach, for each respondent, the prediction error can be compared across models by using the formula (Hagerty and Srinivasan 1991):

$$\mathrm{E\hat{M}SEP_m} = \left(\bar{R}_g^2 - \bar{R}_m^2\right) + \left(1 - \bar{R}_g^2\right)\left(1 + \frac{k}{n}\right) \tag{3.1}$$

where:

$\mathrm{E\hat{M}SEP_m}$ = An estimate of the Expected Mean Squared Error of Prediction of model m (e.g., the vector, ideal point, partworth, or mixed model), expressed as a fraction of the variance of the dependent variable,
$\bar{R}_g^2$ = Adjusted R^2 for the most general (least restrictive) model; for example, in the context of comparing the vector, ideal point, partworth function for a categorical attribute, and mixed models, the most general model is the partworth function model,

$\bar{R}_m^2$ = Adjusted R^2 for model m under consideration,
k = Number of estimated parameters in model m, and
n = Number of stimuli (profiles) used in the estimation.

The model with the lowest prediction error can be deemed as the better model. We note that $\bar{R}_m^2$ is likely to be the smallest (and hence the first term in (3.1) is likely to be the largest) for the vector model because it uses the most restrictive (linear) functional form. However, the number of estimated parameters k, and hence the second term, is largest for the partworth model so that *a priori* it is not obvious which model would have the smallest prediction error. Intuitively, the first term

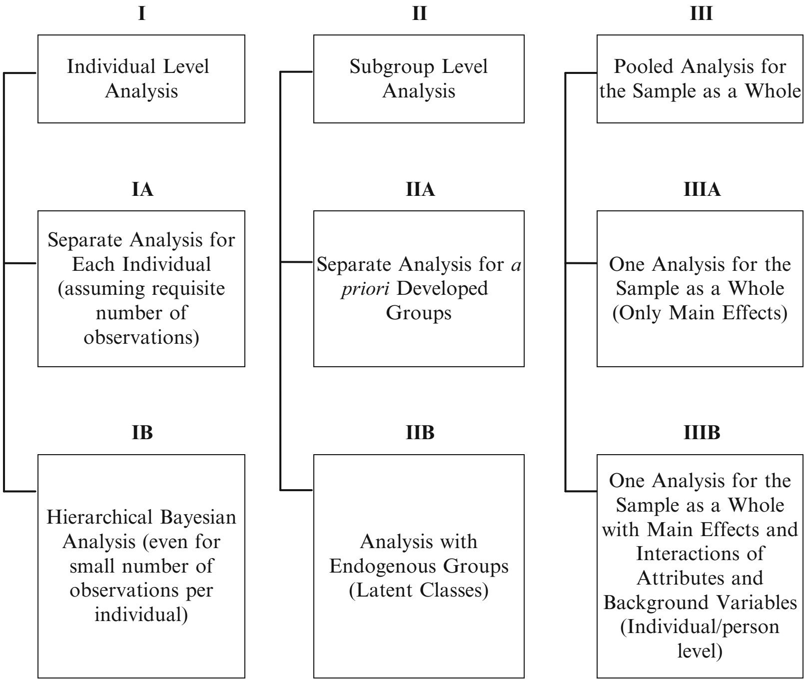

Fig. 3.1 Some ways of analyzing stated preference ratings data

captures the loss resulting from a restrictive functional form while the second term incorporates the loss in predictive power resulting from estimating too many parameters. The two terms correspond to the squared bias and variance respectively, so that their sum provides the mean squared error of prediction (see Mallows 1973).

3.3 Level of Analysis

As noted earlier, a crucial decision for an analyst is to decide upon the level of analysis. Basically, there exist three options: (1) Individual level analysis; (2) Subgroup analysis and (3) Aggregate level analysis.[2] Figure 3.1 lays out the major approaches under these options. We will delve into these alternatives and show some comparisons among them.

[2] Even when one conducts aggregate level analysis, heterogeneity can be included by the use of the componential segmentation approach.

3.3.1 Individual Level Analysis (Approaches IA and IB)

As shown in Fig. 3.1, if one has a requisite number of observations (or response data on profiles) in correspondence with the number of parameters, analyzing data for each individual is quite straightforward and models for each individual can be estimated. If there are too few observations at the individual level for such estimation, one can pool information across individuals and can estimate individual level parameters using hierarchical Bayesian methods. See Appendix 2 for specification of utility functions for various cases.

Approach IA: The IA analysis can be implemented in statistical packages such as SPSS or SAS. Even though it is possible to allow different utility specifications across individuals, it is useful to use the same model specification and estimate models separately for each individual in the sample. If one treats *all* the attributes as categorical, the partworth model for i-th respondent can be written as:

$$Y_{ij} = \beta_{i0} + \sum_{r=1}^{p} \sum_{q=1}^{Q_r} \beta_{irq} D_{rq} \tag{3.2}$$

where the β-parameters are specific to each individual. The β_{irq}-parameters are then used in developing the partworth functions for the i-th respondent as shown above. Further, the individual β-parameters can be clustered to identify market segments. We will discuss an application in Chap. 6.

Similar specifications are used for cases when some attributes are categorical and some are interval-scaled.

Approach IB: The IB analysis employs Bayesian methods. These methods are particularly useful when there is limited data[3] at the individual level to estimate the attribute partworths. This issue is handled in the experimental design used to construct the profiles for evaluation; nevertheless there is some tradeoff between the need for a large number of questions (or profiles) and respondent fatigue, which makes the responses less reliable, in the choice of designs. Further, with standard methods of estimation used for ratings at the individual level, it is not uncommon to obtain partworth estimates with the wrong sign.[4] This problem can also occur when choice data are analyzed at the level of a segment or the full sample.

One way to deal with these issues is to utilize information about the partworths of all the respondents in the sample and employ Hierarchical Bayesian (HB)

[3] This issue of extensive data is one of the challenges in conjoint analysis. One handles this problem by asking relatively few questions to each respondent.

[4] For example, the partworth function for price can sometimes be upward sloping contrary to expectations. This may be due to the information role of price versus its allocative role. One approach to correct this is discussed in Rao and Sattler (2000) and described in Chap. 8; this method calls for collecting two sets of preferences for profiles that include price as an attribute without and with a budget constraint.

methods for estimation of the partworths.[5] For this purpose, each respondent's partworths are characterized by a known distribution to describe the uncertainty in the partworths. Next, the parameters of that distribution are assumed to be different across the population (or the sample). Prior distributions (beliefs) are specified for the parameters, which are updated by data using the Bayes theorem. Given that two stages are specified, the procedure becomes a Hierarchical Bayesian approach. The resulting equations for estimating the parameters are not amenable to an analytical solution. Therefore, individual parameters are estimated by the use of sophisticated Monte Carlo simulation techniques such as the Gibbs sampling and Metropolis-Hastings algorithms. In these methods, restrictions on partworths can also be incorporated with ease. Details are presented in Appendix 3.

3.3.2 Subgroup Level Analysis (Approaches IIA and IIB)

Another way to deal with the heterogeneity issue in conjoint analysis is to develop utility functions for segments of individuals who are deemed homogenous.

Approach IIA involves developing segments of individuals a priori and estimating one utility function for each segment. Various methods exist for forming such segments and cluster analysis is being a commonly used method. See Kamakura (1988) and Vriens et al. (1996). Variables that might be used for such segmentation could be either background variables or responses to profiles or past purchase information or some other individual level data.

Approach IIB involves identifying segments and their utility functions simultaneously. Here, the segments are deemed endogenous rather than known a priori. This approach is the same as identifying latent classes of individuals in the sample. More details are given in Appendix 4.

3.3.3 Pooled Analysis for the Sample as a Whole (Approaches IIIA and IIIB)

Approach IIIA makes a heroic assumption that the individuals in the sample are homogeneous with respect to the utility functions and that one can do a combined analysis by stacking data from various individuals into one run. This approach is almost never preferred. Nevertheless, such an aggregated level analysis may be useful as a simple device to describe the data as a whole (even when individuals are heterogeneous). We should point out that predictions for individual level evaluations from such an aggregated model are likely to be poor.

[5] An alternative way to estimate individual-level partworths is to specify heterogeneity using finite mixture (FM) models and to estimate mixture (or segment) level parameters and recover individual-level parameters using posterior analysis. See DeSarbo et al. (1992). See also Appendix 2.

Table 3.2 Partworth functions for the ENG camera/recorder attributes

Attribute/level	Parameters	Dummy variables				Partworth function before normalization	Partworth function after normalization
		Level	*DV1*	*DV2*			
1. Camera sensitivity (3 levels)	b_{11}, b_{12}	1 High	1	0		25.0	1.0
		2	0	1		6.5	0.51
		3 Low	0	0		0.0	0.33
		Level	*DV3*	*DV4*	*DV5*		
2. Weight (4 levels)	b_{21}, b_{22}, b_{23}	1 Low	1	0	0	12.0	0.65
		2	0	1	0	6.0	0.49
		3	0	0	1	5.0	0.47
		4 High	0	0	0	0.0	0.33
		Level	*DV6*	*DV7*			
3. Packaging of camera and recorder (3 levels)	b_{31}, b_{32}	1	1	0		−5.0	0.2
		2	0	1		3.1	0.42
		3	0	0		0.0	0.33
		Level	*DV8*				
4. Video recorder quality (2 levels)	b_{41}	1 Low	1			−1.0	0.31
		2 High	0			0.0	0.33
		Level	*DV9*	*DV10*			
5. Recording verification (3 levels)	b_{51}, b_{52}	1	1	0		−12.5	0
		2	0	1		−0.5	0.32
		3	0	0		0.0	0.33
		Level	*DV11*				
6. Automatic assembly (edit) (2 levels)	b_{61}	1 No	1			−8.5	0.11
		2 Yes	0			0.0	0.33

Table 3.3 *Estimates of b-coefficients* (Standard errors for these coefficients are approximately equal to 2.8 each)

	b_0	b_{11}	b_{12}	b_{21}	b_{22}	b_{23}	b_{31}	b_{32}	b_{41}	b_{51}	b_{52}	b_{61}
Estimate	37.0	25.0	6.5	12.0	6.0	5.0	−5.0	3.1	−1.0	−12.5	−0.5	−8.5

As an example consider the results of aggregate analysis shown in Tables 3.2 and 3.3 for a conjoint study for electronic news gathering camera/recorders. The study involved six attributes; these attributes were decided by a group of managers (in R&D, sales, production, etc.) of the company that sponsored the project. They were respectively at 3, 4, 3, 2, 3 and 2 levels. Sixteen profiles were developed using a main-effects orthogonal array design. This design allowed only 4 degrees of freedom for error, which is rather small. The respondents were cameramen in various television stations around the country. A two-stage sampling method was used in this study; the first stage was selection of television stations and the second stage was selection of cameramen within each selected television station. The response was a 0 to 100 point scale on the preference for the hypothetical ENG camera. Assuming that the sample of cameramen was homogeneous, one analysis was conducted in this study. A dummy variable regression conjoint model was estimated to describe the responses. This study indicates the levels of attributes that are most desired by this sample. Given the nature of these attributes, there were no surprises in these results.

Approach IIIB directly incorporates heterogeneity among the respondents and comes up with one model for the sample as a whole. The most useful way[6] to do this is to use a common intercept, main effects of attributes (or partworth functions for the attributes) and interactions among attribute variables and descriptor variables to represent individuals in the sample. Of course, the analyst has to identify descriptor variables (background demographics or past usage or other) that are likely to account for heterogeneity among individuals and specify how the coefficients of partworth functions depend on such variables. This formulation assumes that the partworth coefficient for any attribute for an individual is linearly related to the person's background variables.[7]

It is best to lay out the data as shown in Table 3.4 to facilitate this analysis. In this illustration, we show data layout for three categorial attributes at 3, 3, and 2 levels respectively and two background variables for five respondents. Also, respondents 1 and 2 belong to one segment and the other three respondents belong to a second segment. The responses are shown in the column "Response" for nine profiles. In this layout, there are $5 = (3 - 1) + (3 - 1) + (2 - 1)$ dummy variables for the attributes (shown as D_{11}, D_{12}, D_{21}, D_{22}, and D_{31}) and two Z-variables, Z_1 and Z_2 and 10 ($=5 \times 2$) interaction variables (i.e., $Z_1D_{11}, \ldots, Z_2D_{31}$). Given this layout, the specification involves doing regressions on the stated preference scores for the individuals for each profile on the attribute dummy variables, person characteristics, and interactions between attribute dummy variables and person characteristics.

[6] This specification is the same as the "componential segmentation" model (see Green et al. (1989)). The componential segmentation approach involves first identifying significant interactions using an iterative procedure and only the significant interactions are included in the final estimation (in order to minimize the number of parameters). This method is slightly different than including all interactions. We will describe a comparison of it with aggregated and subgroup models later in the chapter.

[7] To understand this, assume that there is only one person descriptor Z. Then, this formulation involves specifying the partworth coefficient for the i-th person for the r-th attribute and q-th level in (3.2) as $\beta_{irq} = \beta_{rq} + \gamma_{rq}Z_i$. The γ-parameter measures the interaction between the attribute dummy variable and the person descriptor. The set-up for this model is shown is shown in Table 3.4.

Table 3.4 Illustration of setting up ratings data for analysis

				Attribute dummy variables					Person characteristics		Interactions between attribute dummy variables and person characteristics	
	Person	Profile	Response	D_{11}	D_{12}	D_{21}	D_{22}	D_{31}	Z_1	Z_2	$Z_1D_{11},\ldots,Z_1D_{31}$	$Z_2D_{11},\ldots,Z_2D_{31}$
Segment 1	1	1	y_{11}									
		2	y_{12}									
		⋮	⋮									
		9	y_{19}									
	2	1	y_{21}									
		2	y_{22}									
		⋮	⋮									
		9	y_{29}									
Segment 2	3	1	y_{31}									
		2	y_{32}									
		⋮	⋮									
		9	y_{39}									
	4	1	y_{41}									
		2	y_{42}									
		⋮	⋮									
		9	y_{49}									
	5	1	y_{51}									
		2	y_{52}									
		⋮	⋮									
		9	y_{59}									

Table 3.5 Background variables and attributes for the Moore study

Background variables and levels	
Sex	*Marital status*[a]
Male	Single
Female	Married
	Other
Residence[b]	*Driving days per week*
Center city	Every day
Suburbs	Three days
Rural	Two days or less
Product attributes and levels	
Gas mileage	*Price*
15 MPG	$3,000
25 MPG	$4,500
35 MPG	$6,000
Place of origin	*Top speed*
America	90 MPH
Japan	120 MPH
Europe	
	Number of seats
	4
	6

Source: Reprinted with permission from Moore (1983), published by the American Marketing Association

[a]The "single" and "other" categories were combined in subsequent analysis because of the small number of people in "other"

[b]The "suburban" and "rural" categories were combined in subsequent analysis because of the small number of people in "rural" category.

3.3.4 Some Comparisons

We will now report two comparisons from published research. The first one is an empirical study by Moore (1980), who explicitly compared the substantive results of a conjoint study analyzed at various levels of aggregation (IA, IIA, IIIA, and IIIB). The second one by Lenk et al. (1996) compared the hierarchical Bayes method (Approach IB) with individual level analyses (Approach IA) and subgroup level analysis with endogenous groups (Approach IIB).

Moore's Study: The context for the application by Moore is the evaluation of hypothetical automobiles described as profiles of attributes using the scale of 1 to 10 (high) by 87 graduate students. The attributes and levels used and background variables included in the study are shown in Table 3.5. Each respondent evaluated 18 profiles which were used for analysis and six other profiles which used for validation.

Four aggregation schemes were compared and the corresponding models were estimated. These were: individual level models (Approach IA), cluster model (Approach IIA), aggregate or pooled model (Approach IIIA), and componential

Table 3.6 Estimation results from four levels of aggregation for the Moore study. IIA: Clustered segmentation clusters

Attributes	IA: individual regression[a]	First[b]	Second[b]	Third[b]	IIIA: pooled regression[b]	IIIB: Componential segmentation[c]
Gas mileage						
15 MPG	3	0.00	0.00	0.00	0.00	0.00
25 MPG	16	1.05	3.47	.78	1.83	1.92
35 MPG	81	*1.60*	*4.78*	*1.91*	*2.55*	*2.62*
Price						
$3,000	48	*0.00*	0.00	0.00	0.00	0.00
$4,500	30	−.50	*.15*	1.20	*.18*	.17
$6,000	22	−1.49	−1.02	*1.61*	−.50	−.61
Place of origin						
America	31	*0.00*	0.00	0.00	0.00	0.00
Japan	14	−.59	.23	−.24	−.20	.20
Europe	55	−.20	*.69*	*.96*	*.40*	*.42*
Top speed						
90 MPH	29	0.00	0.00	0.00	0.00	0.00
120 MPH	71	*.38*	*.39*	*.56*	.43	*.43*
Number of seats						
4	63	0.00	0.00	0.00	0.00	0.00
6	37	−.06	−.38	−1.33	−.51	−.51

Source: Reprinted with permission from Moore (1983), published by the American Marketing Association

[a]Percentage of respondents preferring each level of each attribute

[b]Partworth utilities for each level of each attribute. Most preferred level is italicized

[c]Partworth utilities: main effects coefficients have been transformed (as the zero point is arbitrary) to permit easy comparison with other columns

Table 3.7 Estimated interactions in componential segmentation (III B) for the Moore study

Price/sex		$3,000	$4,500	$6,000
	Male	−.34	.00	.34
	Female	.34	.00	−.34
Residence/gas mileage		15 MPG	25 MPG	35 MPG
	Center city	.09	.00	−.09
	Suburban/rural	−.09	.00	.09
Residence/price[a]		$3,000	$4,500	$6,000
	Center city	−.15	−.13	.28
	Suburban/rural	.15	.13	−.28
Driving days/place of origin		America	Japan	Europe
	Daily	−.15	.15	.00
	Three	.00	.00	.00
	Two or less	.15	−.15	.00
Driving days/gas mileage		15 MPG	25 MPG	35 MPG
	Daily	.00	.00	.00
	Three	−.15	.15	.00
	Two or less	.15	−.15	.00

Source: Reprinted with permission from Moore (1980) published by the American Marketing Association

[a]This interaction term is the sum of two significant interaction terms

segmentation model[8] (Approach IIB). The results estimated with data from the 18 calibration profiles are shown in Tables 3.6 and 3.7; they indicate considerable heterogeneity among the sample of respondents.

The partworth functions for the four aggregation approaches are qualitatively similar, but the actual values differ considerably from one to the other. The predictive powers (average correlations between predicted and stated preferences for six validation profiles) of the four models differ quite a lot. As should be expected, the individual level analyses (with main effects) provide the highest predictive power, followed by clustering approaches. The componential segmentation approach is not that far behind the clustering approaches. As should be expected, the aggregate model (or pooled analysis) is the worst among the four compared. Actual values of predictive power are shown below:

Individual level analyses (IA)	.822
Clustered segmentation[a] (IIA)	.613
Pooled regression (IIIA)	.471
Componential segmentation (IIIB)	.509

[a]The values for the three clusters are .468, .697, and .707

Lenk et al. Study: This study by Lenk and others (1996) utilized individual-level covariates to describe the heterogeneity in the partworths in a study of personal computers. The study was conducted among a sample of 179 first-year MBA students at the University of Michigan. It involved 13 attributes,[9] each at two levels and six subject covariates; the attributes and levels and the covariates used are shown in Table 3.8. The attributes included both intrinsic (technical) features, such as the amount of RAM, CPU speed and extrinsic features, such as technical support and distribution channel. Subject covariates included gender, years of full-time experience, and self-assessment of technical expertise. The authors used a set of 16 profiles designed using an orthogonal main-effects only design and four validation profiles in this study.

The posterior means and standard deviations of the estimates of the relationships between the subject level covariates and the partworths (or the regression coefficients in the second level HB model) are shown in Table 3.9. Many of these coefficients have posterior means that are one or more posterior standard deviations away from zero. Further, two of the covariates, namely, technological knowledge (EXPERT variable) and work experience (YEARS variable) have some definitive relationships to partworths of several attributes. The gender covariate has a significant relationship to the partworths for price and the hot line feature.

In this computer study, the authors showed that the yielded partworth estimates obtained with the HB method (Approach IB) are superior to those obtained with the

[8] We should note that the componential model is slightly different than Approach IIIB as indicated earlier.

[9] Readers may note that this study was probably conducted much earlier than 1996 and therefore some of the technical features and prices may appear not up-to-date.

Table 3.8 Attributes, levels and subject level covariates for the MBA computer study

Attribute	Levels and codes	Attribute	Levels and codes
A. Telephone service hot line	No (−1); Yes (1)	H. Color of unit	Beige (−1); Black (1)
B. Amount of RAM	8 MB (−1); 16 MB (1)	I. Availability	Mail order only (−1); Computer Store only (1)
C. Screen size	14 in. (−1); 17 in. (1)	J. Warranty	1 year (−1); 3 year (1)
D. CPU speed	50 MHz (−1); 100 MHz (1)	K. Bundled productivity software	No (−1); Yes (1)
E. Hard disk size	340 MB (−1); 730 MB (1)	L. Money back guarantee	None (−1); Up to 30 days (1)
F. CD ROM/ multimedia	No (−1); Yes (1)	M. Price	$2,000 (−1); $3,500 (1)
G. Cache	128 HB (−1); 256 KB (1)		
Subject level covariates			
Variable	Description	Mean	S.D.
Female	0 if male and 1 if female	0.27	0.45
Years	Years of full-time work experience	4.4	2.4
Own	1 if own or lease a microcomputer and o if not	0.88	0.33
Tech	1 if engineer or computer professional and 0 if not	0.27	0.45
Apply	Number of software applications	4.3	1.6
Expert	Self-evaluation of expertise on microcomputers (sum of two 5-point scales)	7.6	1.9

standard regression method (Approach IA); the root mean square error for the standard regression method was 0.180 with respect to the HB estimates[10] using all the 16 profiles. Further, in the validation sample, Approach IA (regression method) produced hit rates of 63.7 % compared to the hit rates of 67.0 % with the HB approach. When the same data were analyzed using latent class method with four latent classes (Approach IIB), the root mean square error for the estimates compared to those from the HB approach was 0.221 in the analysis sample. The hit rate for the

[10] Although not germane to this comparison, the HB approach enables one to estimate the partworths with data from fewer profiles. In the computer study, the root mean square error of the partworth estimates from the HB model with data from 4, 8, and 12 profiles (randomly chosen) was 0.066, 0.045, and 0.0.20 respectively as compared with the estimates obtained with data from all 16 profiles. Thus, it is possible to design conjoint more economically when the HB approach is used for estimation.

Table 3.9 Relationship between partworths and subject covariates, MBA computer study

	Covariate						
Variable	Intercept	Female	Years	Own	Tech	Apply	Expert
Intercept	3.698[a]	−0.043	−0.111[a]	−0.158	−0.248	0.112[b]	0.167[a]
	(0.598)	(0.271)	(0.049)	(0.347)	(0.271)	(0.080)	(0.071)
A. Hot line	−0.047	0.226[a]	−0.002	−0.105	−0.019	−0.004	0.026[b]
	(0.195)	(0.087)	(0.016)	(0.115)	(0.084)	(0.025)	(0.023)
B. RAM	0.515[a]	−0.085	−0.003	0.139[b]	0.168[b]	0.043[b]	−0.065[a]
	(0.208)	(0.093)	(0.017)	(0.127)	(0.086)	(0.027)	(0.024)
C. Screen size	0.058	−0.055	−0.009	0.044	0.109[b]	0.005	0.013
	(0.176)	(0.079)	(0.014)	(0.102)	(0.078)	(0.022)	(0.020)
D. CPU	−0.167	−0.101	−0.026[b]	0.158	0.171[b]	0.014	0.059
	(0.279)	(0.131)	(0.023)	(0.172)	(0.127)	(0.038)	(0.033)
E. Hard disk	0.013	−0.157[b]	−0.014	0.037	0.060	0.017	0.015
	(0.183)	(0.082)	(0.014)	(0.105)	(0.080)	(0.023)	(0.021)
F. CD ROM	0.5891[a]	−0.164[b]	−0.010	−0.062	−0.075	0.015	0.001
	(0.251)	(0.113)	(0.020)	(0.148)	(0.107)	(0.033)	(0.029)
G. Cache	−0.266[b]	−0.04	−0.004	0.127[b]	0.019	−0.036[b]	0.049[a]
	(0.192)	(0.092)	(0.013)	(0.118)	(0.087)	(0.026)	(0.023)
H. Color	0.274[b]	−0.047	−0.004	0.017	−0.095[b]	−0.014	−0.019[b]
	(0.160)	(0.070)	(0.013)	(0.093)	(0.072)	(0.021)	(0.019)
I. Availability	0.157[b]	0.037	0.021[b]	0.138[b]	−0.097[b]	−0.011	−0.029[b]
	(0.156)	(0.068)	(0.013)	(0.092)	(0.070)	(0.021)	(0.018)
J. Warranty	−0.089	0.149[b]	0.024[b]	0.029	0.008	0.026[b]	−0.010
	(0.167)	(0.079)	(0.015)	(0.100)	(0.072)	(0.022)	(0.020)
K. Software	0.315[b]	0.009	−0.032[a]	−0.034	0.101[b]	0.010	−0.004
	(0.179)	(0.081)	(0.014)	(0.104)	(0.079)	(0.023)	(0.020)
L. Guarantee	0.023	0.031	0.025[b]	−0.117[b]	−0.081	0.013	0.004
	(0.185)	(0.085)	(0.015)	(0.107)	(0.081)	(0.025)	(0.022)
M. Price	−1.560[b]	0.385[a]	0.040[b]	−0.176	−0.064	0.001	0.041
	(0.398)	(0.173)	(0.031)	(0.233)	(0.170)	(0.052)	(0.047)

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[a]The posterior mean is at least two posterior standard deviations from zero.

[b]The posterior mean is at least one posterior standard deviation from zero.

validation for the latent class method was 38 %. These analyses show the superiority of HB estimation.[11]

The posterior means and standard deviations of the estimates of the relationships between the subject level covariates and the partworths (or the regression coefficients in the second level HB model) are shown in Table 3.9. Many of these coefficients

[11] Aside, the HB method enables one to estimate the partworths with data from fewer profiles. In this computer study, the root mean square error of the partworth estimates from the HB model with data from 4, 8, and 12 profiles (randomly chosen) was 0.066, 0.045, and 0.0.20 respectively as compared with the estimates obtained with data from all 16 profiles. Thus, it is possible to design conjoint study more economically when the HB approach is used for estimation.

have posterior means that are one or more posterior standard deviations away from zero. Further, two of the covariates, namely, technological knowledge (EXPERT variable) and work experience (YEARS variable) have some definitive relationships to partworths of several attributes. The gender covariate has a significant relationship to the partworths for price and the hot line feature.

Further, the HB method enables one to estimate the partworths with data from fewer profiles. In the computer study, the root mean square error of the partworth estimates from the HB model with data from 4, 8, and 12 profiles (randomly chosen) was 0.066, 0.045, and 0.0.20 respectively as compared with the estimates obtained with data form all 16 profiles. Thus, it is possible to design conjoint more economically when the HB approach is used for estimation.

3.4 Methods for Simulation

In Chap. 2 we discussed ways in which estimated partworth functions can be used for answering various "what if" questions. Examples of these questions are:

- What will the market share be for a new product described on the attributes of the conjoint study under certain prespecified assumptions of the marketplace?
- What will be the change in market share for an existing product for prespecified product modifications?
- How will the market share change for an existing product if its competing product changes its characteristics?

These are only but a few of the "what if" type questions that can be answered with the use of conjoint results.

The general method for answering these questions is the use of a choice simulator. The basic idea in a choice simulation is to estimate the utilities of items that are considered by an individual and use certain rules to translate these utilities into choice probabilities. The market demand for each item in the marketplace is estimated from these probabilities. Mathematically, the predicted market demand for an item j under a market scenario s is:

$$D_{j|s} = \frac{1}{F} \sum_{i=1}^{n} Q_i P_{ij|s}$$

where

F is the sampling fraction (or the ratio of sample size to the total number of consumers in the market);

Q_i is the estimated demand for the category by the i-th consumer in the sample; and

P_{ijls} is the predicted probability of choice of the j-th item by the i-th consumer in the sample under the scenario, s.

The set of items considered (or the choice set) is determined by the nature of the "what if" question. For example, if our interest is to predict the market demand for a modified product, the set of items will be the modified product and all other items in the market (except, of course, for the old product before modification). If the interest is in predicting the demand for a new item, the set of items will be the items currently on the market plus the new item. In general, the set of items will vary for each individual in the sample to reflect factors such as availability or budget; i.e. the set s may be subscripted by i.

The critical component in the formula for predicting demand is the probability of choice of an item under a scenario (or choice set) for each respondent in the sample. This probability is based on the predicted utility computed according to the conjoint model. Several alternative rules are possible for converting the utility to choice probability. These are: (1) the maximum utility rule or (the deterministic rule); (2) the Bradley- Terry-Luce (BTL) rule; (3) the alpha power rule; and (4) the logit rule. The max utility rule assigns a probability of choice of 1 to the item with the highest utility and 0 to all others in the choice set. If there is a tie in the predicted utilities the tie is either broken randomly or equal probabilities (e.g., ½) are assigned to the corresponding items. The BTL rule assigns a choice probability to each product in the respondent's choice set proportional to the product's share of the respondent's total utility across all contending items in the choice set. The alpha power rule uses a parameter (alpha) to power the utilities before the BTL rule is employed. The alpha parameter can be chosen to ensure that the estimated market shares for the status quo (or current situation) correspond to the actual shares as much as possible. A logit rule assigns a probability proportional to exp(utility) of the item.

Let the utilities be $u_1, u_2, \ldots, u_J$ for the J items in the choice set for one individual in the sample. Then, the four rules map these computed utilities into probabilities of choice as follows:

Rule	Predicted probability for item j
Max utility rule	$\begin{cases} 1 \text{ if } u_j \text{is } \max(u_1, \ldots, u_J) \\ 0 \text{ otherwise.} \end{cases}$
BTL rule	$u_j \Big/ \sum_{j=1}^{J} u_j$
Alpha power rule	$u_j^{\alpha} \Big/ \sum_{j=1}^{J} u_j^{\alpha};\ \alpha \geq 0$
Logit rule	$\exp(u_j) \Big/ \sum_{j=1}^{J} \exp(u_j)$

There are pros and cons with each of the four rules. In the case of heterogeneous markets involving sporadic, non-routine purchases (e.g., televisions, automobiles, personal computers, etc.), the max utility rule seems quite intuitive and appropriate. In the case of repetitive purchases (e.g., food items, beverages, personal care products, etc.), the BTL and logit rules have more to offer, since one can imagine that consumers' preferences vary over use occasions and choices may be probabilistic. Between the BTL rule and the logit rule, the logit rule is more robust to assumptions associated with the scaling of the computed utility. The BTL rule assumes that the computed utility is measured on a ratio scale while the logit rule assumes an interval scale. For example, adding a constant to the computed utilities will have a dramatic effect on the choice probabilities according to the BTL rule while it has no effect on the logit rule. If the additive constant is very large, the variance in the utilities will be arbitrarily small and the probabilities of choice will be almost equal. However, doubling the utilities has no effect on the probabilities for the BTL rule while it has a dramatic effect on the probabilities of choice (see Green and Krieger 1988, for more discussion of these issues.) Note that the alpha power rule requires additional analysis to determine the value of the power.

3.4.1 Illustration

As an illustration, consider a hypothetical automobile market with three existing alternatives, X, Y and Z. These brands are identical except for type of transmission and gas mileage. Assume that a conjoint study was conducted to determine the partworth functions for these two attributes. The attribute of transmission (A) was at 2 levels of automatic (A_1) and standard (A_2) and the gas mileage attribute (B) was at 3 levels of 10 miles per gallon (B_1), 20 miles per gallon (B_2) and 40 miles per gallon (B_3). The estimated partworth functions for the ten respondents and their current brand are shown in Table 3.10. The current brands and the number of people choosing them in the sample are as follows:

	Attributes		
Brand	A (transmission)	B (gas mileage)	Number choosing in the sample
X	Automatic (A_1)	15	3
Y	Standard (A_2)	30	5
Z	Automatic (A_1)	20	2

In order to begin the simulation, it is important to see how well the estimated partworth functions predict the current choices of the respondents. For this purpose, we compute the utilities for each of the three brands, X, Y, and Z for each respondent. We will use the additive main-effects utility model, which posits that utility is equal to sum of the partworths for the two attributes. The A-attribute is at two levels and the estimated partworth functions can be used directly; but for the B-attribute, the levels used in the conjoint study do not correspond exactly to those for the three brands on the market. Hence, one needs to use interpolation; for example, the partworth for 15 miles per gallon will be estimated as one-half the sum of the partworths for 10 mpg and 20 mpg. In general, we will use linear interpolation. The computed utilities for the three brands are shown in Table 3.11. To verify, we

Table 3.10 Illustration of choice simulation: partworth functions and current brand

	A		B			
Respondent	A_1	A_2	B_1	B_2	B_3	Current brand
1	0.1	0.8	0.1	0.3	0.9	Y
2	0.7	0.1	0.5	0.5	0.7	X
3	0.3	0.4	0.1	0.6	0.8	Z
4	0.1	0.9	0.2	0.4	0.7	Y
5	0.8	0.1	0.4	0.4	0.6	Z
6	0.1	0.7	0.2	0.5	0.9	Y
7	0.2	0.9	0.4	0.6	0.9	Y
8	1.0	0.3	0.1	0.4	0.7	Z
9	1.0	0.2	0.2	0.2	0.5	X
10	0.4	1.0	0.1	0.4	0.6	Y

Table 3.11 Illustration of choice simulation of current market: predicted utilities and choices

Respondent	X	Y	Z	Predicted choice	Current brand
1	0.3	1.4	0.4	Y	Y
2	1.2	0.7	1.2	X or Z	X
3	0.65	1.1	0.9	Y	Z
4	0.4	1.45	0.5	Y	Y
5	1.2	0.6	1.2	X or Z	Z
6	0.45	1.4	0.6	Y	Y
7	0.7	1.25	0.85	Y	Y
8	1.25	0.85	1.4	Z	Z
9	1.2	0.55	1.2	X or Z	X
10	0.65	1.5	0.8	Y	Y
Brand		# Choices expected		Actual choices	
X		1.5		2	
Y		6		5	
Z		2.5		3	

compute the utility of X for respondent #1 as $u(A_1) + u(15) = 0.1 + \frac{(0.1+0.3)}{2} = 0.1 + 0.2 = 0.3$, similarly for other values.

We use the maximum utility rule (or max utility rule) to predict the choices of the ten respondents. The results are shown at the bottom of Table 3.11. This shows that the simulation does a reasonable job of predicting current choices.

We use these data to simulate two market scenarios:

Scenario 1 Brand X is replaced by a modified brand with an improvement on miles per gallon to 25 and no other changes.

Scenario 2 A new product P with the characteristics of automatic transmission and 30 miles per gallon introduced in addition to the current three brands.

As before, the max utility rule is used in predicting choices. Computations are quite similar to those shown in Table 3.11. The results of these simulations are shown in

Table 3.12 Illustration of choice simulation: product modification; X improved on the B-attribute to 25 miles per gallon

	Predicted utilities			
Respondent	Modified X	Y	Z	Predicted choice
1	0.55	1.4	0.4	Y
2	1.25	0.7	1.2	X
3	0.95	1.1	0.9	Y
4	0.575	1.45	0.5	Y
5	1.25	0.6	1.2	X
6	0.7	1.4	0.6	Y
7	0.875	1.25	0.85	Y
8	1.475	0.85	1.4	X
9	1.275	0.55	1.2	X
10	0.85	1.5	0.8	Y
Brand	New expected choices	Old expected choices	Loss (−)/gain (+)	
Modified X	4	1.5	2.5	
Y	6	6	−0.5	
Z	0	2.5	−2.5	

Table 3.13 Illustration of choice simulation: New product introduction; New product P introduced

	Predicted utilities				
Respondent	P	X	Y	Z	Predicted choice
1	0.7	0.3	1.4	0.4	Y
2	1.3	1.2	0.7	1.2	P
3	1.0	0.65	1.1	0.9	Y
4	0.65	0.4	1.45	0.5	Y
5	1.3	1.2	0.6	1.2	P
6	0.8	0.45	1.4	0.6	Y
7	0.95	0.7	1.25	0.85	Y
8	1.55	1.25	0.85	1.4	P
9	1.35	1.2	0.55	1.2	P
10	0.9	0.65	1.5	0.8	Y
Brand	New expected choices	Old expected choices		Loss (−)/gain (+)	
P	4	–		4	
X	0	1.5		−1.5	
Y	6	6		0	
Z	0	2.5		−2.5	

Tables 3.13 and 3.14. We will compare the results of new to the old simulation rather than comparing against current choices. Looking at Table 3.12, the modified X gains 2.5 more choices than the current X in the simulation. In this scenario, brand Z loses out a lot because of its inferior miles per gallon relative to the modified X.

When a new product P with automatic transmission and 30 mpg is introduced, the results show that it dominates both brands X and Z a lot (which have automatic transmission). Brand Y is not affected at all by this new entry.

Extensions: The simulation can be extended to include differential weights for the sample (to reflect the method of sampling used) and other choice rules. Also, the brand name effect (which was excluded in the illustration) can be included; see Green and Krieger (1995) for details. One way of doing this would be to develop a separate model to estimate brand name effect (on a scale comparable to the partworth functions) and add it to the estimated utility before predicting choices.

Another extension is to include different choice sets for each individual (based on some other individual-specific information collected in the survey).

3.5 Estimating the Hybrid Conjoint Model

We discussed in the previous chapter the motivation behind the use of a hybrid conjoint model; it is a solution to deal with the issue of a large number of attributes in commercial studies. The data collected in a hybrid conjoint method include: self-explicated judgments of attribute-level desirability values for the levels of each attribute and attribute importances and evaluative judgments (ratings) on a small number of full profiles drawn from a master design.

3.5.1 Notation

Before describing various approaches to hybrid modeling, it is useful to list some preliminary notation. First, we denote the h-th (h = 1, . . ., H) multiattribute profile (e.g. a verbal product description or the physical characteristics of an actual product) by the vector

$$\mathrm{i}^{(\mathrm{h})} \equiv \left(\mathrm{i}_1^{(\mathrm{h})}, \mathrm{i}_2^{(\mathrm{h})}, \ldots, \mathrm{i}_\mathrm{j}^{(\mathrm{h})}, \ldots, \mathrm{i}_\mathrm{J}^{(\mathrm{h})}\right) \tag{3.3}$$

in which $\mathrm{i}_\mathrm{j}^{(\mathrm{h})}$ denotes level i_j ($\mathrm{i}_\mathrm{j} = 1, \ldots, \mathrm{I}_\mathrm{i}$) of attribute j (j = 1, . . ., J) used in profile h.

In the self-explicated utility elicitation task we let

U_{i_jk} = Respondent k's (k = 1, K) self-explicated desirability score for level i of attribute j,

w_{jk} = Respondent k's self-explicated importance weight for attribute j,

$\mathrm{Y}_\mathrm{h} = \mathrm{Y}_{\mathrm{i}_1\mathrm{i}_2,\ldots,\mathrm{i}_{\mathrm{j},\mathrm{k}}} \equiv$ Respondent k's overall response to some full profile description h (in the conjoint task), and

$v_{i_1}; t_{i_1 i_j}$ = Main effect and selected two-factor interaction effects, respectively, as obtained from analyzing conjoint responses; these parameters pertain to attribute levels of the *stimuli*, and are defined independently of respondent.

J = Number of attributes

The simplest hybrid model (Green 1981) is given by the equation

$$Y_{i_1 i_2,\ldots,i_{j,k}} \cong a + bU_{i_1 i_2,\ldots,i_{j,k}} + \sum_{j=1}^{J} v_{i_1} + \sum_{j<j'} t_{i_1 i_{j'}} \tag{3.4}$$

where $\cong$ denotes least squares approximation (or some other type of fitting procedure). The first term, $U_{i_1 i_2,\ldots,i_{j,k}}$, is found from the respondent's self-explicated data. It is modeled as a weighted linear combination of the self-explicated desirability scores of the attribute levels ($u_{i_j k}$) with self-explicated weights (w_{jk}).

$$U_{i_1, i_2,\ldots,i_{j,k}} = \sum_{j=1}^{J} w_{jk} u_{i_j k}. \tag{3.5}$$

$$Y_{i_1 i_2,\ldots,i_{j,k}} \cong a + b\sum_{j=1}^{J} \left(w_{jk} u_{i_j k}\right) + \sum_{j=1}^{J} v_{t_j} + \sum_{j<j'} t_{i_j i_{j'}} \tag{3.6}$$

These models are estimated by regression. The reader may note that there is no need for multiplicative parameters for the last two terms because they are akin to the main effects and interaction terms in an ANOVA model. Further, these models (3.4) can also be estimated with multiple b- coefficients (b_j) rather than a single b- coefficient.

3.5.2 Models Comparison

The hybrid conjoint model was compared with the self-explicated model (3.3) and two formulations of the traditional conjoint model (one with main effects only and the other with main effects and selected two-way interactions) in three different contexts. Different versions of the hybrid conjoint model were estimated; these were (3.2) without the t's, (3.2) with both the v's and t's (these are called single b-weight models), (3.4) without the v's and t's, (3.4) without the t's, and (3.4) with both the v's and t's (these are called multiple b-weight models) for the sample as a whole.

Each of the preceding metric hybrid models was also fitted at the subgroup level. Respondents were first clustered into three groups based on the commonality of their self-explicated utilities: each hybrid model then was estimated separately for each of the three groups.

Table 3.14 Descriptive results of three cross-validation studies

	Average cross-validated correlation[a]			Percent correct first-choice predictions	
Model tested	GGW	AK	CHP	AK	CHP
Self-explicated model	0.34	0.25	0.53	11	44
Traditional conjoint models					
Main effects only	0.65	0.37	0.62	25	53
Main effects plus interactions	0.61	0.33	—	30	—
Hybrid models—total sample level					
Single b-weight models					
Stage one plus main effects only	0.74	0.33	0.44	25	39
Full hybrid	0.71	0.30	—	18	—
Multiple b-weight models					
Stage one only	0.75	—	0.51	—	28
Stage one plus main effects only	0.76	—	0.44	—	29
Full hybrid	0.75	—	—	—	—
Hybrid models—subgroup level					
Single b-weight models					
Stage one plus main effects only	0.75	—	0.47	—	36
Full hybrid	0.75	—	—	—	—
Multiple b-weight models					
Stage one only	0.76	—	0.50	—	45
Stage one plus main effects only	0.77	—	0.47	—	41
Full hybrid	0.76	—	—	—	—

Source: Reprinted with permission from Green (1984), published by the American Marketing Association

[a]These are true correlations in the case of the Green, Goldberg, and Wiley (GGW) study and product moment correlations in the case of the Akaah and Korgsonkar (AK) and Cattin, Hermer, and Pioche (CHP) studies

The contexts for the three conjoint studies, respectively called GGW, AK, and CHP were:

1. New household appliance; 7 product attributes (2–4 levels for the attributes each); 476 respondents, the CGW study;
2. Health maintenance organization (HMO) plans; N = 80 respondents; 6 attributes (2–3 levels each), the AK study; and
3. Banking services; 42 respondents; 5 attributes (3–5 levels each), the CHP study.

Simultaneous parameter estimation was used in the model-fitting stage (OLS regression), except for selected two-way interaction terms (cross products of dummy variables were used) which entered in a stepwise manner. The cross-validation entailed Kendall's tau correlation, computed at the individual level, between a ranking of the holdout sample evaluations and a ranking predicted by the model under test. (The tau measures the degree of discrepancy of the ranks between the predicted and actual profiles in the holdout sample. To compute this measure, one considers all pairs of profiles and computes the number of concordant pairs and discordant pairs between the actual and predicted values and the measure is the difference between concordant pairs and discordant pairs divided by the number of pairs.) Table 3.14 shows the results of these comparisons. In general, hybrid models show higher cross-validation relative to other models compared.

3.6 Individualized Hybrid Conjoint Models

The data collected in a typical hybrid conjoint study include self-explicated desirabilities and importances and evaluations on a subset of profiles drawn from a master design. The traditional hybrid conjoint model discussed earlier combines these data to estimate partworths typically at a subgroup level. While traditional hybrid conjoint models (described earlier) have proved practical in large-scale industry studies, their application can be cumbersome.

Three questions arise in the application of hybrid models. These are: (1) how should the multiple sources of conjoint data in a hybrid design (i.e., self-explicated desirabilities and importances and profile evaluations) be combined to estimate partworths at the individual level, (2) should the individual's profile data be used to update both self-explicated desirabilities and importances or only the importances?, and (3) when we estimate partworths for an individual, what use can be made of other individual's responses to the same profiles?

3.6.1 Notation

N = number of individuals in the study; denoted by subscript $n = 1, \ldots, N$.
M = number of attributes, denoted by subscript $m = 1, \ldots, M$.
L_m = number of levels for the m-th attribute.

$u_{m\ell}^{(n)}$ = partworth for the ℓ-th level of the m-th attribute for n-th individual; $\ell = 1, \ldots, L_m$; $m = 1, \ldots, M$; $n = 1, \ldots, N$.

$v_m^{(n)}$ = derived importance of the m-th attribute for the n-th individual.

$e_{m\ell}^{(n)}$ = derived desirability for the l-th level of the m-th attribute for the n-th individual.

$w_m^{(n)}$ = self-explicated importance for the m-th attribute for the n-th individual; $0 < w_m^{(n)} < 1;\ \sum_{m=1}^{M} w_m^{(n)} = 1$.

$d_m^{(n)}$ = self-explicated desirability for the m-th attribute for the n-th individual.
P = number of full profiles used in the study (as per the master design).

$h_{ml}^{(p)}$ = indicator variable taking the value 1 if the m-th attribute in the p-th profile takes level l; m = 1, . . . , M; p = 1, . . . , P; l = 1, . . . , L_m.
R = number of profiles administered to an individual (R < P).

$k_r^{(n)}$ = profile number in the master design corresponding to the r-th profile administered to n-th individual.

$s_r^{(n)}$ = Evaluation score given by the n-th individual to the r-th profile.

$$I_{rm\ell}^{(n)} = \begin{cases} 1 & \mathit{if} \quad h_{ml}^{(p)} = 1, \quad \mathit{where}\ p = k_r^{(n)} \\ 0 & \text{otherwise} \quad . \end{cases}$$

With this notation, the self-explicated part of the traditional hybrid conjoint model can be written as:

$$U_r^{(n)} = \sum_{m=1}^{M} w_m^{(n)} \sum_{\ell=1}^{L_m} d_m^{(n)} I_{rm\ell}^{(n)} \tag{3.7}$$

The traditional hybrid conjoint model then is:

$$s_r^{(n)} = a + bU_r^{(n)} + \sum_{m=1}^{M} \sum_{\ell=1}^{L_m} B_{m\ell} I_{rm\ell}^{(n)} + \varepsilon_r^{(n)} \tag{3.8}$$

The parameters a, b, and $B_{m\ell}$; $\ell = 1, \ldots,$ Lm; m = 1, . . ., M are regression parameters estimated at the pooled-sample level (or subgroup level). Additional terms may be added to account for interactions among the attributes (i.e., by using cross-product terms among the I-variables).

Green and Krieger (1996) considered these issues and developed a set of four newer hybrid conjoint models in order to estimate individual partworths in a hybrid design. These four models are:

1. Modified Importances/Desirabilities Model
2. Modified Importances/Constrained Desirabilities Model
3. Modified Importances Model
4. Modified Importances: Convex Combination Model with Group-Level Interactions

The fourth model uses a linear combination of individual's self-explicated desirabilities and partworths coming from stated desirabilities. The associated characteristic equations and estimation methods for these models are shown in Table 3.15 using the above notation.

Green and Krieger (1996) compared the four models using a conjoint data set on cellular phones. The study involved 15 attributes; these were: initial price (4 levels), brand (3 levels), warranty (2 levels) and weight (3 levels), and eleven features (absent or present) such as high-strength battery, 9-number speed dialing and

Table 3.15 Descriptions of individualized hybrid conjoint models

Model and characteristics	Equations	Estimation method
1. *Modified importances/desirabilities Model*	(Omitting the index n)	Iterative least squares regression
Updates both self-explicated desirabilities and importances	$y_{m\ell} = u_{m\ell} + \varepsilon_{m\ell};$ (1) for $m = 1, \ldots, M$ $\ell = 1, \ldots, L_m$ where	Step 1. Set $\mu = 0$ and $\tau = 1$ and using $L_T + R$ observations, estimate $u_{m\ell}$
	$u_{m\ell} = w_{m\ell} d_{m\ell}$ and $(s_r - \mu)/\tau = \sum_{m=1}^{M} \sum_{\ell=1}^{L_m} u_{m\ell} I_{rm\ell} + \delta_r$ (2)	Step 2. Regress s_r on the predicted score using equation (2). The intercept and slope of this regression will yield estimates of μ and τ
	for $r = 1, \ldots, R$ $\varepsilon_{m\ell}$ *and* δ_r are i.i.d. $N(0, \sigma^2)$.	Step 3. Repeat Step 1 with the estimated values of μ and τ in Step 2
	$L_T = \sum_{m=1}^{M} Lm$	Step 4. Repeat Steps 2 and 3 until the change (reduction) in the error sum of squares is no more than a prespecified number or the number of iterations is exceeded
2. *Modified importances/constrained desirabilities model*	(Omitting the index n)	Same as 1 with the additional step, Step 1a (after Step 1). This involves checking whether the order of $u_{m\ell}$ is the same as $d_{m\ell}$ within attribute; if not, an algorithm is used to adjust the $u_{m\ell}$
The order of partworths ($u_{m\ell}$) is restricted to the same as that of self-explicated desirabilities within each attribute	$y_{m\ell} = u_{m\ell} + \varepsilon_{m\ell};$ (1) for $m = 1, \ldots, M$ and $\ell = 1, \ldots, L_m$ where $y_{m\ell} = w_{m\ell} d_{m\ell}$ and $(s_r - \mu)/\tau = \sum_{m=1}^{M} \sum_{\ell=1}^{L_m} u_{m\ell} I_{rm\ell} + \delta_r$ (2) for $r = 1, \ldots, R$ $\varepsilon_{m\ell}$ *and* δ_r are i.i.d. $N(0, \sigma^2)$	
3. *Modified importances model*	$y_m = v_m d_{m\ell} + \varepsilon_m;$	Same as 1 with the change that v_m-parameters are estimated and not $u_{m\ell}$ - parameters
The derived desirabilities are assumed to be the same as self-explicated desirabilities	$m = 1, \ldots, M$ and $(s_r - \mu)/\tau = \sum_{m=1}^{M} v_m \sum_{\ell=1}^{L_m} d_{m\ell} I_{rm\ell} + \delta_r;$ $r = 1, \ldots, R$ $\in_m$ and δ_r are i.i.d. $N(0, \sigma^2)$	
4. *Modified importances: convex combination model with group-level information*	$s_r^{(n)} = \sum_{m=1}^{M} \sum_{\ell=1}^{L_m} \pi_{m\ell} I_{rm\ell}^{(n)} + \delta_r;$ $r = 1, \ldots, R$ and $n = 1, \ldots, N$	Step 1. Dummy variable regression to estimate $\pi_{m\ell}$ using data across all respondents' evaluation scores

(continued)

Table 3.15 (continued)

Model and characteristics	Equations	Estimation method
This model incorporates information from other respondents. Self-explicited desirabilities are not modified	$u_{m\ell}^{(n)} = \alpha^{(n)} p_{m\ell}^{(n)} + \left(1 - \alpha^{(n)}\right)\pi_{m\ell}$ where $p_{m\ell}^{(n)} = w_m^{(n)} d_{m\ell}^{(n)}$	Step 2. Estimate $u_{m\ell}^{(n)}$ as a linear combination of $\pi_{m\ell}$ and self-explicated estimate Step 3. Iterate to find the best value of weighting constant $\alpha^{(n)}$ so as to maximize the correlation $\left(s_r^{(n)}, \hat{s}_r^{(n)}\right)$

Table 3.16 Cross-validation of four individualized hybrid partworth models[a]

Response measure	Convex combination	Modified importances only	Modified importances/ constrained desirabilities	Modified importances/ desirabilities
Calibration fit criterion	0.745	0.819	0.898	0.941
Cross-validation root mean square error	0.175	0.125	0.091	0.063
Correlation	0.547	0.647	0.675	0.720
First choice hit probability	0.436	0.609	0.695	0.731
Rank-position hit probability	0.349	0.401	0.445	0.492

Source: Reprinted with permission from Green and Krieger (1996), Copyright (1996), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

[a]Note: within response measure, all between-model results are significant ($p = 0.05$), based on correlated paired comparison tests

electronic lock. Data were collected from 600 respondents using a hybrid design. The authors cross-validated the above four hybrid partworth models (individualized). Results are shown in Table 3.16.

The fits of the four models improve and four cross-validation measures show consistency in terms of prediction accuracy as we move from the convex combination model to the most general (modified importances/desirabilities) model. The authors also report that these newer models perform much better than the traditional hybrid model and the self-explicated only model.

3.7 Model for Adaptive Conjoint Analysis

As discussed in Chap. 2, in adaptive conjoint analysis (ACA), there are two types of input used: (1) the self-explicated preference rankings and attribute importances collected in Phases I/II and (2) data on paired comparisons of partial or full profiles collected in Phase III. The data from (1) are used in estimating initial values of the partworth functions for the attributes and data from (2) are used in updating these initial values in a Bayesian manner.

The initial values of the partworth functions for any of the attributes are computed by rescaling the self-explicated ranking in Phases I/II such that their mean value is zero and their range is equal to the stated attribute importance. This computation is done separately for each attribute. If we let the stated rankings be $Y_{r1}, Y_{r2}, \ldots, Y_{rL_r}$ for an attribute with L_r levels and we let the stated importance of the attribute r be w_r, then the rescaled value for the l-th level of this attribute is computed as:

$$y_{rl} = w_r \left[\frac{(Y_{rl} - 1)}{(L_r - 1)} - \frac{1}{2} \right]; \; l = 1, 2, \ldots, L_r. \tag{3.9}$$

These y-values are the values of the partworth function for this attribute. (Technically, a simple regression model, $y = \beta + \varepsilon$ is fitted to estimate the βs or the partworth function values for this attribute.) The reader may easily verify that the mean of the values for the ℓ_r levels is zero and that the range of these values is w_r.

As an example, assume that an attribute r has four levels, receives a weight of 3, and the four levels have (reflected) preference rankings $(Y_{r1}, Y_{r2}, Y_{r3}, Y_{r4}) = (2, 1, 4, 3)$; then the respective $(y_{r1}, y_{r2}, y_{r3}, y_{r4}) = (-.5, -1.5, 1.5, .5)$. This computation is done for each attribute separately.

Assume that graded paired comparison data of Phase III is collected on P pairs. Assume that a subset of $t^{(c)}$ attributes, $s_1^{(c)}, s_2^{(c)}, \ldots, s_t^{(c)}$ are selected for paired comparison c, where $t^{(c)}$ can range from two to five attributes. Two "subprofiles" are shown at a time, say $i_1, \ldots, i_t^{(c)}$ and $k_1, \ldots, k_t^{(c)}$, denoting the levels of the attributes $s_1^{(c)}, \ldots, s_t^{(c)}$. The respondent gives a "score" as an integer between 1 and 9. The score indicates the direction and extent to which one profile (left or right side of the screen) is preferred to the other. In preparing the response data for analysis, the integer 5 is subtracted from the raw score leading to an adjusted score $z^{(c)}$ that is integer-valued and ranges from −4 to +4. The ACA model for Phase III then is:

$$z^{(c)} = \sum_{j=1}^{t_c} \left[\beta_{s_j^{(c)} i_j^{(c)}} - \beta_{s_j^{(c)} k_j^{(c)}} \right] + \delta^{(c)} \quad c = 1, \ldots, P \tag{3.10}$$

where the $\delta^{(1)}, \ldots, \delta^{(P)}$ are assumed to be identically and independently distributed as normal variables with zero mean and common variance. The design of the Phase III data collection ensures that all attributes and levels are covered by the P paired comparisons. The above model in (3.10) is a simple regression model of the kind shown above for one respondent; the only difference is some β-values do not appear. The β-values are estimated by minimizing the error sum of squares.

The final estimates of βs (or partworth functions) are obtained by combining the estimates of Phases I/II and Phase III. Please see Chap. 2 for a discussion of some issues with this procedure.

3.7.1 Polyhedral estimation

Toubia et al. (2003) developed an adaptive conjoint analysis method that reduces respondent burden while simultaneously improving accuracy. This method is called Fast Polyhedral Adaptive Conjoint Estimation, with the acronym FastPACE. There are two versions of FastPACE, one for metric paired comparison and the other for choice-based conjoint analysis[12] (CBC). In the first version, the answer to a question in the adaptive conjoint analysis (i.e., a question on choice between two pairs) places a constraint on the possible values that the partworths can take. They use "interior point" developments in mathematical programming which enable one to select questions that narrow the range of feasible partworths as fast as possible. Once the responses to selected questions are obtained, they use the method of analytic center estimation to estimate partworths (i.e. a mathematical programming method to find the best estimate of the partworth values). A probabilistic version of this approach is in Toubia et al. (2007).

The authors compared the polyhedral estimation methods to efficient (fixed) designs and Adaptive Conjoint Analysis using a Monte Carlo simulation study. The context for this simulation is that of a Product Development team interested in learning about the incremental utility of ten product features (each at two levels of present or absent). Using the conventional normalization of assigning zero to the lowest level of a feature, the study involved estimating 10 partworth parameters for the 10 features. They use a fixed upper bound of 100 for these parameters without any loss of generality. In the ACA, there were 10 questions on self-explicated importances. The parameters varied in the simulation were: (1) number of paired comparison questions from 0 to 20; and (2) the error variance of the utility of a product profile; which was assumed to be distributed according to a normal distribution. Having found similar patterns for different errors, they reported simulation results for a standard deviation of error equal to 30 (measured on a zero to 100 point scale). The simulation indicated that no method dominated in all situations. However, the polyhedral algorithms were shown to hold significant potential when (a) profile comparisons are more accurate than the self-explicated importance measures used in ACA, (b) when respondent wear out is a concern, and (c) when the product development and marketing teams wished to screen many features quickly.

Toubia et al. (2003) conducted a conjoint study on an innovative new laptop computer bag that included a removable padded sleeve to hold and protect a laptop computer to validate the polyhedral approach. The bag included a range of separable product features and the study focused on nine of these features, each at two levels (presence or absence); the features were: size, color, logo, handle, holders for a PDA and a mobile-phone, mesh pocket holder, sleeve closure, and boot. The tenth attribute was the price ranging between \$70 and \$100. They used an across-subjects research design among 330 first-year MBA students to provide both internal and external validity for the polyhedral approach (two variations of FastPACE method,

[12] We will discuss CBC methods in Chap. 4.

Table 3.17 Internal and external validity measures for the laptop bag study

Method	Internal validity measure Correlation	External validity measures Correlation	% correct choices	Sample size
Without self-explicated questions				
Fixed efficient design	0.73	0.54	52	88
FP1 method	0.79	0.68	59	88
With self-explicated questions				
ACA	0.81	0.67	52	80
FP2 method	0.83	0.68	64	74

Source: Compiled from tables and text in Toubia et al. (2003)

FP1 with ratings questions and no self-explicated questions and FP2 with self-explicated questions and paired comparisons) against a fixed efficient design (as in the full-profile method) and ACA (adaptive conjoint analysis). Different methods of estimation were employed in the analysis. In addition to self explicated questions (where necessary), respondents answered 16 ratings questions. The authors also examined the sensitivity of results when using data with 8 vs. 16 questions.

The authors tested the internal validity of various methods using four hold-out questions (metric or paired-comparison) beyond the 16 questions of the main conjoint tasks. The measure of internal validity was correlation between observed and predicted responses.

To test the external validity of the methods, respondents were told that they had $100 to spend and were asked to choose between five bags drawn randomly from an orthogonal fractional factorial design of sixteen bags. The respondents were instructed that they would receive the bag that they chose. (Incidentally, this procedure is incentive-compatible, described in Chap. 4.) Using the notion of unavailability of a chosen bag, a complete ranking of all the five bags was also obtained. The correlation between observed and predicted rankings was then used as one measure of external validity. At the end of the study, the respondents were given the bag chosen along with any cash difference (if any) between the price of the chosen bag and $100. A second measure of external validity was the percent correct predictions of the bag choice. The main findings are shown in Table 3.17.

The main results of this study were: (1) The polyhedral approach FP method was superior to the fixed efficient design in both internal and external validity; (2) The FP method was slightly better over the ACA method in internal validity and one measure of external validity.

3.8 Methods for Ranking and Categorical Response Data

Although beyond the scope of this chapter, we briefly mention that data collected as ranks or categories in conjoint studies require special types of analysis. Appendices 4 and 5 describe two methods: linear programming for ranked data and categorical conjoint analysis method for categorical data.

3.9 Summary

This chapter described several models for analysis of conjoint ratings data. The issue of level of analysis (individual to group) is one that the conjoint analyst has to seriously consider while conducting analyses. In general, it is always preferable to conduct the analysis at the individual level. However, given certain designs, it is not always possible.

A second significant issue is how to deal with large numbers of attributes. We described two methods to deal with this problem. These are the method of ACA and hybrid conjoint models. While the traditional hybrid models can only estimate group-level partworths, newer hybrid models enable individual-level estimates. We discussed the variations that exist in these models. In addition, newer FastPACE method was described in some detail.

The chapter also described methods of simulation to utilize the estimated partworths for various decisions. There exist several choice rules to predict the choice for a new profile (product); these are the max utility rule, the BTL rule, the Alpha Power rule, and the logit rule.

Appendix 1

Computation of Trade-offs from Utility Functions in Attributes

Let us consider the case of two attributes and a utility function estimated using an appropriate method (such as conjoint analysis). Let the attributes be denoted by X_1 and X_2 and $U(X_1, X_2)$ be the utility function for one individual. We will consider three cases:

Case 1 $U(X_1, X_2)$ is linear in X_1 and X_2, and X_1 and X_2 are continuous variables (attributes).

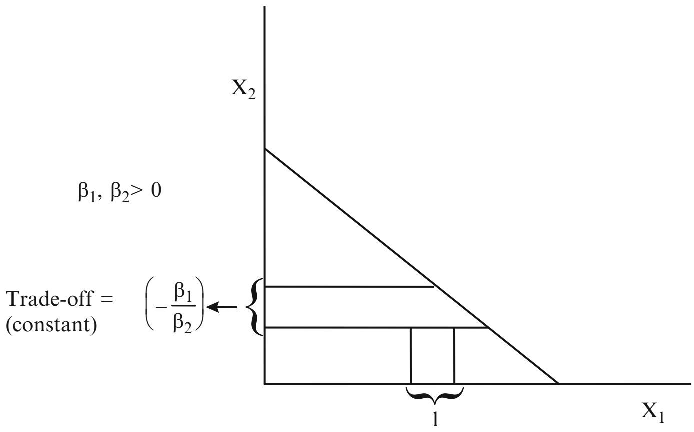
Case 2 $U(X_1, X_2)$ is estimated as piece-wise linear in X_1 and X_2, which are assumed to be nominally scaled attributes.

Case 3 $U(X_1, X_2)$ is a quadratic function in X_1 and X_2, and X_1 and X_2 are continuous attributes.

Case 1

Here, $U(X_1, X_2) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$. The trade-off between the two attributes X_1 and X_2 is computed as $\left(-\frac{\beta_1}{\beta_2}\right)$. The meaning of this quantity is as follows:

The change in X_2 necessary to compensate a one-unit increase in X_1 so as to keep the utility level the same is $\left(-\frac{\beta_1}{\beta_2}\right)$ units of X_2.



Example

$U(X_1, X_2) = 10 + 3X_1 + 4X_2$. The trade-off between X_1 and X_2 is $\left(-\frac{3}{4}\right)$. One unit increase in X_1 is equivalent to $\frac{3}{4}$ units decrease in X_2. Note that the sign of trade-off depends upon the signs of β_1 and β_2. Extension to multiple (>2) attributes is possible.

Case 2

Here, we assume that X_1 and X_2 are nominally scaled. Assume that X_1 has L_1 levels and X_2 has L_2 levels. Let $D_{11}, \ldots, D_{1L_1-1}$ *and* $D_{21}, \ldots, D_{2L_2-1}$ be the dummy variables for the two attributes. Then, the utility function is:

$$\begin{aligned} U(X_1, X_2) &= \beta_0 + \beta_{11}D_{11} + \beta_{12}D_{12} + \ldots + \beta_{1L_1-1}D_{1L_1-1} \\ &\quad + \beta_{21}D_{21} + \beta_{22}D_{22} + \ldots + \beta_{2L_2-1}D_{2L_2-1} \end{aligned}$$

$$D_{1j} = \begin{cases} 1 \textit{ if level of } X_1 \textit{ is } j \\ 0 \textit{ otherwise} \end{cases}$$

$$D_{2j} = \begin{cases} 1 \textit{ if level of } X_2 \textit{ is } j \\ 0 \textit{ otherwise} \end{cases}$$

Here, trade-offs cannot be quantitatively assessed since fractions of nominal attributes do not make sense. However, direct comparisons between changes in one level to another of one attribute with those of another can be made. These are not strictly trade-offs, but are akin to those.

For example, a change from level 1 to level 2 of attribute 1, keeping attribute 2 at the same level, will create a change of β_{12}-β_{11} in the utility score. Similarly, a change from level 1 to level 2 of attribute 2 keeping attribute 1 at the same level will cause a change of β_{22}-β_{21} in the utility score.

Note that the utility scores for the level L_1 of attribute 1 and L_2 of attribute 2 are set at zero.

Case 3
Here,

$$U(X_1, X_2) = \beta_0 + \beta_1 X_1 + \beta_2 X_1^2 + \beta_3 X_2 + \beta_4 X_2^2.$$

The trade-off between X_1 and X_2 can be computed using the total derivative concept.

$$\Delta U = \beta_1 \Delta X_1 + 2\beta_2 X_1 \Delta X_1 + \beta_3 \Delta X_2 + 2\beta_4 X_2 (\Delta X_2)$$

Here, ΔX_1 and ΔX_2 are changes in X_1 and X_2. If the utility is constant when X_1 and X_2 are changed, we can set $\Delta U = 0$. This will give the relationship:

$$\Delta X_1 (\beta_1 + 2\beta_2 X_1) + \Delta X_2 (\beta_3 + 2\beta_4 X_2) = 0$$

$$\text{Therefore, } \Delta X_2 = -\left(\frac{\beta_1 + 2\beta_2 X_1}{\beta_3 + 2\beta_4 X_2}\right) \bullet \Delta X_1.$$

Therefore, the change in X_2 needed for a *one unit* change in X_1, in order to keep the utility level the same, is:

$$-\left(\frac{\beta_1 + 2\beta_2 X_1}{\beta_3 + 2\beta_4 X_2}\right).$$

Note that this depends upon the point (X_1, X_2) under consideration. Also, if the coefficients of squared terms (e.g., β_2 and β_4) are zero, this is the same as Case 1.

Appendix 2

Specification of Utility Functions

This appendix describes the specifications of the utility functions for various cases of analysis in mathematical terms. As a benchmark, we also show the aggregate model (or a pooled model for the sample as a whole). The models are:

1. Aggregated Model (Pooled Regression):

$$Y_{ij} = \beta_0 + \sum_{r=1}^{p} \sum_{q=1}^{q_r} \beta_{rq} D_{rqj} + \text{Error} \quad i = 1, 2, \ldots, I$$

2. Specification 1:

$$Y_{ij} = \beta_{i0} + \sum_{r=1}^{p} \sum_{q=1}^{q_r} \beta_{rq} D_{rqj} + \text{Error};\ i = 1,\ 2, \ldots,\ I$$

3. Specification 2: Componential Segmentation Model:

$$Y_{ij} = \beta_0 + \sum_{r=1}^{p} \sum_{q=1}^{q_r} \beta_{rq} D_{rqj} + \sum_{s=1}^{S} \sum_{r=1}^{p} \sum_{q=1}^{q_r} \gamma_{srq} Z_{is} D_{rqj} + \text{Error}.$$

4. Specification 3:

$$Y_{ij} = \beta_0 + \sum_{r=1}^{p} \sum_{q=1}^{q_r} \beta_{rq} D_{rqj} + \sum_{s=1}^{S} S_s Z_{iS} + \sum_{s=1}^{S} \sum_{r=1}^{p} \sum_{q=1}^{q_r} \gamma_{srq} Z_{iS} D_{rqj} + \text{Error}.$$

The notation is the same as that described earlier. The background variables of the i-th person are described by $(Z_{i1}, Z_{i2}, \ldots, Z_{iS})$. In the cluster-level model, the sample is divided into C clusters (c = 1, 2, ..., C). While β-parameters refer to the intercept and coefficients of attribute (dummy) variables, the γ-parameters refer to interactions among the attribute variables and person background variables. The δ-parameters are the effects of background variables on the intercept term.

The individual level model may be written as:

Individual Level Model for Person i:

$$Y_{ij} = \beta_{i0} + \sum_{r=1}^{p} \sum_{q=1}^{q_r} \beta_{irq} D_{rqj} + \text{Error}$$

Cluster-Level Model:

$$Y_{ij} = \beta_{c0} + \sum_{r=1}^{p} \sum_{q=1}^{q_r} \beta_{crq} D_{rqj} + \text{Error}\ \ i \in c;\ c = 1,\ 2, \ldots,\ C$$

$$j = 1,\ 2, \ldots,\ J$$

Appendix 3

Hierarchical Bayesian Method for Ratings-Based Conjoint Analysis

The conjoint model for ratings data can be written generally as: $y = X\beta + \varepsilon$; where ε is the random error of the model, assumed to be normally distributed with zero mean and variance of σ^2 and y is the rating on a given profile and X is the corresponding set of variables (dummy or other). The β is a px1 vector of partworths. The ratings from the sample of *n* individuals are stacked in the column vector of y. If one estimates this model using OLS, the estimates of the β-parameters will be used to compute the average partworths of the model. Hierarchical Bayesian methods assume that the individual-level parameters are random.

There exist three types of HB methods: (1) a random coefficients Bayesian model, (2) a linear Hierarchical Bayesian model, and (3) linear Hierarchical Bayesian model with a mixture of distributions. In the first model, respondent heterogeneity is assumed to be randomly distributed while in the second, the heterogeneity is governed by some covariates measured at the individual level (as a linear function). The third model is an extension of the second and it assumes that the individual-level data arise from a mixture of distributions (usually referred to as latent segments).

Random Coefficient Bayesian Model: The estimation method for the random coefficients model (method (1) described above) involves specifying prior distributions for the parameters, $\theta = (\beta$ and $\sigma^2)$. These priors are chosen so that the posterior distributions can be easily derived (or in other words, they are conjugate distributions). Given that the model errors are assumed to be normal, a natural conjugate prior[13] is also normal for the β-vector with mean βbar and covariance matrix A^{-1} and inverted chi-squared for σ^2 with g degrees of freedom and prior precision G. Further, the prior distributions for β and σ^2 are assumed to be independent[14]; or $[\beta, \sigma^2] = [\beta]\ [\sigma^2]$. With these assumptions, the HB approach involves deriving conditional distributions for each set of parameters. The conditional distributions can be shown to be:

$[\beta\ |y, X, \sigma^2] \propto [y|X, \beta,\sigma^2]\ [\beta] \sim$ Normal (β^*, V); and
$[\sigma^2|\ y, X, \beta] \propto [y|X,\beta,\sigma^2]\ [\sigma^2] \sim$ Inverted Chi-squared (w, W).
where $\beta^* = (\sigma^{-2}X'X + A)^{-1}(\sigma^{-2}X'y + A\ \beta\text{bar})$, $V = (\sigma^{-2}X'X + A)^{-1}$, $w = g + n$, and $W = G + (y - X\beta)'(y - X\beta)$.

We may now give a short primer on how Gibbs sampling works for estimating the parameters of the model. For a given dataset, the Gibbs sampler repeatedly generates

[13] If the analyst wishes to incorporate no prior information, one sets the initial βbar and A-matrix equal to zero. In that case, the HB estimates will be asymptotically the same as the OLS results. In a similar manner, constraints on signs or the order of partworths (therefore the β-parameters) are incorporated directly in the posterior distribution of the β-vector.

[14] The notation, [u] represents the distribution of u.

random draws of β-vector and σ^2 from their respective conditional distributions as noted above. For each draw of the β-vector, the value of W is computed which is used to draw a sample for σ^2; this process is repeated until there is convergence over draws among the β-vector and for σ^2. The final values will yield estimates of the partworths and their variances. Confidence intervals (e.g., 95 %) can be computed from these posterior distributions.

If the analyst wishes to incorporate no prior information, one sets the initial βbar and A-matrix equal to zero. In that case, the HB estimates will be asymptotically the same as the OLS results. In a similar manner, constraints on signs or order of partworths (therefore the β-parameters) are incorporated directly in the posterior distribution of the β-vector.

Linear Hierarchical Bayesian model (Partworths as Functions of Covariates): For the linear HB model, the conjoint model for the i- th individual level is written as: $Y_i = X_i \beta_i + \varepsilon_i$; for i =1,. . ., N, where Y_i = is a vector of m_i responses (ratings); note that the number of responses can vary over individuals (due to reasons such as incompleteness of data). Further, the subjects' partworths are described in terms of a set of covariates (usually background variables) as $\beta_i = \Theta z_i + \delta_i$ for i =1,. . ., n. Here, z_i is a qx1 vector of individual level covariates and Θ is a (*pxq*) matrix of regression coefficients which represent the relationships between the partworths and subject covariates.

The error terms $\{\varepsilon_i\}$ and $\{\delta_i\}$ are assumed to be mutually independent and distributed as multivariate normal with zero means and covariance matrices $\{\sigma_i^2 I\}$ and Λ respectively, where Λ is a *p*x*p* matrix. The error variances $\{\sigma_i^2\}$ are assumed to have inverse gamma prior distributions. Using these assumptions, one can work out the posterior distributions for the β_i parameters. The various parameters are estimated using the MCMC method and the Metropolis-Hastings algorithm. The third model with latent segments is a simple extension of the second model. For additional details see the Appendix in Lenk et al. (1996).

Linear Hierarchical Bayesian model with Mixture of Distributions: This model is an extension of the second and it assumes that the individual-level data arise from a finite mixture of distributions (usually referred to as latent segments); the model is called the FM model. This method to estimate individual-level partworths involves estimating the parameters for each mixture and recovering individual-level parameters using posterior analysis (DeSarboet al. 1992). In a comparison using simulated data in the context of ratings-based conjoint analysis, Andrews et al. (2002) found that both methods (HB and FM) are equally effective in recovering individual-level parameters and predicting ratings of holdout profiles. Further, HB methods perform well even when the individual partworths come from a mixture of distributions and FM methods yield good individual partworth estimates. Both methods are quite robust to underlying assumptions. Nevertheless, HB methods have become popular recently. See Rossi et al. (2005) for an exposition of Bayesian methods in marketing.

We now illustrate this general approach with two applications.

Application Incorporating Order Constraints: Allenby et al. (1995) implemented the HB method for a conjoint data set collected from 133 undergraduate students. The context was evaluating the performance of 1.5 V, size D, alkaline batteries, a product category with which the respondents were quite familiar. Three product attributes, brand name, average life of a battery, and price per battery were each varied at three levels. Each subject was presented with a complete factorial of 27 product profiles; a fractional factorial design using nine profiles; and 24 or 12 pairwise tradeoff questions in which the respondents were asked to choose one of the two alternatives in the each pair. They used regression methods with the full factorial and fractional factorial design of profiles ratings and logit model for the choice questions.

The six parameters of the utility model for the profile data (with zeros for the omitted levels) are as follows:

Brand name	Topcrest	0
	Eveready	β_1
	Sears DieHard	β_2
Average life	40 h	0
	50 h	β_3
	60 h	β_4
Price per battery	\$1.00	0
	\$1.25	β_5
	\$1.50	β_6

The parameters in the deterministic utility for the logit model are also as shown above.

Given the attribute levels, one can conjecture an order in the values of β-parameters. Thus, the prior expectations on the parameters are:

1. When other factors are all equal, national brands are preferred to private label brand; or β_1 is greater than or equal to zero and β_2 is greater than or equal to zero;
2. Longer life is preferred to shorter life; or β_4 is larger than or equal to β_3 and both are larger than or equal to zero; and
3. Lower price is preferred to higher price; or β_5 is larger than or equal to β_6 and both are less than zero.

The authors analyzed the full profile ratings (for both the full factorial design and fractional design) using HB regression methods placing no constraints on the parameters and with the constraints stated above. They also estimated individual logit partworths using HB methods. Even though only six parameters are being estimated, they found that 29 % of the respondents violated at least one ordinal constraint for the full factorial design profile ratings and 41 % for the fractional factorial data. When data from 12 pair-wise choice questions were used in the estimation, 100 % of the respondents had partworths with at least one ordinal constraint violated, as opposed to 69 % respondents when data from 24 questions were used.

For illustrative purposes, we show below for two subjects the differences between the unconstrained and constrained individual logit partworths and their 95 % confidence intervals estimated with 12 choice questions.[15] These data clearly indicate the

[15] We should point out that confidence intervals are not meaningful in the strict sense.

value of placing order restrictions on the parameters; for example, for Respondent number 10, for the unconstrained partworth for the price of $1.50 of +.15 becomes −0.28 under constraints. The confidence intervals also are quite reasonable under constraints for this parameter. Similar advantages accrue for the other estimates.

Respon-dent number	Unconstrained or constrained	Eveready	Sears Diehard	50 h	60 h	$1.25	$1.50
10	Unconstrained	−0.23	0.09	0.03	0.31	−0.03	0.15
		(−0.65, 0.19)	(−0.15, 0.33)	(0.23, 0.29)	(−0.07, 0.69)	(−0.29, 0.23)	(−0.23, 0.53)
	Constrained	0.12	0.26	0.17	0.61	−0.18	−0.28
		(0, 0.43)	(0.05, 0.47)	(0, 0.45)	(0.31, 0.98)	(−0.45, −0.01)	(−0.62, −0.05)
20	Unconstrained	−0.36	−0.14	0.12	0.35	0.01	0.0
		(−0.72, 0)	(−0.40, 0.12)	(−0.12, 0.36)	(−0.01, 0.71)	(−0.23, 0.25)	(−0.36, 0.36)
	Constrained	−0.14	0.13	0.31	0.72	−0.16	−0.37
		(0.01, 0.53)	(0.01, 0.37)	(0.06, 0.58)	(0.40, 1.11)	(−0.43, −0.01)	(−0.80, −0.09)

Source: Drawn from Table 2 of Allenby, Arora, and Ginter *JMR* (1995)

The authors also collected rank ordered preference data for five profiles and compared the actual ranks with those predicted from the unconstrained and constrained HB estimation. The hit rates (percent of correct predictions for the most preferred profile) were much higher for the constrained method (40 % versus 52 % for the fractional design and 50 % versus 63 % for the full factorial design). Kendall's Tau rank correlation coefficient was also higher for the constrained results.

This application shows the advantages of the hierarchical Bayes estimation method; it not only enables estimates for each individual but also demonstrates higher predictive validity.

Application with Using Covariates: The previous example illustrated how individual partworths can be considered estimated without any information other than the attributes (or design variables) of the conjoint study. The corresponding HB model is called random effects model because individual partworths are drawn from a pre-specified distribution. The random effects model does not enable predicting the partworths for respondents not included in the study (except that they are from a distribution). However, it does permit projection to the population. In several practical cases, it will be useful to predict the partworths for individuals not included in the sample. Such a feature is feasible in the HB methodology by relating the partworths to a set of individual background variables and estimating the parameters of such a relationship. The computer study by Lenk et al. (1996) described in the chapter will serve as an example of this approach.

Appendix 4

Linear Programming Approach to Ranked Response Data

We will consider the LINMAP approach. This approach is applicable to all situations in which ranked responses are obtained from a respondent. The values of the attribute in each profile are assigned a score in the model and the aim is to construct a utility function that corresponds most with observed ranked data. The parameters of the utility function are determined using linear programming methods; see Srinivasan and Shocker (1973).

There are two models—ordinal regression (partworth function model) and ideal point model—in LINMAP. Also varied mode models can be employed as well. The LINMAP attempts to determine the functions by minimizing the amount of violation of the computed function in relation to observed ranked data.

Rather than go into the technical details, we will give a simple example.

Suppose we wish to fit a quadratic utility function for evaluations on 12 houses each described on two attributes of price (X_1) and condition (X_2). Then the utility function except for a constant is:

$$\begin{aligned} U(X_1, X_2) = {} & (\theta_1 - \theta_2)X_1 + (\theta_3 - \theta_4)X_2 + (\theta_5 - \theta_6)X_1^2 + (\theta_7 - \theta_8)X_2^2 \\ & + (\theta_9 - \theta_{10})X_1X_2 \end{aligned}$$

where the θs are all positive and X_1 and X_2 are scaled values for the two attributes. Given a number of pairwise comparisons, a linear program is constructed so as to minimize:

$$\sum_{\alpha=1}^{d} y_\alpha$$

subject to:

$$\begin{aligned} & a_{\alpha 1}\theta_1 + \ldots + a_{\alpha 10}\theta_{10} + y_\alpha > 10 \\ & \alpha = 1, 2, \ldots, d \end{aligned}$$

and $(\theta_1 - \theta_2)x_1^* + \ldots + (\theta_9 - \theta_{10})x_1^* x_2^* = 1$

First d of these conditions reflect the judgments made and the last condition is a normalizing condition.

In words, y_α is the amount of violation of the fitted function in relation to data. In all, there are d judgments. If the function does not violate a judgment, the value of y_α is set equal to zero; otherwise, y_α is the absolute difference between the utility-values. The goal is to minimize the amount of violation and determine the θ-values.

The fit of this model is excellent, judged by the rank correlation between actual and estimated ranks. The value of this correlation after correcting for ties is 0.979.

The ranks are perfectly reproduced at either end of the scale. (Ties occur when the estimated ranks are equal for any tow alternatives.)

For the following data, the fitted function has the θ values as:

$$\theta_1 = \theta_2 = \theta_4 = \theta_5 = \theta_8 = \theta_9 = 0; \quad \text{and}$$
$$\theta_3 = .5251, \ \theta_6 = .5405, \ \theta_7 = .5405 \ \text{ and}$$
$$\theta_{10} = .2008.$$

Comparison between estimated utilities and observed ranks are also shown.

Estimation of utility function by linear programming: an illustration

House number	Attribute scores Price	Condition[a]	Subjective evaluation Rank[b]	Estimated utility Score[c]	Estimated utility Rank[d]
1	2.5	4.5	1	10.00	1
2	2.5	3.5	2	9.73	2.5
3	2.5	1.0	5	9.19	4.5
4	3.0	4.5	3	9.19	4.5
5	3.0	3.5	4	9.73	2.5
6	3.0	1.0	7	8.38	6.5
7	3.5	4.5	6	8.38	6.5
8	3.5	3.5	8	7.30	8.5
9	3.5	1.0	10	6.10	10
10	4.0	4.5	9	7.30	8.5
11	4.0	3.5	11	4.60	11
12	4.0	1.0	12	2.90	12

[a]The three levels of this attribute are scaled arbitrarily at 4.5, 3.5 and 1.0
[b]Rank 1 represents the house judged to be of most worth
[c]These numbers are computed utility scores using the linear program with a constant (9.0) added to keep the scores arbitrarily positive
[d]Ties are assigned split ranks

Appendix 5

A Method for Analyzing Categorical Response Data: Categorical Conjoint Analysis

We will illustrate the method of categorical conjoint analysis to a set of evaluations of houses obtained on a categorical scale. In this study, 36 hypothetical houses in a small city in New York State were evaluated by one respondent on four categories. The categories were: A = very high worth; B = just high worth; C = just low worth; and D = very low worth. Each house was described on the three characteristics: size (or number of bedrooms), price (in \$000’s) and condition. A portion of these data are shown below.

House #	Size	Price	Condition[a]	Evaluation
1	2	125	E	A
2	2	125	G	A
⋮	⋮	⋮	⋮	⋮
35	4	140	G	C
36	4	140	P	D

[a]Condition: *E* excellent, *G* good, *P* poor

The conjoint analysis problem is to build a model to relate evaluation to the attributes of the house (a categorical conjoint problem). Formally, the problem is to find c's and ϕ's such that:

$$c_q = C\left(y_{i_1 i_2,\ldots,i_m}\right) = \phi_{1i_1} + \phi_{2i_2} + \ldots + \phi_{mi_m}$$

where m is the number of attributes.

We are assuming an additive formulation. This can be case as a canonical correlation analysis problem. Let p = number of categories. Define

$$t_{ik} = \begin{cases} 1 & \text{if i- th profile belongs to the k- th category} \\ 0 & \text{otherwise. k = 1,..., p-1.} \end{cases}$$

Then

$$c_q = \sum_{k=1}^{p-1} t_{ik} c_k$$

Also write

$$\phi_{j_{ij}} = \sum_{k=1}^{n_j-1} v_{ijk}\phi_{jk}$$

where n_j = number of levels for the j-th attribute of the conjoint profile. Then,

$$\phi_{1i_1} + \phi_{2i_2} + \ldots + \phi_{mi_m} = \sum_{j=1}^{m}\sum_{k=1}^{n_j-1} v_{ijk}\phi_{jk}$$

Let $m^* = \sum_{j=1}^{m}\left(n_j - 1\right)$

$$\beta = (\beta_1, \beta_2, \ldots, \beta_{m^*}).$$

We can now write:

$$\phi_{1i_1} + \phi_{2i_2} + \ldots + \phi_{mi_m} = \sum_{j=1}^{m^*} g_{ij}\beta_j$$

The conjoint model can be written as:

$$\sum_{k=1}^{p-1} t_{ik}c_k = \sum_{j=1}^{m^*} g_{ij}\beta_j$$

This is a canonical correlation problem between the t-variables and the g-variables (or v-variables).

An alternative method of estimation could be ordered logit.

Results for the House Data

(a) Category values

Solution	Eigenvalue	Category A	B	C	D
1	0.9501	0.2091	0.0557	−0.0923	−0.2865
2	0.5166	−0.1315	0.2172	−0.1747	0.0250
3	0.0880	−0.1494	0.0728	0.2104	−0.2370

(b) Attribute functions by solution

Attribute	Level	Solution number 1	2	3
1. Size of house	2	0.0	0.0	0.0
	3	0.0	0.0	0.0
	4	0.0	0.0	0.0
2. Asking price	125	0.1086	−0.1459	−0.0295
	130	0.0575	−0.0297	0.0446
	135	−0.0584	0.1531	−0.0305
	140	−0.1077	0.0225	0.0154
3. Condition	E	0.1324	0.0428	−0.0383
	G	0.0570	0.0320	0.0563
	P	−0.1894	−0.0748	−0.0133

(c) Analysis of variance tables by solution

Source of Variation	Degrees of Freedom	Solution 1 S.S.	Solution 1 F-Ratio	Solution 2 S.S.	Solution 2 F-Ratio	Solution 3 S.S.	Solution 3 F-Ratio
Size	2	0.0	0.0	0.0	0.0	0.0	0.0
Price	3	0.271	51.6	0.405	8.01	0.036	0.37
Condition	2	0.680	194.2	0.102	2.94	0.052	0.79
Residual	28	0.049		0.483		0.912	

Interpretation

One typically uses the solution corresponding to the first eigen value. The category values for A, B, C, and D for this solution are approximately 0.21, 0.06, −0.09 and −0.29 and they represent the scale values for the four categories of "very high worth" to "very low worth". The partworth functions for the three attributes of the house are shown in panel (b). They show that condition of the house has the largest impact on the evaluations.

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Chapter 4
Choice Based Conjoint Studies: Design and Analysis

4.1 Introduction

One of the major objectives in conjoint analysis has been to predict the choices made by a sample of individuals for a new item which is described in terms of a set of attributes used in a conjoint study.[1] Ratings-based conjoint studies involve the conversion of an individual's stated utility for an item to predict the probability of choice of an alternative under various conditions (e.g. when other alternatives available). As described in Chap. 3, such a prediction is made using preference data (ratings or rankings) collected on a set of hypothetical choice alternatives. A parallel stream of research pursues the path of choice experiments in which an individual makes a choice among a set of choice alternatives, each of which is typically described by a set of attributes; several choice sets are presented to each individual. These choice data, across all the choice sets and all individuals, are then analyzed using a choice model (usually a multinomial logit model and sometimes multinomial probit model) to obtain a function that relates the attribute levels to probability of choice. This approach has come to be known as choice-based conjoint analysis[2] and has its roots in discrete choice analysis; these methods are also called "stated" choice methods (or stated choice experimental methods) because they represent intended choices of respondents among hypothetical choice possibilities. This chapter describes these methods.

Stated choice experiments were (and are) designed to collect choice data that are consistent with random utility theory-based choice models and have the advantage that they can be designed to simulate choices that are made in a way very similar to

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[1] I thank Professor Olivier Toubia for his careful reading of this chapter and suggestions for improvement.

[2] Readers may refer to Diener, Chris, *Using Choice Modeling to Supercharge Your Business*, Ithaca, NY: Paramount Market Publishing, 2008 for a non-technical guide to choice modeling, its benefits, and applications.

V.R. Rao, *Applied Conjoint Analysis*, DOI 10.1007/978-3-540-87753-0_4,

the actual marketplace choices that people make. Rather than collecting evaluations on hypothetical attribute profiles and estimating utility models to predict choices for new products as in the ratings-based approaches, this approach collects stated choice data directly and develops a model giving the probability of choice of an alternative in terms of a set of attributes and their respective attribute levels. To emulate the idea that individuals make choices in the marketplace among a subset of products, this approach involves presenting several choice sets of hypothetical profiles, each set consisting of a few product profiles described by a finite number of attributes. See Batsell and Louviere (1991), Louviere et al. (2001), Louviere (1991) and Ben-Akiva and Lerman (1991).

A major advantage of this method is that it deals with choices rather than ratings for measuring preferences. Standard statistical methods can be employed for analyzing choice conjoint data at the aggregate level or at the subgroup level. More recently, advanced methods using hierarchical Bayesian techniques enable estimation of parameters at the individual level. In all these analyses, interactions among attributes can also be included if necessary.

It is important to stress that choice-based conjoint methods provide several additional advantages such as the ability to value brand-based attributes, an ability to assess competitive effects on choice, an ability to assess price sensitivity to price differences, and ease in using the estimated model to predict real marketplace choices. (We will discuss these applications in later chapters.) The disadvantages of this method are that the design of a choice-based conjoint study is far more complex due to the intricacies of generating an "efficient" series of choice sets. Also, some respondents may find making a choice within some choice sets to be difficult.

This chapter is organized as follows. The first two sections briefly describe the concepts of the choice process and random utility theory that are essential to the design and analysis of stated choice data. The third section gives an illustration of stated choice experiments in conjoint analysis. The fourth section covers various strategies for designing choice sets and data collection methods for choice-based conjoint analysis; this section also includes a brief discussion of designs using Bayesian estimation methods. The fifth section covers a variety of analysis methods for data collected in choice-based conjoint studies; these include the multinomial logit model, which is the most frequently used model and related methods including hierarchical Bayesian logit methods, and some applications of the various methods are given. The sixth section describes various criteria for selecting a conjoint approach (ratings-based conjoint vs. choice-based conjoint) as an applied researcher. The final section concludes with a discussion of some issues related to the choice-based approach to conjoint analysis.

4.2 The Choice Process

We now briefly discuss random utility theory which forms the basis for analyzing stated (or revealed) choice data. Figure 4.1 lays out the relationships that exist in the various stages of consumer decision-making in the marketplace. The boxed

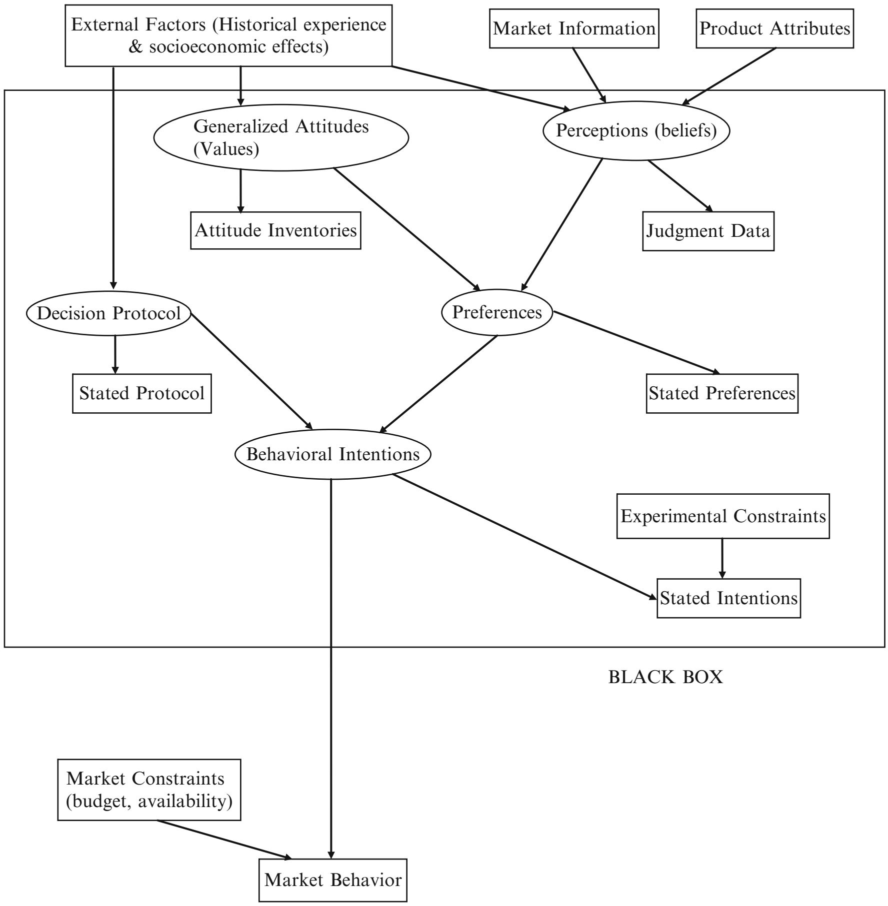

Fig. 4.1 A description of choice process (Source: Reprinted from McFadden (1986), Copyright (1986), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA)

relationships deal with the various stages of the process. In general, any model of market behavior considers three constructs: external factors, market information and product attributes. An individual's past experience (including past purchase behavior) can be included in the model of choice via the "external factors" construct; these factors include choice context and social situation (e.g., group versus individual decision). It describes various latent constructs that lead to choice. This model is applicable to the stated choice data collected in choice-based conjoint studies as well as to revealed choice behavior in the marketplace. It can help guide data collection process for stated choices.

The basic idea in the choice theory is that an individual makes a choice from a set of alternatives such that his utility is maximized. Thus, the utility of the item chosen is the highest among the utilities of all the alternatives (items) under consideration.

Under this premise, the modeling approach is first to recognize that the utility of an item consists of two components: a deterministic component and a random component. The deterministic component can be modeled in terms of various observable factors, including observed product attributes. The random component is assumed to represent all unobservable factors in the choice process (such as unobserved individual idiosyncrasies of tastes). One postulates a distributional assumption for the random component and together with deterministic components of the model derives an expression for the probability with which an item will be chosen. The model is calibrated with data on stated (or revealed) choices. In this chapter, we will restrict much of the discussion to the multinomial logit formulation of the choice model; this model assumes that the errors are distributed according to extreme value distribution and are independent (more details are provided in the Section on Analysis Methods below).

Even though the underlying model for utility is linear (similar to the ratings-based conjoint methods described earlier), the model for the probability of choice is non-linear. The variance-covariance matrix in the linear models (for stated ratings data) depends only on the experimental design as determined by the design matrix while it also depends on the parameters to be estimated in the choice-based conjoint study. This difference creates challenges in the design of choice sets in choice-based conjoint analysis because of the need to have choice alternatives and choice sets that span all possible choice scenarios.

4.3 Choice Experiments for Conjoint Analysis: An Illustration

Choice-based conjoint methods collect data on intended choices of various alternatives in a choice set. Several choice sets are used in such data collection. An example will help clarify the procedure of choice-based conjoint studies. Assume that a credit card company is interested in determining the market potential for a new credit card that it has designed for distribution among its target customers. Assume further, this new card issued under brand name P is expected to compete with three other existing brands, Q, R, and S. Assume that previous marketing research identified that there are four main attributes on which these credit cards differ and determined the following attributes and their corresponding levels:

- Brand name (P, Q, R, and S)
- Annual fee: None, \$20, \$40 and \$60
- Interest rate on balances: 10%, 14% and 18%
- Credit limit possible: \$2,000, \$5,000, and \$10,000
- Use for online purchases: No and yes.

The researcher will generally implement five steps in the design of the choice-based conjoint study in this context:

1. Construct a number of profiles of credit cards using the five attributes: brand name, annual fee, interest rate, credit limit, and online use;

2. Create choice sets for use in the data collection. These sets will show alternative marketplace conditions (choice sets) under which an individual may make a choice;
3. Develop an appropriate question to elicit choice for each choice set. Two aspects need to be considered here: specification of the situation under which an individual will express her choice and whether to include a "no choice" option or not;
4. Implement the data collection for a relevant sample of respondents; and
5. Analyze the data using an appropriate analytical model to obtain partworth values for different levels of each attribute.

For example, a choice set that includes a "no choice" alternative may look like:

Option1	Option 2	Option 3	Option 4	No choice
Brand P $40 Annual fee 10% Interest rate $5,000 credit limit Online purchase	Brand Q $60 Annual fee 18% Interest rate $10,000 credit limit Online purchase	Brand R $20 Annual fee 14% Interest rate $2,000 credit limit No Online purchase	Brand S $40 Annual fee 10% Interest rate $5,000 credit limit Online purchase	None: I would defer my acquiring a card.

The question posed to a respondent would look like:

You are looking to acquire a credit card and these four options (1, 2, 3, and 4) are the only choices, which option would you choose or would you defer acquiring a credit card?

The individual would choose one of the five options (1, 2, 3, 4, and none) from this choice set. This process is repeated for a number of choice sets. The choices made by the individual would constitute the choice-based conjoint data. These data are then used to build a model for the probability of choice of a particular card with a certain set of attribute levels or choosing none for any choice set.

The model developed is based on the assumption that an individual will maximize the random utility for an object for any choice set. The essential tasks in the choice-based conjoint studies are: (1) the design of choice sets; (2) the choice of the specific model to estimate the probability of choices (usually the multinomial logit model); (3) the estimation method (usually the maximum likelihood method); and (4) the level of data aggregation in the estimation.

4.4 Design of Choice Sets and Data Collection for Choice-Based Conjoint Studies

4.4.1 Two Types of Designs

Choice-based conjoint studies are like experiments (implemented with paper-and pencil or on a computer) where, for a series of different choice sets, a subject will "choose" an alternative from the choice set. We will differentiate two types of choice-based conjoint studies; one type is *binary choice* experiments when the response is binary ("yes" or "no"; or "choose" or "do not choose") to a stimulus profile. The second type is *multinomial choice* experiments when the response is multinomial to a set of three or more alternatives, perhaps including a "no choice" option. In this case, the respondent gives a response of which alternative she will choose (and implicitly stating that she will not choose any of the remaining alternatives in the choice set). If the respondent selects the no choice option, she is indicating that she will not purchase any options in the choice set. The credit card illustration in the previous section is an example of the second type of choice experiments.

The two types of experimental design are discussed in more detail below.

Design of Binary Choice Experiments: The first step in designing binary choice experiments is to design profiles of alternatives using the selected attributes and levels. The principles of designing profiles in the ratings-based conjoint studies described in Chap. 2 will directly apply to the design of profiles in the binary choice experiments. Each profile is presented to the respondent seeking the response of yes or no.

Design of Multinomial Choice Experiments: There are two steps in the design of multinomial choice experiments. The first step, as before, is to design profiles of alternatives using various attributes and their levels (similar to that of the binary choice studies). The second step is to design choice sets, each set consisting of a subset of these profiled alternatives. In this step, the researcher has to decide on the set size (fixed or varying or a combination) and the number of choice sets in the study. An additional factor is the efficiency of the design (i.e., designing choice sets such that the parameters can be estimated in a statistically efficient manner). We will discuss the efficiency issue later in this chapter in some detail.

4.4.2 Factors to Be Considered in Choice Set Design

In general, the following factors need to be addressed in the design of choice sets:

(a) How many alternatives are included in a choice set; is there a constant alternative (e.g. none; no choice; delay choice; or stick with my usual brand or some other);
(b) Whether the conjoint study is generic (no brands) or a branded study; if it is branded, what are the brands to be included;
(c) What are the attributes and what are their levels; and
(d) Are there any attributes that apply only to some alternatives (or alternative-specific);

The reader will recognize the third and the fourth factors as these were also factors in the design of ratings-based studies. The main issues arise with the first two factors. These will boil down to the consideration of (1) the number of pieces of information a person needs to process to make a choice and (2) whether or not the alternatives profiles are labeled with brand names to identify them. (If brand names are used to label profiles, respondents will impute meaning to the brand name and there may be a need to include brand-attribute interactions in the estimated model).

Number of Pieces of Information: This first factor is quite obvious. It combines two aspects: how many alternatives in a choice set and how many attributes are used to describe each alternative. The recommendation given by researchers on this issue varies considerably. Some may suggest that a person cannot process more than 20 pieces of information (four alternatives each described on five attributes or two alternatives each described on ten attributes etc.) while others think that individuals are not hard pressed to process several alternatives each described on several attributes. It is better to conduct a pretest to determine how many profiles could be included in a choice set so that the respondent is not overly burdened. It is also advisable to include choice sets with varying numbers of profiles. For example, choice sets of sizes 3, 4, and 5 may be included in a study to test the robustness of the estimated model for different set sizes. Different set sizes in choice sets will also arise in a set of designs called availability designs, discussed in the next section.

Named or generic alternatives: The second factor arises when one is interested in evaluating the effect of brand name (or a product category) in a choice experiment. For example, in a study evaluating the importance of attributes over various automobile attributes (horse power, style, etc.) each profile may be unlabelled or assigned to a specific brand name. The latter case helps in determining the value of a brand name. As noted earlier, use of brand names may engender brand-attribute interactions and accordingly a model needs to incorporate them.

4.4.3 Examples of Designs Used in Some Past Studies

We will now describe several examples of designs used for choice-based conjoint studies.

Example 1. This study was designed to test some advanced methods of choice-based conjoint analysis (described later in this book) and was conducted among 2,255 leading-edge wine consumers recruited in three countries: USA, Australia and New Zealand (Toubia et al. 2007). The purpose was to determine trade-offs between type of wine closure and other features of wine. In addition to four different types of wine closures (traditional cork, synthetic cork, Metacork™, and Stelvin (screw cap)), four other attributes of wine (namely, type of wine, country of origin of wine, size of vintner, and price range) were evaluated by the respondents. First, 16 orthogonal profiles developed from a 4^5 factorial design (using methods described in Chap. 2) and subsequently ten choice sets each consisting of four profiles were constructed using a form of random selection using the customized design procedure (Arora and Huber 2001) described later in the chapter. The sample question used in this study is shown in Fig. 4.2 and screen shots of data collection forms employed are shown in Fig. 4.3.

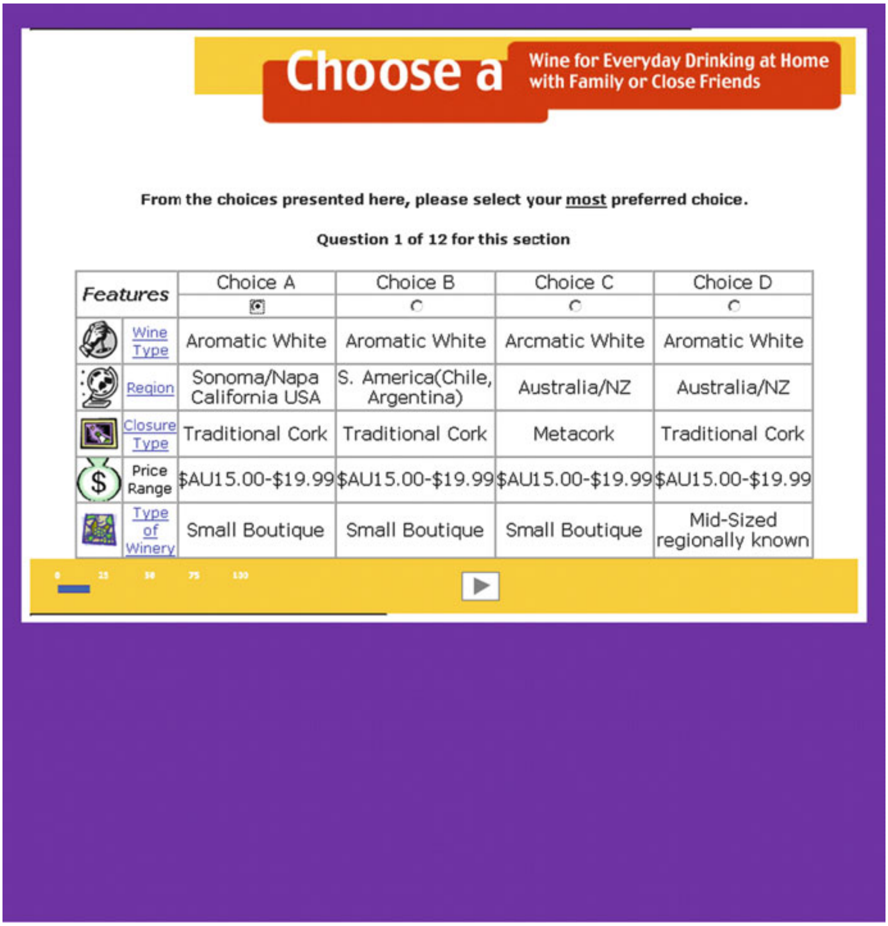

Fig. 4.2 Sample question in the Wine Closure Study (Source: Reprinted from Toubia et al. (2007), Copyright (2007), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA)

Example 2. This example is a study among 99 subjects who indicate choices among fast food menus at various prices (Louviere and Woodworth 1983). First, nine meal combinations were generated using a 1/3 fraction of a 3^3 design where the three factors were: sandwich (three levels), side order (three levels) and soft drink (three levels). These nine meal combinations were treated as nine factors in a 2^9 factorial design where the two levels for each meal were alternative-specific prices. An orthogonal main effects plan with 12 rows was selected and each row corresponded to a choice set of the nine menus at different levels of price. We show in Appendix 1 the construction of these choice sets as a comprehensive illustration.

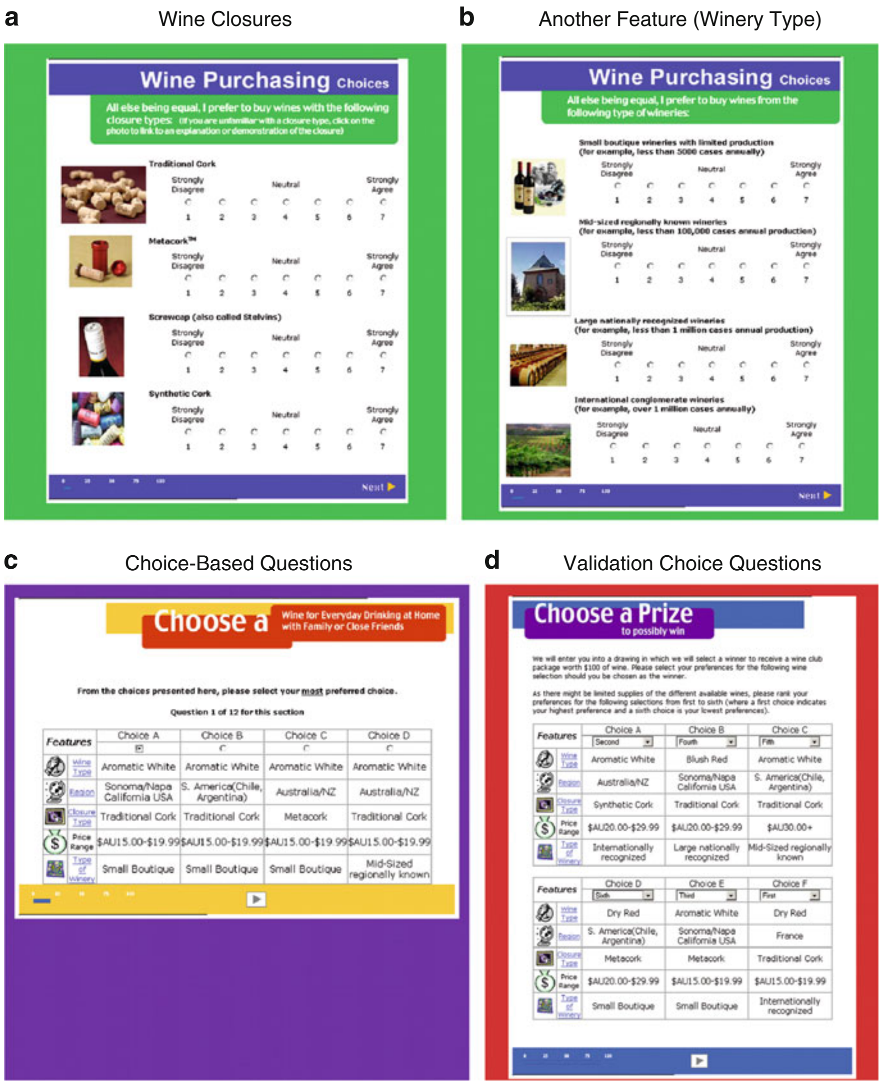

Fig. 4.3 Example screenshots from Wine Closure Preference Study (Source: Reprinted from Toubia et al. (2007), Copyright (2007), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA)

Example 3. This study was designed to elicit choice data from individuals for a set of 11 major brands of soft drinks[3] (Louviere and Woodworth 1983). The design used was a fractional factorial (2^4) out of the possible choice sets of 2^{11} design

[3] The sample consisted of 89 student subjects. The choice responses were aggregated to yield 103 choice frequencies within choice sets for analysis (each of the 11 alternatives appears 8 times + "other" which appears 15 times). The high correlation ($R = 0.95$) between the logarithms of the

(each brand present or absent). Eliminating the alternatives of no brand being present, this design yielded 15 choice sets. Subjects were requested to indicate which of the 11 soft drinks they would be most likely to select on any given visit to a store to buy, or to indicate "other", which serves as a base alternative. In Appendix 2 we describe how designs of this variety can be constructed.

Example 4. Bradlow and Rao (2000) conducted an experiment, on an assortment of choices from a set of eight popular magazines (BusinessWeek, Time, Newsweek, Fortune, People, Sports Illustrated, Rolling Stone, and In Style). In this study, 187 students at a large northeastern university were randomly divided into six different groups; four of the groups were presented with 16 sets of five magazines each {5-tuples); the other two groups received 16 bundles of six magazines {6-tuples}. These sets of 16 options were constructed so that each magazine appeared the same number of times in each set (marginal balance) and an equal number of times with of the seven other magazines (pair-wise balance). For each of the sets, the students indicated which magazines, if any, they would purchase at the given annual subscription prices (there were 32 possible selection patterns for each 5-tuple and 64 for each 6-tuple). Students were told that they had a yearly magazine budget of $200 and that whatever they did not spend on magazines could be used for other purposes. The questionnaire explicitly told students (twice) to consider each assortment choice independently of all other sets.

Example 5. In a study on how individuals make choices among bundles composed of heterogeneous product categories (e.g. PC Systems), the researchers first developed 18 PC Systems composed of a personal computer (three options), monitors (three options), and printers (two options) (Chung and Rao 2003). They then designed 18 choice sets, each containing two to five alternative PC Systems (excluding the "no buy" choice). Bundles in each choice task were randomly determined; five choice sets contained two bundles, ten choice sets contained three bundles, and three choice sets contained four bundles.

These examples show the diversity among the designs used in choice-based conjoint studies.[4]

4.4.4 Criteria for Evaluating Designs

As noted in Chap. 2, two properties characterize efficiency in ratings-based conjoint studies which use linear designs (based on linear models); these are level balance and orthogonality. In choice set designs (which inherently use nonlinear designs because the underlying model is nonlinear), these criteria are important as well and are grouped under the term "statistical efficiency". A consequence of constructing

103 observed relative choice frequencies, f_{ai}/n_i, and the logarithms of the fitted choice probabilities indicates that the MNL model provides a good account of the data from this task.

[4] For other examples see Louviere et al. (2001) and Louviere (1991) for an exposition and Louviere (1988) for origin of these methods. See Krieger and Green (1991) for designing Pareto optimal stimuli for choice experiments.

designs that (attempt to) satisfy the statistical efficiency criterion is the ability of the design to satisfy the criteria of minimal overlap and utility balance. Recently, another criterion called managerial efficiency was proposed; this criterion attempts to construct a design that accommodates efficient estimation of a managerial objective (which is a function of the parameters). We will briefly describe these four criteria for evaluating choice set designs: (1) statistical efficiency; (2) minimal overlap; (3) utility balance; and (4) managerial efficiency. Note that due to the nonlinearity of the underlying model, the designs constructed are not optimal for all cases.

Statistical efficiency is an important criterion and measured by the precision with which partworth coefficients (call them betas) are estimated. This is usually measured by D-efficiency (described in Chap. 2). This criterion is easy to apply in the case of ratings-based designs, because of the linear utility model involved.[5]

The probability of choosing an alternative in a choice-based conjoint study is generally modeled as a logit function in terms of the attribute levels of each of the item with respect to a base alternative in the choice set. Thus, the underlying model for a choice-based conjoint experiment is nonlinear. So in choice-based designs, the variance-covariance matrix[6] of betas will depend on betas. Thus, one needs to have knowledge of the betas to estimate the variance-covariance matrix and come up with a suitable design. But, if one knows the beta values there is no reason to use choice-based conjoint study. This is the chicken-egg problem in developing optimal designs for choice-based studies. There are various ways by which this problem is handled in practice. One method is to ignore the problem and develop profiles as in the ratings-based methods and use those profiles to develop choice sets using heuristics (which we will elaborate below). Another is to conduct a pretest to get some idea on the magnitude of the beta coefficients and use this information in designing choice sets. A third way is to develop designs assuming a prior distribution for the beta coefficients. All of these are intended to develop a statistically efficient design, which is optimal or near optimal.

An illustration of the computed design efficiency for a three attribute study computed in CBC software is shown in Appendix 2.

Minimal Overlap: Minimal level overlap means that the probability that an attribute level repeats itself in each choice set should be as small as possible; this is important because the contrasts (or differences) between the levels of an attribute are used in the calibration of the logit model. If the same level is repeated several times within the choice set, the choices made in that choice set

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[5] In the case of linear model, the variance-covariance matrix of s of the estimates is $(X'X)^{-1}\sigma^2$, where X is the suitably coded design matrix and σ^2 is the variance of the error term. The D-efficiency measure is $1/(n|(X'X)^{-1}|^{1/p})$ where n is the number of observations and p is the number of parameters.

[6] It is $(X'PX)^{-1}\sigma^2$ where P is the matrix of choice probabilities (respondents by choice alternatives) which depends on estimated betas.

do not contribute any information on the value of that attribute because the difference in the attribute levels is zero.

Utility Balance: The property of utility balance implies that the utilities of the alternatives in a choice set are approximately equal. When a design is utility balanced, the variance of the probabilities of choice of alternatives within a choice set will be reduced. Huber and Zwerina (1996) show that achieving such utility balance increases the efficiency of a design to the tune of 10–50 %. The process of swapping and relabeling attribute levels of alternatives in an initial choice set accomplishes this objective. (This procedure is described below.)

Managerial efficiency: This criterion addresses the issue of how the estimates from a choice-based study are utilized for managerial decisions. As suggested by Toubia and Hauser (2007), researchers may find this additional criterion of managerial efficiency important in various applied situations because managerial decisions involve functions of the beta estimates. For example, consider the case of an electronic devices manufacturer who is interested in determining the price to charge for various features; this decision is based not directly on the partworths or betas for features and price but on the partworths of features relative to that of price. In such situations, the authors argue that the criterion of D-efficiency (or minimizing D-error) does not accommodate the managerial objective. They suggest a new criterion called M-efficiency (for managerial efficiency for minimizing managerial errors). This criterion involves modifying the D-efficiency criterion as $q * tr(M(X'X)^{-1}M')/n_m$, where the M-matrix is the matrix that describes the quantities of managerial interest (e.g. willingness to pay for a feature defined as "the partworth for the feature minus scaled partworth for the price") and q is the total number of partworth estimates and n_m is the number of managerial decisions of interest. Appendix 3 describes this procedure with an example based the Toubia-Hauser paper. These authors present algorithms for generating designs that minimize the M-errors. Their approach provides a direct way to incorporate managerial decisions in the choice experiments.

4.4.5 A Taxonomy of Choice Set Designs

Given the array of options[7] in designing choice sets, it is difficult to come up with taxonomy of all possible designs used for choice sets. We will classify *selected* ones using three dimensions: (1) the degree of knowledge of the partworths available to the study designer; (2) whether the designs are common across all respondents or customized; and (3) whether the procedure is manual or computerized. Table 4.1 shows a classification based on these dimensions.

[7] Work in this area spans several years and comes a variety of fields. A bibliography can be found in *citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.106.3364* and a review of methods can be found in Khuri et al. (2006).

Table 4.1 A taxonomy of selected methods for generating choice set deigns

Are choice sets the same for all respondents?	Methods based on linear model (implicitly assume betas are zero)	Methods based on nonlinear model that assume fixed values for betas	Methods based on nonlinear model that assume a prior distribution for betas
Yes (same for all)	Shifting method L^{MA} method Randomized method Availability designs	Utility balance method	Bayesian methods (near-optimal or optimal designs)
No (customized)	Computer randomized method Computer- optimized method		

While the second and third dimensions are obvious, the first dimension requires elaboration. For this, we first restrict our discussion to the multinomial logit (MNL) model for the probability of choosing an alternative in a choice-based conjoint study. note that the underlying model for a choice-based conjoint experiment is nonlinear; (note that the is generally modeled as a multinomial logit function in terms of the attribute differences of the item with respect to a base alternative in the choice set). The variance-covariance matrix[8] of betas will depend on betas in choice-based designs. Thus, one requires knowledge of the betas to estimate it and come up with a suitable design. There are various ways by which this problem is handled in practice.

One method is to ignore the problem and develop profiles as in the ratings-based methods and use those profiles to develop choice sets in some manner (which we will elaborate below); this is akin to using a linear model as shown in the first column of Table 4.1; but, these procedures do not necessarily yield estimates of partworths with minimal standard errors.

The second method is to conduct a pretest to get some idea on the magnitude of the beta coefficients and use this information in designing choice sets; this is essentially what is done in the methods of column 2 of Table 4.1.

A third way is to develop designs assuming a prior distribution for the beta coefficients (which is done in the methods shown in the third column of Table 4.1). All of these extensions to the linear model are intended to develop a design that yields statistical efficiency, which is optimal or near optimal. We will now describe these methods in some detail. We will also include actual designs that can be easily adapted to applied problems.

[8] It is $(X'PX)^{-1}\sigma^2$ where P is a matrix derived from the choice probabilities of choice alternatives, which depends on estimated betas. If all betas are zero (or if the choice probabilities are all equal), the covariance matrix will be similar to that in the ratings data analysis.

4.5 Strategies for Designing Choice Sets

4.5.1 Methods Based on Linear Models

Various methods for designing choice sets under this category are either manual or computer-aided.[9] Computer-aided designs can be customized for each respondent. Three types of manual designs are described below: shifting method, L^{MA} method and randomized method. Computer methods are either randomized or optimized. A particular case of designs, called the availability designs are useful in assessing the effects of availability of brands (or competitive set) as an attribute; the underlying utility model for these designs is linear; This case is described under the heading "other designs".

4.5.1.1 Manually Generated Designs

There are essentially three methods for generating designs for choice sets manually. These are (1) the Shifting Method; (2) L^{MA} Method; and (3) Randomized Method.

1. *Shifting Method:* This method involves first creating an orthogonal design of full profiles according to the plans developed by Addelman (described in Chap. 2). Each row of this design will eventually become a choice set and the profile in the row will be the first profile of the choice sets. The next step involves adding 1 to each level of the first profile (making sure that these numbers are modulus of the number of levels). This step will generate the second profiles in the choice sets. This step is repeated as many times as the number of levels.

As an example, if there are four attributes each at three levels, the orthogonal design will have nine profiles. The 3^4 Shifted design for choice sets is shown in Table 4.2. Note that the levels of the second profile are derived by adding "1" to the corresponding levels of the first profile. If the added number is 4, it will become 1 ($=4 - 3$).

2. *L^{MA} Method:* This method involves generating a master design and developing choice sets from it. Although this method appears a logical way to generate choice sets, one should note that this method is not often used in practice.

To illustrate, let us consider the problem of designing choice sets for A attributes, each with L levels, when the alternatives are generic (or unlabelled). Suppose the choice set size is fixed at M. Because there are M alternatives each to be described on A attributes, we can treat this problem as a factorial with M*A attributes each at

[9] This material is based on the Sawtooth Working Paper, Chrzan, Keith and Bryan Orme, "An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis", 2000. Computer randomized designs and computer optimized designs can be generated with the Sawtooth Software's CBC product. See also Bunch et al. (1996).

Table 4.2 Illustration of a shifted design for nine choice sets of size 3 for four attributes

	Profile 1				Profile 2				Profile 3			
Choice set	Att 1	Att 2	Att 3	Att 4	Att 1	Att 2	Att 3	Att 4	Att 1	Att 2	Att 3	Att 4
1	1	1	1	1	2	2	2	2	3	3	3	3
2	1	2	2	3	2	3	3	1	3	1	1	2
3	1	3	3	2	2	1	1	3	3	2	2	1
4	2	1	2	2	3	2	3	3	1	3	1	1
5	2	2	3	1	3	3	1	2	1	1	2	3
6	2	3	1	3	3	1	2	1	1	2	3	2
7	3	1	3	3	1	2	1	1	2	3	2	2
8	3	2	1	2	1	3	2	3	2	1	3	1
9	3	3	2	1	1	1	3	2	2	2	1	3

Att attribute, 1, 2, 3 are levels of attributes

L levels. Then the total number of combinations will be L^{M*A}; one then selects an orthogonal design for MA attributes each at L levels; each row of this reduced design then becomes used in specifying the choice set; the first A will define the first (unlabelled) alternative or profile, the next A levels the second alternative or profile, and so on. If the alternatives are to be labeled, the procedure is similar and the label is attached to the first A levels, the second label is attached to the next A levels, and so on. As noted earlier, one has to be concerned about the specific inferences respondents may make because of the label attached; this can be handled in the specification of the utility model. Further, to make the choice task realistic, one may add a no choice option or a constant alternative.

Table 4.3 shows an illustration for a 3^{12} design for choice sets of size 3 for four attributes; the master design will be a 3^{12} full factorial; a reduced main-effects design will have 27 choice sets of three options each. If this number of choice sets is too large for a respondent to evaluate, a random subset (e.g. 12 or 14) can be chosen for implementation. A different random subset can be used for each respondent.

As another example, if one is designing choice sets of size 4 for eight attributes each with four levels; the master design will be a 4^{32} full factorial; a reduced main-effects design will have 128 choice sets of four options each (details are not shown). If this number of choice sets is too large for a respondent to evaluate, a random subset (e.g. 16) can be chosen for implementation. A different random subset can be used for each respondent.

3. *Randomized Method*: A random design enables the administering of choice sets randomly and uniquely to different respondents; the procedure is to select profiles from the universe of all possible profiles (with replacement) and place them into choice sets. A problem with this general procedure is that duplications of profiles may occur within a choice set; such duplications should not be allowed for effective data collection. The shifting method described above can reduce duplication of attribute levels within choice sets (a property called minimal overlap). Care can be taken to see that the profiles across all choice sets for any respondent are as orthogonal as possible. Depending on the extent of

Table 4.3 Illustration of a 3^{12} design for choice sets of size 3 for four attributes using the L^{MA} method

	Profile 1				Profile 2				Profile 3			
Choice set	Att 1	Att 2	Att 3	Att 4	Att 1	Att 2	Att 3	Att 4	Att 1	Att 2	Att 3	Att 4
1	1	2	1	3	2	2	3	1	1	3	3	2
2	3	2	3	1	3	1	3	1	2	3	1	2
3	1	2	3	3	2	3	2	2	2	1	2	3
...												
...												
27	3	3	2	1	3	2	1	2	1	1	3	3

Att attribute, 1, 2, 3 are levels of attributes

overlap, these types of randomized designs are able to measure special effects and efficient at measuring main effects in a different way. It turns out that designs with little or no level overlap within choice sets are good at measuring main effects, while designs with a lot of overlap are good at measuring higher-order interaction effects.

4.5.1.2 Computer-Aided Methods

The methods aided by the computer can be divided into computer randomized methods and computer optimized methods. The latter group seeks to find designs that maximize the statistical efficiency of the designs developed.

Computer Randomized Methods: While the randomized methods can be implemented manually, it is often convenient to implement them using a computer algorithm. When this is done, the researcher can generate random choice sets that are unique for each respondent as well as randomize them within a respondent before administering the study.[10] Note that these computer randomized methods do not always generate an optimal output.

Computer Optimized Methods: Kuhfeld et al. (1994) applied computer search algorithms in SAS/QC to evaluate the large number of possible designs for choice sets and select the most efficient for the study on hand. Their methods are programmed in SAS system under the OPTEX procedures. They showed that their designs thus developed show significant improvements[11] in efficiency. New SAS macros have been added specifically for generating efficient choice experiment designs (Kuhfeld 2000). One should note that orthogonal designs[12] are not always more efficient than

[10] Please see the CBC documentation for a description of these different kinds of randomized designs (Sawtooth Software 1999).

[11] These improvements occur also for the ratings-based conjoint designs discussed in Chaps. 2 and 3, particularly when there is asymmetry or unequal number of levels across attributes (or asymmetric plans).

[12] The design matrix X will be coded using orthogonal coding and X'X matrix will be diagonal for orthogonal designs.

Table 4.4 SAS OPTEX code for generating choice sets

```
Title 'Choice Conjoint Analysis of Mobile Phones'
proc plan ordered;
    run;
factors style=4 talk=4 weight=4 brand=4 camera=4;
    output out=design
    style cvals=('Candy Bar' 'Flip Phone' 'Slide Phone' 'Touch
    Screen')
    talk nvals=(9 7 5 3)
    weight nvals=(145 130 115 100)
    brand cvals=('Blackberry' 'Samsung' 'LG' 'Nokia')
    camera nvals=(8 6 4 2)
    run;
proc print data=design;
proc optex data=design seed=12345 coding=orthog;
    class style talk weight brand camera;
    model style talk weight brand camera;
    blocks structure=(18)4;
    run;
output out=try number=1 blockname=blk;
    run;
proc print data=try;
    run;
proc freq data=try;
    run;
```

non-orthogonal designs. In general, it is best to experiment with the OPTEX procedure and choose a design. As an illustration, the OPTEX code for developing 18 choice sets for a study with five factors (style, talk, weight, brand, and camera quality) each at four levels is shown in Table 4.4. The parameters (18 for number of choice sets and 4 for the number of options in a choice set) can be varied to generate other designs.

We now describe a design for choice sets developed using the OPTEX algorithm of the SAS system. The context is that of a food manufacturer who wishes to introduce a line extension in the category of frozen entrees (Kuhfeld et al. 1994). The firm has one nationally branded competitor, a regional competitor in each of three regions, and a profusion of private label products at the grocery chain level. The product comes in two forms: stovetop and microwaveable. The firm believes that the private labels are likely to imitate the line extension and sell it a lower price and thinks that this strategy of private labels will work for the stovetop version but not for the microwaveable form. The firm also wants to test the effect of a shelf talker that will draw attention to the product. These questions can be addressed using choice-based conjoint analysis.

The authors set up a choice-based conjoint for this problem. The alternative factors and levels for this design are shown in Table 4.5; the levels reflect the constraints described above.

Table 4.5 Description of alternative factor levels and brand description for the frozen entrees choice-based conjoint study

Alternative	Factor	Levels	Brand	Description
1	X1	4	Firm	3 prices + absent
2	X2	4	Firm line extension	3 prices + absent
	X3	2		Microwave/stovetop
	X4	2		Shelf talker yes/no
3	X5	3	Regional	2 prices + absent
4	X6	3	Private label	2prices + absent
	X7	2		
5	X8	3	Competitor	2 prices + absent

Source: Reprinted with permission from Kuhfeld et al. (1994), published by the American Marketing Association

Table 4.6 Illustration of a choice set design for a food products study developed from the OPTEX procedure (a non-orthogonal design). Block 1: Shelf talker absent for client line extension

Choice set	Client brand	Client line extension	Regional brand	Private label	National competitor
1	$1.29	$1.39/stove	$1.99	$2.29/mico	N/A
2	$1.29	$1.89/stove	$2.49	N/A	$2.39
3	$1.29	N/A	$1.99	N/A	N/A
4	$1.69	$1.89/μ	N/A	$2.29/μ	$1.99
5	$1.69	$2.39/stove	$2.49	$2.29/stove	N/A
6	$1.69	N/A	N/A	N/A	$2.39
7	$2.09	$1.39/μ	N/A	$2.29/stove	$2.39
8	$2.09	$2.39/stove	N/A	$1.49/stove	$1.99
9	$2.09	N/A	$2.49	$1.49/μ	$1.99
10	N/A	$1.39/μ	$2.49	N/A	$1.99
11	N/A	$1.39/stove	N/A	N/A	$1.99
12	N/A	$1.89/stove	$1.99	$2.29/stove	N/A
13	N/A	$2.39/μ	$1.99	$1.49/μ	$2.39

Source: Reprinted with permission from Kuhfeld et al. (1994), published by the American Marketing Association

The basic design consists of eight factors with 4, 4, 2, 2, 3, 3, 2, and 3 levels respectively. The design that allowed for the estimation of availability cross-effects, direct and cross price effects, and the effects of product formulation (microwaveable and stovetop) presence of shelf talker involved 26 choice sets. These choice sets (in two blocks) are shown in Tables 4.6 and 4.7.

Further, SPSS™ Trial Run can be used to generate computer optimized designs (SPSS 1997 and 2012) as can Sawtooth Software's CVA (www.sawtoothsoftware.com/products/cva). These design strategies are usually suitable for traditional (one profile at a time) conjoint designs, but their capabilities are limited when it comes to designing choice experiments.

Table 4.7 Illustration of a choice set design for a food products study developed from the OPTEX procedure (a non-orthogonal design). Block 2: Shelf talker present for client line extension

Choice set	Client brand	Client line extension	Regional brand	Private label	National competitor
14	$1.29	$2.39/μ	N/A	$2.29/stove	$1.99
15	$1.29	$2.39/stove	N/A	$1.49/μ	N/A
16	$1.29	N/A	$1.99	$1.49/stove	$1.99
17	$1.69	$1.39/μ	$1.99	N/A	$1.99
18	$1.69	$1.89/stove	N/A	$2.29/μ	$1.99
19	$1.69	$2.39/μ	$2.49	$1.49/stove	N/A
20	$2.09	N/A	N/A	$1.49/μ	$2.39
21	$2.09	$1.39/stove	$2.49	N/A	$2.39
22	$2.09	$1.89/μ	$1.99	N/A	N/A
23	N/A	N/A	$2.49	N/A	N/A
24	N/A	$1.39/μ	N/A	$2.29/μ	N/A
25	N/A	$1.89/μ	$2.49	$1.49/stove	$2.39
26	N/A	$2.39/stove	$1.99	$2.29/μ	$2.39

Source: Reprinted with permission from Kuhfeld et al. (1994), published by the American Marketing Association

4.5.2 Methods Based on Nonlinear Models for with Assumed Beta Values

4.5.2.1 Utility Balance Method

Computer optimization enables the researcher to model attributes with large numbers of levels or complex special effects. Huber and Zwerina (1996) add the criterion of utility balance to further improve computer optimization of designs. The property of utility balance implies that the utilities of the alternatives in a choice set are approximately equal. When a design is utility balanced, the variance of the probabilities of choice of alternatives within a choice set will be reduced. Huber and Zwerina show that achieving such utility balance increases the efficiency of a design to the tune of 10–50 %. In these designs, the analyst sets betas to some nonzero prior vector.

The method is implemented as follows. First, initial choice sets are developed in one of any number of ways including orthogonal arrays or availability designs described above and D-efficient (possibly non-orthogonal) designs developed by the OPTEX procedure. The process of swapping and relabeling attribute levels of alternatives in an initial choice set accomplishes this objective. Swapping involves increasing one level of an attribute within a choice set by one level.

An illustration of a utility balanced design is given in Table 4.8. This design is based on an orthogonal array for a 3 × 3 × 3 factorial design for three attributes labeled A, B, and C consisting of nine profiles. The nine rows of the orthogonal array are used to develop the first row of each choice set. The second and third rows of each choice set are obtained by cycling through the attribute levels by adding one to the

Table 4.8 Illustration of a utility balanced design

Choice set	Alternative	Original $3^3/3/9$ design A	B	C	Sum	Probability of choice	Swapped $3^3/3/9$ design A	B	C	Sum	Probability of choice
1	I	1	1	1	3	0.002	3	1	3	7	0.665
	II	2	2	2	6	0.047	2	2	2	6	0.245
	III	3	3	3	9	0.951	1	3	1	5	0.090
2	I	1	2	2	5	0.045	3	1	2	6	0.333
	II	2	3	3	8	0.910	2	3	1	6	0.333
	III	3	1	1	5	0.045	1	2	3	6	0.333
3	I	1	3	3	7	0.488	3	2	1	5	0.333
	II	2	1	1	4	0.024	2	1	3	7	0.333
	III	3	2	2	7	0.488	1	3	2	6	0.333
4	I	2	1	3	6	0.333	3	1	1	6	0.090
	II	3	2	1	6	0.333	1	3	3	7	0.665
	III	1	3	2	6	0.333	2	2	2	5	0.245
5	I	2	2	1	5	0.045	2	1	3	6	0.245
	II	3	3	2	8	0.910	3	3	1	7	0.665
	III	1	1	3	5	0.045	1	2	2	5	0.090
6	I	2	3	2	7	0.488	2	3	1	6	0.245
	II	3	1	3	7	0.488	3	2	2	7	0.665
	III	1	2	1	4	0.024	1	1	3	5	0.090
7	I	3	1	2	6	0.333	1	3	2	6	0.245
	II	1	2	3	6	0.333	3	1	1	5	0.090
	III	2	3	1	6	0.333	2	2	3	7	0.665
8	I	3	2	3	8	0.910	2	3	2	7	0.665
	II	1	3	1	5	0.045	3	2	1	6	0.245
	III	2	1	2	5	0.045	1	1	3	5	0.090
9	I	3	3	1	7	0.488	1	2	3	6	0.333
	II	1	1	2	4	0.024	3	1	2	6	0.333
	III	2	2	3	7	0.488	2	3	1	6	0.333
	D_P-error					0.381					0.280

Source: Reprinted with permission from Huber and Zwerina (1996), published by the American Marketing Association

level of the previous alternative until it is at the highest level (in this case 3). This design is shown in the left panel of Table 4.8.

The second step involves swapping. A swap involves switching one level of an attribute within a choice set. The utilities for the alternatives are computed using partworth values of -1, 0 and 1 for the levels of each attribute (prior values for the betas). The corresponding choice probabilities, computed using the logit rule, are shown in the column, "probability of choice". Note that the alternative III dominates the other two in the first choice set in the original design garnering 95 % of the expected choices. The swaps shown switch the first and third levels of attributes A and C, thereby resulting in more equal alternatives. The range (and therefore the variance) of the probabilities of choice for the swapped design is much lower once the level of an attribute is switched. The swapped design has a lower error in computing the standard errors[13] of the contrasts (0.280 versus 0.381). Thus, the design is achieving more utility balance than the initial orthogonal design for choice sets.

The designs developed using the utility balance criterion are essentially customized to achieve lower errors. They can be applied to a sample of heterogeneous respondents. Arora and Huber (2001), who adapt the utility balance design to customize choice sets for an average respondent in a conjoint study, find that the D-errors can be lower for customized designs as compared to those based on orthogonal utility-balanced designs with better model predictions.

4.5.3 Bayesian Methods Based on Nonlinear Model for a Prior Distribution for Betas

If one is able to make priori assumptions about the distribution of partworth estimates, Bayesian methods can be used to create more efficient designs for choice-based conjoint experiments. Such prior assumptions may be based on past studies or on a pilot study on the same topic or on analysis of a small sample of the data collecetd in the study. Building on the ideas of Huber and Zwerina (HZ) for MNL models, Sandor and Wedel (2001) develop methods for creating designs when prior information is available. Their procedure involves finding a design (or X-matrix) that minimizes the expected value of the errors of parameters. Their algorithm for the design development uses the tools of relabeling, swapping, and cycling; GAUSS codes for this are available from the authors. Their method is shown to yield lower standard errors than the HZ method with higher predictive validity. Illustrations of designs based on this method are shown in Table 4.9, which shows that the error is considerably reduced with these methods.

In addition, these authors also developed procedures for designing choice experiments for mixed logit models[14]; see Sandor and Wedel (2001).

4.5.4 Other Methods

Availability Designs: Changes in the competitive set in the marketplace can influence choice behavior of respondents in two ways: characteristics of items in the set and

---

[13] These standard errors are called D_p-errors because they are errors with reference to the estimate of the parameters for attributes centered around the average of weighted probabilities of choice of the items, as opposed to D_o-errors, which refer to the errors when the reference values are the simple means of attribute values.

[14] Mixed logit models are described later in the chapter.

Table 4.9 Standard and Bayesian 34/2/15 designs with improved efficiency

		HZ: standard relabeled				B1: Bayesian relabeled				B2: Bayesian swapped				B3: Bayesian cycled			
		Attributes															
Choice set	Profile	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	I	3	2	3	2	2	1	2	1	2	1	2	1	2	1	2	1
	II	1	3	2	1	1	2	1	2	1	2	1	2	1	2	1	2
2	I	3	1	2	1	2	3	1	2	2	1	1	2	2	2	1	2
	II	1	2	1	3	1	1	3	3	1	3	3	3	1	1	3	3
3	I	3	3	2	3	2	2	1	3	2	2	1	3	2	2	1	3
	II	1	1	1	2	1	3	3	1	1	3	3	1	1	3	2	1
4	I	3	2	1	1	2	1	3	2	2	1	3	2	2	3	3	2
	II	1	3	3	3	1	2	2	3	1	2	2	3	1	1	2	3
5	I	3	1	1	2	2	3	3	1	2	3	2	1	2	2	2	1
	II	1	2	3	1	1	1	2	2	1	1	3	2	1	1	1	2
6	I	1	1	2	2	1	3	1	1	1	3	1	1	2	3	1	1
	II	2	2	1	1	3	1	3	2	3	1	3	2	3	1	2	2
7	I	1	2	3	3	1	1	2	3	1	1	2	3	1	2	2	3
	II	2	3	2	2	3	2	1	1	3	2	1	1	2	3	1	1
8	I	1	1	1	1	1	3	3	2	1	3	3	2	3	1	3	2
	II	2	2	3	3	3	1	2	3	3	1	2	3	2	2	2	3
9	I	1	3	1	3	1	1	3	3	1	2	3	3	2	2	3	2
	II	2	1	3	2	3	2	2	1	3	3	2	1	3	3	2	1
10	I	1	3	3	1	3	2	2	2	1	2	2	2	1	2	2	2
	II	2	1	2	3	2	3	1	3	3	3	1	3	3	1	1	3
11	I	2	2	2	2	3	1	1	1	3	1	1	1	3	2	1	1
	II	3	3	1	1	2	2	3	2	2	2	3	2	1	3	3	2
12	I	2	3	3	1	3	2	2	2	3	2	2	2	2	1	2	2
	II	3	1	2	3	2	3	1	3	2	3	1	3	1	3	1	3
13	I	2	2	2	3	3	1	1	3	3	1	1	3	3	3	2	2
	II	3	3	1	2	2	2	3	1	2	2	3	1	1	2	3	1
14	I	2	3	1	2	3	2	3	1	3	2	3	1	3	2	3	1
	II	3	1	3	1	2	3	2	2	2	3	2	2	2	3	2	2
15	I	2	1	3	3	3	2	2	3	3	3	2	1	3	2	2	1
	II	3	2	2	2	2	1	1	1	2	1	1	3	2	1	1	3
Dp-error		0.296				0.281				0.272				0.263			
Dg-error		1.121				1.052				0.993				0.834			

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availability of the item at the time of choice. One can assess these effects in choice-based conjoint studies with the help of availability designs (Lazari and Anderson, 1994); they utilize the determinant optimality criterion for each brand and for the overall design in the construction of availability choice set designs. That is to say, they seek choice set designs that maximize the determinant of the information matrix $X'X$ for the overall matrix, and each of the individual brand sub design matrices X_i, $i = 1,2,\ldots,m$. This criterion would minimize the covariance between the estimates. The factors in such designs are the brands in the study, with each factor

Table 4.10 Availability design for four brands each at two levels

Choice set no.	Brand A	Brand B	Brand C	Brand D
1	0	0	0	0
2	0	0	1	1
3	0	0	2	2
4	0	1	1	1
5	0	1	2	2
6	0	1	0	0
7	0	2	2	2
8	0	2	0	0
9	0	2	1	1
10	1	0	0	0
11	1	0	1	1
12	1	0	2	2
13	1	1	1	1
14	1	1	2	2
15	1	1	0	0
16	1	2	2	2
17	1	2	0	0
18	1	2	1	1
19	2	0	0	0
20	2	0	1	1
21	2	0	2	2
22	2	1	1	1
23	2	1	2	2
24	2	1	0	0
25	2	2	2	2
26	2	2	0	0
27	2	2	1	1

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Levels 1 and 2 correspond to the two levels (for example high or low price) and level 0 correspond to the brand not being present

(for a brand) at some number of levels (S-1) and a level for being absent in the choice set. Thus, for an m brand choice set construction, with each brand at (S-1) levels and one level for being absent, one looks for a fraction of an m^S design (if one is available). The level zero or non-zero for a brand in a choice set picks up the effect of availability.

As an example, assume that there are four brands in the problem and that each brand has two levels (high and low) for an attribute. The larger design for constructing the choice sets of size 4 will be a 3^4 design. The levels 0, 1, and 2 for any column will correspond to the absence of a brand, a brand at low level and high level respectively. The row [1 0 2 2] in such a design will imply that Brand 1 is at the low level of an attribute and Brands 3 and 4 are at the high level and Brand 2 is absent from the choice set. This design with 27 choice sets is shown in Table 4.10.

Availability designs can be constructed from various orthogonal designs. Lazari and Anderson (1994) have published several designs, which can be used in practice.

Table 4.11 36 choice sets for the availability design up to 12 brands

Set no./brand	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	1	1	1	2	2	0	0	0	0
3	0	1	2	2	2	0	1	2	0	0	0	0
4	0	0	2	2	1	0	0	1	0	0	0	0
5	2	0	0	0	2	2	0	2	1	1	1	1
6	0	2	1	0	1	2	1	2	2	0	1	0
7	2	1	0	1	2	0	2	1	2	0	1	0
8	0	2	0	1	2	2	1	1	0	2	0	1
9	2	0	1	2	2	1	1	0	0	2	1	0
10	0	0	1	0	2	1	2	1	2	1	0	2
11	0	1	0	2	1	2	2	0	0	1	1	2
12	1	0	0	2	0	2	1	1	2	1	2	0
13	1	1	1	1	1	1	1	1	1	1	1	0
14	1	1	1	2	2	2	0	0	2	0	0	2
15	1	2	0	0	0	1	2	0	2	2	1	2
16	1	1	0	0	2	1	1	2	0	0	2	0
17	0	1	1	1	0	0	1	0	2	2	2	2
18	1	0	2	2	2	0	2	0	0	1	2	1
19	0	2	1	1	0	1	0	2	0	1	2	1
20	1	0	1	1	0	0	2	2	1	0	1	2
21	0	1	2	0	0	2	2	1	1	0	2	1
22	1	1	2	1	0	2	0	2	0	2	1	0
23	1	2	1	0	2	0	0	1	1	2	2	0
24	2	1	1	0	1	0	2	2	0	2	0	1
25	2	2	2	2	2	2	2	2	2	2	2	2
26	2	2	2	0	0	0	1	1	0	1	1	2
27	2	0	1	1	1	2	0	1	0	0	2	2
28	2	2	1	1	0	2	2	0	1	1	0	0
29	1	2	2	2	1	1	2	1	0	0	0	0
30	2	1	0	2	0	1	0	1	1	2	0	2
31	1	0	2	0	1	2	1	0	1	2	0	2
32	2	1	2	0	1	1	0	0	2	1	2	0
33	1	2	0	1	1	0	0	2	2	1	0	2
34	2	2	0	2	1	0	1	0	1	0	2	1
35	2	0	2	1	0	1	1	2	2	0	0	1
36	0	2	2	1	2	1	0	0	1	0	1	2

Source: Reprinted with permission from Lazari and Anderson (1994), published by the American Marketing Association

One such design is reproduced in Table 4.11. In this design, there are 12 brands each at two price levels (low and high). There are 36 choice sets drawn from a 3^{12} design with level 0 corresponding to the absence of a brand in a choice set and 1 corresponding to the presence of a brand in a choice set.

An empirical application of this approach is given in Appendix 5.

Selected Algorithms for Design: Street and Burgess (2007) developed various procedures for the construction of stated choice experiments and present various algorithms. Technical details of their procedures are quite advanced for this

Table 4.12 Optimal choice sets for estimating main effects only for m = 5 and k = 9 (Burgess and Street)

Choice set no	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	000000000	000000111	111111000	000111111	111111111
2	000101001	000101110	000101001	000101001	000101001
3	001011100	001011011	110100100	001100011	110100011
4	001110101	001110010	110001101	001001010	110001010
5	010111011	010111100	101000011	010000100	101000100
6	010111011	010111100	101000011	010000100	101000100
7	011001110	011001001	100110110	011110001	100110001
8	011100111	011100000	100011111	011011000	100011000
9	100000111	100000000	011111111	100111000	011111000
10	100101110	100101001	011010110	100010001	011010001
11	101011011	101011100	010100011	101100100	010100100
12	101110010	101110101	010001010	101001101	010001101
13	110010101	110010010	001101101	110101010	001101010
14	110111100	110111011	001000100	110000011	001000011
15	111001001	111001110	000110001	111110110	000110110
16	111100000	111100111	000011000	111011111	000011111

Source: Table 1 in Burgess and Street (2003)
Note: 0 and 1 are the two levels of binary attributes

Table 4.13 Near-optimal choice sets for estimating main effects and two-factor interactions for m = 3 and k = 4 (Burgess and Street)

Choice set	Profile 1	Profile 2	Profile 3	Choice set	Profile 1	Profile 2	Profile 3
1	0000	1100	0110	17	0000	1100	0111
2	0001	1101	0111	18	0001	1101	0110
3	0010	1110	0100	19	0010	1110	0101
4	0011	1111	0101	20	0011	1111	0100
5	0100	1000	0010	21	0100	1000	0011
6	0101	1001	0011	22	0101	1001	0010
7	0110	1010	0000	23	0110	1010	0001
8	0111	1011	0001	24	0111	1011	0000
9	1000	0100	1110	25	1000	0100	1111
10	1001	0101	1111	26	1001	0101	1110
11	1010	0110	1100	27	1010	0110	1101
12	1011	0111	1101	28	1011	0111	1100
13	1100	0000	1010	29	1100	0000	1011
14	1101	0001	1011	30	1101	0001	1010
15	1110	0010	1000	31	1110	0010	1001
16	1111	0011	1001	32	1111	0011	1000

Source: Table 2 in Burgess and Street (2003)
Note: 0 and 1 are the two levels of binary attributes

monograph and interested readers should consult this important work and develop suitable designs (that are near-optimal) for their studies. Nevertheless, we reproduce two sets of 2^k designs for binary attributes. Tables 4.12 and 4.13 show the optimal design for estimating only main effects for and (k=4.12 and 4.13) 9 binary attributes and choice sets of (m =) 5 profiles and Tables 4.12 and 4.13 shows the a "near-optimal" design for estimating main effects and two-factor interactions for choice sets of (m =) 3 profiles and (k =) 4 binary attributes. They are self-explanatory and can be employed in practice. For more details, see Burgess and Street (2003).

Polyhedral Methods for Choice-Based Conjoint Analysis: We reviewed the methodology of polyhedral methods for ratings-based conjoint analysis in Chap. 3. Similar approaches were developed for adaptive choice-based conjoint analysis (Toubia et al. 2004). They include question design as well as analysis. These methods involve designing questions that quickly reduce the sets of partworths that are consistent with respondent's prior choices using the interior point algorithms. The authors have recently extended this approach to probabilistic polyhedral methods (see Toubia et al. 2004).

4.5.5 Which Method to Use for Developing Designs?

The foregoing review of various methods for developing choice sets raises the question of which method to use in practice. Actual choice for any applied problem naturally depends on the statistical skills of the researcher. The general objective is to choose a design that maximizes the efficiency (as measured by the D-efficiency). The cost and feasibility considerations (e.g. time a respondent can devote to the task) will come into play as well. However, the easiest method is to use computerized software to develop choice sets. Manual methods described will also be useful in case one does not have access to computer software. Several designs shown in this chapter may be examined to determine if any of them will fit the study under question.

4.6 Incentive-Aligned Methods

An issue in the data collection in conjoint studies (in general and in choice-based conjoint studies in particular) is whether respondents experience strong incentives to expend their cognitive resources (or devote adequate time and effort) in providing responses (ratings or choices) to hypothetical stimuli presented as profiles or in choice sets. The literature on experimental economics suggests that data collected without such incentive-compatibility may be inconsistent, erratic, and possibly, untrustworthy. Incentive compatibility can be implemented using the BDM procedures (Becker et al. 1964). In a recent paper, Ding et al. (2005) provide experimental evidence to strongly indicate that conjoint data collected which are incentive-aligned[15] outperform those without such alignment in terms of out-of-sample predictive power.

[15] We should note that for some contexts incentive-alignment is not easy to accomplish; for example, consider a conjoint study in which hypothetical movies are evaluated.

The authors conducted a comprehensive field experiment in a Chinese restaurant using Chinese dinner specials as the context. The study compared hypothetical choice-conjoint method with incentive-aligned choice conjoint method and incentive-aligned contingent evaluation method. In the hypothetical choice conjoint method, the restaurant served the meal chosen by the subject in the holdout choice task and the cost was deducted from the compensation given to the subjects. In the incentive-aligned method, the Chinese dinner special for any subject was randomly chosen from the choices made in the main task of evaluating 12 choice sets at the posted price. The authors assessed the goodness of fit of the incentive-aligned conjoint method versus the usual hypothetical choice conjoint method using the logit estimation. While the in-sample predictions (hit rates for the four alternatives including the alternative of "none of the above.") for the incentive-aligned conjoint were lower than the hypothetical choice conjoint (32 % vs. 41 %), the out-of-sample predictions were far superior (48 % vs. 26 %); the out-of-sample predictions were about ten times that of a naïve forecast of about 5 %. Further, the prediction results for the top two choices are equally impressive, with 59 % and 26 % correct predictions in the incentive aligned choice and hypothetical choice conditions, respectively. In addition to better out-of-sample forecasts, the aggregate parameter estimates based on the incentive aligned tasks are markedly different from the estimates of the non-incentive-aligned task. This random lottery procedure is widely used in experimental economics and it minimizes the effect of reference point and wealth.

Wertenbroch and Skiera (2002) also show that willingness to buy estimates for products using contingent evaluation procedures are lower when the incentive-compatibility constraint is not imposed. This stream of research has obvious implications for collecting conjoint data in practice. See Ding (2007) for a more complete discussion of a truth-telling mechanism for conjoint applications.

4.7 Partial Profile Choice Experiments

We have so far considered alternatives that contain all attributes. It is possible to design choice experiments with partial attribute profiles as well. In this approach, the researcher will first develop subsets of attributes and construct profiles based on each such subset. The procedure is essentially the same as for designs with all attributes. Choice sets consisting of pairs, triples, or quads etc. can be constructed for the partial profiles. The data can be analyzed using a variation of the MNL model. Respondent learn about the missing values in profiles as they make choices from partial choice sets. Bradlow et al. (2004) developed models to incorporate such learning. Their method is described in detail in Chap. 5.

4.8 Analysis Methods for Choice-Based Conjoint Data

We will give a brief introduction to possible analysis methods for choice-based conjoint data in this short section and elaborate on them later in the chapter. In general, researchers analyze the choice-based conjoint data using the multinomial logit model and maximum likelihood methods. Such analysis is done for the sample as a whole or for subgroups. As noted earlier, the hierarchical Bayesian methods (HB) are used for obtaining estimates at the individual level. Given that the multinomial model uses some strong assumptions on the nature of implied substitution among the alternatives, there is a variety of other analysis methods such as multinomial probit and heteroscedasticity logit methods.

4.9 Multinomial Logit Model for Choice-Based Conjoint Data

We now discuss the choice model, called multinomial logit model for analyzing choice-based conjoint data. This model is highly versatile and is based on sound theoretical assumptions. We will present it for multinomial choice experiments, although the same model is applicable for binary choice experiments described before. For binary choice experimental data, the choice set consists of two alternatives "choose the profile presented" and "do not choose it".

Refer to Fig. 4.1 and the corresponding discussion for reviewing general premises of the choice process. To recapitulate the prior discussion, the utility of the item chosen is the highest among the utilities of all the alternatives under consideration. Under this premise, the modeling approach is first to recognize that the utility of an item consists of two components: a deterministic component and a random component. The deterministic component can be modeled in terms of various factors. The random component is assumed to represent all unobserved factors in the choice process (such as unobserved individual idiosyncrasies of tastes). One postulates a distributional assumption for the random component and derives an expression for the probability with which an item will be chosen. See Maddala (1983), Louviere et al. (2001) and Greene (2012) for various details of estimation methods.

4.9.1 Modeling Utility

Consider the problem of building a model for the choice an individual makes among a choice set, S of n alternatives.[16] Let $\tilde{u}_k$ be the random utility derived by the individual from brand k $(\in S)$. It can be decomposed as:

[16] If a "no choice alternative" is included in the design, we can treat that option as having zero utility (for normalization purposes).

$$\tilde{u}_k = v_k + \in_k \tag{4.1}$$

where v_k is the deterministic component and $\in_k$ is the random component of the utility.

Modeling the Deterministic Component: Based on the premise that the deterministic component of a utility is derived from attributes of the brands (perceived or actual), individual characteristics and descriptors of the environment, we can model v_k as follows:[17]

$$v_k = \sum_{j \in T} b_{jk} x_{jk} \tag{4.2}$$

where T is the number of variables included in the model, x_{jk} is the observed value of the k-th alternative for the j-th attribute, and b_{jk} is the weight associated with x_{jk}.

The x-variables may belong to any of three groups: (1) attributes specific to alternative k, such as alternative-specific constants (2) attributes common to all attributes, and (3) variables specific to the individual.

The third set of variables specific to the individual drops out of the model when comparisons of alternatives are made for each individual. Therefore, we will not consider them in this model. Let T_k and T_c be the number of attributes specific to the k-th alternative and common to all alternatives. Then, (4.2) can be written as:

$$v_k = \sum_{j \in T_k} b_{jk} x_{jk} + \sum_{j \in T_c} b_j x_{jk} \tag{4.3}$$

The functional form is linear in parameters (b-coefficients) and it is the most versatile in estimation. It is quite general and can accommodate nonlinear functions of the x-variables.

We will therefore specify the v-function accordingly, as shown in (4.2) and (4.3).

Random Component: The multinomial logit model is based on the assumption that the random components or errors ($\in_k$) associated with the alternatives in a choice set are independent and are identically distributed according to the double exponential distribution (also called Type-I extreme value distribution). The cumulative distribution function for this distribution is:

$$P(\in_k \leq \in) = \exp(-\exp(-\in)), -\infty < \in < \infty \tag{4.4}$$

The form of this distribution[18] fixes the mean and variance arbitrarily at 0.575 and 1.622 (or $\pi^2/6$) respectively; both these values are dimensionless. This

[17] See Meyer and Johnson (1995) for a discussion on empirical generalization in modeling consumer choice including the functional specification.

[18] Variance of the error can be introduced as an additional parameter; in that case, the distribution becomes $P(\in_k \leq \in) = \exp(-\exp(-\in/s)), -\infty < \in < \infty$, where s is the scale for the error term.

assumption does not have any effect on the development of the model since the scaling of utility is arbitrary.

Probability of Choice: Given the assumptions made so far, we can develop a function to describe the probability of choice of any alternative for the individual. If the alternative k is chosen, it implies that the random utility associated with k is the highest (higher than the remaining item in the choice set). Let y_j denote the observed choice. Further, we let $y_j = 1$ if the j-th alternative is chosen and 0 otherwise. Then,

$$\begin{aligned} P[y_j = 1] &= P[\tilde{u}_j \geq \tilde{u}_m; m \in S] \\ &= P[v_j + \in_j \geq v_m + \in_m; m \in S] \\ &= P[\in_j - \in_m \geq v_m - v_j; m \in S]. \end{aligned}$$

or

$$P[y_j = 1] = P[\in_m \leq v_j - v_m + \in_j; m \in S]. \tag{4.5}$$

The expression in (4.5) can be evaluated using the assumptions made on the distribution of errors. The solution to this problem is:

$$P[y_j = 1] = \frac{\exp(v_j)}{\sum\limits_{m \in s} \exp(v_m)} = \frac{1}{1 + \sum \exp(v_m - v_j)} \tag{4.6}$$

The equation (4.6) is the multinomial logit model of choice. The probability of choice of any alternative depends on the deterministic utility values of the alternatives. Further, the choice probability of any alternative is proportional to the exponent of its deterministic utility value.

We will describe below the implications of this formulation.

Written in terms of attributes, the probability of choice of the k-th alternative (denoted by P_j) is:

$$\begin{aligned} P_j &= \frac{1}{1 + \sum\limits_{m \in s} \exp(v_m - v_j)}; or \\ P_j &= \frac{1}{1 + \sum\limits_{m \in s} \exp\left[\sum\limits_{k \in T} b_{jm}(x_{jm} - x_{kj})\right]} \end{aligned} \tag{4.7}$$

The unknown parameters in the expression (4.7) are the b-values.

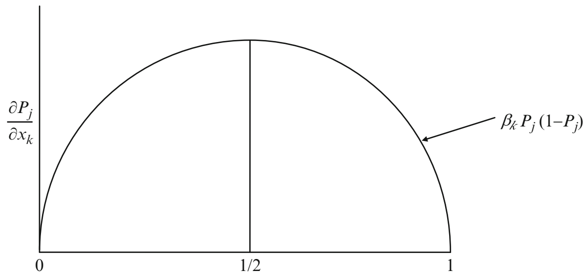
The variance of the error term then is $\pi^2 s^2/6$. Implicitly the scale parameter is set equal to 1 in most applications. We will return to this issue alter.

If the choice set contains a "no choice" alternative or an alternative that does not have attributes that vary, it is assigned a utility value of zero. In that case, the attribute levels for the "no choice option" will be zero and the x-values of the alternatives (not differences as shown above) will be used directly in the model.

4.9.2 Interpretation of Coefficients

Marginal Effects: It is easy to verify that the change in the probability of choice of the k-th brand with respect to changes in the j-th x-variable for one individual is:

$$\frac{\partial P_j}{\partial x_k} = b_k P_j (1 - P_j).$$



If the X-variable is a dummy variable, the effect of that variable on the probability can be evaluated as the difference in the probabilities computed when that variable if 1 to that when it takes the value zero. Of course, this effect will depend on the values of other X-variables included in the model. One appropriate way to determine the effect is by using the mean values of all other values in the computation of the probability.

Thus, the effect of any x-variable is not constant, but it varies with the value of the probability of choice (P). For the continuous X-variables, It is highest when P = 1/2. (See the Figure above).

This is the case of the X-variable is continuous. If the X-variable is a dummy variable, one can simply use the effect computed as described above.

Elasticities: In addition we can compute the elasticity of P_j with respect to x_j is:

$$E_k = \frac{x_k}{P_j} \bullet \frac{\partial P_j}{\partial x_k} = b_k \frac{(1 - P_j)}{P_j}.$$

4.9.3 Data Structure

Data: To calibrate the multinomial logit model for data from choice-based conjoint studies, the analyst needs data on brand choices made by a (representative) sample of individuals at one (or more points in time) and data on attributes of the brands. The data format will be as follows; shown for the first individual and for two choice sets. The same format will be used for other choice sets of the first individual and for other individuals.

Individual	Choice set	Alternatives	y- values for the alternatives (y = 1 if chosen, 0 otherwise)	X- variables $X_1, \ldots, X_p$
1	1	1	Y_{111}	$x_{11} \ldots x_{1p}$
	1	2	Y_{112}	$x_{21} \ldots x_{2p}$
	1	3	Y_{113}	$x_{31} \ldots x_{3p}$
	...	...	...	...
	1	s1	Y_{11s1}	$x_{s11} \ldots x_{s1p}$
1	2	1	Y_{111}	$x_{11} \ldots x_{1p}$
	2	2	Y_{112}	$x_{21} \ldots x_{2p}$
	2	3	Y_{113}	$x_{31} \ldots x_{3p}$
	...	...	...	...
	2	s2	Y_{11s2}	$x_{s21} \ldots x_{s2p}$

The x-variables (or attribute values) for the choice alternatives are suitably coded for analysis. For example, if one attribute is the brand name a number of dummy variables (one less than the number of brands) will be used. The reader is referred to the discussion of methods of variable coding in Chap. 3. The y-variable takes the value 1 for the chosen alternative and 0 for those not chosen in each choice set.

Method of Estimation: The method of maximum likelihood is most suitable to calibrate the logit model using data at the individual level. (We describe the method of weighted least squares appropriate for grouped data in an Appendix 5 to this chapter.) Assuming that brand choices are available for N individuals, let the choice for the i-th person be denoted by $(y_{i1}, \ldots, y_{is_i})$ where S_i is the choice set of the i-th person and each y is equal to 1 or 0 according to whether the corresponding brand is chosen or not.

The principle of estimation is to determine the values of parameters in the model so as to maximize the probability (or likelihood) of the observed data.

For the i-th individual with choice set $S_i = \{1, 2, \ldots, s_i\}$, the likelihood of observing the choices $\{y_{i1}, \ldots, y_{is}\}$ is:

$$L_i = \prod_{m=1}^{S} P_{im}^{y_{im}}$$

The joint likelihood for the sample as a whole is $L = \prod_{i=1}^{N} L_i$. L is a function of the unknown b-parameters; $L = L(b_1, \ldots, b_T)$. The b-values are determined by maximizing L with respect to the b's using calculus methods. The resulting first order equations will be nonlinear. They are solved using optimization algorithms of the kind available in GAUSS or MATLAB. The LIMDEP software can also be used in analyzing data from choice experiments.

The CBC System of the Sawtooth Software Inc. is quite suitable, both for the design and analysis of choice-based conjoint studies (Orme 1999).

4.9.4 Model Fit and Test

The fit of the logit model to the data can be determined by the following statistic:

$$U^2 = \rho^2 = 1 - \frac{L(X)}{L_0}$$

where:

L(X) = log likelihood of the calibrated model with explanatory variables, X, and
L_0 = log likelihood of the null model.

These logarithms are natural logarithm values.

The null model is that for which choice probabilities are equal to market shares of choice alternatives. The measure, U^2 is analogous to R^2 in the regression analysis. If $L(X) = L_0$, then $U^2 = 0$. If $L(X) = 0$ (perfect fit), then $U^2 = 1$. Various statistics are available for testing the model; these include chi-square, AIC and BIC.

Chi-Square Statistic: The statistic $-2(L(X) - L_0)$ is distributed as a chi-square with degrees of freedom equal to the number of parameters (excluding the intercept term) of the model.

Akaike Information Criterion (AIC): The statistic 2*(k -L(X)), where k is the number of estimated parameters that can be used to compare two non-nested models. The model with higher value of AIC indicates a preferred model in terms of fit. AIC penalizes models with larger numbers of parameters.

Bayesian Information Criterion (BIC): This statistic is developed using information theory. It is: [k*ln(n) – 2*L(X))] where k is the number of estimated parameters and n is the number of independent observations. BIC also penalizes models with larger number of parameters.

Model Comparison: Two nested models can be tested using a chi-square test. 2 log [likelihood of model B to model A] is distributed as a chi-square with degrees of freedom equal to the difference between the degrees of freedom for model B and that of model A. For non-nested models, one could use AIC or BIC.

Implications of IIA: One of the implications of the logit model described above is that the ratio of probabilities of choice of any two alternatives is independent of other alternatives in the choice set. This property is called independence of irrelevant alternatives or IIA for short. This property arises due to the assumption of independent errors.

This property is both a blessing and a curse. While it makes analysis very simple, it has severe consequences in using the model to predict market shares for new products.

As an example, consider the following situation of an individual choosing between two almost identical products such as a blue bus and red bus, each with a probability of 1/2. Suppose now that the alternative of car is introduced such that car is equally preferred to either red bus or blue bus. Then, the logit model will predict that the probability of choice of the three alternatives – car, red bus and blue bus – to be 1/3. But, in reality, the probabilities of choice should be 1/2 for car and 1/4 each for the two buses. This is because the two alternatives of the buses are similar and third alternative is different from these two. Once the similarity structure among the items is included, the problem of IIA disappears in the logit model; one such model is nested multinominal logit model. See Ben-Akiva and Lerman (1991) for an extensive discussion of discrete choice analysis including the multinomial logit model described above.

4.9.5 Some Examples of MNL Analyses

Example 1. We first describe the classic illustration of the use of choice-based conjoint and estimation of an aggregated MNL model with the help of a study reported by Louviere (1984). This study evaluated the attractiveness of five different strategies for each of three fast food restaurants (McDonald's, Hardee's and Wendy's) based on data collected from 119 undergraduate subjects at a Midwestern U.S. university. From the design point of view, the author first constructed a ½ factorial to describe combinations of the five strategies for each firm (similar to that shown in Table 4.2). These 16 combinations were ordered from 1 to 16 for each restaurant and then the three restaurant combinations ordered "one" were assigned to the first choice situation, the three ordered "two" to the second choice situation and so on. Thus, a total of 16 choice sets were developed. The base case was also used as no change in current strategies of any of the restaurants. In addition, each choice situation consisted of a constant description for all other restaurants with the words "Any other fast food restaurant like it is now". The descriptions of the four of the choice sets are shown in Tables 4.14 and 4.15. The order of options with each choice set is randomized before presenting to the respondents.

The choice frequencies for each choice for each choice set were calculated. The natural logarithm of the choice frequencies, relative to choosing "any other restaurant", was the dependent variable in this study (thus, this is an aggregate analysis). Using generalized least squares and dummy variables for describing the choice options in for each restaurant, Louviere estimated "main-effects only" utility

Table 4.14 Strategies and choice sets for the fast food study. Panel (a): Strategies

Strategy	McDonald's	Hardee's	Wendy's
1	Serve entire menu including breakfast all day (MAD)	Offer its breakfast biscuits all day (HBB)	Open a new location somewhere in the downtown/campus area, preferably in an enclosed shopping mall (WML)
2	Open a new location somewhere in the downtown/campus area, preferably in an enclosed shopping mall (MML)	Offer soft ice cream (HIC)	Open a new location in the suburb of Coralville, proximate to the Interstate 80 interchange and a large concentration of apartment complexes (WCV)
3	Offer a complete salad bar (MSB)	Offer a salad bar (HSB)	Offer a breakfast menu f French toast and pancakes (WBF)
4	Offer a "dinner platter" consisting of a hamburger steak, French fries, and a salad (MST)	Offer fried onion rings (HOR)	Offer tacos made with Wendy's chili (WTC)
5	Offer fried chicken as it does in some other countries, for example, Australia (MFC)	Offer fried mushrooms (HMR)	Offer burritos with Wendy's chili (WBR)

4 out of 17 shown
Source: Adapted with permission from Table 10.5 of Louviere, J., Hensher, D and Swalt, D. *Stated Choice Methods. Analysis and Application*, Cambridge University Press, 2000.

Table 4.15 Strategies and choice sets for the fast food study. Panel (b): Selected choice sets

Choice set	McDonald's	Hardee's	Wendy's	Any other fast food restaurant
1	Like it is now	Like it is now	Like it is now	Like it is now
2	MAD + MML	HBB+ HIC	WML + WCV	Like it is now
3	MSB + MML	HBB + HSB	WML + WCV	Like it is now
4	MSB + MST + MAD + MFC	HOR + HMR	WBF + WTC	Like it is now

4 out of 17 shown
Source: Adapted with permission from Table 10.5 of Louviere, J., Hensher, D and Swalt, D. *Stated Choice Methods. Analysis and Application*, Cambridge University Press, 2000.

functions (deterministic components of the random utilities) in the MNL model. [The details of this classic method are given in Appendix 6. We must note that this method has been superseded by the maximum likelihood methods, which are now quite common.] The strategies were coded as +1 if included in the choice option and −1 if not. The estimated utility functions are shown below:

$$\begin{aligned}
\text{V(McDonald's)} &= 1.08 + 0.03\text{MAD} \\
&\quad + 0.41\text{MML} + 0.20\text{MSB} + 0.25\text{MFC} + 0.21\text{MST}; \\
\text{V(Hardee's)} &= 0.11 - 0.09\text{HBB} + 0.08\text{HIC} + 0.33\text{HSB} + 0.31\text{HOR} + 0.431 \\
&\quad \text{HMR; and} \\
\text{V(Wendy's)} &= 0.91 + 0.53\text{WML} + 0.08\text{WCV} + 0.17\text{WBF} + 0.26\text{WTC} \\
&\quad + 0.04\ \text{WBR}.
\end{aligned}$$

Many of these effects were significant at the 5 % level. The alternative–specific effects are much larger for McDonald's, followed by Wendy's and Hardee's in that order (as expected). Also, the strategy of setting up a restaurant in a new location received larger effect for Wendy's than McDonald's. For McDonald's, a new location strategy will have a more positive impact than a salad bar strategy; least impact is for the strategy of serving its entire menu all day.
The estimated utility functions can be used for predicting market shares for the three restaurants using the aggregated MNL model. For example, for the case of Wendy's implementing a new location in the downtown mall and offering tacos with chili while others remain as they are, the model would predict that 60 % of the sample will try Wendy's while 6 % will remain loyal to Hardee's and 14 % to McDonald's; the remaining 20 % will visit any other restaurant.

Example 2. We now illustrate the use of MNL model that uses individual-level data from choice-based conjoint studies using the maximum likelihood method for estimation. This analysis uses data collected by Erdem and Swait (1998) from a convenience sample of 92 undergraduate students at a major North-American University on choices for jeans; this analysis is reported in Louviere et al. (2001). The brands considered were Calvin Klein, Gap, Lee, Levi's and Wrangler. Each brand's price was varied at four levels ($24.99, $34.99, $44.99, and $54.99). Each respondent evaluated 17 choice sets and each choice set consisted of showing the five brands at different prices. The no choice option was also included in each choice set. These individual-level choice data were analyzed using a multinomial logit model, using the maximum likelihood method. The predictor variables were the logarithm of prices of the brands and perceived quality measures for each brand. The model also included brand-specific constants. The results are shown in Table 4.16.
The fit of this model is quite good. The results indicate high brand values for Gap. Calvin Klein, and Levi's brands; Wranglers seems to have a low value in the minds of the respondents.
The price effects are in the expected direction; there seems to be a high degree of price sensitivity for the three brands with high brand values.

4.10 Some Alternatives to MNL for Stated Choice Data

There exist several ways of dealing with the problem due to IIA. The first option is to utilize experimental designs that enable estimation of at least some first order interactions. The next option is to relax the assumption of independence among errors and specify different distributional assumption (other than the extreme value distribution). The three selected choice models described below along with the corresponding assumptions will resolve this problem. These three alternatives are mainly used in practice.

Table 4.16 MNL model for jeans choice data

Parameters	Estimates (t-statistics in parentheses)
Brand-specific coefficients	
Calvin Klein	19.286 (18.3)
Gap	20.482 (18.9)
Lee	13.149 (5.8)
Levi's	19.139 (19.1)
Wranglers	5.668 (2.8)
Perceived quality (PQ) measures	
PQ-Calvin Klein	1.041 (14.1)
PQ-Gap	(13.1)
PQ-Lee	1.077 (7.6)
PQ-Levi's	1.182 (14.0)
PQ-Wranglers	1.350 (9.8)
Natural logarithms of prices	
Ln (Price-Calvin Klein)	−5.209 (−17.6)
Ln (Price-Gap)	−5.547 (−18.3)
Ln (Price-Lee)	−4.367 (−6.5)
Ln (Price-Levi's)	−5.047 (−18.3)
Ln (Price-Wranglers)	−2.467 (−4.2)
Summary statistics	
Log likelihood (random choice)	−2734.22
Log (likelihood at convergence)	−1398.57
Number of parameters	15

Source: Louviere et al. (2001), p. 294

Choice model (alternative to multinomial logit model)	Relevant assumptions
Multinomial probit model	Errors are assumed to follow a multivariate normal distribution (with or without covariances). There will be an additional (n − 2) variance terms if no covariances are used and additional (n − 2) × (n − 2)/2 covariance terms in the model
Heteroscedastic logit model (HEV Model)	Errors are assumed to have unequal variances, with one variance set equal to 1
Random coefficients logit model	The coefficients are assumed to be specific to the individual in the sample. The coefficient for the i-th individual for the k-th attribute (b_{ik}) is modeled as: $b_{ik} = \bar{b}_k + z_i\theta_k + \sigma_k\nu_{ik}$ where ν_{ik} is assumed to be normally distributed and z_i is a vector of individual-specific characteristics. The parameter $\bar{b}_k$ is the mean value around which individual level coefficients vary. θk and σ_k are the parameters to be estimated at the attribute level
	In some cases, the coefficients are simply assumed to be random with no specified relationship to individual level characteristics

Another alternative is the nested multinomial logit model which imposes a nested structure (like a tree) on the choice alternatives. As an example, consider sixteen choice alternatives 1, 2, . . ., 16 with the nested structure shown in Figure 4.4

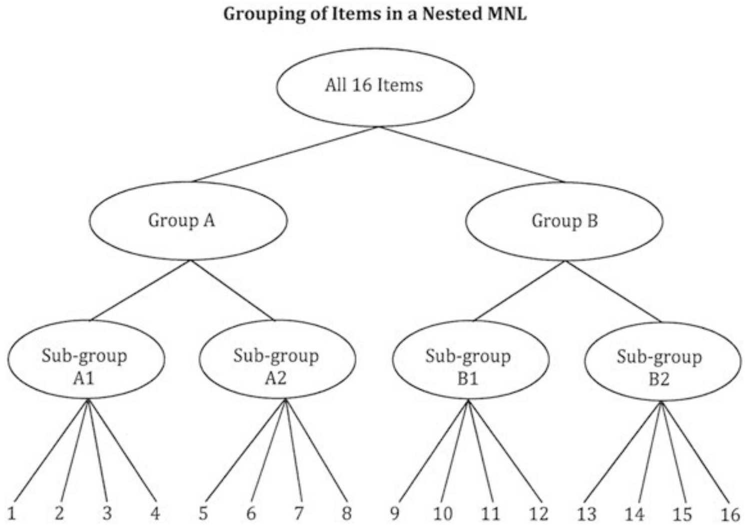


Fig. 4.4 Grouping of items in a nested MNL

with two levels and the first level items are classified into two groups A and B and further assume that the items under the group A (or B) are further divided into subgroups A1 and A2 (or B1 and B2). Further, the items at the lower level of the structure will be similar and different from others in different subgroups. Then, the nested multinomial model assumes the multinomial logit model to be applicable for the items in the four subgroups (A1, A2, B1, and B2) and further the items under the A group will be related to the items under the B group. Further details of this model are beyond the scope of this book; for more details, see Greene (2012) or Ben-Akiva and Lerman (1991).

Illustration. We will now illustrate two of these choice-based conjoint methods (and compare with the basic multinomial logit model) using a set of data[19] on smart phone choices by a sample of graduate students. The context was that of a wireless provider firm interested in determining trade-offs among various features of a smart phone (a technologically advanced product with a number of features). While a number of features such as color, package contents, vibrating alert, telecom services, operating System, memory, call features, processor, input device, digital camera, display, GPS, expansion and connectivity are predetermined, the study focused on five features. Table 4.17 shows the levels of the five features varied in the study.

[19] These data collected by Vishal Narayan, Vithala R. Rao and Carolyne Saunders in 2008 were part of a larger study on how individuals adapt their tradeoffs with new information; our focus here will be on one element of this study.

Table 4.17 Variable smart phone attributes

Attribute	Levels 1	2	3	4
Style	Candy bar 	Slide phone 	Flip phone 	Touch screen 
Brand	Blackberry	Nokia	LG	Samsung
Talk-time	3 h	5 h	7 h	9 h
Weight	100 g	115 g	130 g	145 g
Camera quality	2 Mega pixels	3 Mega pixels	6 Mega pixels	8 Mega pixels

Having predetermined a number of standard features, the study focused on the trade-offs among five attributes, namely, style of the phone, brand name, talk-time, weight, and camera quality. Price attribute was not included because it was part of a contract with the wireless provider and was about the same for all brands. Each of these five attributes is varied at four levels. Eighteen choice sets of size 4 were generated using the OPTEX code package in SAS; the code for this was shown in Table 4.4. The efficiency of the orthogonal design (measured using D-efficiency) was greater than 95 %.

An illustration of a choice set is shown below:

	Phone 1	Phone 2	Phone 3	Phone 4
Style	Candy bar	Slide phone	Touch screen	Flip phone
Brand	Blackberry	Nokia	LG	Samsung
Talk-time	7 h	3 h	9 h	5 h
Weight	100 g	145 g	130 g	115 g
Camera quality	2 megapixels	4 megapixels	8 megapixels	6 megapixels

The questions within each phase were randomized for each respondent. The survey was carried out using Qualtrics in a computer lab. To ensure incentive compatibility, each participant was offered a $10 reward for the completion of the survey and in addition, was entered into a lottery to win one of two $150 vouchers from Best Buy.

The estimated parameters[20] for three models[21] – multinomial logit model, multinomial probit model and heteroscedastic logit model (HEV Model) – are shown in Table 4.18.

The three methods yield similar results. But, the fit of the model is better for the multinomial probit and heterogeneous logit model than the simple multinomial logit model. In general, the effects (or partworths) for touch screen and Blackberry brand are positive and significant. Also, longer talking time, less weight and higher quality cameras are desirable. The HEV model shows that the scale values for the error term are not equal across the alternatives; this shows scale heterogeneity among the individuals. We refer the reader to a generalized multinomial model recently developed by Fiebig et al. (2010), which combines different kinds of heterogeneity (scale and random variation among parameters); discussion of this general model is beyond the scope of this monograph. The multinomial probit model shows that some variances (STD1) and STD2) are statistically significant and one correlation (RHO31) and has a higher likelihood than that of the multinomial logit model.

[20] I thank Yu Yu of Georgia State University for her help with these analyses. The MDC procedure in the SAS system was used.

[21] The MDC procedure does not enable estimating a random coefficients logit model. We will show the estimates from the Bayesian method in the next section.

Table 4.18 Parameter estimates for the smart phone data[b]

Attribute	Level/Value	MNL model estimate	MNP model estimate	HEV model estimate
Style	Slide phone	0.2628	0.1222	0.2294
		(0.1153; 2.28)	(0.0783; 1.56)	(0.1429; 1.60)
	Touch screen	0.7442	0.4873	0.8104
		(0.1099; 6.77)	(0.0881; 5.53)	(0.1295; 6.26)
	Flip phone	0.2776	0.1266	0.2103
		(0.1138; 2.42)	(0.0911; 1.39)	(0.1405; 1.50)
Brand	Samsung	0.0683	0.0337	−0.0200
		(0.1138; 0.60)	(0.0799; 0.42)	(0.1448; −0.14)
	Nokia	−0.0388	−0.0211	0.4573
		(0.1186; −0.33)	(0.0838; −0.25)	(0.1341; 3.41)
	Blackberry	0.4644	0.3271	0.4573
		(0.1119; 4.15)	(0.0738; 4.43)	(0.1341; 3.41)
Talk time	Hours	0.2420	0.1644	0.2794
		(0.0184; 13.12)	(0.0196; 8.37)	(0.0266; 10.52)
Weight	Grams	−0.0114	−0.0067	−0.0177
		(0.0024; −4.77)	(0.0017; −3.93)	(0.0028; −4.16)
Camera quality	Megapixels	0.0915	0.0649	0.1203
		(0.0171; 5.34)	(0.0132; 4.92)	(0.0234; 5.13)
STD1		–	1.0448	0.7679[a]
			(0.2345; 4.46)	(0.08883; 8.69)
STD 2		–	0.8649	0.8729[a]
			(0.2940; 2.94)	(0.1024; 8.53)
RHO 21		–	0.0718	0.7669[a]
			(0.4217; 0.17)	(0.0861; 8.91)
RHO 31		–	0.5156	–
			(0.1728; 2.98)	
RHO 32		–	−0.1758	–
			(0.3448; –0.51)	
Log likelihood		−1,044	−1,035	−1,040
AIC		2,105	2,098	2,103
BIC		2,148	2,165	2,161
No. of observations		864	864	864
No. of parameters		9	14	12

[a]These are the estimated scales values 2, 3, and 4 in the HEV Model
[b]Standard errors and t-values are shown in parentheses

4.11 Bayesian Methods for Choice-Based Conjoint Analysis

When the data are collected via choice-based conjoint study, the procedure of estimating parameters using HB methods is quite similar to that for ratings-based methods described in the previous chapter. First, a model for the probability of choice is specified; it is usually a logistic one such as:

Prob (choosing i ε C) $=\mathrm{Pr}_i = \exp(v_i)/\sum_{k\varepsilon C} \exp(v_k)$ where C is the choice set and the summation in the denominator is taken over all the elements of the choice set C.

Let N denote the multinomial outcome with the i-th element equal to one if the i-th alternative is chosen and 0 otherwise. The observed choices {ys} are now related to the attributes, X via the model for the probabilities of choice. The likelihood will then be:

$$[\mathrm{N}|\mathrm{y}]\ \left[\mathrm{y}\middle|\mathrm{X},\ \beta,\ \sigma^2\right]\ [\beta]\ [\sigma^2].$$

The model, [N|y] relates the latent utilities to the discrete outcomes (ys). This is an additional step in the Gibbs sampling procedure; this step involves drawing a sample of ys from the conditional distribution of v given X, β, and σ^2 ; the value of y_i is chosen with the probability equal to the choice probability using the method of rejection sampling. (See Allenby and Lenk (1994) for additional details.)

One of the challenges in conjoint analysis is to get sufficient data to estimate partworths at the individual level with relatively few questions. This issue is handled in the experimental design used to construct the profiles for evaluation; nevertheless there is more tension in the choice of designs that require a large number of questions (or profiles) and respondent fatigue, which makes the responses less reliable. Further, when standard methods of estimation (such as those discussed in the previous chapter are used for ratings at the individual level), it is not uncommon to obtain partworth estimates with the wrong sign. This problem can also occur when choice data are analyzed at the level of a segment or the full sample.

A way to deal with these issues is to utilize information about the partworths of all the respondents in the sample and employ Hierarchical Bayesian (HB) methods for estimation of partworths. For this purpose, each respondent's partworths are characterized by a known distribution to describe the uncertainty in the partworths. Next, the parameters of that distribution are assumed to be different across the population (or the sample). Prior distributions (beliefs) are specified for the parameters, which are updated by data using the Bayesian theorem. Given that the two stages are specified, the procedure becomes a hierarchical Bayesian approach. The resulting equations for estimating the parameters are not amenable to analytical solution. The parameters are estimated by the use of sophisticated techniques such as the Gibbs sampling and Metropolis-Hastings algorithms. In these methods, restrictions on partworths can also be incorporated with ease. See Allenby et al. (1998) for some details.

Illustration. We use the WINBUGS package[22] and estimate the individual level parameters for the smart phone data analyzed above. The actual code employed for WINBUGS is shown in Table 4.19. Given that there are no covariates in the data, a random coefficient multinomial logit model with no second hierarchy of levels.

[22] I thank Chang Hee Park of Binghamton University for his help with this analysis.

Table 4.19 WinBugs code for analysis of smart phone data

```
model {
  for (i in 1:NoSubjects) {
    for (j in 1:NoSets) {
      Choice[(Start[i]+(j-1)*4):(Start[i]+(j-1)*4+3)] ~ dmulti(p[(Start[i]+(j-1)*4):(Start[i]+(j-1)
   *4+3)],1)
      for (k in 1: NoOptions) {
        p[Start[i]+(j-1)*4+k-1] <- phi[i,j,k] / sum(phi[i,j,])
        log(phi[i,j,k]) <- b[i,1]*x1[Start[i]+(j-1)*4+k-1] + b[i,2]*x2[Start[i]+(j-1)*4+k-1]
                + b[i,3]*x3[Start[i]+(j-1)*4+k-1] + b[i,4]*x4[Start[i]+(j-1)*4+k-1] + b[i,5]
                *x5[Start[i]+(j-1)*4+k-1]
                + b[i,6]*x6[Start[i]+(j-1)*4+k-1] + b[i,7]*x7[Start[i]+(j-1)*4+k-1] + b[i,8]
                *x8[Start[i]+(j-1)*4+k-1]
                + b[i,9]*x9[Start[i]+(j-1)*4+k-1] + 0*SubjectID[Start[i]+(j-1)*4+k-1]
                + 0*Set[Start[i]+(j-1)*4+k-1] + 0*Profile[Start[i]+(j-1)*4+k-1]
      }
    }
  }
  for ( i in 1:NoSubjects) {
    b[i,1:9]~dmnorm(mub[],sigmab[,])
  }
  for ( m in 1:9) {
  mub[m]~dnorm(0,0.01)
  }
  sigmab[1:9,1:9]~dwish(R[,],20)
  for ( m in 1:9) {
    for ( n in (m+1):9) {
      R[m,n]<-0
      R[n,m]<-0
    }
    R[m,m]<-0.1
  }
  ssigmab[1:9,1:9]<-inverse(sigmab[1:9,1:9])
}
list(NoSubjects=54, NoSets=16, NoOptions=4)
```

Diffuse priors for the mean vector of parameters and the variance-covariance matrix are used in this analysis as shown the code.

The results are shown in Table 4.20. While the order of parameter estimates partworth is the same within each attribute, the values differ from those of the estimates shown in Table 4.18. This difference may be attributed to heterogeneity among the individuals in the sample.

A Comparison of Bayesian and Classical Estimation Methods: In a recent study, Huber and Train (2001) compared the estimates obtained from Hierarchical Bayesian methods with those from classical maximum simulated likelihood methods. In both the methods, the partworths at the individual level are assumed to follow a normal distribution and the probability of choice of an alternative as the multinomial logit

Table 4.20 Parameter means and other statistics of the individual level estimates Bayesian method – smart phone data

		Bayesian estimates					
Attribute	Level	mean	Standard deviation	2.50 %	median	97.50 %	MNL model estimate
Style	Slide phone	0.1422	0.1311	−0.1208	0.1406	0.398	0.2628
	Touch screen	0.2588	0.1543	−0.05016	0.2598	0.5607	0.7442
	Flip phone	0.06739	0.136	−0.2094	0.06754	0.3245	0.2776
Brand	Samsung	0.1061	0.1245	−0.1459	0.1054	0.3575	0.0683
	Nokia	−0.1885	0.1454	−0.4698	−0.1871	0.1004	−0.0388
	Blackberry	0.3362	0.1317	0.06619	0.3371	0.5918	0.4644
Talk time	Hours	0.2715	0.0304	0.2131	0.271	0.3327	0.242
Weight	Grams	−0.00694	0.007116	−0.02097	−0.00694	0.007035	−0.0114
Camera quality	Megapixels	0.1448	0.02616	0.09421	0.1445	0.1971	0.0915

function. Their objective was to compare the average of the expected partworths across individuals for the two methods.

Their empirical analysis was based on a choice-conjoint data in which 361 respondents made choices for 12 choice sets, each choice set consisting of four electricity suppliers. The suppliers of the study were described on five attributes: fixed price in cents per kilowatt hour (two levels at 7 or 9 cents), length of contract (four levels of 0, 1, 2, or 3 years), type of company (three levels described as local utility, well-known company but not local, or unfamiliar), time-of-use rates (fixed at one level), and seasonal rates (fixed at one level). The authors found that the average of the expected partworths for the attributes to be almost identical for both methods of estimation. They also found the prediction of a holdout choice to be almost identical for the two methods (with hit rates of 71 % and 72 % for the Bayesian and classical methods). This empirical research is useful in determining which approach is best suited to a given problem. When there is a large number of partworths to be estimated, the likelihood function for the classical approach may have multiple maxima and can use up a large number of degrees of freedom; in such a case the Bayesian approach can be very useful. Further, identification is less of an issue for the Bayesian approach because the prior distributions for the parameters can provide the needed identification. It is also worth noting that there are differences in the way partworths need to be interpreted under the two methods.

4.12 Which Conjoint Approach (Ratings-Based or Choice-Based)?

One study (Elrod et al. 1992) empirically compared the two approaches to conjoint analysis (ratings-based and choice set-based) in terms of their ability to predict shares in a holdout choice task using the context of apartment choices by students. The ratings-based approach was represented by three models fitted to individual-level ratings of full profiles, whereas the choice set-based approach was represented

Table 4.21 A comparison of ratings-based and choice-based conjoint methods

Attribute of comparison	Ratings-based	Choice-based
Task for subjects	Evaluation (judgment) rather than choice	Choice among several alternatives
Number of alternatives evaluated	Either pairs or one at a time usually	Usually a number of alternatives in a choice set; several choice sets
Indication of complete dislike	Generally no chance to indicate	None option can be included in the choice set
Closeness to real-world decision making	Less	More
Aggregation level for analysis	Usually at individual respondent level	Aggregate level (for the sample as a whole or for subgroups)
Number of attributes in the design	Can be many	Usually 4–6
Analysis model for estimation of effects (partworths)	Usually a linear model and main effects are estimated	Well-suited for estimation of interaction effects among the attributes
Judgment process	Usually compensatory or trade-off	Can account for lexicographical preferences
Usual estimation method	Regression	Multinomial logit

by a multinomial logit model fitted to choice shares for sets of full profiles. The predictions of holdout choices for nine choice sets indicated that the two modeling approaches predict very well based on the predictive validity criterion. But, one should not generalize on the basis of one study.

Even though the ratings-based and the choice-based methods are intended for similar purposes, their details differ in a number of ways. Table 4.21 shows these differences. An applied researcher should consider these factors in the choice of the specific methodology for a given study. In practice, the specific choice of one approach over another (ratings-based or choice-based conjoint methods) should be based on several criteria such as the purpose of the study (e.g. market segmentation, share predictions for new alternatives) and desire for detailed individual-level estimates and so on.

4.13 Software for Design and Analysis

There exist several software packages or programs for the design of choice sets and analysis of data form choice-based conjoint studies. We will mention a few of them below. The particular software selected will naturally depend on the statistical sophistication of the researcher. A default is of course the one provided by the Sawtooth Software.

Sawtooth Software: A versatile package of programs including CBC; it includes both design, data collection, and analysis.
Ngene: a package developed by Choice Metrics that enables a researcher efficient deigns for choice experiments. It is quite comprehensive.
OPTEX: A procedure included the SAS system to design choice sets.
Limdep: An econometric software package that is versatile for estimating various kinds of multinomial and probit models; this is a versatile package for analyzing various kinds of choice and other data.
WINBUGS: A package for analysis of data with Bayesian methods.
Custom-made: A researcher can develop codes in MATLAB mainly for analysis of choice data.

4.14 Summary

This chapter has introduced the issues of design and analysis of choice-based conjoint studies. The concept of choice-based conjoint studies is intuitively appealing because of the nature of response sought and the task given to the respondents. Choice sets of alternatives are created to reflect potential conditions in the marketplace and stated choices are elicited from the respondents. The data are then analyzed using the multinomial logit model, which implies the independence of irrelevant alternatives. Some alternative analysis models that will not result in this assumption of IIA include the nested logit model (not much discussed in the chapter), multinomial probit model, heteroscedastic logit model, and random coefficients logit model; but, the estimation of such models is generally more complicated.

The major task in utilizing the choice-based conjoint studies is the design of choice sets. Basically, the analyst first designs choice alternatives using some kind of orthogonal main-effects design and then creates choice sets in which some or all of these created alternatives are included. Usually several choice sets are presented to a respondent and she is asked to indicate the one she is likely to choose. The option of 'no choice' is included in some cases.

The designs called availability designs are useful when the effects of availability of an alternative (brand) need to be estimated. Using such designs, one can estimate self-and cross-effects for the brands in a competitive set.

The ratings-based conjoint studies compete quite well with the choice-based conjoint studies. The design process for the ratings-based studies is much simpler than the choice-based studies. But, additional steps are involved in developing choice probabilities when the ratings-approach is employed. Thus, the choice-based approach can be a mixed-blessing, but with several significant advantages.

More recent research has focused on developing designs for choice sets that improve their efficiency. One of these is the set of designs that seek utility balance (Huber and Zwerina 1996). In these designs the alternatives in the choice sets are balanced in utility and therefore have similar choice probabilities. Theses designs with utility balance have the potential for reducing the number of respondents needed to achieve pre-specified error levels for the parameters estimated. The concept of M-error has potential for incorporating managerial objectives directly in the design of choice experiments

Appendix 1

Illustration of Designing Choice Sets

This is an elaboration of Example 2 in this chapter. Let us call the three sandwich options as Sandw A, Sandw B, and Sandw C. Similarly, let us call the side order as Sideo A, Sideo B, and Sideo C and the drink options as Drink A, Drink B, and Drink C. Fist, the nine meal combinations (1/3 of the 3^3 factorial design) can be constructed using a Latin Square design as follows:

	Sandw A	Sandw B	Sandw C
Sideo A	Drink A	Drink B	Drink C
Sideo B	Drink C	Drink A	Drink B
Sideo C	Drink B	Drink C	Drink A

The nine cells, {Sandw A, Sideo A, Drink A}, {Sandw A, Sideo B, Drink C},. . ., {Sandw C, Sideo C, Drink A} will be the nine meal combinations. Let us call these meals Meal 1, Meal 2, . . ., Meal 9.

Now to create choice sets, we use the 12 rows of the Plan 4 of Hahn and Shapiro (1966) using the first 9 columns. Calling the two price levels low and high, the 12 choice sets are as follows:

Choice set	Meal 1	Meal 2	Meal 3	Meal 4	Meal 5	Meal 6	Meal 7	Meal 8	Meal 9
1	Low	Low	Low	Low	Low	Low	Low	Low	Low
2	High	High	Low	High	High	High	Low	Low	Low
3	Low	High	High	Low	High	High	High	Low	Low
4	High	Low	High	High	Low	High	High	High	Low
5	Low	High	Low	High	High	Low	High	High	High
6	Low	Low	High	Low	High	High	Low	High	High
7	Low	Low	Low	Low	Low	High	High	Low	High
8	High	Low	Low	Low	High	Low	High	High	Low
9	High	High	Low	Low	Low	High	Low	High	High
10	High	High	High	Low	Low	Low	High	Low	High
11	Low	High	High	High	Low	Low	Low	High	Low
12	High	Low	High	High	High	Low	Low	Low	High

The researcher will show the first row of 12 meals at the corresponding prices as the first choice set and so on.

Appendix 2

Design Plans for Pre-specified Holistic Alternatives Using Fractional Factorial Method

If there are J possible alternative choice options, the possible design plans for developing choice sets are as follows:

- All possible choice sets of J alternatives; usually this will be a very large number for most studies ($2^J - 1$).
- Use all pairs of the J alternatives; this will yield J * (J − 1)/2 choice sets.
- Use one choice set in which all J alternatives are present; the task can be unrealistic for respondents if J is large.
- Use a fractional factorial of the 2^J design with levels being present or absent for each alternative.

In order to implement the last option, one can consult plans for 2^m designs.

If availability designs are employed, one needs to utilize a fractional design of a suitable 3^m design, if one exists.

Appendix 3

Illustration of Design Efficiency in Choice-Based Conjoint Designs

We now illustrate how the Sawtooth Software's choice-based conjoint studies software, called CBC reports the design efficiency of the designs it develops. CBC is popular software used for choice-based conjoint studies. We will show an example[23] of main effects choice designs. The aim of the study was to determining golfers' preferences for golf balls described on three attributes: Brand name (four levels); Drive distance (three levels); and Price (four levels). Choice tasks were randomly generated using the method of balanced overlap. The design efficiencies computed for sample sizes of 5 and 150 respondents each with 15 choice tasks are shown below each level of the attributes.

			Sample size = 5			Sample size = 150		
Attribute	Level	Description	Actual	Ideal	Efficiency	Actual	Ideal	Efficiency
1	1	High-Flyer Pro, by Smith and Forester	This level deleted			This level deleted		
1	2	Magnum Force, by Durang	0.2193	0.2116	0.9309	0.0385	0.0384	0.9914

(continued)

[23] These were computed using the CBC software on August 20, 2009.

			Sample size = 5			Sample size = 150		
Attribute	Level	Description	Actual	Ideal	Efficiency	Actual	Ideal	Efficiency
1	3	Eclipse+, by Golfers, Inc.	0.2089	0.2116	1.0263	0.0383	0.0384	1.0017
1	4	Long Shot, by Performance Plus	0.2112	0.2116	1.0039	0.0384	0.0384	0.9973
2	1	Drives 5 yards farther than the average ball	This level deleted			This level deleted		
2	2	Drives 10 yards farther than the average ball	0.1770	0.1728	0.9524	0.0314	0.0314	0.9957
2	3	Drives 15 yards farther than the average ball	0.1720	0.1728	1.0093	0.0314	0.0314	1.0003
3	1	$4.99 for package of 3 balls	This level deleted			This level deleted		
3	2	$6.99 for package of 3 balls	0.2087	0.2106	1.0183	0.0383	0.0383	1.0047
3	2	$8.99 for package of 3 balls	0.2145	0.2106	0.9638	0.0384	0.0383	0.9993
3	4	$10.99 for package of 3 balls	0.2077	0.2106	1.0277	0.0383	0.0383	1.0036

We now give more details on this “Test Design”. Dr. Rich Johnson of Sawtooth Software kindly provided the following details on how the efficiencies are calculated:

A “design matrix” is created by combining information for all concepts seen by all respondents. For example, if there were 10 respondents in a data set, and each had seen 6 choice tasks in which there were an average of 4 concepts per task, the design matrix would have $10 \times 6 \times 4$ rows.

As is usually the case with least squares estimation involving “dummy variables,” it is necessary to omit one level of each attribute. That is because of built-in dependencies among the levels of each attribute. Since each concept has exactly one level of each attribute, if we know whether or not a particular concept has each of the first $n-1$ levels of an attribute, we can deduce whether it has the nth.

Each element of the design matrix has a value of 1 if that concept has that attribute level, or 0 otherwise.

The design matrix is then further processed by computing the average of each column for the concepts in each task, and then subtracting that average. As a result, the column sums for each task for each respondent are zero. This is done to be analogous to multinomial logit estimation, which is concerned only with differences among the concepts in each choice tasks.

Sums of squares and cross-products of columns are computed and stored in a symmetric matrix, which is then inverted. Diagonal elements of that inverse matrix are proportional to error variances of estimates for main effects for each attribute level, contrasted with the omitted level.

If the design matrix were strictly orthogonal, then all cross products would be zero except for those within each attribute, which would be negative. An estimate is also made of what the standard errors would be if the between-attribute cross products were zero.

The relative efficiencies which are displayed are obtained by dividing error variances for the actual design by those estimated for the corresponding hypothetical orthogonal design.

With OLS the parameter estimates have error variances proportional to the diagonal elements of the inverse of X'X, where X is the design matrix after each column is centered to have sum of zero. (The constant of proportionality is the variance of the dependent variable.)

Suppose there are n rows in the design matrix, and suppose a particular level occurs np times in the design matrix. Then the corresponding diagonal element of X'X (which is the sum of squares of elements in that column) will be $np(1 - p)$.

As a numerical example, let X have one column, with three rows, and let $p = 1/3$. After centering, its values are $2/3, -1/3, -1/3$. The sum of their squares is $6/9 = 2/3$, which is equal to $np(1 - p) = 3 * 1/3 * 2/3$.

Now if this column of X were orthogonal to all other columns, then the corresponding diagonal element of the inverse of X'X would be just the reciprocal of the corresponding diagonal element of X'X. So the error variance of the parameter estimate would be proportional to $1/[np(1 - p)]$. As a check on reasonableness, you can see that the variance decreases as n increases, and is minimized when $p = 1/2$.

This design uses a relatively simple method based on OLS principles (assuming each concept is actually a card from a traditional card-sort conjoint design). The latest version of our CBC software has an “Advanced Design” report, that simulates random respondent answers, computes an aggregate logit solution, and then lists the standard errors of the effects and the relative d-efficiency overall of the design.

Appendix 4

Illustration of Managerial Efficiency

This illustration is drawn from Toubia and Hauser (2007). The context is that of a electronic devices firm making decisions on adding five binary attributes (features) to the device. It is interested in deciding the value of each feature to the consumer and if it is greater than the price the firm must charge based on marginal cost of providing each feature. Assume that the cost of each feature is \$16.50 and the difference between the low and high levels of price is \$50. Let u_1, u_2, …, u_5 represent the partworths (utilities) for the five attributes and let u_p represent the partworth of a \$50 price reduction, and let C be the intercept in the estimation of the utility function (calibrated in terms of the five features and price). The managerially relevant willingness to pay (WTP) criterion will be in terms of $m_1 = u_1 - 0.33u_p, m_2 = u_2 - 0.33u_p, \ldots, m_5 = u_5 - 0.33u_p$. (Note that $0.33 = 16.50/50$).

First, we show in Panel A the orthogonal and balanced design without the consideration of the wtp values and the corresponding covariance matrix of the six parameter estimates (five features and price). Note that the variances of the estimates are 0.0833 each.

Panel B shows the augmented managerial quantities without the intercept and showing the coefficients for the five wtp values. Panel B also shows the covariance estimates for the managerially relevant quantities under the design X. The variances are 0.0924 for each, which are about 10 % higher than the partworth estimates.

Panel C shows the augmented matrix of managerial quantities; this matrix has an additional row for the intercept. The corresponding design matrix is also shown. The variance-covariance matrix of the parameter estimates is also shown. It is interesting that the errors are now reduced. These errors are A-error (M_A-error) and D-error (M_D-error) for the managerially relevant estimates.

Panel A

Orthogonal and balanced design, X

$$X = \begin{bmatrix} +1 & +1 & -1 & -1 & -1 & -1 & -1 \\ +1 & -1 & +1 & -1 & +1 & +1 & +1 \\ +1 & +1 & +1 & +1 & -1 & +1 & +1 \\ +1 & -1 & -1 & +1 & +1 & -1 & +1 \\ +1 & +1 & +1 & -1 & +1 & +1 & -1 \\ +1 & +1 & -1 & +1 & -1 & +1 & +1 \\ +1 & +1 & -1 & -1 & +1 & -1 & +1 \\ +1 & -1 & -1 & -1 & -1 & +1 & -1 \\ +1 & -1 & +1 & -1 & -1 & -1 & +1 \\ +1 & -1 & +1 & +1 & -1 & -1 & -1 \\ +1 & +1 & +1 & +1 & +1 & -1 & -1 \\ +1 & -1 & -1 & +1 & +1 & +1 & -1 \end{bmatrix}$$

Covariance matrix of the parameter estimates

$$\Sigma = (X'.X)^{-1} = \begin{bmatrix} 0.0833 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.0833 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0833 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.0833 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0833 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.0833 \end{bmatrix}$$

Panel B

Managerial quantities

$$M_{WTP} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & -0.33 \\ 0 & 0 & 1 & 0 & 0 & 0 & -0.33 \\ 0 & 0 & 0 & 1 & 0 & 0 & -0.33 \\ 0 & 0 & 0 & 0 & 1 & 0 & -0.33 \\ 0 & 0 & 0 & 0 & 0 & 1 & -0.33 \end{bmatrix}$$

Covariance matrix of the managerial estimates under X

$$\Sigma^M = M_{WTP}(X'.X)^{-1}.M'_{WTP} = \begin{bmatrix} 0.0924 & 0.0091 & 0.0091 & 0.0091 & 0.0091 \\ 0.0091 & 0.0924 & 0.0091 & 0.0091 & 0.0091 \\ 0.0091 & 0.0091 & 0.0924 & 0.0091 & 0.0091 \\ 0.0091 & 0.0091 & 0.0091 & 0.0924 & 0.0091 \\ 0.0091 & 0.0091 & 0.0091 & 0.0091 & 0.0924 \end{bmatrix}$$

M_A-error(X) = 1.1089
M_D-error(X) = 1.0908

Panel C

Augmented matrix of managerial quantities

$$M^{+}_{WTP} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & -0.33 \\ 0 & 0 & 1 & 0 & 0 & 0 & -0.33 \\ 0 & 0 & 0 & 1 & 0 & 0 & -0.33 \\ 0 & 0 & 0 & 0 & 1 & 0 & -0.33 \\ 0 & 0 & 0 & 0 & 0 & 1 & -0.33 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix}$$

Managerial design, X_{WTP}

$$X_{WTP} = \begin{bmatrix} +1 & +1 & -1 & -1 & -1 & -1 & 0.98 \\ +1 & -1 & +1 & -1 & +1 & +1 & -0.32 \\ +1 & +1 & +1 & +1 & -1 & +1 & -0.98 \\ +1 & -1 & -1 & +1 & +1 & -1 & 0.34 \\ +1 & +1 & +1 & -1 & +1 & +1 & -1.00 \\ +1 & +1 & -1 & +1 & -1 & +1 & -0.32 \\ +1 & +1 & -1 & -1 & +1 & -1 & 0.34 \\ +1 & -1 & -1 & -1 & -1 & +1 & 0.98 \\ +1 & -1 & +1 & -1 & -1 & -1 & 1.00 \\ +1 & -1 & +1 & +1 & -1 & -1 & 0.32 \\ +1 & +1 & +1 & +1 & +1 & -1 & -1.00 \\ +1 & -1 & -1 & +1 & +1 & +1 & -0.34 \end{bmatrix}$$

Covariance matrix of the managerial estimates under X_{WTP}

$$M_{WTP}(X'_{WTP}.X_{WTP})^{-1}.M'_{WTP} = \begin{bmatrix} 0.0833 & 0 & 0 & 0 & 0 \\ 0 & 0.0833 & 0 & 0 & 0 \\ 0 & 0 & 0.0833 & 0 & 0 \\ 0 & 0 & 0 & 0.0833 & 0 \\ 0 & 0 & 0 & 0 & 0.0833 \end{bmatrix}$$

M_A-error(X_{WTP}) = 1.00 M_D-error(X_{WTP}) = 1.00

Appendix 5

Empirical Illustration of Availability Designs

In this appendix, we illustrate the use of availability design using the empirical application provided by Lazari and Anderson; it deals with a hypothetical market situation for frozen foods marketed by six producers. The experiment assumes that Swanson will introduce a new product line priced well below their current products and directly competing with the Banquet products. The other products were: Tyson, Health, Le Menu, and Armour. With the new brand, called Swanson's New there are 12 brands in the market each at two price levels as shown below. The objective of this study was to assess the market penetration, in particular the cannibalization effects of the other products (including Swanson's) of the new brand, Swanson's New. The availability model is extremely suitable to assess these cross-effects as well as main effects and cross-brand effects within the product lines.

The choice sets were developed out of the design shown above; the set of 36 was divided into two subsets of 18 each and each respondent was given the 18 choice sets and two other sets (for validation). In all, 103 respondents participated in the study.

Using the modeling aspects of this chapter, we may describe the MNL model the authors applied to the data. The deterministic part of the utility for any brand i in a choice set A ($V_{i|A}$) is modeled as:

$$V_{c/A} = \alpha_i + \beta_i XL_c + \sum_{c \neq L} (\gamma_{iL'} XL_{c'} + \delta_{iL'} z_{c'})$$

α_i = intercept for brand i,
β_i = attribute effect for brand i,

where:

$$XL_i = \begin{cases} -1 & \text{if brand i is present with attribute level 1,} \\ +1 & \text{if brand i is present with attribute level 2,} \end{cases}$$

$\gamma_{ii'}$ = attribute cross effect of brand i' on brand I,
$\delta_{ii'}$ = availability cross-effect of brand i' on brand I,

$$XL_{i'} = \begin{cases} -1 & \text{if brand i}' \text{ is present with attribute level 1,} \\ +1 & \text{if brand i}' \text{ is present with attribute level 2,} \end{cases}$$

$$Z_{i'} = \begin{cases} -2 & \text{if brand i}' \text{ is not present, and} \\ +1 & \text{if brand i}' \text{ is present with attribute level 1 or 2,} \end{cases}$$

The β-coefficients measure the own-price effects of brands in this analysis (because price is the only attribute), and the γ-coefficients measure the cross-price effects while the δ-coefficients measure the availability effects. Given the large number of parameters in this model, the authors estimated a reduced model which includes all brand intercepts, all own-price effects, all cross price effects of all three Swanson brands (two existing and one new) with the remaining nine brands, and cross price effects of brands produced by the same firm. The availability effects included in the model were similar to those of the cross price effects.

The parameters were estimated using maximum likelihood methods. The signs of the estimated price effects and availability effects were as expected. The authors conducted simulation of market shares under six scenarios of price conditions and found that Swanson's market share (with and without the new brand) would be as below. Based on these results, it seemed worthwhile for Swanson to introduce the new brand.

Swanson new (SN)	Price scenario (high or low prices)	Estimated market share for Swanson's brands (%)
Absent	High for all other brands	19.5
Absent	Low for all other brands	17.2
Present	High for all brands	38.0
Present	SN low and high for all other brands	31.4
Present	SN low and low for all other brands	30.8
Present	SN high and low for all other brands	25.6

Appendix 6

Weighted Least Squares Method

If the data are aggregated to a group level, the method of weighted least squares can be used for estimating the b-values in the MNL model. The deterministic component for an alternative a in a choice set A_k is:

$$V_a = \beta_{0a} + \sum_k \beta_{0a} \bullet x_k \tag{4.8}$$

Using the assumption on the errors, we develop the choice probability as:

$$p(a\,|\,A) = \frac{e^{V_a}}{\sum\limits_{j \in A} e^{V_j}} \tag{4.9}$$

Note that the denominator in (4.9) is constant in each choice set in a particular study; that is, suppose a design involves I choice sets, $A_1, \ldots, A_I$, then

$$p(a\,|\,A_i) = \frac{e^{V_a}}{k_i} \tag{4.10}$$

where k_i is a constant applicable to the i-th choice set ($i = 1, 2, \ldots, I$).

Define the dependent variable is $Y_{ai} \equiv \ln(f_{ai})$, where f_{ai} is the number of times (frequency) alternative a was chosen from choice set A_i. The y-values are the frequencies aggregated across the respondents who stated their choices in the choice set A_i. Now, Y_{ai} is approximately normally distributed with expected value, $E(Y_{ai})$, and variance, $Var(Y_{ai})$.

$$E(Y_{ai}) = \ln[n_i \bullet p(a\,|\,A_i)] = V_a + \log(n_i/k_i)$$
$$Var(Y_{ai}) = \ln[n_i \bullet p(a\,|\,A_i)]^{-1} = \frac{1}{w_{ai}}$$

Then,

$$Y_{ai} = \mu + \alpha_a + \gamma_I + e_{ai}$$

Where e_{ai} is approximately normally distributed with zero mean and variance $1/w_{ai}$, is the constant term,

$$\alpha_a = V_a - \mu$$

$$\gamma_i = \log(n_i/k_i)$$

The parameters of this model can be estimated by weighted linear regression[24] with weights w_{ai}, and the independent dummy variables, x_j and c_j, where

$$x_j = \begin{cases} 1 & \textit{if} \qquad j = 1 \\ 0 & \textit{otherwise}. \end{cases}$$

$$c_i = \begin{cases} 1 & \textit{for choice set } i \\ 0 & \textit{otherwise}. \end{cases}$$

Then, $\hat{\alpha}_j$, the regression coefficient of x_j, is an estimate of $V_j - V_J$.

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Chapter 5
Methods for a Large Number of Attributes

5.1 Introduction

In the previous chapters we discussed various conjoint analysis methods for ratings-based ad choice-based studies.[1] One problem that nags applied researchers is how to deal with the issue of large numbers of attributes (and levels) to be included that arise in any practical problem (see Green and Srinivasan (1978, 1990) and Hauser and Rao (2004)). This problem may arise particularly for technologically complex products which usually have a large number of attributes. Over the years, researchers have come up with different methods to deal with this problem. While we have mentioned tangentially some of the applicable methods, this chapter will pull together various methods developed. In the next section (Sect. 5.2), we will describe the main problem when a conjoint study has to deal with a large number of attributes and then present an overview of the methods available in the literature. In Sect. 5.3, we will describe each method in some detail (data collection approach and analysis method) along with an application. Section 5.4 compares the methods on a set of relevant criteria. Finally, we will offer several directions for future research on the issue of a large number of attributes in any conjoint study and conjecture possible newer developments. Some newer data collection methods that use auctions also deal with the large number of attributes problem.

5.2 Alternative Methods for Massive Number of Attributes

As described in the previous chapter, the researcher has essentially two options: to collect stated preference data or stated choice data. For the former, the respondent is given a number of profiles of product concepts, each described on the attributes under study and the respondent is asked to rate each profile. In the choice-conjoint methods, the respondent is given a number of choice sets, each choice set consisting

[1] This material is mainly drawn from the paper by Rao et al. (2008).

V.R. Rao, *Applied Conjoint Analysis*, DOI 10.1007/978-3-540-87753-0_5,

of a small number (typically 4 or 5) profiles and is asked to indicate which profile she would choose. Based on these data, a utility function is estimated for each respondent (or for a subgroup of respondents); typically[2] the methods of multiple regression are used for the preference (ratings) data and a multinomial logit model (MNL) is used for the choice data. The use of the MNL model is based on the theory of random utility (McFadden 1973).

As we have seen, a categorical attribute (such as low, medium, or high) can be converted into a number of dummy variables (one less than the number of levels). A continuous attribute (such as price of a product) can be used directly with only a linear term or with both linear and quadratic terms to account for any nonlinear effects. With suitable redefinitions of variables, the utility function for the ratings-methods can be written as $y = X\beta + \varepsilon$; where ε is the random error of the model assumed to be normally distributed with zero mean and variance of σ^2, y is the rating on a given profile, and X is the corresponding set of p dummy (or other) variables. The β is a px1 vector of partworths among the levels of attributes. The MNL model for the choice-based conjoint data will be: probability of choosing profile j in choice set $C = \exp(v_j)/\sum \exp(v_k)$ where the summation is taken over all the profiles in the choice set C and v_j is the deterministic component of the utility for the profile j. The deterministic utility function, v, is specified as a linear combination of various X-variables similar to the function for y in the ratings methods. Here maximum likelihood methods are employed in the estimation. Both the types of data can be analyzed using hierarchical Bayesian methods (MCMC simulation methods) or classical estimation methods (see Rao (2008)).

The number of parameters to be estimated will depend on the number and levels of the attributes being investigated. For example, in a study with 4 attributes with levels of 5, 3, 2, and 2 respectively, a total of 8 $(= 5 - 1 + 3 - 1 + 2 - 1 + 2 - 1)$ parameters are to be estimated. The number of parameters will become quite large when the number of attributes becomes large; this is the problem a study designer is confronted with when there is a large number of attributes. For example, if there are 10 attributes each with four levels, one needs to estimate 30 $(= 10 * (4 - 1))$ parameters (in addition to an intercept in some cases). Naturally, the number of data points (either ratings or choices) collected from any respondent will need to be much larger than the number of parameters. It is generally not feasible to have a respondent evaluate a large number of profiles (or choice sets[3]) in a study due to fatigue, boredom, and other factors. Given that the data collection task needs to be manageable, researchers have developed an array of methods to deal with large numbers of attributes. The approaches include (1) ways to reduce the number of profiles or choice sets using all attributes presented to the respondent, (2) ways of combining or reducing the attributes included in any profile, (3) use of

[2] We will consider additive utility functions only. Extensions to utility functions with interaction terms or utility functions taking alternative functional forms are possible, however.

[3] Some researchers have employed a large number of choice sets with no difficulty; but this practice is not common.

compositional methods (self-explicated techniques), (4) sequential or adaptive ways of collecting data, and (5) ad hoc combinations of various methods. Some newer data collection methods that use upgrading technique also deal with the large number of attributes problem. For convenience, we will categorize these methods into six categories as shown in Table 5.1

5.3 Details of the Methods and Applications

5.3.1 *Methods of Category A: Profile Methods*

If a ratings-based conjoint method is employed, the researcher can only utilize a fraction of all possible full profiles using fractional factorial designs (Green 1974); we described this approach in significant detail in Chap. 2. Sometimes, the researcher may present profiles described on only a subset of attributes; such a procedure is called partial profile conjoint analysis (Bradlow et al. 2004). Both of these methods help reduce the total number of product profiles that respondents are required to evaluate in order to estimate the partworth parameters of interest, and we discuss each of these in turn.

5.3.1.1 Fractional Factorial Designs

The procedures employed here involve orthogonal arrays (a form of fractional factorial design) and incomplete block designs (balanced or partially balanced) (see Cochran and Cox (1955), Winer (1973) and Clatworthy (1955)). In these designs, some interactions are confounded (Fisher 1942). Another procedure as discussed by Green (1974) involves the development of a three-stage method for cases where the number of levels within a factor is so large (e.g. ten or more) that even fractionated designs are not practical. The procedure involves the following: (1) separate estimation of the respondent's utility scale for each (single) factor, (2) design of an orthogonal array drawn from a 2^n factorial design made up of the "end-point" utility-level descriptions, and (3) rescaling of the single-factor utilities with the common scale unit derived from evaluating the orthogonal array stimuli in the second stage. While the three-stage process entails more work for the researcher, it nevertheless allows for a considerable degree of flexibility for dealing with a relatively large (and not necessarily equal) number of levels within each factor or attribute.

5.3.1.2 Partial Profile Conjoint Analysis

One way to reduce the number of profiles presented to respondents, particularly when the number of product attributes involved is large, involves the presentation of partial product profiles (i.e., each profile is described on a subset of attributes).

Table 5.1 A classification of extant methods for large number of attributes

Category	Main feature	Specific methods
A. Profile methods	Uses all attributes or subsets of attributes so that all attributes are somehow covered or linked	A1. Fractional factorial designs (Green 1974) A2. Partial profile conjoint analysis (Bradlow et al. 2004)
B. Attribute simplification methods	In these methods, attributes are first grouped into subgroups or facets and these facets become the main focus of the study. Facets or groups are constructed judgmentally or with the use of factor analysis	B1. Staged approach: facets used in the first stage and attributes within facets used in the second stage (Wind et al. 1989) B2. Method of hierarchical information integration (Oppewal et al. 1994) B3. Use of meta-attributes (Ghose and Rao 2007)
C. Self-explicated methods	This is a compositional approach	C1. Self-explicated method (Green and Srinivasan 1990) C2. Adaptive self-explicated method (Netzer and Srinivasan 2011)
D. Methods combining several approaches	These methods are generally ad hoc and use several approaches to tackle the problems	D1. Hybrid conjoint analysis (uses self-explicated techniques and fractional factorial designs) (Green 1981, 1984) D2. Customized conjoint analysis (Srinivasan and Park 1997) D3. Adaptive conjoint analysis (Johnson 1987) D4. Bridging methods (Baalbaki and Malhotra 1995)
E. Upgrading method	Bids for willingness to pay amounts for product profile upgrades sequentially for various levels of attributes. Collected bids are cleared using BDM theory	E. A Web-based upgrading method (Park et al. 2008)
F. SVM methods	A method of estimation based on statistical learning theory	F. Support vector machines method (Evengeniou et al. 2005)

Bradlow et al. (2004) develop a learning-based method of imputing missing attribute levels in partial conjoint profiles. The method is based on the premise (and empirical finding) that respondents learn to impute missing levels of the attributes over the course of the conjoint task. Further, the relative importance of their attribute partworths can shift when they evaluate these partial profiles, suggesting that intrinsic partworths (and hence preferences) can be influenced by the conjoint task and are thus sensitive to the order in which the profiles are presented. Additionally, the respondent's learning process can be further influenced by manipulating the prior information they have about the product category. One advantage of the proposed method is that it can infer not only missing attribute levels from prior levels presented of the same attribute, but from prior levels of other attributes as well.

To explain the imputation model behind the proposed method, some illustrative notation is needed. Suppose there are N respondents (denoted by $i = 1,\ldots,N$) in the (ratings-based) conjoint experiment. Each respondent rates T product profiles (denoted by $M_i(t)$, $t = 1,\ldots,T$), each product profile has J attributes (denoted by $j = 1,\ldots,J$) and each attribute j has two levels, with attribute level $x_{ij}(t) = 1$ or 0. Respondent i's rating for profile $M_i(t)$ is given by $y_i(t)$. Further, $r_{ij}(t)$ denotes an indicator variable which takes the value 1 if the attribute j is missing in the t-th profile for respondent I and 0 otherwise. The model assumes that each respondent does not ignore a missing attribute level but constructs an imputed value for it based on some prior information. If $x'_{ij}(t)$ denotes this imputed value and I is the indicator variable, then:

$$x'^{ij}(t) = \begin{cases} x_{ij}(t) & \text{if } r_{ij}(t) = 1 \\ Ix_{ij}(t) & \text{if } r_{ij}(t) = 0 \end{cases}$$

Estimation of the partworths of the attributes is done via the following regression:

$$y_i(t) = \alpha_i + \sum_{j=1}^{J} [\beta_{ij} x_{ij}(t) + \beta'_{ij} x'_{ij}(t)] + \varepsilon_i(t)$$

Table 5.2 illustrates a hypothetical example of the imputation model behind the proposed method. There are four product attributes ($J = 4$) and three different profiles, $M_i(1)$, $M_i(2)$, $M_i(3)$, rated sequentially by respondent i and presented at time $(t) = 1, 2, 3$. Each profile has one missing attribute, denoted as MA. For example, for profile $M_i(3)$ shown at time $t = 3$, $x_{i1}(3) = 1$, $x_{i3}(3) = 1$, $x_{i4}(3) = 0$, and attribute 2, which is missing, has an imputed level of $x'_{i2}(3) = 1$ or 0 (in a real experiment, the respondent does not see "MA" but rather sees a product profile with only attributes 1, 3, and 4). The attributes are classified into three types, the omnipresent (OM) type, which is always present, the presence-manipulated (PM) set with present or non-missing attributes (non-missing PM), and the PM set with

Table 5.2 Hypothetical example of imputation model (Source: Reprinted with permission from Bradlow et al. (2004), published by the American Marketing Association)

	OM	PM		
Time (t)	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	1	0	MA[a]	1
2	0	1	1	MA
3	1	MA	1	0

[a]*MA* missing attribute

missing attributes (missing PM). In profile $M_i(3)$, attribute 1 is an OM attribute, attribute 2 is a missing PM attribute, and attributes 3 and 4 are non-missing PM attributes.

Respondents are commonly assumed to impute information about missing attribute levels in two ways – the first assumes that respondents take the missing attribute level to be the last level of the same attribute they saw (the recency model), while the second assumes that respondents infer the missing attribute level by averaging all previously shown levels of the missing attribute (the averaging model). While these methods use only the currently missing PM attribute to impute information about that attribute, the method proposed here uses information from all three types of attributes. This is done by utilizing two importance pieces of information to impute the value of the missing attribute. The first is the complete set of profile patterns ($M_i(1)$ and $M_i(2)$) shown to the respondent before the current profile, $M_i(3)$ – if some of these profiles occur more frequently, their values for the missing attribute might be more salient. The second is the correlation between the values of the missing attribute and those of the other attributes – for example, if attribute 1 is negatively correlated with attribute 2 in previous profiles, this correlation is likely to occur for the current profile as well. As with other methods, the imputation model then calculates the probabilities that the missing attribute will take its possible values (1 or 0 for missing attribute 2) to determine the imputed value.

Bradlow et al. (2004) compare their proposed method with the other existing methods of respondent inference of missing attribute levels, in particular the recency and averaging methods, using a conjoint experiment involving ratings of digital camera profiles (additionally, the recency and averaging models that the authors estimated were enhanced by including a decay factor over time). There were two phases in the experiment, a learning phase, where respondents were given prior information about the digital cameras, followed by the ratings phase. The results of the experiment suggest that the proposed method outperforms the other methods in terms of model fit (using the log harmonic mean of the likelihood) as well as both in-sample and out-of-sample predictive validity (using the mean absolute error). To examine whether these findings are robust to the manipulation of the given prior information, the authors replicated the experiment without the learning phase on a different but demographically similar sample of respondents. While the estimated partworths for the second experiment are different from that of the first – suggesting that changing the prior information affects the respondents' imputation process – the results of the second experiment also show that the proposed method outperforms the other methods in terms of model fit and predictive validity, thus demonstrating the robustness of the model to prior information manipulation.

This method thus offers an alternative way of reducing the number of required product profiles in a conjoint task involving many attributes through the use of partial product profiles, and imputing the necessary information for the omitted product attributes using the proposed imputation model. See Alba and Cooke (2004), Rao (2004), and Bradlow et al. (2004) for additional comments on this approach.

5.3.2 *Methods of Category B: Attribute Simplification Methods*

Attribute simplification methods tackle the issue of large numbers of product attributes by grouping the attributes into subgroups, either judgmentally or via factor analysis. The subgroups then become separate clusters of related attributes within the same product, and respondent evaluation centers around these clusters. We discuss three different methods in this section – a staged approach using facets developed by Wind et al. (1989), the Hierarchical Information Integration method proposed by Oppewal et al. (1994); and a method that uses meta-attributes for choice-based conjoint analysis developed by Ghose and Rao (2007). Although in some cases (e.g. Wind et al. 1989) the attribute simplification method does not significantly reduce the number of required profiles unless it is used in conjunction with a fractional factorial design method, it nevertheless allows for the evaluation of a massive amount of product attributes by respondents in a logical and systematic manner that reduces the respondent's cognitive fatigue and at the same time ensures that all required attributes are included in the conjoint task. Another advantage of this method is that the facets also form natural clusters for managerial decision-making relevant to specific subsets of product attributes.

5.3.2.1 Staged Approach for Using Facets

The staged approach to attribute simplification developed by Wind et al. (1989) first involves the identification of subgroups of attributes known as facets, followed by an evaluation (could be ratings or rankings) of the attributes within each facet. In the second stage, a multi-faceted evaluation of a "complete" offering with a full-profile description is then carried out using a fractional factorial design. This method was applied by Wind et al. (1989) in a consumer study that the authors conducted for Marriott, from which the company developed the Courtyard by Marriott chain of hotels.

The purpose of the Marriott study was to establish an "optimal" design of hotel facilities and services aimed at a new segment of consumers (specifically low to mid end business and pleasure travelers) who are not current patrons of Marriott's other hotel offerings in a manner that meets the company's growth and profit objectives. On top of its faceted approach, the study was designed primarily as a hybrid conjoint task (Green 1984), incorporating both self-explicated and fractional design approaches (the hybrid method was described in Chap. 3). In addition, the study involved supplementary analysis of other issues such as consumers' price sensitivities, demographic and psychological characteristics, attitudes, and usage of hotels. From an initial list of 50 hotel attributes, each of which consist of two to eight levels, seven facets were identified, namely: (1) external factors, (2) rooms, (3) food-related services, (4) lounge facilities, (5) services, (6) facilities for leisure-time activities, and (7) security factors. In the evaluation task that followed, respondents were given seven cards, one at a time. Each card represented a facet and contained a ratings task of all the attributes (and attribute levels, including price, if applicable) within that facet. For each attribute level, which are essentially hotel amenity-price combinations, the respondents were asked to provide one of three possible responses: (1) the combination is unacceptable, (2) the combination is most preferred, and (3) the combination is acceptable. The respondents were also asked to rank the relative importance of the various attributes within each facet. All 50 attributes (with a total of 167 attribute levels) were considered. The way the study was designed through the systematic use of facets, however, helped to minimize respondent fatigue and ensured that good responses were obtained.

In the second stage, the respondents were asked to evaluate full profiles of complete hotel offerings that encompassed all facets. In this stage, five cards were shown, one at a time, to each respondent. Each of the seven facets was considered as an "attribute" or experimental factor with five levels each. This gives a total of 5^7 possible hotel profiles, and a computer-aided fractional factorial design procedure (an orthogonal main effects design) was used to reduce the number of profiles to 50. Each set of five cards was balanced within subject and was drawn from the possible set of 50 cards in a manner that ensured respondents received various combinations of the 50 hotel profiles. For each of the hotel profiles received, the respondents were also asked to indicate their likelihood of staying there on a five- point ratings scale. From these data, the partworths of each attribute can be estimated and used to indicate their relative contribution to the respondent's utility from each of the hotel profiles, and the market attractiveness of each hotel profile (essentially a bundle of attributes of hotel facilities and services) can be evaluated.

Despite the extremely large number of hotel attributes (and attribute-levels) that had to be explicitly accounted for in the conjoint task, this staggered, faceted conjoint approach worked well for Marriott. The study's respondents were provided with product alternatives that made sense to them (and were not too difficult to evaluate from a cognitive perspective), the researchers were given access to sufficient data to make unbiased and statistically significant inferences, and Marriot was provided with enough practical knowledge to design a new hotel offering services that met their strategic and tactical objectives. We will describe additional details of the Marriott study in Chap. 6.

5.3.2.2 Method of Hierarchical Information Integration

Oppewal et al. (1994) propose an extended Hierarchical Information Integration (HII) method as an extension of Information Integration Theory to handle the problem of massive number of attributes in conjoint analysis. The theory postulates that individuals categorize product attributes with respect to particular constructs and integrate information about them to form specific impressions of these constructs. They then integrate the separate construct impressions to evaluate the product alternatives (profiles) holistically. The method separates the overall conjoint task into sub-experiments that focus on subsets or clusters of attributes – the results from these sub-experiments can then be analyzed either separately (if managerial decisions need to be made on specific clusters of attributes) or jointly to estimate one overall preference or choice model for the product. Additionally, the validity of the proposed hierarchical structure can also be tested to see if it accurately represents the way respondents make decisions.

The conventional HII approach was first developed by Louviere (1984) and illustrated by Louviere and Gaeth (1987). This approach classifies attributes into a number of distinct sets based on theory, logic, empirical evidence, or the requirements of the practical application, so that the sets represent specific constructs being studied (e.g. "quality" or "value-for-money"). Sub-experiments are then conducted to define each construct in terms of the attributes that make up the construct, and a holistic bridging design based on the constructs that concatenates the results of the various sub-experiments and overall design into one complete utility model that accounts for all attributes is developed. The key advantages of this approach are that it removes the need for self-explicated weights and scale values, are less affected by missing information, and the bridging design is based more on statistical theory rather ad hoc judgment, although the approach is not without its limitations (the reader is referred to Oppewal et al. 1994, p. 92–94, for a more detailed discussion). The extended HII method currently proposed by the Oppewal et al. (1994) aims to extend Louviere's (1984) conventional approach and overcome many of its limitations as well as those of other methods of profile reduction.

To explicate the extended HII approach, consider first the design of the conventional HII choice experiment. Let the respondent's choice be influenced by a set X containing N total attributes. The N attributes are categorized into various subsets that map into various decision constructs. Let there be I constructs, denoted by G_i ($i = 1,\ldots,I$), where each construct is associated with a subset X_i that contains N_i attributes X_{in} ($n = 1,\ldots,N_i$). Each attribute is assumed to match only one construct, hence $\sum_i N_i = N$. A total of $I + 1$ separate sub-experiment would then be designed: one sub-experiment for each attribute setting X_i that defines a decision construct G_i, and one bridging experiment. Respondents in each sub-experiment will only evaluate profiles of attributes from set X_i that defines construct G_i and will ignore the other constructs and attribute sets. They would then evaluate profiles of hypothetical evaluations of all I constructs in the bridging experiment.

The proposed HII method extends the conventional method by including summary measures of the other decision constructs G_j ($j \neq i$) as additional design variables in each sub-experiment. Here, alternatives are described as combinations of attribute levels and construct levels. Since each profile potentially describes all I aspects of an alternative, the respondents' overall evaluations (preference or choice) should provide information about their utilities and preferences regardless of the construct experiment. Although this extension increases the size and complexity of each sub-experiment, it removes the need for the bridging experiment, because the conjoint models estimated from each sub-experiment are theoretically equivalent. The separate sub-experiments can also be concatenated to estimate all attribute parameters simultaneously. To estimate the parameters of each individual sub-experiment, one can use standard techniques like OLS regression for preference data, and MNL regression for choice data. For the single overall model obtained by concatenating sub-experiments, one estimates a common vector of parameters across sub-experiment designs and makes the following assumptions: (1) the same decision process operates in each sub-experiment, (2) any biases induced by separate experiments cancel out across all experiments, (3) error variances are equivalent across tasks. The results from this overall model can be used to predict the utility of new or existing alternatives.

The proposed method of information integrated choice experiments was illustrated within the context of consumers' choice of shopping centers (Oppewal et al. 1994). The respondents consisted of a sample of 396 randomly selected households in Maastricht, The Netherlands. Based on a literature review, interviews, and considerations of manager relevance, a large number of attributes for shopping centers were generated, and these were categorized into four groups based on logical and practical considerations and assumed to correspond to specific decision constructs. They are: (1) Location convenience and accessibility, (2) Appearance layout and furnishings, (3) Selection of stores for food and packaged goods, (4) Selection of stores for clothing and shoes. Each of these constructs cover a series of related attributes (e.g. for location convenience and accessibility, there are five attributes: parking costs, travel time, parking convenience, public transport accessibility, and number of other services, facilities, or offices (e.g. banks, post office). Orthogonal fractional factorial designs were constructed for each sub-experiment, and choice data based on the MNL choice model were collected. MNL models were estimated for the individual sub-experiments. The results of the analysis demonstrate the applicability of the proposed method within the product context under study and show its viability as a method of carrying out a conjoint analysis when dealing with many attributes.

5.3.2.3 Use of Meta-attributes

Ghose and Rao (2007) propose a method to handle the problem of a large number of attributes that assumes that respondents simplify their decision-making task when evaluating products by relying on a few global benefit dimensions (referred to as meta-attributes) rather than each individual attribute (or product feature). It draws upon theory from a number of research streams including decision making, conjoint analysis, and bundling. Unlike the attribute subgroups discussed above that may apply only to a specific product context (e.g. the "rooms" facet in Wind et al. 1989 hotel study) these meta-attributes (e.g. comfort, convenience) are more general and can apply across product categories. Not only does the method reduce the number of profiles needed for the respondent's evaluation task, it also makes the respondent's task easier. Evaluating meta-attributes is usually easier than evaluating physical product features because the latter can be highly technical in nature and would also be highly applicable to the problem of designing new products or re-designing old products based on consumer preferences for these meta-attributes. The proposed method utilizes a (choice-based) conjoint consumer choice model where the alternatives are bundles of meta-attributes, obtained from respondent ratings of the meta-attributes. These meta-attributes were mapped from a corresponding bundle of product features, so the initial design of the choice-based conjoint experiment is based on the bundles of product features. A mapping relationship is then developed that maps the product features into meta-attributes, and optimization involves finding the level of meta-attributes that maximizes the respondent's utility. After this is done, reverse mapping of the meta-attributes is carried out to identify the corresponding optimal levels of product features that can then be used for product design purposes.

The authors illustrate their proposed method using a pilot study on automobile options. Using personal interviews among a small sample, they first identified a small number of meta-attributes for each category. They then determined the mapping between the meta-attributes and physical product features using the ratings data on meta-attributes collected in the main choice-based conjoint study. Additionally, for model comparison purposes, they also collected the same data in another choice-based conjoint study that used only product features and not meta-attributes. For automobiles, they identified 10 product features (each at two levels), in addition to price, to be included in the options package: transmission, GPS, remote keyless entry, seats, temperature control, drive train, rear parking assist warning, voice recognition system, xenon adaptive headlights, and rear view mirror. Five meta-attributes correspond to these features, namely: safety, prestige, comfort, ease of serviceability, and value for money. The pilot results show that the models using meta-attributes outperform those using product features in terms of model fit, suggesting the potential of the method as an alternative to traditional conjoint analysis using product features.

5.3.3 Methods of Category C: Self Explicated Methods

Even when using fractional factorial designs and other methods of reducing the number of profiles for products with a large number of attributes, the number of profiles needed to yield reasonable partworth estimates is sometimes still too large for a respondent to handle. Self-explicated methods of conjoint analysis (and other advanced methods like hybrid, customized, and adaptive conjoint analysis, which will be described in the next section) are developed in part because of this problem.

As described in Chap. 2, self-explicated methods are compositional methods – both the importances of each attribute and desirability levels within each attribute are obtained directly from the respondents and the utility value for any product profile is obtained from a weighted sum of importances and desirability values. While self-explicated methods can greatly reduce the total number of profiles needed for the conjoint task and minimizes profile information overload because the respondent is questioned separately on each attribute, one potential drawback of the method is that it assumes that respondents can provide valid and accurate evaluations of attribute weights that are consistent with their actual preferences and are applicable in the given product context. Various studies (e.g. Akaah and Korgaonkar 1983; Leigh et al. 1984; Agarwal and Green 1991; Srinivasan and Park 1997) have compared the performance of self-explicated methods vis-à-vis other conjoint methods and shown that the former can perform just as well, if not better, in terms of predictive validity and reliability, hence it remains a viable method to use when dealing with a large number of product attributes.

Adaptive methods of conjoint analysis, as the name implies, allow questions to be customized according to respondents' responses to earlier questions. In many cases, it allows more accurate information about respondents' preferences to be obtained because, instead of having all respondents answer a standard set of questions for all attributes (some of which have little to do with the respondent's preferences), the adaptive process brings the researcher closer to the respondent's actual preferences with successive questions. These are decompositional methods and, like regular ratings-based or choice-based methods, estimate the partworths from either stated preferences for a number of profiles or stated choices for a series of choice sets. More on adaptive methods in general will be elaborated under the section on Adaptive Conjoint Analysis under Category D; in this section, we focus specifically on self-explicated and adaptive self-explicated methods.

5.3.3.1 Self-explicated Method

The defining feature of self-explicated conjoint methods is that they involve the gathering of attribute preference data directly from the respondents, though the actual data gathered may differ across respondents (see Wilkie and Pessemier (1973)). Typically, the data gathered include the importance of each attribute to the respondent as well as the desirability of certain levels of the attributes. It can, and usually is, used in conjunction with other conjoint methods like fractional factorial methods and adaptive methods. In this section, we discuss an example of the self-explicated method using the approach proposed by Srinivasan (1988).

Srinivasan (1988) models consumer choice among multi-attributed products using a two-stage process. The first is a conjunctive stage that removes from the respondent's consideration those profiles with totally unacceptable attribute levels. The second is a compensatory stage that trades off remaining products on multiple attributes. The proposed method is shown to have a slightly higher predictive validity compared to traditional conjoint analysis. The specific steps of the approach are as follows.

Information about all the attributes and their levels are first provided to the respondent. Attribute levels that are "totally unacceptable" (meaning the product will be rejected even if all the other attributes are very attractive) are then identified and removed. From the remaining attributes, the most and least preferred levels of each attribute are obtained. The critical attribute that is most preferred is then given an importance rating of 100, and importance ratings (0–100) for other attributes are obtained using the critical attribute as the anchor. Next, ratings of the desirabilities of the different acceptable levels within each attribute are obtained, using the same 0–100 scale. Finally, the partworths for the (acceptable) attribute levels are calculated by multiplying the importance rating with the desirability rating. For convenience, these partworths can be reset to the same 0–100 scale by dividing them by 100.

The proposed method is illustrated in an empirical application within the context of MBA students choosing among job offers. With a sample size of 85, the study was done through a series of questionnaires. In the first questionnaire, respondents were given information on job attributes and levels and asked to state the relative importance of the factors by assigning each factor a score ranging from 0 (not at all important) to 100 (extremely important). The eight factors (attributes) considered are: business travel, region, company's growth rate, advancement opportunity, functional activity, local environment, salary, and people, and comprise of two to six levels each. Two weeks after the first survey, a second questionnaire was sent to respondents to collect the data for conjunctive-compensatory self-explicated preference measurement as described above. From this survey, the totally unacceptable factors were removed, and the importance and desirability ratings for the remaining acceptable factors were obtained. Finally, 4 months after the second survey, a third questionnaire was sent to the respondents to collect information on the job offers received by the respondents and the jobs they accepted so as to validate the proposed preference measurement method. Only 54 respondents out of the original 85 responded to this survey, out of which nine had received only a single job offer. The remaining 45 respondents thus constitute the prediction sample. In this sample, the third questionnaire provided the levels of the eight attributes for each of the job offers, and the conjunctive-compensatory preference data from the second questionnaire was used to predict which offer would be chosen. This prediction was then compared with the offer that was actually chosen by each respondent. Twenty-seven percent of the respondents had received one or more offers that the conjunctive model predicted to be unacceptable, and none of the respondents chose any of the unacceptable offers, thereby providing strong empirical support for the predictive validity of the conjunctive stage of the model and the method used to measure the unacceptable levels.

Additionally, the author also examined the predictive validity of the proposed approach to measuring attribute importances relative to a "random" model (i.e. a model that makes random predictions – for e.g. if a respondent had two job offers, the random chance that a prediction would be correct is 50 %) as well as a model that assumed equal importance weights. The results show that the proposed approach outperforms these models in terms of predictive validity.

5.3.3.2 Adaptive Self-explicated Method

As the readers know, the self-explicated method requires information on attribute importances.[4] Two methods used in practice to obtain attribute importances information in the self-explicated method are: ratings and constant-sum allocation. Both these methods have limitations for a study with a large number of attributes (say over 10). While rating attribute importances, respondents may consider every attribute to be important and one will not be able to capture the attribute tradeoffs well. The constant sum allocation method overcomes this limitation but the task becomes onerous for respondents to complete. Netzer and Srinivasan (2011) developed a technique called the adaptive self-explicated method (hereafter ASE, pronounced as ACE) to deal with this issue. In the web-based implementation of this method, the respondent is asked to rank order the attributes in terms of importance and then is asked to provide a sequence of constant sum paired comparisons in an adaptive manner (not two partial product profiles at a time as in ACA or FPM). Thus, the task becomes simpler than performing a constant sum task across all attributes because of the reduced number of questions and it also provides standard errors for attribute importances.

The various steps involved in the mechanics of this method[5] are as follows: (1) Ask the respondent to initially rank the J attributes in terms of importance and re-label the attributes as 1 for the most important attribute, 2 for the second most important attribute etc.; (2) Ask three questions to compare the attribute ranked first with the attribute ranked last; the attribute ranked first with the attribute ranked middle (i.e., the attribute ranked $(J + 1)/2$ for odd J or the attribute ranked J/2 for even J); and the attribute ranked middle with the attribute ranked last and elicit constant sum scores for each pair (3) Estimate the importance of the attributes ranked 1st, last, and in the middle $(J + 1)/2$ using a log-linear regression[6];

[4] This discussion is based on the article by Netzer and Srinivasan (2011), “Adaptive Self-Explication of Multi-Attribute Preferences”,

[5] The authors also tested a method called fixed orthogonal approach to elicit attribute importance scores; but, the method of ASE described below is superior.

[6] For this regression, let r_{1J}, r_{1M}, r_{MJ} be the constant sum values for the three pairs (1J); (1M) and (MJ) (M is the middle attribute). Further, let $V_j = \log(W_j)$, where Wj is the importance weight for the j-th attribute. The equations for regression are: $V_1 - V_J = \log(r_{1J})$, $V_1 - V_M = \log(r_{1M})$, and $V_M - V_J = \log(r_{MJ})$. The predictors in this regression are zero, +1 or −1 depending on the pair. For scaling, we can fix V_1 at some positive value a. This regression will yield estimates of V_M and V_J as well as their standard errors.

Table 5.3 Attributes and levels for the ASE digital cameras study

Feature	Levels
1. Brand	Canon, HP, Nikon, Olympus, Sony
2. Battery life	150, 300, 450, 600 pictures
3. Built in memory	8MB, 16MB, 32MB
4. Camera size	Pocket size, medium size, SLR size
5. LCD size	1.5, 2, 2.5 in.
6. Light sensitivity	100–200, 100–400, 100–600 ISO
7. Optical zoom	2X, 3X, 4X, 5X
8. Price	\$500, \$400, \$300, \$200
9. Resolution	2, 3, 4, 5 MegaPixels
10. Shot lag	3 s, 2 s, 1 s
11. Video clip	Not included, included
12. Warranty	No Warranty, 1–3 years warranty

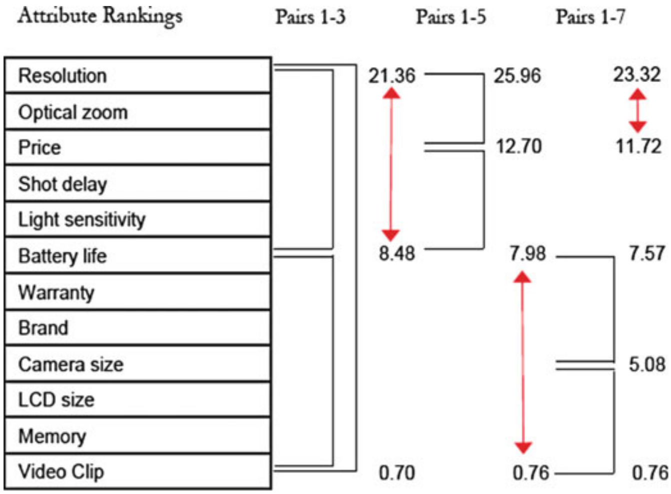
Source: Reprinted with permission from Netzer and Srinivasan (2011), published by the American Marketing Association

(4) Select[7] one of the two intervals – between the first ranked attribute and the middle ranked attribute and the middle ranked and the last ranked attribute – and repeat the paired comparison task with respect to the top and bottom and middle attribute of that interval and the OLS estimation; and (5) Repeat Step (4) iteratively until the number of preset paired comparison questions is reached or until the t-ratio for the difference of W-values in an interval is below a pre-specified value.

The authors designed a computer-aided procedure to implement this method. The illustration was for digital cameras; the list of attributes and levels chosen are shown in Table 5.3.

Figure 5.1 shows how the adaptation is done for this application; the computer asked three paired comparison questions comparing the highest ranked attribute (resolution) for this respondent with the lowest ranked attribute (video clip), the highest ranked with the middle ranked (battery life), and the middle ranked with the lowest ranked. The log-linear regression estimates of the importance for resolution, battery life, and video clip are also shown in Fig. 5.1 as the first column of numbers (these numbers are scaled in such a way that the importance for these three attributes together with those of the remaining nine attributes obtained through interpolation add to 100). Based on the estimates from the first iteration, the algorithm evaluates which interval to open next, Resolution – Battery Life or Battery Life – Video clip. The first interval of resolution and battery-life is 12.88 (= 21.36 − 8.48) units with four intermediate attributes. The second interval of battery – life and video – clip is 7.78 (= 8.48 − 0.70) units and the number of intermediate attributes is five. Thus, following the interval choice criterion in Step (4) above, the algorithm opened the interval Resolution – Battery Life. Price (the attribute at the middle of that interval) was chosen as the next attribute resulting in two paired comparison questions: (Resolution – Price) and (Price – Battery Life).

[7] The choice of the interval is based on the criterion of minimizing the maximum possible interpolation error, which is akin to the area of the triangle between the linear interpolation and the horizontal and vertical lines defined by the top and bottom attributes.



*The lines connect the paired comparison questions asked at each stage. The arrows represent the interval to be opened in the next step. The numbers are the estimated importances following every pair of paired comparison questions.

Source: Netzer, Oded and V. Srinivasan (2011), "Adaptive Self-Explication of Multi-Attribute Preferences", *Journal of Marketing Research*, 48 (February), 140-156.

Fig. 5.1 An example of the adaptive process for selecting the first seven paired comparison questions (The *lines* connect the paired comparison questions asked at each stage. The *arrows* represent the interval to be opened in the next step. The numbers are the estimated importances following every pair of paired comparison questions; Source: Netzer and Srinivasan (2011))

The algorithm then used log-linear regression to estimate simultaneously the importances of all four attributes (the original three plus price) from the five paired comparisons collected so far. These numbers are reported as the next column of numbers in Fig. 5.1. At the next iteration there are three intervals: (a) Resolution – Price, (b) Price – Battery Life, (c) Battery Life – Video Clip. While (a) has the largest gap between the top and bottom in terms of importances, (c) has the largest number of intermediate attributes. Following the interval choice criterion in point (4) above, the algorithm chose the interval (c). This procedure is repeated until the stopping criterion is reached.

The authors applied the ASE method in two empirical studies (of choices of job offers by MBA students and preferences for digital cameras) and compared the predictive validity relative to some other methods.

The validation results for the MBA job choice study (as measured by % of job choices correctly predicted) were 65.9 % for the Fixed orthogonal design self-explicated method as compared to 61.1 % for the Adaptive Conjoint Analysis showing a slightly higher (not statistically significant) predictive validity compared to Adaptive Conjoint Analysis. Both the validation results are substantially and statistically significantly ($p < 0.001$) better than the percentage of choices correctly predicted by random choice (36.2 %).

We will now describe the second application in some detail. Based on pretest and consulting search sources, the authors selected 12 attributes of digital cameras each with varying levels as shown in Table 5.3. They implemented the ASE method as described before and compared its predictive validity against three other methods; these methods are Sawtooth Software's Adaptive Conjoint Analysis (ACA), the adaptive Fast Polyhedral Method[8] (FPM; Toubia et al. 2004) and the Self-explicated method (SEM). In addition, the data were estimated using Hierarchical Bayesian methods for comparison. The study was implemented among 151 respondents who were recruited through the behavioral lab of a West Coast university in 2004. Subjects were randomly assigned to one of three preference measurement conditions: ASE ($n = 52$), ACA ($n = 49$) and FPM ($n = 50$). The SEM method was a precursor for the methods of ACA and FPM and has a sample size of 99.

Respondents first completed a validation task, described subsequently. Following the validation task, respondents completed the preference measurement task. This method may have reduced any possible effect of the preference measurement task on the validation task and the reverse bias of the validation task influencing preference measurement is possibly minimal because all the methods first measured the relative desirabilities of all the levels of all 12 attributes (with a total of 42 levels) right after the validation task. A post survey evaluation included ratings of the preference measurement task in terms of difficulty, clarity, enjoyment, and perceived ability to capture one's preferences and subject's background characteristics such as age, gender, familiarity, and ownership of digital cameras.

The estimation methods were in accordance with the procedure described for ASE, procedures implemented in the Sawtooth's software for ACA, and the procedures developed by Toubia et al. for the FTP method (the reader is encouraged to consult the original article for specific details). The validation task (common for all the three methods) involved each respondent ranking the four digital cameras (described on the 12 attributes) in terms of their preferences in each of the two choice sets randomly chosen from the four possible choice sets.[9]

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[8] The open source code in http://mitsloan.mit.edu/vc was used to implement the FPM adaptive survey and estimate the partworths using the analytical center approach and the Sawtooth's SSI-Web Version 3.5.0 was used for the ACA questionnaire design and estimation. This method was described in Chap. 3.

[9] The researchers ensured that each choice set was Pareto-optimal (i.e., none of the cameras within the choice set dominated any other) using detailed procedures (e.g. first creating 64 profiles using fractional factorial design, random sampling of 100 choice sets of four profiles each, eliminating choice sets with more than four ties of attribute levels for at least one pair of alternatives or choice sets had at least one identical attribute level across the four alternatives. From the remaining choice sets we chose four choice sets that minimize the Kendal Tau measure. The Kendal Tau statistic for each pair of alternatives A and B is calculated as

$$\tau = \sum_{j=1}^{J} |I\ (LjA) - I(LjA)|\ /\sum_{j=1}^{J} (\ J - I(LjA = LjB))$$

where LjA and LjB are the levels of profiles A and B on the jth attribute and I is the indicator function which take the value 1 if the condition is true and 0 otherwise

Table 5.4 Comparison of individual-level predictive validity: ASE study on digital cameras

	Choice set hit rates		Pairs hit rates	
Method[a] (sample size)	Mean	Std. error	Mean	Std. error
ASE (n = 52)	0.606	0.050	0.718	0.024
ACA (n = 49)	0.398	0.044	0.641	0.024
FPM (n = 50)	0.440	0.049	0.655	0.020
SEM (n = 99)	0.449	0.034	0.666	0.015
ASE/HB (n = 52)	0.644	0.052	0.727	0.024
ACA/HB (n = 49)	0.408	0.050	0.658	0.024
FPM/HB (n = 50)	0.480	0.051	0.687	0.020

Source: Reprinted with permission from Netzer and Srinivasan (2011), published by the American Marketing Association
[a]HB refers to hierarchical Bayesian estimation method

Table 5.4 shows the predictive validity results complied from individual level hits for the three methods using two methods of estimation (regression and Hierarchical Bayesian method). These results show that ASE method using the regression estimation method was able to predict the highest ranked alternative in 61 % of the choice sets and the pairs hit rates in 72 % of the pairs. These hit rates were substantially and significantly higher than those of the other two methods with an improvement in the order of 35–52 %. Also, ASE showed considerable improvement over the standard SEM approach. Further, the authors found that the ASE method did not underestimate the importance of the price attribute (as could normally be expected due to social sensitivity of the responses for price). Based on the post survey feedback, the researchers found no significant difference in terms of perceived task difficulty for the three methods. In summary, we think that the ASE method offers high potential for handling large number of attributes.

5.3.4 Category D: Methods Combining Several Approaches

The self-explicated methods described in the previous section use a compositional approach to obtain partworths by multiplying the importance weights by the attribute-level desirability ratings. However, this method can have several major problems (Green and Srinivasan 1990): (1) ambiguity of the importance measurement, (2) additive partworth assumption, (3) double counting for similar attributes, (4) accuracy of the linearity of desirability ratings for quantitative attributes, and (5) unavailability of likelihood evaluations. To cope with these limitations, methods that combine self-explicated with other approaches have been developed. They can be classified into (1) hybrid conjoint analysis (Green et al. 1981), (2) customized conjoint analysis (Srinivasan and Park 1997); and (3) adaptive conjoint analysis (Johnson 1987).

The choice set's overall Kendal Tau is calculated by averaging the Kendal Tau across the 6 pairs of alternatives in each choice set of four options.

5.3.4.1 Hybrid Conjoint Analysis

Green et al. (1981) proposed a hybrid model that combines both compositional (self-explicated) and decompositional (conjoint) approaches, with the purpose of overcoming the limitations in the self-explicated method and the information overload problems in the full-profile method. The key distinction between compositional and decompositional approaches is in parameter estimation; in the former approach the importance weights and desirability scores are directly given by respondents, while in the later approach, parameters are estimated from statistical analysis, described this approach in Chap. 3. See also Moore and Semenik (1988) for discussion on the strong cross-validation evidence for the hybrid method; further these authors found that complexity of the design (due to large number of attributes) did not lead to higher cross-validation for the hybrid methods relative to traditional ratings-based confined to methods.

5.3.4.2 Customized Conjoint Analysis

A second alternative of combining the self-explicated method and full-profile approach is customized conjoint analysis (CCA), developed by Srinivasan and Park (1997). This approach first utilizes the self-explicated method to identify those important (core) attributes and then conducts a full-profile conjoint analysis customized to the respondent's core attributes. Similar to the hybrid method, customized conjoint analysis also involves the self-explicated task in the first stage. The two approaches are different in that the full-profile conjoint analysis in the CCA is customized to each person while in the hybrid method it is universal to all respondents.

Customized conjoint analysis includes three stages. The first stage uses the self-explicated method for data collection and is composed of three parts. The first part identifies attribute levels that would be unacceptable to respondents, obtains the desirability ratings of all levels, and collects attribute importance ratings. The attribute importance here is defined as the value of the improvement from the least preferred but acceptable attribute level to the most preferred level. The second part calculates the self-explicated partworths for acceptable attribute levels by multiplying the importance ratings by the desirability scores. The third part selects the most important attributes for the full-profile conjoint analysis to be conducted in the next stage.

In the second stage (conjoint analysis), a fractional factorial design is used to construct profiles based on the selected small number of acceptable levels for each of the core attributes. The validation profiles are constructed in a similar way. With the stated preference data (obtained as rankings or ratings) collected on these full profiles, the partworths are estimated and rescaled so that they are comparable to the self-explicated partworths.

The third stage combines the self-explicated and conjoint partworths for the core attributes to obtain the weighted partworth P^w_{ijk} in the following equation:

$$P^w_{ijk} = w_i P^c_{ijk} + (1 - w_i) P^s_{ijk}$$

where P^c_{ijk} is the partworth from conjoint analysis for the individual i for attribute j and level k and P^s_{ijk} is the corresponding partworth value obtained from self-explicated method. The weight w_i is identified through the following optimization method. Different weights from 0 to 1 with a small increment, e.g. 0.01, are simulated in calculating the weighted partworths, which are then used to predict the preferences for the validation set. The optimal weight w_i^* is the one that gives the highest cross-validity. Let C_i denote the set of the core attributes for respondent i and NC_i denote the set of the remaining non-core attributes. The final model for predicted preference of individual i toward new stimulus (product) with level k_j for attribute j is composed of two components as follows:

$$U_i = \sum_{j \in C_i} \left[w_i^* P^c_{ijk} + (1 - w_i^*) P^s_{ijk} \right] + \sum_{j \in NC_i} P^s_{ijk}$$

where the first component represents the utility contribution from those core attributes that are the weighted partworths from self-explicated and conjoint methods, and the second component represents the utility contribution from those non-core attributes which simply come from the self-explicated method.

An empirical application was conducted in the context of MBA students choosing among job offers. The self-explicated preference data are collected with a computer-assisted telephone interview. Four of the most important factors, varying from person to person, from the eight job attributes are chosen as core attributes for each respondent. Based on these four core attributes, the authors then construct 18 profiles for calibration and 6 profiles for validation through fractional factorial designs customized to each respondent. The second stage conjoint data collection was conducted 2 weeks after the first stage self-explicated method. Rank orders were collected for these profile evaluations separately in calibration and validation sets. The optimal weight that leads to highest cross-validity was used for each respondent. The partworths from conjoint analysis receive higher weights for the majority of respondents. To evaluate the predictive validity of the customized conjoint analysis, the authors compared the proposed approach with the self-explicated and conjoint methods. Surprisingly, the self-explicated method gave the best predictive validity. In addition, the self-explicated method using only the core attributes also predicted slightly better than full-profile conjoint analysis that also uses core attributes only.

5.3.4.3 Adaptive Conjoint Analysis

To cope with problems arising from large number of levels and attributes in traditional conjoint methods, Johnson (1987) develops adaptive conjoint analysis (ACA), a data collection technique that combines self-explicated importance ratings with pair-wise trade-off tasks and full-profile conjoint analysis. The approach is named "adaptive" because the computer-administered interviews are tailored to each respondent and each question is continuously updated and chosen based on respondent's previous answers to provide the additional information most efficiently. We described this method in Chap.2.

An interview with ACA involves the following four steps (as described in Green et al. 1991). First, respondents rank their preferences for each level of each attribute and select those levels that are completely unacceptable to them. Those relatively unimportant levels of attributes can be eliminated to reduce the length of the questionnaire. Second, given their best and worst levels obtained from the first section, respondents provide importance ratings for each attribute. Third, respondents are asked a number of "trade-off" questions, which are pair-wise partial profiles composed of two to five attributes. For each paired comparison, respondents indicate which of the two profiles is preferred and by how much. This is the "adaptive" stage, where the computer updates its estimates of the respondent's utilities, and uses this new information to choose the next question. Preliminary estimates of the respondent's utilities before this stage are made to serve as priors for a Bayesian updating process. In the last step, respondents are asked to provide evaluations, for example, on a 0–100 likelihood-of-purchase scale, for some full profiles which are chosen by the software. The utilities can be estimated by either least squares or hierarchical Bayes methods.

Several studies compared the validity of ACA with full-profile and self-explicated methods, but the results were mixed. Finkbeiner and Platz (1986) compared ACA with the full-profile conjoint method in the context of checking accounts. Their results showed that both methods are similar in terms of predictability. Although the six-attribute study showed that ACA took longer than the full-profile method, the authors suggested the use of ACA for a study with much larger number of attributes for time efficiency. Huber et al. (1993) also conducted a study in which each respondent completes both full profile ratings and ACA judgments on refrigerators for similar purposes. Their results showed that adaptive conjoint analysis, besides having the advantages of training opportunity and being more enjoyable to respondents, also performed better than the full-profile method. Green et al. (1991) compared ACA with simple self-explicated method and found that the latter method out-predicted the ACA approach, although Johnson (1991) suggested that their results might be due to a failure in controlling the order of the task. At this point, the issue is still worth further investigation.

A comparison of various features of the three approaches: (1) hybrid conjoint analysis, (2) customized conjoint analysis, and (3) adaptive conjoint analysis is shown in Table 5.5. All three approaches combine self-explicated and full-profile methods. The interaction effects between levels of attributes can only be modeled in the hybrid approach. However, the CCA and ACA approaches are customized at the individual-level while the hybrid approach can make adjustments to the partworths from self-explicated method at the segment-level. In terms of attractiveness and involvement of respondents, the computer-interactive ACA was found to be the best approach among the three. Some existing studies showed that the hybrid approach outperformed self-explicated method, while the CCA and ACA outperformed the full-profile method.

Table 5.5 A comparison of hybrid, customized, and adaptive conjoint analysis

	HCA (hybrid)	CCA (customized)	ACA (adaptive)
Combining self-explicated method	Yes	Yes	Yes
Combining full-profile method	Yes	Yes	Yes
Modeling main effects	Yes	Yes	Yes
Modeling interaction effects	Yes	No	No
Customized to each respondent	No	Yes	Yes
Computer interactive	No	No	Yes
Attractive to respondents	No	No	Yes
Outperforms self-explicated method	Yes	No	No
Outperforms full-profile method	No	Yes	Yes

5.3.4.4 Bridging Methods

The main idea of bridging methods is to divide the large number of attributes into smaller subsets and put some common attributes in all these subsets. These common attributes are then used as connectors to bridge these subsets into one complete master design. The bridging methods help overcome the information overload problem arising from a large number of attributes/factors. Baalbaki and Malhotra (1995) applied the bridging methods to measure the impact of marketing management variables on the degree of standardization of international marketing strategy.

The general design of bridging methods can be summarized into the following five steps: (1) selecting common bridging factors which will appear with equivalent numbers of levels and identical labels in all sub-designs; (2) dividing the total number of factors into several small subsets and letting each subset contain the selected bridging factors; (3) creating a separate design for each subset; (4) asking respondents to examine all factors and give importance ratings to each factor; (5) asking respondents to examine and rate each set of profiles in the sub-design separately where a small number of profiles are selected according to a fractional factorial design.

The data analysis for bridging methods includes three steps. First, each sub-design is analyzed separately to obtain the partworths for each of the factors in that particular sub-design. Second, all sub-designs are bridged (using a software called "BRIDGER" developed by Clark Software Inc.) to compose an overall master design. Note that only two sub-designs are bridged at a time. Finally, after all sub-designs are bridged together, the partworths of each factor level and relative importance of all factors in the master design can be obtained using CONJOINT ANALYZER.

In their study, Baalbaki and Malhotra selected two common bridging factors (attitude toward foreign products and competitive environment) among the 18 factors that may influence the standardization decision of international marketing strategy. Four separate designs were developed and each design includes six factors, two of which are common across all designs. After respondents provided their importance ratings on a 7-point scale for all 18 factors, they were then asked to examine four set of profiles corresponding to one of the four designs. Each set contained 12 profiles, 8 of which were used for model calibration and the rest were used for validation. In order to control for the order effects, the sequence of the four conjoint designs was randomized. Based on the 74 received and qualified questionnaires, the data were analyzed at the individual level, the segment level, and aggregate level with CONJOINT ANALYZER. The authors tested both internal and external validity and showed satisfactory results. In addition, the reliability of partworths for the bridging factors across different designs is examined. The stable correlations between partworths across the four designs showed that the partworths were reliable over the changes in the designs. It should be pointed out that as the number of bridging factors increased, the reliability also increased. However, there has not been much empirical research on comparing bridging methods with the other aforementioned methods in dealing large number of attributes.

5.3.5 Category E: Upgrading Methods

5.3.5.1 Upgrading Conjoint Method

The upgrading method is a new web-based method that collects incentive-aligned conjoint data.[10] This method combines the merits of the conjoint approaches of self-explicated method and choice-based method. Briefly, the upgrading method first endows a subject with a product profile and a budget, and allows the subject to upgrade it, one attribute at a time, to a more desirable product configuration. In this data collection process the respondent states one's willingness to pay (WTP) for each potential upgrade (or more desirable levels of an attribute) of interest to him or her. Subsequent application of the BDM procedure (Becker et al. 1964) ensures that it is in the best interest of a subject to state truthfully WTP. Subjects will receive their upgraded product by the end of the study after the rounds of upgrading. The authors (Park, Ding and Rao) implemented this procedure on the Web in an empirical implementation with digital cameras. This procedure is shown to significantly improve the predictive validity. Given the recency of this method, we will describe in detail some aspects such as the method design and empirical results from one study subsequently.

Upgrading Method Design: In this procedure, a subject can undertake several sets of upgrading of attributes. In any upgrading set, a subject will be endowed with a particular version of the product. The subject will then attempt to upgrade it to a more desirable product configuration. The upgrading procedure[11] is organized such that a subject can only upgrade one attribute at a time (round), and only have one

[10] This material is drawn from the article, Park et al. (2008).

[11] We describe below one possible implementation of upgrading method used in the empirical study reported in the published paper. Alternative implementations are possible and are discussed later in this section.

chance to upgrade any specific attribute. The method is implemented at the individual level, over a web-interface, which allows for dynamic customization of data collection based on each subject's responses and outcomes as they evolve.

Specifically, the steps involved in an upgrading set are shown in Fig. 5.2. First, a subject accesses the survey instrument via a web browser (e.g., Internet Explorer). In the survey, the subject is endowed with a (bare bone) configuration of the product and is shown all attributes that are available for upgrading (with ability to upgrade only once for each attribute), and is asked to select the attribute to upgrade next. Then, the subject is shown all levels in that attribute, and is asked to state one's willingness to pay (WTP) to upgrade from her current level to each of the levels of interest for that attribute. The computer then randomly generates a cutoff price for each level, and determines whether a level is upgradeable (defined as when the stated WTP for this level is larger or equal to the randomly drawn cutoff price for the same level). The product is not upgraded if no level is upgradeable, otherwise it will be upgraded to one of the upgradeable levels (randomly chosen by the computer), but only pays the randomly chosen cutoff price for the upgraded level. These upgrading steps are repeated until the subject has upgraded all attributes of interest to, or the subject decides not to upgrade on remaining attributes.

At the end of the upgrading, a subject will receive her final upgraded configuration of the product, and pay the cumulative cost of the upgrades she has made. Following the standard practice of experimental economics, we recommend endowing each subject with an amount of cash at the start of the study, and the cost of upgrading is then subtracted from this cash endowment[12] (thus a subject does not need to take money out of her own pocket). The actual upgrade for any attribute is determined according to the Becker-DeGroot-Marschak (BDM) (1964) procedure, which involves drawing a random number from a uniform distribution (with the range relevant to the possible amounts for the WTP values) and if the number drawn is higher than the stated WTP, the subject will not be able to purchase the item, but if the number drawn is lower than or equal to the stated WTP, the subject will be able to purchase the item but pay only the randomly drawn number (price). These steps will ensure that the method of eliciting the WTP values for attribute levels is incentive compatible.[13] The authors compared this method with that of the self-explicated approach[14] in the empirical study.

[12] If the product under study is expensive and endowing every subject is not financially feasible, a lottery mechanism may be used to determine which participant will end up receiving the final product (which is what was done in the Park et al. 2008 paper).

[13] There are several issues about the implementation of this general procedure that are discussed in the Park et al., *JMR* (2008) paper and interested readers should consult that article.

[14] The self-explicated approach directly provides unbiased individual-level estimates because each subject is expected to state the desirability of each level for a given attribute and the importance of each attribute. Under the upgrading approach, on the other hand, WTP data are not collected for some attributes/levels for some subjects. The hierarchical Bayesian estimation employed in the *JMR* (2008) paper yields estimates of WTP values for all levels and for all attributes because of the ability to share data across subjects in the sample.

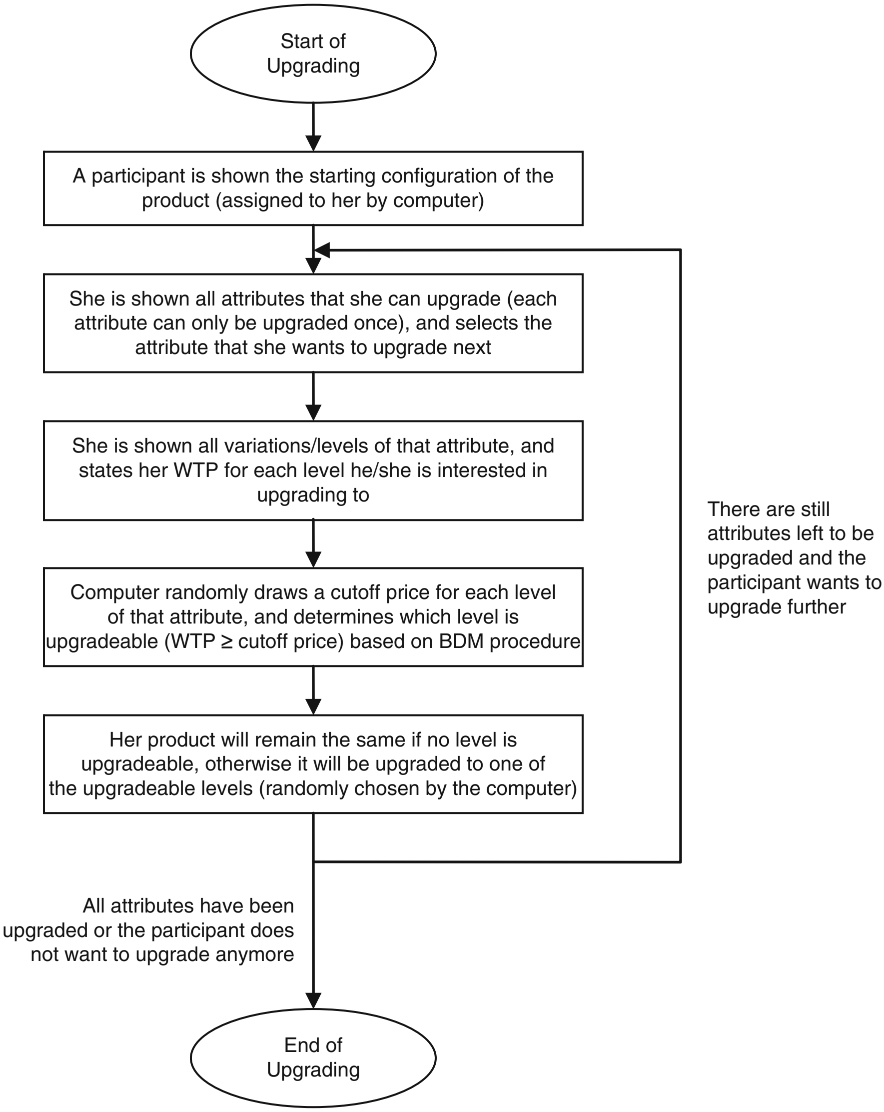

Fig. 5.2 Upgrading method (flowchart for one set of upgrading) (Source: Reprinted with permission from Park et al. (2008), published by the American Marketing Association)

Empirical Study: In order to validate the upgrading method empirically, the authors conducted a within-subject contrast experiment between the upgrading method and the benchmark self-explicated approach. The researchers selected digital cameras the product category for this study for because of the familiarity of the student subjects with the category and its relevance to them. The category also is technically complex with a large number of attributes and levels and is suitable for testing the upgrading approach.

Based on a comparison search at Bestbuy.com, the authors selected the 11 most important product attributes with a total of 60 attribute levels across the 11 attributes: 10 levels for optical zoom, 9 levels for brand, 7 levels for Weight, 5 levels for Resolution, Warranty-Parts, Warranty-Labor, Focus Range, Viewfinder Size, 3 levels for Text Overlay, Video, and Flash Range (see Table 5.6 for a detailed description of the attributes and levels). A total of 88 subjects at a major U.S. university participated in the study in a campus computer lab.

Each subject in the experiment completed four tasks: self-explicated task, upgrading task, external validity task, and a brief survey on oneself and the experiment. The general instructions contained directions for the experiment, a description of the attributes and levels to be used in the experiment and a glossary explaining the terms used to describe the attributes and levels. Each subject received $7 for participating in the study. Further, the researchers randomly selected one subject out of every 40–50 subjects and gave away a digital camera (the specific configuration of camera was determined by her choice/outcome in the upgrading method and external validity task) and some cash (the difference between $400, the maximum a student subject was willing to pay for a digital camera and the price of the digital camera received). This feature ensures incentive-alignment. In addition, the Becker-DeGroot-Marschak procedure was applied to guarantee that respondents state their true WTP.

The self-explicated task was designed following the standard format in the literature (Green and Srinivasan 1990) discussed in Chap. 2. Subjects evaluated one attribute at a time, how desirable each level within this attribute was by assigning a number between 1 and 10 to each level, with the most preferred level as 10 and the least preferred level as 1 and rated the importance of attributes by allocating a total of 100 points to all attributes.

The upgrading task closely followed the theoretical design described in the previous section and each subject completed two mandatory sets of upgrading, with the option to do as many additional sets of upgrading as they wanted to. The external validity task (for the predictive validity test) had two choice questions. In each choice question, a participant evaluated 17 different digital cameras, and decided which camera she would like to buy. To make the choice task more natural, the option of not buying any of the cameras was included. A subject who selects a no purchase option was excluded for the validation purpose, as the self-explicated approach does not predict this outcome. The profiles of digital cameras in the first choice question were generated using the SAS experiment design macros (or the OPTEX procedure) to ensure objectivity, and after eliminating clearly dominant profiles. The profiles of digital cameras in the second choice question were generated from real digital cameras from *Bestbuy.com*. Finally, subjects completed

Table 5.6 Attributes and levels for the digital camera study (upgrading method)

	Attribute	Total levels	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10
1	Brand	9	Canon	Fuji	HP	Kodak	Minolta	Nikon	Olympus	Samsung	Sony	–
2	Resolution	5	4 mp	5 mp	6 mp	7 mp	8 mp	–	–	–	–	–
3	Optical zoom	10	1×	2×	3×	4×	5×	6×	7×	8×	9×	10×
4	Warranty – parts	5	6 months	12 months	18 months	24 months	36 months	–	–	–	–	–
5	Warranty – labor	5	6 months	12 months	18 months	24 months	36 months	–	–	–	–	–
6	Focus range	5	1–6″ to inf	6–12″ to inf	13–18″ to inf	19–24″ to inf	24–36″ to inf	–	–	–	–	–
7	Viewfinder size	5	1.0″	1.5″	2.0″	2.5″	3.0″	–	–	–	–	–
8	Text overlay	3	No	Date	Date and time	–	–	–	–	–	–	–
9	Video	3	No	Video only	Video and audio	–	–	–	–	–	–	–
10	Weight	7	3–4 oz	4–5 oz	5–6 oz	6–7 oz	7–8 oz	8–9 oz	9–10 oz	–	–	–
11	Flash range	3	< 8′	8–12′	12–18′	–	–	–	–	–	–	–

Source: Reprinted with permission from Park et al. (2008), published by the American Marketing Association a brief survey on their general experience with cameras as well as feedbacks on the study.[15]

Analysis: The data from the self-explicated approach was used directly to compute the utility of items in the validation tasks for each of the 88 subjects.

The researchers analyzed the data from the upgrading method, using a random-effects hierarchical Bayesian logit model, similar to the model specified by Allenby et al. (1998); as described in Chap. 4. Assuming a linear utility specification, the probability that the *i*-th subject chooses the *k*-th alternative (the profile after potential upgrade) from the *j*-th pair (including both profiles before and after potential upgrade, plus the amount of offer made for the profile before upgrading) is given by[16]

$$p_{ij}^{k} = \frac{\exp\left(\beta_i^T x_{ij}^{k}\right)}{\sum_{l} \exp\left(\beta_i^T x_{ij}^{l}\right)},$$

where x_{ij}^{k} (including the stated amount of offer if applicable) describes the *k*-th camera by the *i*-th subject from the *j*-th pair, and β_i is a vector of the partworths for the *i*-th subject. We assume a hierarchical shrinkage specification for the individual partworths, where a priori,

$$\beta_i \sim N(\bar{\beta}, \Lambda).$$

This specification allows for estimation of partworths β_i at the individual-level, and the aggregate or average partworth, $\bar{\beta}$, as well as of the amount of heterogeneity (Λ), assumed to be diagonal. Diffuse priors were used for the average amount of offers

[15] A subject completed an average of 2.67 sets of upgrading (std. dev. = 0.77, max = 5.00) indicating significantly higher interest than what was mandatory in the upgrading approach. The average amount of offers made across all 11 attributes is \$33.09 (std. dev. = \$30.25) and 3.02 offers for upgrading in a given attribute (std. dev. = 2.07). The average time to complete one set of the upgrading method was 332 s, compared to 426 s for completing the self-explicated method. Also, subjects understood well the details of the upgrading task; the average responses from the subjects is 4.06 (on a scale from 1 to 5, with 1 being not clear at all and 5 being extremely clear). They found the upgrading method to be more stimulating than the self-explicated method (p-value = 0.00 on the paired-t test).

[16] If an attribute has 4 levels (e.g., A, B, C, and D), a participant started with level A, and is interested in upgrading to C or D (but not B), she will state one offer (say, \$10) for upgrading to level C and one offer (say, \$15) for upgrading to level D. In this example, the researchers inferred two paired comparisons. That is, the subject's utility for the product profile before upgrading (with level A on the attribute) plus \$10 is less than his or her utility for the upgraded product (with level C on the attribute). Similarly, her utility for the product profile before upgrading (with level A on the attribute) plus \$15 is less than her utility for the upgraded product (with level D on the attribute).

made for each attribute level and the researchers ensured that the algorithm for the Markov Chain Monte Carlo analysis converged properly.

The mean (and standard deviation) of self-stated partworths from the self-explicated method and partworth estimates from the upgrading method are shown in Table 5.7. The partworths from the upgrading method can be interpreted in dollar value as the preferences for the levels and those from the self-explicated approach are relative measures. Therefore, while no direct comparison between these two sets of partworths is possible, their preference order for levels within an attribute can be compared. For most attributes with uniform directional benefit (either more is better or less is better), the preference order of the partworths across the levels within an attribute is remarkably similar between the two methods. Some interesting comparisons can be observed from Table 5.7. The upgrading method, however, appears to recover nonlinear preference, compared to the self-explicated method.[17] Further, it is worth noting that for the attribute of brand, the rank order of the levels is remarkably similar between the self-explicated method and the upgrading method and almost identical for the more preferred levels.

Regarding the important comparison of predictive validity, the researchers implemented holdout tasks with 17 different digital cameras, which is more realistic than using smaller choice sets. Figure 5.3 shows the results for the two holdout tasks mentioned earlier. The upgrading method leads to significantly better predictive performance: the percent of matches between the actual choice and the top predicted option are 42 % for the first holdout task (computer-generated profiles) and 26 % for the second holdout task (Bestbuy.com profiles) under the upgrading method, versus 27 % and 19 % under the self-explicated method, respectively. Note the baseline prediction in a naïve model is 6 % (i.e. randomly select 1 of 17 choices). This result provides strong empirical evidence for the validity and managerial usefulness of the proposed upgrading method in understanding preferences for complex products.

Based on this discussion it should be clear that the upgrading method shows considerable promise for better understanding consumer preferences for technologically complex products. This method builds upon the benchmark self-explicated method while ensuring the merits of both decompositional and compositional approaches are incorporated, and subjects are incentive-aligned to reveal their true preferences. Further, the upgrading method is built upon a realistic task that most people are familiar with (e.g., upgrading from a default computer, one attribute at a time, to a configuration that she likes most, given the cost of each upgrade).

[17] This is consistent with Green and Srinivasan (1990)'s observation that participants in self-explicated approach tend to assign linear preference to different levels of an attribute, if these levels are linear.

Table 5.7 Model parameter estimates

	Model 1: self-explicated method		Model 2: upgrading method		
Variables	Mean	Std. Dev.	Mean	95 % posterior interval	Heterogeneity
Intercept			0.38	[−1.15, 2.46]	2.14
Brand					
Canon	83.71	63.81	46.77	[45.60, 47.43]	6.75
Fuji	52.87	46.53	27.49	[20.68, 31.60]	1.78
HP: Base	45.01	41.73	0.00	–	–
Kodak	60.13	50.94	24.88	[20.52, 29.12]	1.51
Minolta	35.73	40.00	26.61	[19.83, 32.53]	2.21
Nikon	69.92	52.50	35.32	[32.09, 37.46]	4.04
Olympus	67.02	53.15	39.58	[32.69, 43.37]	1.16
Samsung	58.13	45.52	30.62	[28.96, 32.45]	1.54
Sony	88.72	61.12	56.24	[53.11, 58.20]	6.72
Resolution					
4 mp: base	18.14	25.59	0.00	–	–
5 mp	60.49	49.19	15.96	[10.03, 22.19]	3.73
6 mp	95.13	70.42	21.75	[20.19, 23.83]	0.98
7 mp	117.52	87.20	40.08	[36.06, 45.04]	1.42
8 mp	143.19	102.70	50.53	[46.50, 53.46]	0.60
Lens (optical)					
1×: base	12.94	6.83	0.00	–	–
2×	22.95	13.18	2.13	[−0.75, 4.75]	1.91
3×	35.14	23.11	16.55	[10.50, 21.25]	1.62
4×	52.33	33.46	27.49	[23.44, 30.34]	0.99
5×	64.61	41.08	29.27	[26.81, 31.99]	2.68
6×	79.67	50.58	36.24	[34.89, 38.00]	2.58
7×	90.77	52.36	41.82	[39.89, 43.86]	3.36
8×	104.24	66.57	42.88	[39.27, 45.84]	2.36
9×	113.24	68.93	56.36	[53.23, 58.32]	2.05
10×	127.23	70.11	60.84	[54.39, 67.01]	0.97
Warranty – parts					
6 months: base	5.64	5.16	0.00	–	–
12 months	20.82	22.12	14.16	[8.55, 17.16]	0.54
18 months	29.55	28.43	16.48	[13.46, 18.89]	0.49
24 months	38.07	31.10	36.13	[33.72, 38.79]	7.88
36 months	45.33	32.91	38.74	[34.40, 42.49]	0.40
Warranty – labor					
6 months: base	5.71	6.67	0.00	–	–
12 months	19.90	22.05	15.70	[11.80, 18.26]	0.33
18 months	27.27	26.71	17.93	[13.34, 24.04]	1.18
24 months	35.76	30.59	28.18	[25.19, 30.68]	1.18
36 months	44.17	32.93	35.27	[28.70, 41.33]	2.78
Focus range					
1–6″ to inf	81.75	64.73	47.20	[45.78, 50.35]	0.52
6–12″ to inf	64.93	61.52	35.71	[32.05, 38.42]	1.00
13–18″ to inf	47.14	38.81	22.42	[18.72, 25.83]	1.71

(continued)

Table 5.7 (continued)

Variables	Model 1: self-explicated method		Model 2: upgrading method		
	Mean	Std. Dev.	Mean	95 % posterior interval	Heterogeneity
19–24″ to inf	31.73	25.27	9.61	[4.24, 12.77]	1.16
24–36 to inf: base	17.75	27.27	0.00	–	–
Viewfinder					
1.0″: Base	8.81	10.13	0.00	–	–
1.5″	22.69	19.46	12.41	[8.30, 14.72]	1.39
2.0″	46.20	54.30	20.00	[17.42, 22.18]	1.32
2.5″	69.31	81.94	34.23	[31.05, 38.66]	0.50
3.0″	83.75	99.86	43.81	[40.79, 48.20]	0.99
Text overlay					
No: Base	5.41	9.59	0.00	–	–
Date	18.17	19.94	17.82	[12.60, 20.71]	0.51
Date/time	29.37	27.43	21.97	[17.27, 25.72]	0.43
Video mode					
No: Base	7.80	10.97	0.00	–	–
Video only	35.40	55.87	16.24	[13.15, 18.81]	1.56
Video and audio	73.63	110.80	45.70	[42.20, 51.53]	6.08
Weight					
3–4 oz	75.78	51.03	56.63	[53.32, 58.68]	1.62
4–5 oz	66.82	48.49	40.50	[38.09, 42.69]	6.99
5–6 oz	51.13	37.78	25.58	[22.54, 27.54]	5.92
6–7 oz	40.75	30.78	22.36	[19.68, 24.37]	1.28
7–8 oz	26.98	21.75	18.74	[12.84, 20.34]	0.63
8–9 oz	17.87	17.99	8.54	[6.32, 10.65]	2.53
9–10 oz: base	9.52	8.98	0.00	–	–
Flash range					
<8′: base	9.37	11.69	0.00	–	–
8–12′	38.96	33.43	21.03	[17.33, 23.03]	4.26
12–18′	66.46	61.03	41.76	[38.72, 44.68]	4.94
Price					
$149	121.52	154.57			
$189	90.91	105.85			
$229	76.56	90.84			
$269	60.73	72.24			
$309	37.78	45.83			
$349	23.96	31.05			
$389	13.00	15.36			
WTP ($)			−2.15	[−3.67, −0.32]	1.60

Source: Reprinted with permission from Park et al. (2008), published by the American Marketing Association

5.3.6 Category F: SVM Methods

As the number of attributes increases, the data become more noisy, more nonlinear, and in a larger number of dimensions. Estimating preference models accurately for this kind of data has been a major problem for researchers and practitioners.

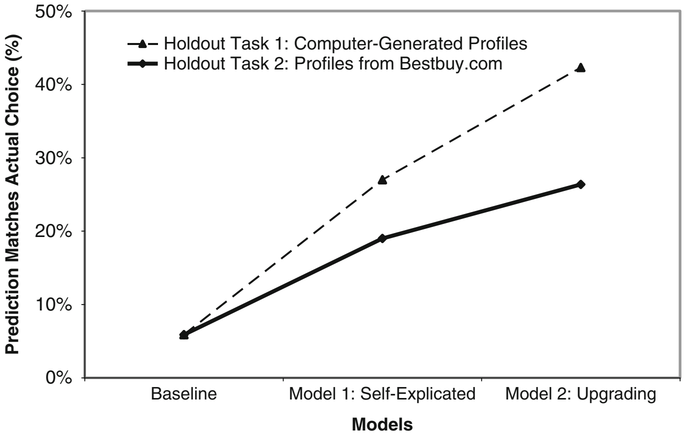

Fig. 5.3 Predictive performance for the external validity tasks (Source: Reprinted with permission from Park et al. (2008), published by the American Marketing Association)

Evgeniou et al. (2005) propose a Support Vector Machine (SVM) method from statistical learning theory to model preference in conjoint analysis. Although the authors do not address the issue of questionnaire design for conjoint analysis, the suggested estimation method can be highly nonlinear and robust to noise, which usually happens when there is a large number of attributes, or interactions among different levels and attributes, or incomplete information about choices.

The SVM method formulates an optimization procedure where an appropriate cost function is minimized without assuming a particular probabilistic distribution for the data. This differs from traditional conjoint estimation approaches such as logistic regression and hierarchical Bayesian methods. To briefly illustrate the SVM model, the following notations are needed. Suppose there are n choices in the data, and the ith choice is between two products denoted as $\{x_i^1, x_i^2\}$. Let x_i^1 be the preferred product. Suppose there are m attributes for the full-profile conjoint analysis, and then the j-th product for choice i can be represented as $x_i^j = \{x_i^j(1), \ldots x_i^j(m)\}$. Let $w_1, \ldots, w_m$ represent the partworths utilities to be estimated. The main idea of the SVM method is to simultaneously minimize the errors or inconsistencies on the data by minimizing the slack variables ξ_i with the following optimization problem:

$$\min_{w_1,\ldots w_m,\xi_i} \sum_{i=1,\ldots,n} \xi_i + \lambda \sum_{f=1,\ldots,m} w_f^2$$

$$\text{Subject to : } \sum_{k=1}^{m} w_k x_i^1(k) \geq \sum_{k=1}^{m} w_k x_i^2(k) + 1 - \xi_i \text{ for } \forall i \in \{1, \ldots, n\}, \text{and } \xi_i \geq 0$$

where the parameter λ controls the trade-off between fitting the data and the complexity of the model. This parameter can be chosen iteratively as that giving the smallest cross validation error. Note that no control for the complexity of the model is incorporated in the existing estimation methods for conjoint analysis. Therefore, the SVM method is expected to be more accurate and robust to noisy data.

To validate the performance, the authors compare the proposed method with logistic regression, hierarchical Bayes, and polyhedral methods (Toubia et al. 2004) using simulated data. The data, including products with four attributes, each attribute having four levels, are generated through Monte Carlo simulations according to the probability distributions assumed by regression and hierarchical Bayes methods. Hundred respondents are simulated and 16 questions are constructed per respondent through an orthogonal design. Each question consists of four products to choose from. All experiments are repeated five times and a total of 500 respondent utilities are estimated.

The root mean squared error (RMSE) of the estimated partworths and hit rates for first choices are used in comparing alternative methods. The results show that the proposed SVM method outperforms both logistic regression and the polyhedral method. This suggests that the SVM method can be useful for analyzing large amounts of data that are noisy or for estimating interactions among attributes. Another pioneering study in applying the support vector machine to the common choice situation in marketing research can be found in Cui and Curry (2005). They compare the SVM's prediction hit-rates with those from the multinomial logit model and show that the SVM significantly out-predicts the MNL models.

5.4 A Comparison of Methods

The extant literature has evolved over time to provide pragmatic solutions to the problem of implementing conjoint analysis studies with large numbers of attributes. Some of the methods reviewed (e.g. method of meta-attributes) require extensive empirical work. In Table 5.8, we briefly summarize *our view* of the advantages and disadvantages of the methods available for handling the problem of large number of attributes in conjoint analysis. In Table 5.8, we provide our subjective assessment of these methods with ratings on five criteria: theoretical basis, adherence to incentive compatibility criterion in the data collected, ease of implementation, and estimation of partworths. Some researchers have shown the superiority of data collected with incentive compatible methods (see Ding 2007; Ding et al. 2005).

Based on this subjective assessment, the methods of partial profiles, self-explicated methods, and upgrading methods stand out; they seem to offer considerable promise for the future to tackle the problem of large number of attributes. While the self-explicated approach and its variant stand out as methods that are easy to implement for the problem of large number of attributes, they are not in the spirit of the decompositional approach that is so well identified with the conjoint analysis. The basic tenet of conjoint methodology is its ability to decompose an overall judgment (stated preference or stated choice) into components specific to the

Table 5.8 Advantages and disadvantages of different methods for large number of attributes

Category	Method	Brief description	Advantages	Disadvantages	Theoretical basis	Is the method incentive compatible?	Ease of implementation	Estimation of partworth functions
A	A1	Use of fractional factorial designs	Based on sound statistical methods	Can be cumbersome for very large number of attributes Respondent fatigue and potential low reliability	Based on statistical theory of designs	No	High	Based on standard regression methods
	A2	Partial profile conjoint analysis	Uses imputations based on a learning model	Requires sophisticated modeling and analysis	Based on a learning model	No	Moderate	Requires sophisticated methods
B	B1	Stage approach with facets	Handles very large number of attributes and works well	Can be quite involved in implementation	Not so clear	No	Moderate	Based on standard regression methods
	B2	Method of hierarchical integration	Seems to follow the natural simplification process of humans	Can be quite involved in implementation; requires a good knowledge of statistical experiments	Exists	No	Low	Based on logit methods
	B3	Method of meta-attributes	Enables comparison of results from different studies due to the construct of meta-attributes	Needs additional empirical studies	Exists	No	Low	Requires sophisticated methods
C	C1	Self-explicated approach	Quite easy to implement and shows good predictive validity Pragmatic	The constructs of importances and desirabilities can be overlapping	Exists	No	High	Quite easy

	C2	Adaptive self-explicated approach	Handles the issue of collecting attribute importances in a easy-to-implement way	The constructs of importances and desirabilities can be overlapping	Exists	No	High	Relatively easy
D	D1	Hybrid conjoint analysis	Tackles the main problem of large number of attributes in the spirit of full profile methods Pragmatic	Theoretical basis is arguable Subgroup- level (not individual level) partworth functions are estimable	Not so clear	No	Low	Based on standard regression methods
	D2	Customized conjoint analysis	Tackles the main issue of large number of attributes and can estimate individual partworths Pragmatic	Theoretical bases is arguable	Not so clear	No	Moderate	Relatively easy
	D3	Adaptive conjoint analysis	A method that yields individual level partworths due to the unique nature of question design and administration of survey	Theoretical bases is arguable	Not so clear	No	Low	Requires sophisticated methods

(continued)

Table 5.8 (continued)

Category	Method	Brief description	Advantages	Disadvantages	Theoretical basis	Is the method incentive compatible?	Ease of implementation	Estimation of partworth functions
	D4	Bridging methods	Methods involve setting aside a core set of attributes and dividing the rest into subsets of attributes and including the core set in each of the subsets and adopts fractional factorial profiles method	While practical, theoretical basis is arguable	Not so clear	No	Low	Requires sophisticated methods
E	E1	Method based on upgrades and auctions	Is incentive-aligned Natural way for subjects to provide data Implementable on the web	Needs additional empirical studies	Exists	Yes	Moderate	Requires sophisticated methods
F	F1	Support vector machines	A good way to estimate utility functions with a large number of parameters	Requires considerable technical sophistication	Exists	No (perhaps not applicable)	Not applicable	Requires sophisticated methods

attributes. The upgrading method is in the same spirit of the self-explicated approach, but the approach is incentive compatible. Such incentive compatibility is not assured in the other approaches reviewed in this paper. We suggest that data collected with incentive compatibility are far superior for conjoint studies in practice.

5.5 Summary

This chapter provides a review of the published conjoint methods for large number of attributes that have been applied in various contexts. We also offer our subjective assessment of the advantages and disadvantages of various methods.

We should note that there is no single study that has systematically applied these potential alternative methods to a specific applied problem to assess the intricacies with each alternative method. Our guess is that the payoff for such an exercise is limited while a large scale simulation study may be feasible to compare the methods.

Further, we believe that an approach to tackle the large number of attributes problem (in the spirit of decompositional approach) is to conduct a study in which subsamples of respondents provide stated preference or choice data based on choice sets or profiles on a subset of attributes with some linkages among the sets; we further believe that such data should be collected under conditions of incentive compatibility. Hierarchical Bayesian methods can then be applied to such data to develop estimates of partworth values at the individual level. This method may offer future possibilities.

Another approach to deal with large numbers of attributes is a recent method, called "Barter Conjoint Mathod"; we will discuss this is some detail in Chap. 10.

Despite the need for additional comparisons, practitioners have ample choice of alternative methods to deal with large number of attributes. We find that three methods (self-explicated method, partial profiles approach, and upgrading method) seem to stand out.

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Chapter 6
Applications for Product and Service Design and Product Line Decisions

6.1 Introduction

The methodology of conjoint analysis has been most frequently used to tackle the difficult marketing problem of product/service design and product line selection. The typical conjoint approach for these problems is to implement a conjoint study (as per the details discussed in Chaps. 2, 3 and 4) and to use the results to estimate attribute partworths preferably at the individual respondent level. These partworths are then used to determine the values of attributes (or design characteristics of a product or service) so as to optimize an objective function for a firm. This process requires the knowledge of the competitive set in which the new product(s) or product lines will compete and product costs (as a function of the product attributes). Usually the firm's objective is to maximize the long-run profit potential for the new product(s) or product lines based on stable market shares of the new product(s). If cost information is not available, the objective of long run sales in units or revenue is used. See Table 6.1 for a list of steps involved.

Often such an optimization is not feasible for the researcher. In this case, a choice simulator is used to test the profit potential for a set of new product concepts and determine the concept that optimizes the objective function. Here, one is considering possibly a sub-optimal solution to the product design problem.

In most cases, the firm's product decision is in connection with its existing products. The problem here is to determine the best set of product characteristics that will complement those of the current products so that the whole product line is optimal. We call this the product line decision problem.

Against this brief introduction, this chapter is organized as follows. In the next section, we describe the general problem of design for new products and product lines. In Sect. 6.3 we describe a unified approach to the problem of product design with special emphasis on the use of a choice simulator. Selected applications to product design are described in Sect. 6.4 and for product line decisions in Sect. 6.5. These applications include not only those in the public domain but also applications

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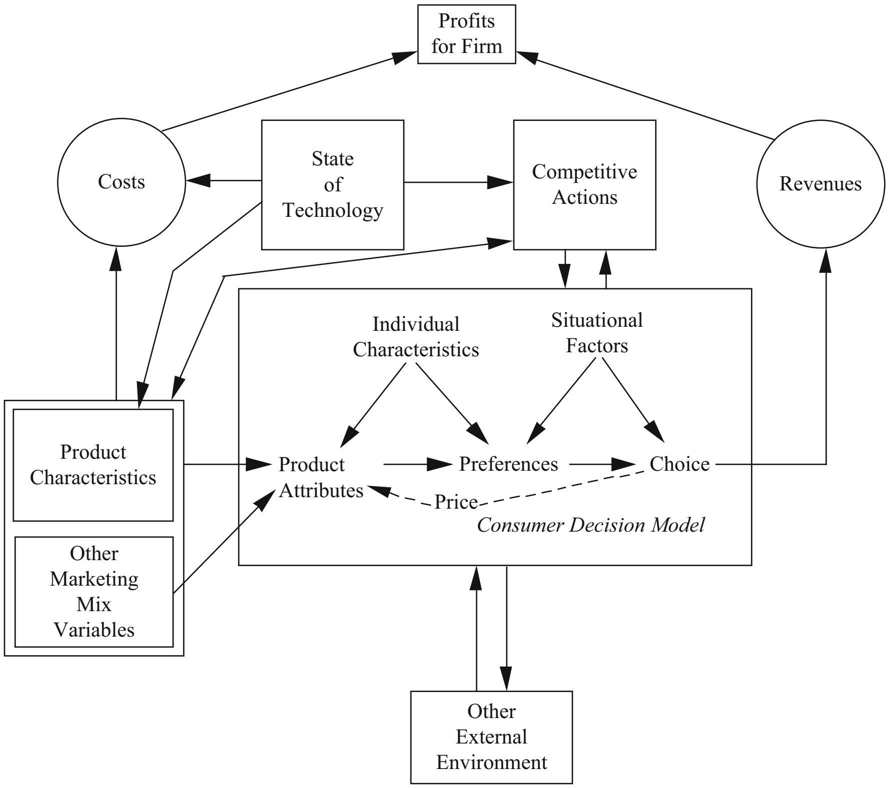
Table 6.1 Steps in using the ratings-based methods for product/service design

Step	Step	General associated methods
1.	Experimental design and stimulus preparation	Fractional factorial designs; orthogonal arrays etc. Construction of visuals for stimuli (cards, pictures or videos etc.)
2.	Sampling and data collection	General sampling methods (RDD, multi-stage sampling etc.) Face-to-face interviews, mail surveys, self-administered questionnaires, telephone interviews, e-mail surveys; and combinations of methods (e.g. phone-mail-phone)
3.	Utility function estimation	Several methods depending upon the study design (e.g., hybrid conjoint, adaptive conjoint etc.)
4.	Choice simulators	Developed using various choice rules; some are proprietary
5.	Estimation of response function and objective function	Use of the choice simulators to estimate these for a few test design concepts
6.	Optimization for categorical and continuous variables	Several integer programming, mixed-integer programming and nonlinear programming algorithms
7.	Sensitivity analysis	Straight forward estimation of the change in the objective function for changes in the levels of categorical attributes and one unit changes in continuous attributes
8.	Time path forecasting	Use of a Markov brand switching process

by selected companies suitably disguised to protect confidentiality. We conclude this chapter with a discussion of some research and pragmatic issues in the use of conjoint methods to help/aid product design and solve portfolio problems.

6.2 General Problem of Product and Product Portfolio Design

In order to maintain and enhance its level of products and its position in the marketplace in light of various external forces, a firm must continuously redesign or/reposition its existing products or introduce new products. These decisions are affected by several factors as shown in Fig. 6.1. Four key aspects are relevant to the product design and positioning problem: (1) defining the set of alternatives that compete with the firm's current or yet-to-be introduced new products; (2) identifying important product attributes; (3) modeling the consumer decision process; and (4) using the firm's criteria to position and design products. Methods for (1) are beyond the scope of discussion in this book; interested readers are referred to Urban and Hauser (1993) and Rao and Steckel (1998) for understanding and determining sets of competitive products. We discussed methods for (2) and (3) in previous chapters; conjoint analysis methods are an integral part of these methods. While a firm can use various criteria, it is accepted that profit contribution should be the economic criterion to evaluate the firm's decisions. Because of the



Source: Reprinted with permission from Kaul, A. and V.R. Rao (1995), "Research for Product Positioning and Design Decisions: An Integrated Review," *International Journal of Research in Marketing*, 12, 293-320.

Fig. 6.1 A conceptual framework for the single product positioning and design problem (Source: Kaul and Rao (1995))

difficulty in getting relevant cost data, most models in the literature use sales, revenue, or market share as the decision criterion. Actual choice will depend upon the specifics of the situation. Conjoint methods are ideally suited when one uses market share or sales as the criterion for determining product design and positioning decisions. See also Green et al. (1981), Gupta and Kohli (1990), and Yoo and Ohta (1994).

6.3 An Unified Framework for Product Design

The decision problem of product design for a firm can be described as follows. To start with, we will assume that the firm has no entries in the product category of interest and that there are *n* competing products (brands) in the marketplace.

Further, let R denote the number of product characteristics (attributes) in addition to price on which the n products are described. Then, the problem of product design for the firm is to choose the values (or levels) of the R characteristics and price so as to maximize a prespecified objective function such as sales or revenue or market share. The reader will easily note that the objective function will depend on the choices made by consumers (usually based on a sample) among the n current offerings and the new offering of the firm. The choice made by an individual consumer will depend upon the utilities of the $(n + 1)$ products, which are estimated by conjoint partworth functions. In this analysis, there are at least four implicit assumptions made. These are:

1. There is no reaction of the existing products to the entry of the new product;
2. The partworth functions estimated from data collected prior to the firm's new product entry will remain the same even after the entry of the new product;
3. Dynamic effects are not important in the estimation of consumer choices; and
4. Other effects due to advertising and distribution are not important (or are ignored) in this estimation.

When the firm currently markets products in the category, the analysis will be similar with one major exception. In this case, the objective function will involve the total sales to the firm for all its offerings (including the new offering). Thus, the effects of cannibalization of the new product with the firm's current products will be explicitly included in the analysis.

A mathematical description of the product design problem is given in the Appendix 1. It is a general formulation that includes the decisions on marketing mix variables other than price in addition to those on product characteristics and price. Inclusion of these decisions will make the problem, called the product positioning problem, quite general,. As indicated above, if these decisions are *not* involved, the problem simply is one of product design. We will return to this issue in the next chapter.

6.3.1 Role of Choice Simulators

It should be quite clear from this discussion that the optimization problem to determine the optimal characteristics of a new product to be offered by the firm is quite complicated. It is unclear whether a unique solution can be found to this problem. But, one can identify a number of feasible product configurations and evaluate the objective function and choose that product for which the value of the objective function is highest. Such a procedure is highly facilitated by conjoint simulators described in Chap. 3. Use of simulators is critical if one wishes to utilize the individual differences in the partworth functions for estimating the purchase probabilities for the new product under consideration.

6.4 Applications for New Product Design

6.4.1 Application 1: Design of a Truck

This application is based on a project conduced for a large automobile firm. The firm was interested in the design characteristics of a V-8 diesel engine for a truck. The implicit comparison was to the V-8 gasoline engine. The conjoint component was part of a larger study in which truck drivers test drive several trucks equipped with different types of engines. After the test drive of trucks equipped with both diesel and gasoline engines, respondents were given profiles of future diesel trucks and were asked to evaluate them on a 10 point liking scale. The total sample was over 400 truck drivers drawn from three cities in the Midwest.

The study involved six attributes, selected through prior studies and with discussions with the respective management personnel. The attributes were: (1) fuel economy improvement over V-8 gasoline engines at three levels; (2) engine noise level at three levels; (3) engine price differential over the V-8 gasoline engine at three levels; (4) pickup and acceleration at two levels; (5) exhaust odor at two levels; and (6) engine durability expressed in miles at three levels. Due to the confidential nature of the study, the attribute levels will not be revealed here. Sixteen profiles of the diesel engines were developed using a fractional factorial design for the study. In addition to rating data, some background data on the respondent and the type of truck he/she drives were collected. The data were analyzed at the subgroup and total sample level using dummy variable regression. The relative importances for the six attributes for the aggregate sample were: fuel economy (17 %), noise (10 %), price (55 %), pickup and acceleration (12 %), exhaust odor (2 %), and durability (4 %). The first four important attributes indicated that respondents wanted a diesel truck that is fuel-efficient over the gasoline truck, same noise level as a gasoline truck, priced moderately above a gasoline truck. There were considerable differences in the partworth values across respondents depending upon the type of truck (make, age, and size) they drove and the main purpose for the use of the truck. The partworth results at the individual respondent-level were submitted to a simulation to determine the attractiveness of some engine designs under consideration by the management. These simulation analyses were the basis for the development of new truck engines.

6.4.2 Application 2: Design of a SLR Camera

This application is based on a pilot study conducted by Rao and Winter (1978). The context was that of the design of a new pocket camera by a well-known Japanese manufacturer of high quality SLR (single lens reflex) cameras (the name was disclosed in the study). The firm is interested in the anticipated behavior of potential camera buyers if the camera were to include or exclude the following features:

built-in exposure meter, shutter speed adjustment, built-in electronic flash, and a focus adjustment. As each feature included two possibilities (feature is included or excluded), in all 2^4 or 16 possible combinations were involved. Respondents for this study were a convenience sample of 45 MBA students enrolled in introductory marketing classes at a large university. The topic addressed in the study was essentially one of various alternative forms of a new camera. Though the sample was not representative of the entire potential market, 73 % of the subjects owned cameras. Also, there was considerable variance in film usage and involvement in photography.

The survey involved questions on general photography/camera preferences and related behavior (questions were on the camera owned by the subject, measures on photography interest, annual film usage and media exposure). A glossary of terms on the features of the new camera under design was given to the subjects.

Each respondent was asked if he/she would buy each of the 16 hypothetical cameras versus the brand previously indicated as the next intended purchase. The base price was given as $50 (no features) and the full-featured model was specified at $95. The data obtained were 1 or zero for each camera. The authors fitted a multinomial probit regression model to these data for each individual. The regression coefficients for the four features and the constant term were used in identifying market segments. In all, four segments were identified (we will describe the analytical procedure used for this purpose in the next chapter). The data were used to estimate the purchase probability for each of the 16 combinations for each segment. Results are shown in Table 6.2. Segment 4 was not responsive to any of the 16 product concepts. Although Segment 3 yields nonzero purchase probabilities only to concepts A, I, and J, the small magnitude of these probabilities suggests that offering any of these concepts is unprofitable. Even though Segments 1 and 2 are very much different in their response to product features, both can be reached with concept P. Segment 2 also would be responsive to concept O. These data can be used to evaluate the economic viability of the concepts P and O by the firm.

These purchase probability data can be used to evaluate the additional gain to the firm by offering a second concept in addition to the concept P. For example, suppose that the firm wishes to offer a camera with exposure meter (i.e., concept I) in addition to concept P. This two-product strategy will be viable as opposed to a one product situation if the additional costs incurred in production, inventory, and marketing that accrue are lower than the gain in the contributory margin from concept I. This example shows how the general model described in Appendix 1 can be operationalized.

6.4.3 Application 3: Design of a Course at a University

Here we report a straightforward application of a ratings-based conjoint analysis as applied to the problem of designing an ideal direct marketing course at the undergraduate level (Katzenstein et al. 1994). The study was conducted among a sample

Table 6.2 Segments' expected purchase probabilities for the 16 product concepts

		Probability of purchase for segment			
Product concept	Concept description[a]	1	2	3	4
A	No additional features	0	0[b]	0.004	0
B	Fl	0	0	0	0
C	Sh	0	0	0	0
D	Sh, Fl	0	0	0	0
E	Fo	0	0	0	0
F	Fo, Fl	0	0	0	0
G	Fo, Sh	0	0.21	0	0
H	Fo, Sh, Fl	0.89	0	0	0
I	Ex	0	0	0.05	0
J	Ex, Fl	0	0	0.002	0
K	Ex, Sh	0	0.07	0	0
L	Ex, Sh, Fl	0.11	0	0	0
M	Ex, Fo	0	0.09	0.003	0
N	Ex, Fo, Fl	0.90	0	0	0
O	Ex, Fo, Sh	0.10	1	0	0
P	Ex, Fo, Sh, Fl	1	1	0	0

Source: Reprinted with permission from Rao and Winter (1978), published by the American Marketing Association

[a]Fl is flash, Sh is shutter, Fo is focus, and Ex is exposure meter

[b]Zero is actually a rounded result of a very small number. One represents a number very close to 1

of 107 undergraduate students who were enrolled in a direct marketing course; the sample was drawn from students enrolled in courses taught by four different professors in the New York metropolitan area. For this study, the authors identified four attributes as essential in the design of a course. These were course content, teaching method, teaching aids, and real-world experience respectively at 4, 4, 3, and 4 levels. Details of the attributes and their levels are shown in the first column of Table 6.3. The first two attributes of course content and teaching method were considered to be the necessary building blocks in the design of any course and the third and fourth attributes were identified as salient based on extensive discussions with faculty and students. Each student evaluated 21 profiles developed using the four attributes; data for 16 profiles constructed according to a fractional factorial design were used in the estimation of partworth functions and the data for the remaining five profiles were used for cross-validation.

Estimated partworth functions using the average ratings are also shown in Table 6.6. The fit of the model was quite good with an R-square of 0.98. The model when applied to the five validation profiles also showed good predictive validity. The distribution of correlation between the predicted and actual ratings was as follows: over 0.74 (33 %), between 0.5 and 0.74 (24 %), 0.25–0.49 (13 %), 0 and 0.25 (8 %) with the remaining correlations being negative. The validation results are not highly encouraging, probably due to the estimation of an average model without taking into account individual differences. Nevertheless, this is an interesting application of the conjoint method to the design of a course. Based on the partworth functions, the ideal course can be described as follows:

Table 6.3 Estimated partworth utilities for pooled preferences for a direct marketing course

Attributes and levels	Partworths	Importance[a]	Rank[b]
Course content		0.072	Third
DM core	−0.037		
DM core + database marketing	−0.006		
DM core + database marketing + media planning and communications	0.008		
DM core + database marketing + media planning and communications + creative aspects	0.035		
Teaching methods		0.061	Fourth
Lecture/discussion	−0.027		
Lecture/discussion + case studies	−0.009		
Lecture/discussion + student presentations + case studies	−0.002		
Lecture/discussion + student presentations + case studies + guest speakers	0.034		
Teaching aids		0.074	Second
Transparencies	−0.041		
Transparencies + videotapes	0.004		
Transparencies + videotapes + DM promotional materials (e.g., letters, inserts, catalogs)	0.033		
Real-world experience		0.199	First
Projects in DM	0.013		
Field trips	0.060		
Internships	0.064		
None	−0.136		

Source: Katzenstein et al. (1994)
[a]Attribute importance obtained by taking the difference between the highest and the lowest utility levels for an attribute
[b]Rank order of the four attributes based on their importance to students

Course content: DM core plus the topics of data base marketing, media planning and communications and creative aspects;
Teaching methods: Lecture/discussion plus student presentations plus case studies plus guest speakers;
Teaching aids: Transparencies, videotapes, promotional materials (e.g., letters, inserts, catalogs); and
Real-World Experience: Internships.

It is not clear whether such a course was designed and implemented by the professors who conducted the study. It would be interesting to see the results of student satisfaction and learning from such an ideal course.

6.4.4 Application 4: Design of Microfinance Products

The main objective of this study was to develop new options in a participatory way to improve access to financial services for rural people in Northern Vietnam

(Dufhues et al. 2004) (this issue is quite important to several emerging economies of the world). The researchers utilized several methods as research tools (e.g. unstructured interviews among key administrative officials and secondary data analysis) and collected data from three different levels: the households (demand side), financial institutions (supply side), and the community in order to develop and implement solutions. The demand side study component utilized conjoint methods in the design of microfinance options and is described below (parenthetically, this application shows how deep the diffusion of conjoint methods has been over the years).

Given that the perception of the rural people is important for implementation, the researchers adopted different participatory rural appraisal (PRA) tools in the design and implementation of the research on the demand side. The tools included cash-flow diagrams, economic mobility maps, wealth rankings, visualization workshops, role pays with an external moderator and Venn diagrams. The objective is to ensure that respondents understand the purpose of research and be able to participate in the research design and analysis.

Conjoint methods were used because of the multiple attributes involved in the financial products (both for credit and savings). At the time of the study, a state–owned commercial bank called VBARD and a non-profit state-owned bank, VBP, were the main players in the rural financial system in Vietnam. VBP was the lending outlet of VBARD. Based on qualitative interviews, several attributes were selected for the microcredit and microsavings services, some of which were dropped after presentation to the target group (because of their low importance). The researchers came up with six attributes for the microcredit product and four attributes for the microsavings product. These attributes and levels are shown in Table 6.4.

An additional explanation of the attributes is as follows. The attribute of incentive for the savings microfinance product involved clients receiving a free ticket for the monthly lottery of a 10,000 VND deposit. If the client withdraws any amounts, they will skip 3 months of lottery unless they deposit 10,000 VND more than they have withdrawn. For every 50,000 VND in their account, they will receive one lottery ticket.

The researchers employed an orthogonal design to reduce the total number of combinations of hypothetical microfinance products to 16 for microcredit and 9 for microsavings profiles. These profiles were presented as pictograms on cards. The data were collected from 258 households, selected according to a stratified sampling method in the Ba Be and Yen Chau districts of Vietnam; the stratification was based on wealth classes. One representative from each household was interviewed in the survey. Further, the researchers employed the choice-based conjoint method to collect choice data from the set of all profiles and were asked to select the three best alternatives or the “no choice” option. Thus, the data consisted of either three options selected or no option for each of the microfinance products. These data were analyzed using a multinomial logit model. The utility of “no choice option” was included in the model. The analysis was implemented with the Sawtooth CBC2.6 Software. The chi-square values for the fits indicate that the

Table 6.4 Attributes and levels for the microfinance products

Microcredit product		Microsavings product	
Attributes	Levels	Attributes	Levels
1. Interest rate	1. High (1.2 % per month) 2. Low (0.5 % per month)	1. Savings term	1. High (1.2 % per month) 2. Low (0.5 % per month)
2. Insurance of investment in livestock	1. Premium of 5,000 VND[a] per month 2. No livestock insurance	2. Incentive	1. With a lottery scheme 2. No lottery scheme
3. Disbursal time of loan	1. Quick (7 days from first day of action to receipt of loan) 2. Slow (60 days)	3. Place of transaction	1. District 2. Commune 3. Village
4. Lending scheme	1. Group lending scheme (group leader conducts all activities for loan) 2. Individual lending scheme	4. Minimum deposit amount at opening	1. 20,000 VND 2. No minimum deposit necessary
5. Collateral	1. Land use rights (Green and Red Books) 2. Durable consumer goods 3. No collateral required		
6. Place of credit negotiations and information	1. District 2. Commune 3. Village		

Source: Compiled from Dufhues et al. (2004) with permission of the publisher
[a]Vietnam Dong

respondents' choices were significantly affected by the attribute composition of the microfinance product concepts. The estimates of the "partworths" and relative attribute importances for the aggregated analysis are shown in Table 6.5.

Given that almost all households chose the cheaper credit (or lower interest rate option), it was not possible to estimate the partworth values for that attribute and it is omitted in Table 6.8. For the credit products, the analysis reveals no surprises. Households would like livestock insurance, lower disbursal time, individual lending, collateral with land use rights, and village as the location of transaction. Further analysis by wealth classes (not shown here) revealed that the pattern of partworth values for indigent households (134 out of 258) and for medium wealth households (82 out of 258) to be the same for the aggregated analysis. But, for rich households (42 out of 258) none of the parameters were significant, which makes sense intuitively.

For the savings products, the preferred combination of attributes is no interest, no lottery, village or district as the place of transaction and no minimum requirement for deposit. When analyzed by wealth class, the pattern for indigent households is the same as that for the aggregated analysis and there was no parameter significant for other classes.

Table 6.5 Partworth estimates for aggregated analysis of microfinance products choice data in Vietnam

Microcredit products (N = 258)			Microsavings products (N = 258)		
Attribute/level	Estimate	t-value	Attribute/level	Estimate	t-value
Livestock insurance			*Monthly interest rate and term*		
Yes	1.562	9.353	No interest/demand deposit	−1.401	−3.702
No	−1.562	−9.353	0.3 % for a 3-month deposit	−0.347	−1.075
Relative importance (%)	20 %		0.5 % for a 3-month deposit	1.747	8.243
			Relative importance (%)	38 %	
Disbursal time			*Incentive scheme*		
Seven days	1.947	7.032	No lottery	−0.612	−2.070
60 days	−1.947	−7.032	Lottery	0.612	2.070
Relative importance (%)	24 %		Relative importance (%)	15 %	
Lending scheme			*Location of depositing/withdrawing*		
Group lending	−1.184	−5.414	Village	1.448	8.077
Individual lending	1.184	5.414	Commune	−0.251	−0.839
Relative importance (%)	15 %		District	−1.196	−4.755
			Relative importance (%)	32 %	
Collateral requirement			*Minimum deposit amount at opening*		
Land use rights	1.261	5.744	No minimum	0.589	3.045
Durable consumer goods	−2.298	−5.989	20000VND	−0.589	−3.045
No collateral	1.037	3.658	Relative importance (%)	14 %	
Relative importance (%)	22 %				
Location of transaction			Not applicable		
Village	1.669	6.519			
Commune	−0.281	−0.823			
District	−1.388	−5.763			
Relative importance (%)	19 %				
No option	3.521	9.100		1.864	
Percent households choosing none option	10 %			13 %	
Chi squared value	734.149		459.531		

Source: Compiled from Dufhues et al. (2004) with permission of the publisher
Note: All estimates (except for commune) are statistically significant at 5 % level or 1 % level

These analyses provided direction for the design of microcredit and microsavings products. While there were no surprises in the results, the study did provide insight and confidence in the design for such products for rural households in Vietnam.

6.4.5 Application 4: Design of Dental Benefit Plans

A group of researchers at the University of Iowa (UI) (Cunningham et al. 1999) implemented a choice-based conjoint study to determine the relative importance of attributes of dental benefit plans. Seven attributes (five features of dental benefit plans and two characteristics of facility that offers treatments) were identified for developing various profiles of dental plans. Each attribute was varied at three levels, covering a realistic range of plans (for e.g. for premium the levels were \$20, \$15 and \$10 per month). First, 27 profiles were developed from the 3^7 factorial design of all possible plans. In all 36 choice sets of four profiles each were administered to a large sample of 773 respondents (all from the UI staff of the year 2000 with a response rate of 40 %). The response task was to select one plan from each set of four. The data were analyzed at the aggregate level using the multinomial logit model. The analysis revealed the following ranges of partworth values for each of the seven attributes: maximum annual benefit (0.98), orthodontic coverage (0.72), routine restorative (0.70), major restorative (0.67), time to complete treatment (0.61), clinic hours of operation (0.47), and premium (0.18). These were converted into attribute importances as shown in Table 6.6.

All of the parameter estimates (except for the premium cost) were statistically significantly different from other estimates within each attribute at the 5 % level. Further market simulation showed the market share for University of Iowa Dental Clinics (UIDC) to be 27 % if all attributes were set to the middle level and an estimated 57 % if all attributes were set to the best level. Knowing the market share estimates enabled the UI administration in establishing resources needs for the UIDC. But, we should point out the need to validate the results via some form of pretest market.

6.4.6 Application 5: Design of a Hotel

One of the high-profile applications of conjoint analysis to product design is the design of the Courtyard hotel by the Marriott Corporation. This application is extensively described in the paper by Wind et al. (1989). The authors conducted a large-scale consumer study among business and non-business travelers to help design an “optimal” hotel for Marriott. Marriott needed a new hotel chain to meet the company’s profit and growth objectives and to establish a market position that offered a substantial competitive advantage over its competition. One other objective was to minimize cannibalization with Marriott’s other hotel offerings.

The questions that the study was designed to answer were:

- Does sufficient demand exist for a new hotel concept aimed at the low business and leisure segment to meet growth and financial objectives?
- What is the best competitive positioning for the new hotels?

Table 6.6 Parameter estimates from an aggregated MNL model for dental benefit plans

Attribute	Levels	Range and (relative importance)	Parameter estimates
Annual maximum benefits per person	$375 ($750 in UI predoctoral dental clinic)[a]	0.98 (23 %)	0.00
	$560 ($1,120 in UI predoctoral dental clinic)		0.58
	$750 ($1,500 in UI predoctoral dental clinic)		0.98
Orthodontic coverage	No coverage[a]	0.72 (17 %)	0.00
	10 % plan copayment/90 % patient copayment		0.51
	20 % plan copayment/80 % patient copayment		0.72
Routine restorative services	80 % plan copayment/20 % patient copayment[a]	0.70 (16 %)	0.00
	90 % plan copayment/10 % patient copayment		0.47
	100 % plan copayment/0 % patient copayment		0.70
Major restorative services (including crowns, endodontics and non-surgical periodontics)	50 % plan copayment/50 % patient copayment[a]	0.67 (15 %)	0.00
	60 % plan copayment/40 % patient copayment		0.58
	70 % plan copayment/30 % patient copayment		0.67
Total time from initial appointment to complete treatment compared to private dental provider	4 times more	0.61 (14 %)	0.00
	3 times more		0.27
	2 times more		0.61
Hours of operation	Regular (Monday–Friday 9 am – 5 pm)	0.47 (11 %)	0.00
	Regular + Saturday 9 am – 12 pm		0.32
	Regular + Saturday 9 am – 12 pm + 2 weeknights 5–9 pm		0.47
Premium costs per month for employee only/employee and family	$0/$20[a]	0.18 (4 %)	0.00
	$0/$15		0.18
	$0/$10		0.03

Source: Cunningham et al. (1999), reprinted with permission of the authors
[a]Indicates current UI dental benefits plan attributes

- Of the various hotel features and services that could be offered, which combination should be offered?
- What should the pricing strategy for rooms in the new hotels be?
- What should be the location strategy for the new hotels be?

The study provided specific guidelines for selecting target market segments, positioning the hotel within the market, and designing an improved facility in terms of layout and services.

The research team identified 50 factors that described hotel features and services each at different numbers of levels; the total number of levels was 167. These 50 factors were divided into seven categories called facets as follows:

Facet	Associated hotel factors
External factors	Building shape, landscape design, pool type and location, hotel size
Rooms	Room size and décor, type of heating and cooling, location and type of bathroom, amenities
Food-related factors	Type and location of restaurant, room service, vending services and stores, in-room kitchen facilities
Lounge facilities	Location, atmosphere and type of people (clientele)
Services	Reservations, registration and check-out, limo to airport, bellman, message center, secretarial services, car rental and maintenance
Facilities for leisure-time activities	Sauna, exercise room, racquetball courts, tennis courts, game room, children's playroom and yard
Security factors	Security guards, smoke detectors, 24-h video camera and so forth

The hybrid conjoint method was employed to obtain evaluations of partworth functions for various features and levels of a hotel. The procedure was administered in various tasks, labeled Task 1a, Task 1b, Task 2, Task 3, and Task 4. We describe each of these to give an idea of the richness of data collected and the associated methodologies involved.

Task 1a This involved collection of self-explicated evaluations of various hotel features, organized in terms of the seven facets described above. For each facet, the respondent indicated whether or not the feature-level was present in the hotel where he/she stayed last time, degree of acceptability of each feature-level, and whether or not he/she was willing to pay for the feature-level and by how much. An example of the data collection instrument for the Rooms facet is shown in Fig. 6.2. This was a systematic procedure to collect self-explicated preferences for all levels of all attributes involved.

Task 1b In this task, the respondents were shown five cards, one at a time, each containing a full-profile description of a "complete" hotel offering. These five were drawn from possible 50 cards, designed according to a 5^7 full factorial design of the seven hotel-feature facets varied at five levels each. The respondent was asked to indicate the degree of intention to stay at the hotel on a five-point scale. An example of a card is shown in Fig. 6.3. Stimulus cards of this type were used for all seven facets for the self-explicated conjoint analysis task.

Rooms

Most Frequently Used Hotel Chain

"X" the TRIANGLE (Δ) in the block that comes closest to describing your current hotel (ONLY "X" ONE)
"X" the CIRCLE (O) in the block (s) that you find to be completely unacceptable (YOU MAY "X" NONE, ONE, OR MORE THAN ONE)
"X" the SQUARE (☐) in the block that represents what you want and are willing to pay for (ONLY "X" ONE)

Features	**Alternative Descriptions**					**Enter Price of Wanted Block**
Entertainment	Color TV (.00) ΔO☐	Color TV with movies which are 9 months ahead of HBO, $5 each (.00) ΔO☐	Color TV with 30 channel cable (.25) ΔO☐	Color TV with HBO movie channel, sports news channel (.40) ΔO☐	Color TV with free in-room movies (choice of 3) (2.50) ΔO☐	______
Entertainment/ Rental	None (.00) ΔO☐	Rental cassettes available for use with in-room Atari or Intellivision (.40)+ ΔO☐	Rental cassettes available. In-room stereo cassette player (1.35)+ ΔO☐	Rental movies, in-room video cassette player (BetaMax) (1.35)+ ΔO☐		______
Size & Furniture	Small--typical size motel/hotel room ΔO☐	Somewhat larger-- 1 foot longer ΔO☐	Much larger-- 2 1/2 feet longer ΔO☐	Small suite-- 2 rooms ΔO☐	Large suite-- 2 rooms ΔO☐	______
Quality of Décor (in standard room)	Similar to Days Inn and other budget motels ΔO☐	Similar to older Holiday Inn, Ramada, Rodeway ΔO☐	Similar to newer and better Holiday Inns ΔO☐	Similar to newer and better Hilton and Marriott ΔO☐	Similar to Hyatt Regency and Westin "Plaza" hotels ΔO☐	______
Heat/Cooling	Through-wall unit. Full control of heating and cooling year round ΔO☐	Through-wall unit (soundproofed). Full control of heating and cooling year round ΔO☐	Either central heating or cooling (not both), depending on season ΔO☐	Full control of central heating and cooling year round ΔO☐		______
Bath size	Standard bathroom and tub/shower as in most hotels. Sink in bath only. ΔO☐	Somewhat larger bath and standard tub/shower. Sink in separate area outside bathroom ΔO☐	Much larger bathroom with large tub/shower ΔO☐	Large bathroom with sunken tub for 2 ΔO☐		______
Sink location	Sink in bath only ΔO☐	Sink in separate area outside bathroom ΔO☐	Sink in bathroom and a sink outside bathroom with ΔO☐			______
Bathroom features	None ΔO☐	Shower massage ΔO☐	Whirlpool (Jacuzzi) ΔO☐	Steam bath ΔO☐		______
Amenities	Small bar of soap ΔO☐	Large soap, shampoo packet, shoe shine mit ΔO☐	Large soap, bath gel, shower cap, sewing kit, shampoo, special soap ΔO☐	Large soap, bath gel, shower cap, sewing kit, special soap, toothpaste, etc. ΔO☐		______

Importance Ranking

TOTAL ______
(Transfer Total Cost to Worksheet)

*This is the stimulus for the second facet. Each respondent received cards corresponding to all facets.

Fig. 6.2 Data Collection Instrument for Rooms Facet (Source: Reprinted from Wind et al. (1989), Copyright (1989), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA)

The data from Tasks 1a and 1b were used in estimating partworth functions for each respondent.

Task 2 In this task, each respondent received five cards, each card showing four existing hotels (LaQuinta, Marriott, and newer and older Holiday Inns) and two new hotel concepts (described in terms of various features), each at a specific price. The existing hotels were deemed

ROOM PRICE PER NIGHT IS $44.85

BUILDING SIZE, BAR/LOUNGE
Large (600 rooms) 12-story hotel with:
- Quiet bar/lounge
- Enclosed central corridors and elevators
- All rooms have very large windows

LANDSCAPING/COURT
Building forms a spacious outdoor courtyard
- View from rooms of moderately landscaped courtyard with:
  - Many trees and shrubs
  - The swimming pool plus a fountain
  - Terraced areas for sunning, sitting, eating

FOOD
Small moderately priced lounge and restaurant for hotel guests/friends
- Limited breakfast with juices, fruit, Danish, cereal, bacon and eggs
- Lunch—soup and sandwiches only
- Evening meal—salad, soup, sandwiches, six hot entrees including steak

HOTEL/MOTEL ROOM QUALITY
Quality of room furnishings, carpet, etc. is similar to:
- Hyatt Regencies
- Westin “Plaza” Hotels

ROOM SIZE & FUNCTION
Room 1 foot longer than typical hotel/motel room
- Space for comfortable sofa-bed and 2 chairs
- Large desk
- Coffee table
- Coffee maker and small refrigerator

SERVICE STANDARDS
Full service including:
- Rapid check in/check out systems
- Reliable message service
- Valet (laundry pick up/deliver)
- Bellman
- Someone (concierge) arranges reservations, tickets, and generally at no cost
- Cleanliness, upkeep, management similar to:
  - Hyatts
  - Marriotts

LEISURE
- Combination indoor-outdoor pool
- Enclosed whirlpool (Jacuzzi)
- Well-equipped playroom/playground for kids

SECURITY
- Night guard on duty 7 p.m. to 7 a.m.
- Fire/water sprinklers throughout hotel

“X” the ONE box below which best describes how likely you are to stay in this hotel/motel at this price:

Would stay there almost all the time	Would stay there on a regular basis	Would stay there now and then	Would rarely stay there	Would not stay there
☐	☐	☐	☐	☐

Fig. 6.3 Example of a card used in the Hotel Design Study (Source: Reprinted from Wind et al. (1989), Copyright (1989), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA)

to compete with the new hotel concept. The task was to allocate 100 points among the hotel-price combinations based on how likely they would stay at each hotel at the given price. The prices were developed according to an experimental design involving 32 combinations. (We describe this procedure more fully in Chap. 7 on pricing decisions). These data were used in determining pricing policies for the new hotel. This full profile description of a hotel offering is one of the 50 cards developed by a fractional factorial design of the seven facets each at the five levels (developed by the Marriott's development team). Each respondent received five cards following a blocking design.

Task 3 In this task, the respondent allocated 100 points among a set of locations, each described in terms of closeness to business, shopping, night life, theaters, airport, major highways etc. These data were used in guiding locations of new hotels.

Task 4 This task involved collecting respondents' background demographic data and other information on past hotel stays.

In addition to these four tasks, secondary conjoint analyses were conducted on seven additional design factors, including room size, quality of décor, type of heating etc. Respondents were also asked to evaluate hypothetical hotels on the degree to which they desired several characteristics and the degree to which they would compare favorably or unfavorably to Holiday Inn. In addition, 11 different names were raked by respondents and the name Courtyard was the best liked.

The study was conducted in four metropolitan areas – Atlanta, Dallas, San Francisco, and Chicago – selected on the basis of a previous psychographic segmentation study. Pre-tests were conducted prior to the main study. The tasks for the respondent were administered according to the tasks identified above.

Partworths were estimated for each target segment and the total sample for the attributes contained in each facet. The method of categorical hybrid conjoint analysis was used for this purpose. An illustration of these partworths for the external factors/facilities facet along with the associated price premiums is shown in Table 6.7. For example, a two-story hotel of smaller size (125 rooms) with enclosed corridors and a rectangular pool in the courtyard and minimal landscaping etc. is the preferred hotel profile for the external factors facet.

The partworth data were used for various simulations and specific attribute levels were identified for the Courtyard hotel. These are shown in Table 6.8. The study found some features that were not desired given additional costs; these were action lounge, upscale restaurant and room service, and large amounts of meeting and convention space. The data from Task 2 were used in determining price-elasticities (the procedure for this is discussed in Chap. 7). This procedure also yielded information on the potential source of business and the expected share of the hotel concepts tested by each price versus current competition.

The most effective validation of the study results is the success of the *Courtyard by Marriott* hotel. As of 1989, 175 Courtyard hotels were open, or under construction or under contract and 111 were opened by end of 1988. This study led the way to other types of hotel niche concepts. It also changed the Marriott's organizational structure and operating systems to emphasize customer service.

Table 6.7 Partworths for attribute levels within the external factors facet

Attribute	Levels	Description	Partworths
Hotel size	1	Small (125 rooms) 2-story hotel (0.00)[a]	1.06
	2	12-story (600 rooms) with large lobby, meeting rooms, etc. (7.15)	0.00
Corridor/ view	1	Outside stairs and walkways to all rooms. Restricted view. People walking outside window. (0.00)	0.00
	2	Enclosed central corridors and stairs. Unrestricted view. Rooms have balcony or large window. (0.65)	1.85
Pool location	1	Not in courtyard (0.00)	0.00
	2	In courtyard (0.00)	1.37
Pool type	1	No pool (0.00)	0.61
	2	Rectangular pool (0.45)	1.25
	3	Freeform pool (0.50)	0.29
	4	Indoor/outdoor pool (0.85)	0.00
Landscaping	1	Minimal landscaping (0.00)	0.81
	2	Moderate landscaping (0.10)	0.97
	3	Elaborate landscaping (0.50)	0.00
Building shape	1	"L" shape building with modest landscaping (0.00)	0.00
	2	Building forms an outdoor landscaped courtyard for sitting, eating, sunning, etc. (0.45)	0.37

Source: Reprinted from Wind et al. (1989), Copyright (1989), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA
[a]Figure in parentheses after each description represents the corresponding price premium

6.4.7 *Application 6: Design of Electronic Toll Collection System*

An electronic toll collection (ETC.) consists of providing commuters with small trans-receivers (tags) that emit a tuned radio signal. Receivers are placed on tollbooths and identify the commuter associated with the particular signal. Commuters establish ETC. accounts that are debited for each use of a toll-based roadway or facility, thus eliminating the need for commuters to pay by cash or token. Because the radio signal can be read from the car in motion, ETC. can reduce traffic jams at the toll plazas by allowing the tag holders to pass through at moderate speeds. This service has come to be called EZPass.

This study was conducted in 1992 for a task force of the New York-New Jersey regional transportation agencies (Green et al. 1997) (at this time, the electronic toll collection was already being successfully used in Texas and Louisiana). The study objectives were to identify the ideal configuration of ETC. service attributes for each agency's commuters, to determine how similar or different these configurations might be across agencies, and to assess the commuter demand for EZPass to determine the level of resources that should be allocated to its implementation. The task force identified the following seven design characteristics of EZPass to be of interest to them:

1. How and where would a user apply and pay for EZPass? (six levels)
2. What lanes would be available for EZPass and how would they be controlled? (five levels)

Table 6.8 Attribute levels selected for the courtyard hotel

Facet	Attribute	Level selected
External factors	Building shape	Outdoor courtyard
	Pool type	Rectangular shape
	Pool location	In courtyard
	Corridor view	Enclosed access/unrestricted view/balcony or window
	Hotel size	Small (125 rooms, 2 stories)
Rooms	Entertainment	Color TV with HBO, movies, etc.
	Entertainment/Rental	None
	Size	Slightly larger (1 ft)
	Quality of décor (in standard room)	New Hilton décor
	Heating and cooling	Wall unit/soundproof/full control
	Size of bath	Slightly larger/sink separate
	Sink location	In separate area
	Bathroom features	None
	Amenities	Large soap/shampoo/shoeshine mitt
Food	Restaurant in hotel	Restaurant/lounge combo, limited menu
	Restaurant nearby	Fast food or coffee shop and good restaurant
	Room service	None
	Store	No food in store
	Vending service	Soft drink, snack, and sandwich machines
	In-room kitchen facilities	Coffee maker only
Lounge	Atmosphere	Quiet bar/lounge
	Type of people	Open to public—general appeal
	Lounge nearby	None
Services	Reservations	Call hotel directly 800 reservation number
	Check-in	Standard
	Check-out	At front desk Bill under door/leave key
	Limo to airport	None
	Bellman	None
	Message service	Light on phone
	Cleanliness/Upkeep/Management skill	Nonconvention Hyatt level
	Laundry/Valet	Client drop off and pick up
	Special services (Concierge)	None
	Secretarial services	None
	Car maintenance	None
	Car rental/Airline reservations	None
Leisure	Sauna	None
	Whirlpool/Jacuzzi	Indoor
	Exercise room	Basic facility with weights
	Racquet ball courts	None
	Tennis courts	None
	Game room/entertainment	None
	Children's playroom/playground	None
	Pool extras	None

(continued)

Table 6.8 (continued)

Facet	Attribute	Level selected
Security	Security guard	7 p.m. to 7 a.m.
	Smoke detector	In rooms and throughout hotel
	Sprinkler system	Lobby/hallways/rooms
	24-h video camera	None
	Alarm button	None

Source: Reprinted from Wind et al. (1989), Copyright (1989), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

3. How many facilities were needed to open an account and how many invoices would the user receive? (two levels)
4. Would the EZPass tag be transferable? (two levels)
5. What would be the acquisition cost and would there be a periodic surcharge? (four levels)
6. What would the toll price be with EZPass? (four levels)
7. What other potential uses would commuters find valuable for the EZPass tag? (three levels).

Thus, the total number of combinations (or configurations of EZPass) is $6 \times 5 \times 2 \times 2 \times 4 \times 4 \times 3$ or 5,760. The problem then is finding an optimal configuration for EZPass.

This problem was ideally suited to the application of conjoint analysis. A hybrid conjoint method was used to collect ratings data using a fractional factorial design; in all 49 combinations were used in the study. The set of 49 were divided into seven different and balanced sets of seven profiles each; each respondent in the study received one set of eight EZPass cards consisting of one of these subsets and a universal card. The universal card allowed recalibration of responses across sample respondents.

However, because the product, EZPass, was a dynamic innovation and really new, the researchers had to come up with innovative ways to apply the conjoint methods to this project. The main problem was to create a level of familiarity for the commuters with the service concept that they could make meaningful choices between different configurations of EZPass. The researchers developed an 11-min "infomercial" videotape to demonstrate the EZPass service to commuters; this tape became an important component of the research process for this project.

The method of phone-mail-phone sequence was used for the study. First, the sample of commuters using the roadways of the agencies was identified by the method of random digit dialing method (phone) and one commuter was recruited for each household. Each recruited commuter was sent a survey kit consisting of videotape, a self-administered questionnaire (with a glossary of all terms used) and the set of eight full profile scenarios of EZPass offerings. After viewing the videotape, respondents completed the self-administered questionnaire and sorted

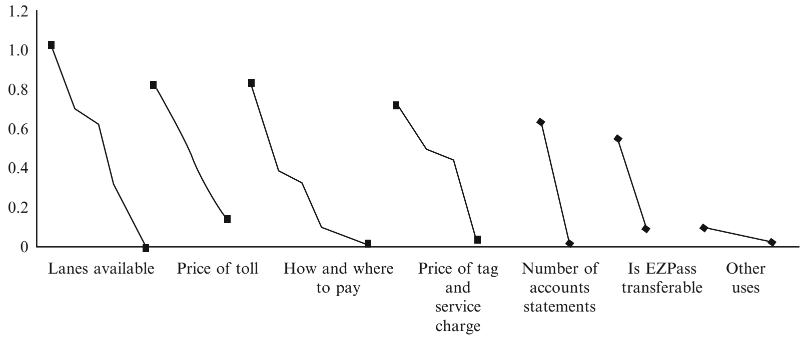


Fig. 6.4 Average partworths from conjoint model for the EZPass application (Source: Reprinted with permission from Green et al. (1997), published by the American Marketing Association)

the eight full profile scenarios in order of preference; after that they either were contacted by telephone or called an 800 number to complete the interview. The response rate for this project was 52 % with an ultimate number of 3,369 completed interviews.

The data were analyzed using the hybrid conjoint model discussed in Chap. 3. The average partworths are shown in Fig. 6.4. Some of these attributes were not "monotonic" in their partworths; this could not have been anticipated before the project. For the non-monotonic attributes, the average partworths estimates generally agreed with the prior expectations. Interestingly, they show the magnitude of changes from one level of the attribute to another; for example, for the price of toll they show the gain in partworth from 10 % discount to 20 % discount.

The estimated attribute importances are shown in Table 6.9. Pricing and service charges display less variability than the attributes of lanes and control features of the EZPass system.

The researchers estimated the demand for EZPass (for various configurations) using a proprietary simulation model (SIMPRO of Green and Krieger 1987a) and compared those estimates with other data on "likelihood of using EZPass" judgments also collected in the survey. The simulation predicted that 38–50 % of the agencies' commuters would adopt EZPass as compared to 25–35 % as estimated by the likelihood data; these estimates were based on the assumption of a multi-agency implementation of the system. The agencies thought that either of these estimates was quite high relative to their expectations and sought from the researchers those configurations with lower predicted estimates of commuters' take-rate (demand).

After 4 years after the survey, three of the seven agencies adopted the EZPass system and two more agencies were expected to adopt the system in the subsequent 2-year period. The reported adoption rate was 40 % after the first 6 months of operation at the Verrazano-Narrows Bridge in New York City, the first agency to adopt the system.

Table 6.9 Importance of EZPass features

Feature	Importance rating (%)
What lanes are available for EZPass and how they are controlled	21
Price of toll with EZPass	18
How and where you pay for EZPass	17
Number of accounts necessary/number of statements received for multiple facility usage	15
Is the EZPass tag transferable?	12
Other potential uses for the EZPass tag	4
Total	100

Source: Reprinted with permission from Green et al. (1997), published by the American Marketing Association

6.4.8 Optimal Design of a Pharmaceutical Product

This application uses the SIMOPT (SIMulation-OPTimization) model developed by Green and Krieger (1992). Details of the SIMOPT model are given in Appendix 2.

The managerial problem entailed the product design and positioning of a new liquid dietary supplement marketed by a company called Beta (disguised). The main competitors in this market were Gamma and Delta. The market shares for the three brands, Beta, Gamma and Delta were 36 %, 35 %, and 29 % respectively. The conjoint study involved nine attributes with three or four levels each as shown in Table 6.10. Some of these attributes (e.g., source of protein and percent of calories from protein) are objective while others were subjective (e.g., health professionals' endorsement).

The objective of this study was to identify the attribute levels (positioning) for a new product of Beta. The optimal design should consider the potential cannibalization of the new product with the existing products of Beta. The researchers designed a ratings-based conjoint study, which was implemented by a national market research study. The respondents were 365 hospital dieticians, who were the primary brand specifiers of the liquid dietary supplements. A hybrid conjoint approach was employed. Also, the Beta accounting personnel estimated direct cost data on manufacturing and distribution at the individual attribute level. These data enabled the use of contribution (to overhead and profit) as criterion in determining the choice of an optimal product in the SIMOPT model.

The new product profiles for the Beta product(s) under different scenarios developed by the SIMOPT model are shown in Table 6.11 along with the expected shares for the three firms in the market for each scenario. It is worth noting that the optimal product would yield a return of $17.43 (as opposed to the current yield of $2.94) assuming no competitive retaliation (see first column of Table 6.11). The second column of Table 6.11 shows the effect of finding an optimal product for Beta under constraints on the source of protein (meat/eggs as opposed to soy/caseinate) and an increase in side effects (10 % vs. 5 %). The simulation

Table 6.10 Attribute levels for liquid dietary supplement study

Source of protein	Percent disliking taste
1. Amino acids	1. 5 % of patients
2. Meat, eggs (natural)	2. 15 %
3. Casein	3. 25 %
4. Soy/caseinate	4. 35 %
Percent calories from protein	Flavor base
1. 24 %	1. Fruit juice
2. 18 %	2. Chocolate flavored milk
3. 12 %	3. Unflavored
4. 6 %	Convenience of preparation
Caloric density	1. Ready to use liquid
1. 2.0 cal/ml	2. Powder—to be mixed with water
2. 1.5	3. Powder—to be mixed in blender
3. 1.0	Health professionals' endorsement
Incidence of diarrhea, cramps (Side effects)	1. Most recommend
1. 5 % of patients	2. Most are neutral
2. 10 %	3. Most are neutral to negative
3. 15 %	Therapy cost per patient per week
4. 20 %	1. $40
	2. $50
	3. $60
	4. $70

Source: Reprinted from Green and Krieger (1992), Copyright (1992), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

model showed that this option yielded a lower return. The SIMOPT model has other features that can answer various what-if questions.

Luo et al. (2007) developed an approach to design a new product that takes into account retailer's acceptance criteria as well as competitors' potential reactions. Their approach merges individual-level conjoint partworth functions and game theoretic models of retailer and manufacturer behavior. This approach offers promise for the future to develop an integrated process of designing a new product based on conjoint methods. A related approach that uses analytical cascading method is due to Michaelek, Feinberg and Papalambros (2005).

6.5 Applications for Product Line Decisions

Product line design decisions have all the intricacies of designing a new product design with the added complexity that the individual models of products in a product line are "closely" related. These relationships occur in both the demand side and the cost side so that decisions made about one model in a line affect the sales and/or costs of the other items in the product line.

The general approach described in the Appendix 1 to this chapter is still applicable for the product line decision problem. The difference will be in terms of deciding how many items to include in the line and how their characteristics will

Table 6.11 New product profiles, based on illustrative SIMOPT runs

	Beta (Current)	Unconstrained (Beta)	Constrained (Beta)	Line extension (Beta)	Added segment (Beta)	Unconstrained (Delta)
Source of protein	Meat, eggs (natural)	Soy/caseinate	Meat/eggs	Soy/caseinate	Soy/caseinate	Soy/caseinate
Percent calories	6 %	12 %	Same	Same	Same	Same
Caloric density	1.0	1.0	Same	Same	Same	Same
Side effects	10 %	5 %	10 %	5 %	5 %	5 %
Percent disliking taste	15 %	5 %	Same	Same	Same	Same
Flavor base	Chocolate	Chocolate	Chocolate	Unflavored	Unflavored	Chocolate
Convenience of preparation	Ready to use	With water	With water	Ready to use	In blender	With water
Health professionals' endorsement	Most are neutral	Neutral/ negative	Same	Same	Same	Same
Therapy cost	$40	$70	Same	Same	Same	Same
Return		$17.34	$13.42	$12.71 alone	$12.06 alone	$16.34
Market shares (%)						
Beta	36	44	25	52	50	28
Gamma	35	20	45	27	28	30
Delta	29	36	30	21	22	42

Source: Reprinted from Green and Krieger (1992), Copyright (1992), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA be determined. Undoubtedly, the optimization problem is quite complicated and simulation methods are usually employed. The firm first has to decide on a certain number of items to be introduced and different configuration sets will need to be decided. The conjoint simulation will then enable the analyst in estimating the demand for each configuration set (i.e. one option for the product line) in light of scenarios for competitive products. Such a simulation will take into account any demand interdependencies among the items in the product line; the estimated market shares for the items in the line will be the net of any cannibalization effects of the other items in the line. The total sum of the market shares of the items will determine the market share of the firm for the configuration of the product line.

While market share estimates are possible from conjoint simulation, no such information is possible on the cost side. Additional information is necessary to determine how costs will change due to the economies of scope and scale within the firm. Internal cost aspects are usually beyond the scope of a conjoint analyst. Therefore, the analysis is generally done with market share (or revenues) as the objective to be maximized.

Conjoint simulations are implemented for each individual in the sample and aggregated using appropriate weights to project the demand to the market as a whole. Such a simulation will also enable an analyst to determine the sources of demand for each item in the product line; whether it is from other items in the line for the same firm or from products of competing firms. Such a detail is extremely useful in the design of promotional and advertising strategies for the firm. See Belloni et al. (2008) for a comparison of different methods of optimizing product line decisions and Michalek et al. (2011) for methods of product line design which interface engineering and consumer evaluations.

We describe two applications of conjoint analysis to the product line decision problem. The first application was the redesign of product lines at the Sunbeam Corporation and the second was the design of product line extensions for the Alpha Herbicide Company (a disguised name).

6.5.1 Application 1: Redesigning Product Lines at the Sunbeam Appliance Company

This application occurred around 1983, when the Sunbeam Appliance Company (SAC) decided to redesign its many mature lines of small kitchen appliances (the article by Page and Rosenbaum (1987) is the basis for this discussion.) The specific application was for food processors. The company at that time had three basic models with two slightly different versions of each for a total of six items in the line with a total market share of less than 10 % (fifth-ranked in market share). These three models were priced between $60.00 and $125.00 (the midrange of the prices for this product in the marketplace). It had no high-end product to compete with the Cuisinart, Kitchen Aid, and others.

Table 6.12 Food processor attributes and levels (Sunbeam study)

I. Price	VII. Configuration
1. $49.99	1. Motor compartment and bowl situated side by side
2. $99.99	2. Bowl is situated on top of motor
3. $199.99	3. Processor is installed under the cabinet or counter top
II. Motor power	VIII. Bowl type
1. Regular	1. Regular
2. Heavy duty	2. Side discharge
3. Professional power	IX. Type of feed tube pusher
III. Number of processing blades	1. Regular solid pusher
1. Three	2. A pusher made up of three interchangeable components to push smaller pieces of food
2. Five	X. Size of feed tube
3. Seven	1. Regular
IV. Bowl size	2. Large
1. 1½ quarts	XI. Bowl shape
2. 2½ quarts	1. Cylindrical
3. 4 quarts	2. Spherical
V. Number of speeds	XII. Pouring spout
1. One	1. Present
2. Two (high/low)	2. Absent
3. Seven	
VI. Other uses	
1. Food processor only	
2. As a blender also	
3. As a blender and mixer also	

Source: Reprinted from Page and Rosenbaum(1989) with permission of the publisher

The firm conducted a conjoint study to determine consumer preferences for various attributes of food processors. Based on group interviews and managerial judgment, the researchers identified 12 attributes of food processors as salient for the study. The list of these attributes and levels are shown in Table 6.12. There were 7 attributes at 3 levels, 2 attributes at 5 levels each and 3 attributes at 2 levels each. An orthogonal array consisting of 27 profiles was selected from the $3^7 \times 5^2 \times 2^3$ full factorial combinations possible. Complete sketches were developed for these profiles and presented to the respondents for evaluation. Respondents ranked the 27 sketches in terms of their preference toward buying the item at the price identified. Data were collected from over 500 women in four geographically dispersed locations. A quota sampling method was used in selecting the respondents (homemakers) from among the people who visited shopping malls in these areas. Quotas were set on the basis of respondent age and food processor ownership.

In this application, preference data were analyzed using monotone analysis of variance methods suitable for the ranked data collected. The analysis yielded 12 partworth functions, one for each attribute and for each individual in the sample. The relative importances of the 12 attributes for the sample as whole are shown in Table 6.13.

Table 6.13 Relative importances of attributes in the Sunbeam study

Attribute	Relative importance (%)	Actual and predicted market shares for the base case: Firm	No. of models	Actual market share	Predicted market share (base case)
Price	13.8	Sunbeam	6	7 %	10.2 %
Number of speeds	4.7	Cuisinart	4	29	29.8
Bowl shape	7.6	General electric	3	24	23.1
Bowl size	11.7	Hamilton beach	7	8	10.8
Motor power	17.7	Kitchen aid	1	1	0.1
Other uses	10.6	Moulinex	2	19	21.7
Configuration	5.4	Robot coupe	5	1	0.7
Bowl type	4.4	J.C. Penney	2	1	0.4
Type of feed tube	2.5	Sears	2	9	2.1
Pusher	1.4	Others	?	1	1.1
Size of feed tube	18.3				
Number of blades	2.3				
Pouring spout					

Source: Compiled from Page and Rosenbaum (1989) with permission of the publisher

As one would expect, the attributes home makers considered to be most critical in the design of a food processor were price, number of blades, bowl size, and motor power. The attributes differ in terms of numbers of levels (3 and 2); therefore, one should be cautious in interpreting these relative importances (see Wittink et al. (1982) for an elaboration of this point).

The authors implemented the conjoint simulation for the base case; this case involved 32 models (products) from nine firms. The predicted market share (weighted for brand awareness and distribution of the individual models marketed by the firm) and actual market share for these firms for the base case are also shown in Table 6.13. The correlation between the predicted shares and actual shares for the models was 0.96; this indicates that the base case is a good starting point for the simulation of new scenarios of product line designs for Sunbeam.

Assuming that competitors' models remain unchanged, the researchers simulated some 50 alternative scenarios for the product lines for Sunbeam. Table 6.14 shows descriptions of two of these scenarios and the market share results estimated from the conjoint simulation.

Based on simulations of several scenarios, the firm redesigned its food processor line with three basic models that were felt to cover the intended target segments. The actual line contained three completely new models: a full featured high end professional model at a retail price of $200, a two-speed promotionally priced low-end model at a retail price of $35–$45, and a seven-speed, heavy duty, midrange model at a retail price of $99. In addition, they introduced an additional model

Table 6.14 Two scenarios for the Sunbeam food processor product line simulation

Scenario	Scenario 1	Scenario 2
Product line for Sunbeam	Four models for Sunbeam and competitive models assumed unchanged	Five models for Sunbeam and competitive models assumed unchanged
Description of models	Keep the two models currently in the product line (the high end professional processor and the low end processor) and add two multispeed models with larger 4-quart bowls, side discharge, and large feed tube priced at $59 and $79 to strengthen the middle of the line	Same as scenario 1 plus an additional low end model, with two speeds, 3 quart bowl, a regular size feed tube, no side discharge, priced at $99.
Estimated market shares		
Sunbeam		
Model 1	7.1	7.0
Model 2	3.3	3.2
Model 3	5.8	4.0
Model 4	8.7	8.7
Model 5	–	3.9
Sunbeam total	24.9	26.8
Cuisinart	25.8	25.0
General electric	21.5	21.1
Hamilton beach	9.5	8.9
Kitchen aid	0.2	0.2
Moulinex	16.0	15.9
Robot coupe	0.7	0.6
J. C. Penney	0.4	0.4
Sears	1.3	1.3

Source: Compiled from Page and Rosenbaum (1989) with permission of the publisher

derived from the midrange model for the department stores. The four-model line moved the firm into fourth rank in terms of market share. Sunbeam later introduced a second-generation food processor model and subsequently redesigned its product line. It seems that simulations based on conjoint studies were useful to the firm in its product redesign. See Wittink (1989) for a comment on the Sunbeam study.

6.5.2 Application 2: Redesign of Product Lines for an Herbicide Company

This application (Green and Krieger 1987b) is quite similar to the extensive discussion of the application for the Sunbeam Appliance Company. It involved an assessment of the addition of two new items to the product line with and without retaining the parent brand of a herbicide company, called Alpha (a disguised name). The firm was also interested in determining the best line of products it should offer to the market. The firm has two other competitors (called Beta and Gamma). The researchers used the methodology of hybrid conjoint analysis and conjoint simulations to investigate these questions.

First, the researchers determined the appropriate attributes and levels for inclusion in the conjoint study. They identified 9 attributes, one at 6 levels, 2 at 4 levels, 3 at 3 levels, and 3 at 2 levels; details are shown in Table 6.15. The total number of levels across all attributes is 29 (=6 + 8 + 9 + 6). Given that there is a total of 20,736 combinations of hypothetical product profiles, the hybrid approach was a natural choice for this conjoint study. The study involved collection of self-explicated desirabilities of the attribute levels and importances of the 9 attributes and collection of ratings for a subset of all possible profiles. For the latter task, a master set of 64 profiles was first designed and subsets of 8 each were used in the administration of a hybrid procedure. Questions were also asked on the most likely brand of herbicide that will be used for the next growing season, acreage involved for the soybeans and other crops, and a small set of demographics. The study was conducted among a sample of 108 commercial growers of soybeans using a combination of phone contact and questionnaire mailing and interviewing over the telephone. The interview took about 35–40 min.

The hybrid model that included an individual-specific intercept was estimated from the conjoint data. These individual-level models enabled the researchers to estimate the utility for any hypothetical product. The conjoint results were summarized as a 108 × 29 matrix of partworths. In particular, they used this matrix to estimate the individual's likelihood of choosing each of the three current brands for the next herbicide purchase as well as likelihood of choosing any of the new products that the Alpha Company might introduce in the future. The attribute levels for the current products of Alpha, Beta, and Gamma were respectively 411-113-112, 311-121-162, and 111-113-122 respectively. This information was useful in the simulations.

The mathematical problem of determining the best line extensions is a difficult one; firstly, this depends upon the number of line extensions to be introduced. In order to obtain an approximately optimal solution to the difficult optimization problem, the researchers developed heuristics to determine the best possible line extensions that the Alpha Company should pursue (details on these programs are given in Appendix 3.) These heuristics identified the following product profiles as best possible line extensions for Alpha for the three scenarios shown:

Scenario	Profile of best line extension(s)
1. Alpha adds one extension to its current product	New: 111-111-132
2. Alpha replaces its current product by two new products	New1: 311-111-132
	New2: 411-113-232
3. Alpha adds two extensions to its current product	New: 111-111-132
	New3: 311-121-162

Table 6.15 Attribute levels used in herbicide study

1. Controlling grasses
All annual
All perennial
Some annual and most perennial
Most annual and some perennial
2. Controlling broadleaves
Good control if used alone
Good control if used with crop oil
3. Combination effectiveness
Enhanced effectiveness if combined with broadleaf killer
Separate broadleaf treatment is required
Crop oil or surfactant is required
4. Length of effectiveness
May require more than one treatment under abnormally high seasonal temperatures
May require more than one treatment under abnormally low rainfall
Definitely requires two or more treatments
5. Carryover
Little risk of carryover
Possible injury for 1 year
6. Weather risk
Reduced control if heavy rain
Reduced control if no rain
Reduced control from high temperatures
7. Product form
Liquid
Wettable powder
Dry flowable
Granular
8. Packaging
Metal containers
Plastic containers
Rubber containers
Wax-lined box
Plastic bag in a box
Waterproof fiberboard pail
9. Crop injury
Some risk of stunted growth
Some risk of burning leaves

Source: Green and Krieger (1987b)

It is interesting to note that one of the line extensions in the third scenario is the same as the best when one line extension is to be introduced. The estimated market shares for these three scenarios and the current scenario (of three brands in the market) are shown below:

Brand	% Market share for the Scenario			
	Current	Scenario 1	Scenario 2	Scenario 3
Alpha	43	40	0	36
Beta	19	17	17	17
Gamma	38	18	16	17
New	–	25	–	19
New1	–	–	21	–
New 2	–	–	46	–
New 3	–	–	–	11

Source: Compiled from Tables 2, 3, and 4 in Green and Krieger (1987b) with permission of the publisher

These simulations indicated that the Alpha firm was better off either replacing its current brand by two new line extensions, New1 and New2 or by adding two line extensions, New and New3 to its current brand. Obviously, the costs of marketing and R&D need to be reckoned in the specific strategy of line extension for the firm. This application shows the complexities of product line decisions even when the number of brands is quite small (compare this with the Sunbeam study which involved a multitude of models of food processors; in that study even the use of heuristics would have been difficult).

6.6 Conclusions

This chapter described various applications of conjoint methods to the problems of product design and product line decisions. While the concept of designing best products or product lines and how conjoint analysis fits into this problem can be easily understood, closed-form solutions to the corresponding optimization problems are hard to find, particularly when a large number of attributes and levels is involved. But, the design of a suitable conjoint study for estimating partworth functions at the individual level and the use of conjoint simulations enable an analyst to begin to tackle these important problems for management. What we have described is a way to determine the impact of introducing any one of a set of prespecified new product configurations using the conjoint simulators. The criterion of optimization in almost all of the applications described in the chapter is maximization of market share for the brand or the firm. In principle, the criterion of contribution to profit can be utilized in these simulations but cost data need to be compiled. In general, cost information is difficult to obtain for a new product or product lines.

If the firm knows in advance the specification of the product lines it intends to introduce, it is straightforward to use the conjoint simulators (in a manner to similar to new product design). The optimization of the number and profiles of product lines is a particularly difficult problem to solve. Because of this, heuristic solutions are often used. For additional details on this problem, the reader is referred to Green and Krieger (1985) and Dobson and Kalish (1993).

One issue the conjoint simulators do not consider is the time path the new product takes to stabilize in the marketplace. A related issue is the dissemination of the attribute information among all the target consumers. These two issues relate to diffusion processes of the new product in the marketplace. Conjoint analysis models that incorporate these processes offer significant future research opportunities.

Appendix 1

A Mathematical Formulation of the Product Design and Positioning Problem

Notation

We use the following notation to describe the relationships between constructs of Fig. 6.1. This material is drawn from Kaul and Rao (1995). The subscript "0" is used to refer to the firm's current product (or own product).

θ_{oq} = Value of the qth product characteristic for the firm's own product, o.
$\boldsymbol{\Theta}_o = (\theta_{oq})$, q = 1, . . ., Q.
θ_{cq} = Value of the qth product characteristic for product's competitors.
$\boldsymbol{\Theta}_c = (\theta_{cq})$, q = 1, . . ., Q.
y_{op} = Value of pth product attribute for firm's product.
$\mathbf{Y}_o = (y_{op})$, p = 1, . . ., P.
y_{cp} = Value of pth product attribute for product's competitors.
$\mathbf{Y}_c = (y_{cp})$, p = 1, . . ., P.
z_{or} = Value of the rth factor from the group of factors (e.g. advertising, promotion strategy, etc.) that affect $\mathbf{Y}_o$ for the firm's own product.
$\mathbf{Z}_o = (z_{or})$, r = 1, . . ., R.
z_{cr} = Value of the rth factor from the group of factors (advertising, promotion strategy, etc.) that affect $\mathbf{Y}_c$ (for the firm's competitors).
$\mathbf{Z}_c = (z_{cr})$, r = 1, . . ., R.
P_o = Price of firm's own product.
P_c = Price of competitor product c.
$\mathbf{P}_c = (P_c)$, c = 1, . . ., C.
$\mathbf{T}$ = Vector of relevant technology variables that affect product design.
x_{ip} = Value of the ideal point on the pth dimension for the ith consumer.
$\mathbf{X} = (x_{ip})$, p = 1, . . ., P.
ϕ_{ia} = Value of the ath situational factor (e.g. product availability, time and monetary budget.)
$\boldsymbol{\Phi} = (\phi_{ia})$, a = 1, . . ., A.
ψ_{ib} = Value of the bth background characteristic for the ith consumer.
$\boldsymbol{\Psi} = (\psi_{ib})$, b = 1, . . ., B.

The relationships between product attributes and product characteristics, prices, and other marketing mix variables are expressed as

$$Y = \begin{bmatrix} Y_o \\ Y_c \end{bmatrix} = f\begin{bmatrix} \Theta_o & Z_o & P_o & \psi \\ \Theta_c & Z_c & P_c & \psi \end{bmatrix}.$$

If X is the set of all consumer ideal points, we can say

$$X = h(\Psi).$$

The choice rule employed by the consumer will determine the choice (in case of a deterministic choice rule) or the probabilities associated with choice of different products (in case of probabilistic choice rule). In the remaining description, we assume a stochastic utility probabilistic choice rule for the consumer. In this case, the utility that a consumer i derives from a product j is given by

$$U_{ij} = V_{ij} + \varepsilon_{ij},$$

where

V_{ij} = Deterministic part of the utility of ith consumer for product j.
ε_{ij} = Random part of the utility for ith consumer for product j.

We express the relationship between the deterministic part and price and distance from ideal points as

$$V_{ij} = v\left(d_{ij},\ P_j\right),$$

where

d_{ij} = Distance of the product j from the ith consumer's ideal point.

The distance of product j from ith consumer's ideal point in the attribute space is given by the following general relationship:

$$d_{ij} = \left[\sum_{p=1}^{P} \omega_p |y_{ijp} - x_{ip}|^{\alpha}\right]^{1/\alpha}, \ \alpha \geq 1$$

where

y_{ijp} = Location of product j on attribute p.
x_{ip} = Location of consumer i's ideal point on attribute p.
ω_p = Importance weight attached to attribute p.

The distance measure becomes the city-block distance measure if $\alpha = 1$ and Euclidean distance if $\alpha = 2$. The Euclidean measure is commonly used because of analytic convenience. In order to include the "no buy" decision and the concept of consideration sets in the model, we can assume a threshold value for the distance between the products and the consumer ideal points. The idea is that if the distance between the product and the ideal point is greater than the threshold value, the product will have a zero probability of choice and hence will not be part of the consideration set. If all the products lie at a distance greater than the threshold distance, no product will be chosen by the consumer.

Having assumed a distribution for the random component of utility $\left(\varepsilon_{\mathrm{ij}}\right)$ and going through utility maximization, we arrive at the probability of choice ϑ_{ij} for each product for each consumer. Whether a consumer finally chooses the product or not will be affected by situational factors such as product availability, budget and time constraints. If we have a measure of the probability of a situational factor affecting the purchase decision of a consumer, the augmented probability of choice will be given by the product of the two probabilities – probability of choice ϑ_{ij} and probability of impact of the situational factor ζ_{ij}.[1] Once augmented probabilities are available for all products, we can obtain the probability of choice for each consumer by dividing each augmented probability by the sum of all augmented probabilities. Thus the final choice probability for each product will be given by

$$\wedge_{\mathrm{ij}} = \frac{\vartheta_{\mathrm{ij}} \bullet \zeta_{\mathrm{ij}}}{\sum_{\mathrm{k=1}}^{\mathrm{C+1}} \vartheta_{\mathrm{ik}} \bullet \zeta_{\mathrm{ik}}}.$$

Depending upon the sampling plan employed, some weighting of the probabilities may be needed to get the final market shares of the products. Multiplying these market shares by the total size of the market gives us the demand for each product and more particularly for the firm's product.[2]

Thus the number of consumers choosing a product will be a function of the product's position in the attribute space $\mathbf{Y}_{\mathrm{o}}$, the product's price $\mathbf{P}_{\mathrm{o}}$, the consumer's ideal points $\mathbf{X}$ and situational factors $\boldsymbol{\Phi}$. Since $\mathbf{Y}_{\mathrm{o}}$ and $\mathbf{X}$ are also functions of individual characteristics of the consumers $\boldsymbol{\Psi}$, we can say that the number of consumers choosing the product will also depend on $\boldsymbol{\Psi}$. Further, sales of the product will also depend on competitor product's positioning and price. So, we can express the relationship between unit sales of the product, Q, and the various factors that affect it as:

$$\mathrm{Q} = \mathrm{F}(\mathbf{Y}_{\mathrm{o}},\ \mathbf{P}_{\mathrm{o}},\ \Psi,\ \Phi,\ \mathbf{P}_{\mathrm{c}},\ \mathbf{Y}_{\mathrm{c}}).$$

The total revenue that the product will generate is

$$\mathrm{R} = \mathrm{P}_{\mathrm{o}} \bullet \mathrm{Q} = \mathrm{P}_{\mathrm{o}} \bullet \mathrm{F}(\mathbf{Y}_{\mathrm{o}},\ \mathbf{P}_{\mathrm{o}},\ \Psi,\ \Phi,\ \mathbf{P}_{\mathrm{c}},\ \mathbf{Y}_{\mathrm{c}}).$$

[1] Suppose that the base probability of choice of a product is 0.5 and probability that the product will be available is 0.8, then the augmented probability of choice would be $0.5 \times 0.8 = 0.4$.

[2] Here we assume that each consumer buys only one unit of the product thus abstracting from the quantity choice decision. See the section on future research ideas on how to take this into account.

The cost of the product will be a function of research, development and manufacturing costs such as the cost of developing and producing a particular level of product characteristics (higher levels of product characteristics might cost more), product positioning costs (advertising and other marketing costs) and state of technology T. So mathematically, we can write

$$K = \kappa(\Theta_o, \mathbf{Z}_o, \mathbf{T}).$$

Finally, the profit for the firm is given by

$$\prod = R(\mathbf{Y}_o,\ \mathbf{P}_o,\ \Psi,\ \Phi,\ \mathbf{P}_c,\ \mathbf{Y}_c) - \kappa(\Theta_o,\ \mathbf{Z}_o,\ \mathbf{T})$$

The objective of the firm would thus be to maximize total profit with respect to the variables that are under its control, i.e., $\mathbf{\Theta}_o$, $\mathbf{Z}_o$ and $\mathbf{P}_o$ (note $\mathbf{Y}_o$ is also a function of $\mathbf{\Theta}_o$, $\mathbf{Z}_o$ and $\mathbf{P}_o$). Hence the firm's problem is

$$\max_{\Theta_o, Z_o, P_o} \prod = R(\mathbf{Y}_o,\ \mathbf{P}_o,\ \Psi,\ \Phi,\ \mathbf{P}_c,\ \mathbf{Y}_c) - \kappa(\Theta_o,\ \mathbf{Z}_o,\ \mathbf{T})$$

Given this framework, the positioning problem can be defined as selecting the product attributes $\mathbf{Y}_o$ and price $\mathbf{P}_o$ to maximize profit Π. The product design problem can be defined as selecting the product characteristics $\mathbf{\Theta}_o$ and price $\mathbf{P}_o$ to maximize profit Π. The problem of choosing optimal marketing mix variables can similarly be defined as selecting $\mathbf{Z}_o$ and $\mathbf{P}_o$ to maximize the firm profits. Thus we see that this formulation is more general in nature and that product positioning, product design and marketing mix selection are special cases of this generalized framework.

Appendix 2

Details on the SIMOPT Model

Source: This material is drawn from Green and Krieger (1992).

The primary data input to the model consists of a matrix of K individuals' partworths. In the simpler case, where no interaction effects are included, the general entry is

$p_{m,j}^{(k)}$ = partworth for level j of attribute m for individual k; $j = 1, 2, \ldots, L_m$; $m = 1, 2, \ldots, M$; $k = 1, 2, \ldots, K$;

$a^{(k)}$ = intercept term for individual k;

where L_m denotes the number of levels for attribute m, and M is the number of attributes. Each row vector of partworths enables the user to compute a utility for any product/supplier profile for any individual k. A profile is defined by its levels ($j_1, j_2, \ldots, j_M$). The utility of this profile to individual k is given by

$$U_k(j_1, j_2, \ldots, j_M) = \left[\sum_{m=1}^{M} p_{m,j_m}^{(k)} + a^{(k)}\right]^+$$

where $[x]^+ = \max(x, 0)$.

We assume that in any given run of SIMOPT, each supplier is represented by a profile vector j_s; $s = 1, 2, \ldots, S$. Hence, we can compute

$$U_{k,s} \equiv U_k(j_s)$$

as the utility of individual k for supplier s. The "market share" of individual k for supplier s is

$$\pi_{k,s} = \frac{U_k^{\alpha}(j_s)}{\sum_{s=1}^{S} U_k^{\alpha}(j_s)}$$

for a specified value of α.[3]

Once we have computed the $\pi_{k,s}$, we can combine them into a total market share by using $\sum_{k=1}^{K} W^{(k)} \pi_{k,s}$ where $W^{(k)}$, the weight for individual k, is nonnegative, with $\sum_{k=1}^{K} W^{(k)} = 1$.

Market Segments

The individual weights can be further modified by considering various market segments. We assume that an additional input matrix of demographic (or general background) classification variables is also available. We let

$D_n^{(k)}$ = the demographic category of individual k for variable n; $n = 1, 2, \ldots, N$, where N denotes the total number of demographic variables.

[3] In the unlikely event that $U_{k,s} = 0$ for all s, we set $U_{k,s} = 1/S$.

We also have weights E_n, one weight for each of the N demographics; $E_n \geq 0$; $\sum_{n=1}^{N} E_n = 1$.

In SIMOPT, we can specify the number of demographics H we want to use, which demographics, $t_1, t_2, \ldots, t_H$, and the levels l_h for each demographic t_h (more than one level within a demographic can be included). We then have

$$V_t^{(k)} = W^{(k)} \sum_{h=1}^{H} I_h^{(k)} E_{t_h} \quad \text{where}$$

$$I_h^{(k)} = \begin{cases} 1 & \text{if} \qquad D_{t_h}^{(k)} = l_h, \\ 0 & \text{otherwise,} \qquad \text{and} \end{cases}.$$

$$V^{(k)} = \frac{V_t^{(k)}}{\sum_{k=1}^{K} V_t^{(k)}}$$

The overall market share for supplier/product s is then given by

$$M_s^* = \sum_{k=1}^{K} V^{(k)} \pi_{k,s}.$$

(Note that M_s^* implicitly depends on the profiles of each of the S suppliers.)

Initial Supplier Profiles, Market Shares, and Costs/Returns

Initial conditions for applying the model entail both a set of initial supplier profiles and initial market shares I_s. These initial supplier profiles are associated with market M_s^{*b} and, hence, multipliers given by $f_s \equiv I_s / M_s^{*b}$.

The adjusted market shares are then given by

$$\hat{M}_s = \frac{f_s M_s^*}{\sum_{s=1}^{S} f_s M_s^*}.$$

Finally, the model can incorporate costs/returns and can optimize over this measure (as well as over market share). First, we let:

$R_{m,j}$ = return for level j of attribute m.

(Note: The default value is $R_{m,j} = 1/M$ for all j and m.) We can then compute the return for any brand/supplier profile as

$$T(j_1, j_2, \ldots, j_M) = \sum_{m=1}^{M} R_{m,j_m}.$$

Hence, for each supplier we have a total return:

$$T_s \equiv T(j_s).$$

This gives us a respective unadjusted and adjusted return for each supplier of

$$O_s^* = M_s^* T_s \text{ and } \hat{O}_s = \hat{M}_s T_s$$

with the default value of $T_s = 1$.

SIMOPT's Computational Features

The model's outputs consist of market shares or dollar contributions to overhead and profits for each supplier. In the latter case, direct (or variable) costs/returns have to be estimated at the individual attribute level for each supplier – a daunting task in most real-world settings.

In any given run of the model, the user obtains market share (return) for each supplier on both an unadjusted and adjusted (for initial share) basis. Outputs can be obtained for both the total market and for any segment defined by the user from the available demographic variables.

The user is then able to perform four types of analysis:

1. A sensitivity analysis. This shows how shares (returns) change for all suppliers as one varies the levels within each attribute, in turn.
2. An optimal attribute level analysis. If this option is chosen, the model computes the best attribute profile for a given supplier, conditioned on specified attribute levels for all competing suppliers.
3. A cannibalization analysis. If the optimization option is chosen, the user can also specify one or more ancillary products. If so, the model finds the optimal profile that maximizes share (return) for the set of chosen products (that can include the firm's existing products). This profile can be compared to the best product for a given supplier that does not take into account interactions with the firm's existing products.
4. A Pareto frontier analysis. In most real-world problems the marketing strategist is not only interested in finding the "best" product in terms of (say) return but also wishes to get some feel for the tradeoff between return and market share.

SIMOPT provides a capability to trace out the (Pareto) frontier of all profiles that are undominated with respect to return and share. The user can then find out what the potential value may be in giving up some amount of return for an increase in market share, or vice versa.

Through a sequential series of new product additions the user can examine the effect of adding/deleting products in the firm 's line.

The Alpha Constant

Before starting the various SIMOPT analyses a further step remained. The researchers had to calculate the value of the decision constant, alpha in equation for market share, that when applied to product utilities at the individual respondent level would best approximate the actual current shares, shown in Table 2. The best fitting value of alpha was 4.3. This value is fairly close to a BTL rule (in which alpha is 1.0) but will lead to somewhat greater sensitivity to profile changes than BTL.

Appendix 3

Description of Algorithms for Product Line Design

The total number of possible products in a conjoint study with p attributes is $\prod_{i=1}^{p} \ell_i$ where ℓ_i is the number of levels for the ith attribute; this number grows with the number of attributes and can be quite large in most business applications. Because of this, two tasks arise when conjoint study results are used to determine the "best" products (one or a line). These are to determine a set of "good" products to be considered by the firm and to select the "best" subset (one or more) of the identified products. We should note that the single product design problem is a special case of the product line problem when the length of the product line is one. The problem of identifying optimal product line of multi-attributed items is deemed NP-hard, which implies that it requires unacceptable time to find the guaranteed optimal solution. For example, if there are four attributes of three levels each, there is a total of $3^4 = 81$ possible product combinations to evaluate for finding the best single product. If the firm wishes to introduce three items in the product line, it needs to evaluate 21,330 product line combinations, making this problem NP-hard.

Over the years, there have been attempts to tackle the product line design problem; these include: heuristic dynamic programming (Kohli and Sukumar 1990), Beam Search (Nair et al. 1995), Greedy heuristic (Green and Krieger 1985, 1987a, 1987b), Divide-and-conquer heuristic (Green and Krieger 1993), and Genetic algorithms (GA) introduced by Balakrishnan et al. (1994). [We must note that the GA algorithms approach was first applied successfully for the single product design problem by Balakrishnan and Jacob (1996)]. In this appendix, we will review two of these methods – Greedy-heuristic and GA approach. Both these methods start with partworths developed by any of the conjoint methods.

Greedy- Heuristic Approach

Algorithm for Identifying Good Products

First, we describe an algorithm called "partworth-based" greedy algorithm uses the partworth values estimated at the individual level in the conjoint study. Each individual's current product in use is the status quo and it is used in comparing the products being considered. It sequentially builds a set of products to be considered. It works as follows:

1. Determine the first product as the one that is formed by selecting the level with the highest sum of partworths, across all individuals (buyers), for each attribute in return.
2. Determine the best product for each individual by looking at the attribute partworths (by selecting the levels for which the partworths are highest in his/her utility function). Then, compute the utility for the first product identified in Step 1 for each individual using his/her partworths. If the buyer i's utility for the first product to enter is within a user-specified ε of buyer i's best product, that buyer is assumed to be satisfied.
3. Repeat Step 2 for all buyers in the sample. Remove the buyers who are satisfied from consideration and repeat Step 1 for the remaining buyers.

The result will be a set of J products; the size of this set will depend upon the value of ε and the heterogeneity of partworths among the individuals in the sample. If this set is large, an interchange heuristic is used to arrive at a manageable set; this involves interchanging an item in J with one not in J in a systematic manner. For details, see Green and Krieger (1985).

The above steps are not needed when a set of J products has been prespecified and the utility values for these J products are available for the sample of individuals. In either case, the problem is one of choosing a subset of products that are best from the individuals' perspective. This problem is called the buyer's problem. The algorithm is called the product-greedy algorithm.[4]

The buyer's problem can be described mathematically[5] as follows.

[4] In addition to the product-based greedy heuristic, one could consider three other heuristics. These are: (a) best-in heuristic; (b) the top-K heuristic; and (c) the divide-and-conquer heuristic. For details, see Green and Krieger (1987a).

[5] This notation differs slightly from other parts of the book.

Let $I = \{1, \ldots, M\}$ be the set of individuals (buyers) and $J = \{1, \ldots, N\}$ be the total set of products. Let u_{ij} be the utility of the jth product for the ith individual (computed from his/her partworths). We assume that u_{ij} values are comparable across individuals. Then, the optimal subset $S \subset J$ consisting of K elements will maximize $\sum_{i \in I} z_i$, where $z_i = \max_{j \in S} u_{ij}$.

Let y_j take the value 1 if the product j is in S and 0 otherwise and x_{ij} take the value 1 if the individual i does choose product j and 0 otherwise.

If K is fixed, the problem then is to find x_{ij} and y_j so as to maximize $Z = \sum_{i \in I} \sum_{j \in J} u_{ij} x_{ij}$, subject to $\sum_{j \in J} x_{ij} = 1$ for $i \in I$; and $\sum_{j \in J} y_j = K$, where $0 \leq x_{ij} \leq y_j \leq 1$ for $i \in I$, $j \in J$ and x_{ij} and y_j are 0-1 variables.

The preceding model is expressed in a 0–1 (integer) programming framework, with a linear objective function and linear constraints; the problem has combinatorial features. If N is large (e.g., N = 100 product options), then choosing K items from N options can result in a formidable number of distinct combinations for evaluation. For example, with N = 100, if K is only 7, the number of possible combinations is well over a billion. The greedy algorithm is a heuristic to tackle this problem.

We illustrate this algorithm with the results from a conjoint study on computer terminals (Green and Krieger 1987b). In this study, hybrid conjoint analysis was used to estimate 55 partworths (for 16 product attributes) for a sample of 187 respondents. The number of levels for each attribute ranged between 2 and 4. When the partworth-based greedy algorithm was applied to these data, a total of 19 products were needed to satisfy all buyers in the sense described above. The product combinations are:

ε	Product attribute levels	Cumulative number satisfied
0.01	3, 2, 1, 1; 2, 2, 2, 1; 2, 4, 4, 3; 3, 2, 2, 3	1
0.05	3, 2, 1, 1; 2, 3, 2, 1; 2, 4, 4, 3; 3, 2, 2, 3	10
0.08	3, 2, 2, 1; 3, 1, 2, 1; 2, 4, 4, 3; 3, 2, 2, 3	29
0.10	3, 2, 2, 1; 3, 1, 2, 1; 2, 4, 1, 3; 3, 2, 2, 3	42
0.11	3, 2, 1, 1; 3, 3, 2, 1; 2, 4, 4, 3; 3, 2, 2, 3	53
⋮		
0.31	4, 4, 4, 4; 4, 4, 3, 3; 2, 4, 4, 3; 3, 3, 3, 4	187

The product-based greedy algorithm was applied next to identify the best subset of four products from these 19 contenders obtained by the direct enumeration of the $\binom{19}{4} = 3,876$ combinations. The best four products were:

Description
3, 2, 1, 1; 2, 2, 2, 1; 2, 4, 4, 3; 3, 2, 2, 3
3, 2, 1, 1; 3, 1, 2, 1; 2, 4, 1, 3; 3, 2, 2, 3
2, 2, 1, 1; 2, 1, 1, 1; 2, 4, 1, 1; 1, 1, 3, 1
4, 4, 4, 4; 4, 3, 3, 3; 2, 4, 4, 3; 3, 3, 3, 4

This set of four products resulted in a share of choices of only 83 % across the 187 buyers. In the remaining cases, the respondent's utility for the status quo alternative exceeded those of the best four products.

Algorithm for Identifying Best Product or Product Line

Once a set of good products is identified, we need to consider which of these is best from the firm's (seller's) point of view. The seller's problem is quite similar to that of the buyer's problem with the additional consideration of the seller's welfare determined by the value of each buyer and each product to the firm. This algorithm (seller's greedy) can be described as follows (for details, see Green and Krieger (1985)).

As before, we assume that each consumer i chooses at most one product. The product choice is the one with the highest utility provided that the utility exceeds u_{i0}, the utility associated with one's status quo. The value to the seller is given by the v_{ij} corresponding to product j chosen by buyer i. Further, assume that the total return Z(K) equals the sum of the return across buyers and K products. We let

$$y_j = \begin{cases} 1 & \text{if product j is in the subset,} \\ 0 & \text{if product j is not in the subset,} \end{cases}$$

with $y_0 = 1$. Also, let

$$x_{ij} = \begin{cases} 1 \text{ if } u_{ij}y_j \geq u_{i\ell}y_l; & \ell = 0, \ldots, N, \\ 0 \text{ otherwise.} \end{cases}$$

Let $x_{ij} = 1$ for only the smallest j for which $x_{ij} = 1$ above. Then the problem is to

$$\max \ Z = \sum_{i=1}^{M} \sum_{j=1}^{N} x_{ij} v_{ij}, \qquad \text{subject to}$$

$$x_{ij} \leq y_j,$$

$$\sum_{j=0}^{N} y_j \leq K + 1 \qquad \text{and}$$

$$x_{ij},\ y_j \text{ are 0-1 variables.}$$

In contrast to the high lower bound in the buyer's problem, the seller's greedy (denoted G) can lead to arbitrarily poor results, compared to the optimal solution. The seller's greedy heuristic is described formally below with a small numerical example. The heuristic consists of four stages.

Stage 1: Initialization

$S^{(0)} = \emptyset$ (there are no products in the subset),
$k = 0$ (where k is the number of products in the subset),
$y_0 = 1$ (the status quo product is assumed to be in the subset),
$y_j = 0$ for $j = 1, \ldots, N$ (all other products are not in the subset),
$x_{i0} = 1$ for $i = 1, \ldots, M$ (buyer i chooses the status quo at this stage),
$x_{ij} = 0$ for $i = 1, \ldots, M$; $j = 1, \ldots, N$ (buyer i does not choose product j).

Stage 2: Induction Step
Let

$$w_{ij} = \begin{cases} 1 \text{ if } u_{ij} > u_{il} y_\ell \text{ for all } \ell = 0,\ 1, \ldots,\ N, \\ 0 \text{ otherwise}, . \end{cases}$$

(i.e., w_{ij} is equal to 1 only when product j's utility exceeds the current best utility for buyer i).

Let $T_j = \sum_{i=1}^{M} w_{ij} \left(v_{ij} - \sum_{j=1}^{N} x_{ij} v_{ij} \right)$; $j = 1,\ N$ (i.e., T_j is the *increment* in the objective function if product j is added to the subset).

If $T_j \leq 0$ for all j, stop. (In this case, continuation would not increase the objective function.)

Stage 3: Updating Step
Let j* correspond to the product with maximum T_j.
$S^{(k+1)} = S^{(k)} \cup j^*$,
$y_{j^*} = 1$ (i.e., product j* is in the subset),

$$x_{ij} = \begin{cases} 0 \text{ if } j \neq j^* \text{ and } w_{ij^*} = 1, \\ 1 \text{ if } j = j^* \text{ and } w_{ij^*} = 1, \\ x_{ij} \text{ if } w_{ij^*} = 0. \end{cases}$$

(i.e., product j* is the product of choice for buyer i if $w_{ij^*} = 1$; otherwise, the buyer's choice does not change at this step).

Stage 4: Termination Step
Set k to be k + 1 (subject size is increased from k to k + 1). If k = K, stop; otherwise, go to the induction step.

Numerical Example

We now consider a simple numerical example of the seller's greedy heuristic. Let $M = 10$, $N = 6$, and $K = 3$. Consider the following buyer's and seller's utility matrices:

	U Matrix							V Matrix						
	0	1	2	3	4	5	6	0	1	2	3	4	5	6
1	55	47	56	27	61	39	42	0	8	7	9	7	9	7
2	62	55	72	55	70	71	79	0	7	9	8	2	8	5
3	71	63	70	60	80	79	60	0	8	8	9	8	8	7
4	47	55	43	61	60	50	40	0	6	4	7	7	8	4
5	90	95	48	91	50	71	80	0	7	9	8	5	8	7
6	70	62	81	60	47	61	82	0	6	3	8	6	7	4
7	63	58	71	60	69	42	55	0	5	5	7	8	5	6
8	59	47	62	53	48	79	71	0	8	6	5	4	5	8
9	81	83	80	77	82	71	90	0	5	4	6	9	6	8
10	77	66	78	67	79	32	60	0	6	2	5	9	8	9

We will show the analysis using this algorithm for a subset of K = 3 products.

First, we consider the addition of one product in addition to the current product (0). There are six possible candidates, products k = 1, …,6. For selecting the first product 1, the values of w_{ij}s are as follows (these are obtained by comparing the buyer's utility for the product versus the current product 0; if the utility is higher it yields the value of 1 and 0 otherwise).

	X_{ij}- values							W_{ij} -values						
i	1	1	2	3	4	5	6	0	1	2	3	4	5	6
1	1	0	1	0	1	0	0	0	0	1	0	1	0	0
2	1	0	1	0	1	1	1	0	0	1	0	1	1	1
3	1	0	0	0	1	1	0	0	0	0	0	1	1	0
4	1	1	0	1	1	1	0	0	1	0	1	1	1	0
5	1	1	0	1	0	0	0	0	1	0	0	0	0	1
6	1	0	1	0	0	0	1	0	0	1	0	0	0	1
7	1	0	1	0	1	0	0	0	0	1	0	1	0	0
8	1	0	1	0	0	1	1	0	0	1	0	0	1	1
9	1	1	0	0	1	0	1	0	1	0	0	1	0	1
10	1	0	1	0	1	0	0	0	0	0	0	1	0	0

k = 1

The incremental value for the seller by offering the first product is computed by multiplying the w-column with the corresponding v-columns. For the first possible product 1; the incremental value will be: $0 * 8 + 0 * 7 + 0 * 8 + 1 * 6 + 1 * 7 + 0 * 6 + 0 * 5 + 0 * 8 + 1 * 5 + 0 * 2 = 18$; similarly for other five possible products. The values of T_j; j = 1,…, 6 are shown below:

1. $0 + 0 + 0 + 6 + 7 + 0 + 0 + 0 + 5 + 0 = 18$
2. $7 + 9 + 0 + 0 + 0 + 3 + 5 + 6 + 0 + 2 = 32$
3. $0 + 0 + 0 + 7 + 8 + 0 + 0 + 0 + 0 + 0 = 15$
4. $7 + 2 + 8 + 7 + 0 + 0 + 8 + 0 + 9 + 9 = 50$* (maximum)
5. $0 + 8 + 8 + 8 + 0 + 0 + 0 + 5 + 0 + 0 = 29$
6. $0 + 5 + 0 + 0 + 0 + 4 + 0 + 8 + 8 + 0 = 25$

The fourth product, 4 yields the maximum gain to the seller will be 50 and hence the first product to be added will be k =4.

	Buyer	1	2	3	4	5	6	7	8	9	10
status quo	**u:**	61	70	80	60	90	70	69	59	82	79
(Product 4)	**v:**	7	2	8	7	0	0	8	0	9	9

k = 2

Now, to add the second product, the same process will be repeated with the updating as described above. The values of x_{ij} after the inclusion of the 4-th product are:

	X_{ij}- values							W_{ij} -values						
i	0	1	2	3	4	5	6	0	1	2	3	4	5	6
1	1	0	1	0	1	0	0	0	0	1	0	1	0	0
2	1	0	1	0	1	1	1	0	0	1	0	1	1	1
3	1	0	0	0	1	1	0	0	0	0	0	1	1	0
4	1	1	0	1	1	1	0	0	0	0	1	1	1	0
5	1	1	0	1	0	0	0	0	1	0	0	0	0	1
6	1	0	1	0	0	0	1	0	0	1	0	0	0	1
7	1	0	1	0	1	0	0	0	0	1	0	1	0	0
8	1	0	1	0	0	1	1	0	0	1	0	0	1	1
9	1	1	0	0	1	0	1	0	1	0	0	1	0	1
10	1	0	1	0	1	0	0	0	0	0	0	1	0	0

The computation for the first product, k =1 given that k = 4 is already in the set will use the revised wij values and the increment (or decrement) in the supplier values.

1. $0 + 0 + 0 + 0 + 7 + 0 + 0 + 0 + (5–9) + 0 = 3$
2. $0 + (9–2) + 0 + 0 + 3 + (5–8) + 6 + 0 + 0 = 13$
3. $0 + 0 + 0 + (7–7) + 8 + 0 + 0 + 0 + 0 + 0 = 8$
4. 0
5. $0 + (8–2) + 0 + 0 + 0 + 0 + 0 + 5 + 0 + 0 = 11$
6. $0 + (5–2) + 0 + 0 + 0 + 4 + 0 + 8 + (8–9) + 0 = 14$* (maximum)

	Buyer	1	2	3	4	5	6	7	8	9	10
status quo	**u:**	61	79	80	60	90	82	69	71	90	79
(Products 4; 6)	**v:**	7	5	8	7	0	4	8	8	8	9

k = 3

1. $0 + 0 + 0 + 7 + 0 + 0 + 0 + 0 + 0 = 7$
2. $0 + 0 + 0 + 0 + 0 + 0 + (5–8) + 0 + 0 + 0 = -3$
3. $0 + 0 + 0 + (7–7) + 8 + 0 + 0 + 0 + 0 + 0 = 8$* (maximum)
4. 0
5. $0 + 0 + 0 + 0 + 0 + 0 + 0 + (5–8) + 0 + 0 = -3$
6. 0

Final Solution: Products 4, 6, 3

	Buyer	1	2	3	4	5	6	7	8	9	10
status quo: (Products 3; 6; 4)	**u:**	61	79	80	61	91	82	69	71	90	79
	v:	7	5	8	7	8	4	8	8	8	9
Buyers' Choice		1	2	3	4	5	6	7	8	9	10
Product		4	6	4	3	3	6	4	6	6	4

The greedy solution for this example consists of products 3, 6, and 4. Interestingly enough, if complete enumeration is run on this (small) problem, the optimal solution is identical to the greedy solution (of course, this will not be true in general).

Genetic Algorithms Approach

The concept of Genetic algorithms was first proposed by John and Holland (1975). The basis for the algorithm is how species adapt to their environment using the processes of reproduction, mutation, and natural selection.

In order to apply these algorithms to product line (or single product) design problem,[6] each product is encoded as a string of binary (0 or 1) variables each variable representing the absence or presence of a specific level of a particular attribute. As an example, if there are three attributes A, B, and C with 3, 4, and 3 levels respectively, a product with levels A1, B3, and C2 is (100, 0010, 010); it can also be denoted as 1 3 2. For product line of two items, (A1, B3, C2) and (A2, B1, C1), the string will be: 100, 0010, 010| 010, 1000, 100 or 1 3 2 |2 1 1.

We can now illustrate the three processes. In the reproduction process, the best (fittest) strings (usually about 50 %) at time t are retained for next generation (or t + 1). In the crossover process, parts of the strings are exchanged between any pair of strings; for example if the strings are (010, 1000, 100) and (001, 0100, 010); the strings after crossover could be (001, 1000, 010) and (010, 0100, 100). In the mutation process, some aspects of the strings are altered with pre-specified probabilities. A mutated string for (001, 0100, 010) could become (100, 0100, 010), where the first attribute's level is altered probabilistically. With these processes, the number of strings (or the size of the population at a given time) will grow; some algorithms allow the size to grow to twice the current size for the next time period. By applying the criteria for retention, the population size can be reduced. One criterion in the product design application is the number of consumers

[6] This material is based on the published work by P.V. (Sundar) Balakrishnan and his colleagues; references noted in the bibliography.

who would choose each of the strings relative to their current product at any given time; this number is a measure of fitness of the string. In this calculation, the utility of each of the strings is computed using the partworth values for the individuals in the sample. Weaker strings with fitness values below a pre-specified cutoff will be eliminated in the next generation (or t + 1).

With this basic understanding, we may describe a genetic algorithm with the following sequence in time (t):

1. At the beginning (t = 0), an initial population, POP (t) is generated according to some heuristic or randomly;
2. Each string in POP (t) is evaluated according to some criterion; if the criterion is satisfied, the process stops; if not the process continues to the next step;
3. Various genetic operators (reproduction, mutation, or selection) are applied to the strings in POP (t) to generate POP (t + 1) and evaluated as before; and go to Step 2.

As noted above, Balakrishnan and his colleagues (2009) had contributed to the application of genetic algorithms for product design or product line design. There are several technical details that are too advanced for us to discuss here; but, the sources cited will assist any interested readers (see Balakrishnan (2009) and Balakrishnan et al. (2004)).

We will use the material in the document by Balakrishnan et al. (2009) to illustrate the type of results one would get from their implementation of GA algorithms for product/product line design and the unpublished case developed by Balakrishnan and Roos (2008) entitled "Case: Televisions 4'US Optimal Product Line Designs" (source: http://faculty.washington.edu/sundar/PRODLINE-RELEASE).

The context of this application is the design of a product line of four televisions for a large retailer. Each product is described on six attributes with the following levels:

Attribute	Level 1	Level 2	Level 3	Level 4
Brand name	JVC	RCA	Sony	–
Screen	30″ CRT	36″ Plasma	32″ LCD	–
Sound	Dolby sound	Stereo sound	Surround sound	–
Parental controls	Present	Not present	–	–
On screen program guide	Present	Not present	–	–
Price	$300	$400	$500	$750

The analysis was based on partworth data for 200 individuals. The competitive product set consisted of five brands, each of which is described on the same six attributes. The corresponding strings for these five brands are:

Brand 1: 100, 100, 100, 10, 10, and 1000
Brand 2: 100, 010, 010, 01, 01, and 0100
Brand 3: 010, 001, 001, 10, 01, and 0010
Brand 4: 010, 100, 100, 10, 10, and 1000
Brand 5: 001, 010, 001, 01, 01, and 0001.

The reader may note that Brands 1 and 2 are JVC (with different characteristics), Brand 3 and 4 are RCA (with different characteristics), and Brand 5 is Sony (which is the premium brand in the set).

The initial product line of four items was developed from Dynamic Programming Optimization method and yielded a market share of 52 %. The individual products in the line and the corresponding market share) are as follows:

Product 1: Sony, 32″LCD, Surround Sound, Parental Controls, No Program guide, $300 (34.0 %);
Product 2: RCA, 32″LCD, Surround Sound, Parental Controls, No Program guide, $400 (9.0 %);
Product 3: JVC, 30″CRT, Surround Sound, Parental Controls, No Program guide, $300 (6.5 %); and
Product 4: Sony, 36″Plasma, Surround Sound, Parental Controls, No Program guide, $750 (2.5 %).

However, when the genetic algorithm as described above was applied with this initial product line, the optimal market share is 91 %. The items in the product line along with their market shares are as follows:

Product 1: Sony, 30″CRT, Surround Sound, Parental Controls, On-Screen Program guide, $300 (30.0 %);
Product 2: RCA, 32″LCD, Surround Sound, Parental Controls, On-screen Program guide, $400 (31.0 %);
Product 3: JVC, 36″ Plasma, Surround Sound, Parental Controls, No Program guide, $300 (14.5 %); and
Product 4: Sony, 32″LCD, Surround Sound, Parental Controls, On-screen Program guide, $750 (15.5 %).

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Chapter 7
Applications for Product Positioning and Market Segmentation

7.1 Introduction

As we discussed in the previous chapter, there is a subtle difference between product design and product positioning. While product design deals with decisions on the "optimal" characteristics of a product, product positioning deals with issues of how best to communicate the corresponding benefits (or attributes) to the target consumers (for more details, see Kotler and Keller (2012) and Kaul and Rao (1995)). Naturally the benefits of a product arise from its characteristics and the way consumers interpret them. In applications of conjoint analysis to product positioning, an analyst describes the possible benefits and their levels in the same way as one would in the case of product design; then the problem of determining the best positioning is identical to that of product design. In some cases, the analyst may include both product benefits and characteristics.

A related (or dual) problem to product positioning is the identification of an appropriate market segment (or segments) of consumers to whom that positioning would appeal most. For this purpose, the first step is to identify market segments of consumers who are relatively homogeneous within a segment with one segment being quite different from another segment. There are several bases (or types of variables) for identifying market segments (see Wedel and Kamakura 2000; Kotler and Keller 2012; Rao and Steckel 1998). The methodology of identifying market segments uses one of two main approaches depending upon which sets of variables (background-descriptor or behavior-related variables) are available. There is considerable evidence that behavior-related variables are more useful in forming market segments. The individual level partworths for attributes (as determined by conjoint methods) are more like behavior-related variables and are therefore more useful in segmentation than an individual's background variables. The methodology of forming market segments using conjoint results is an approach that belongs to behavior-based market segmentation.

Against this brief background, this chapter describes several applications of conjoint analysis to the two problems of product positioning and market segmentation. Some of

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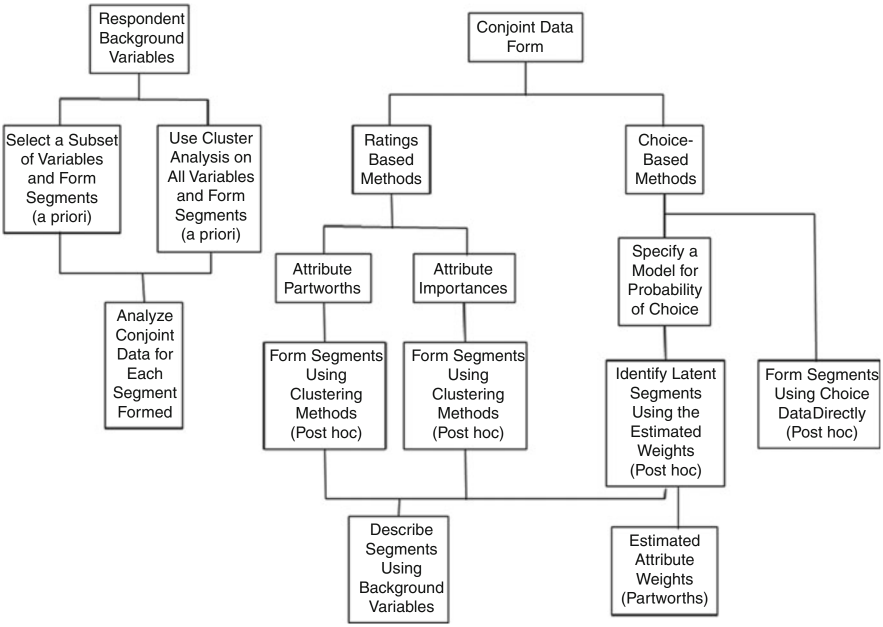

Fig. 7.1 Market segmentation in the context of conjoint analysis

these applications are drawn from the literature and the rest from applied company projects. In Sect. 7.2, we describe the specific analysis methods applied to conjoint results for market segmentation. Section 7.3 describes two applications for product positioning. Section 7.4 describes four applications of market segmentation. Section 7.5 describes some emerging approaches to market segmentation using conjoint analysis and an empirical comparison. The last section provides a summary.

7.2 Methods of Forming Segments with Conjoint Results

The method of segmentation based on background variables is called a priori segmentation while that based on conjoint results is called post hoc segmentation. The general method of forming segments is cluster analysis. Several types of cluster analysis exist in the literature; these include k-means clustering method, Ward's method of clustering, and average linkage. The segmentation methods can be combined with optimization methods for determining "optimal" products that a firm may wish to market. Figure 7.1 shows some alternative methods of segmentation in the context of conjoint analysis.

The reader will recall the two types of conjoint research introduced earlier—the ratings based approach and the choice-based approach. In either approach, some background questions on the respondents including demographic/social/economic variables are collected as a matter of routine; in addition, depending upon the context of the study, psychographic or technographic questions are included in the set of background variables. The conjoint analysis usually yields partworth functions (and therefore importances) for each attribute in the design at the individual level. These data (partworths and importances) and background variables form the basis for segmentation. We describe ways of developing segments of respondents with such data.

When choice-based conjoint analysis is utilized for a study, the analysis model (i.e., probability of choice of an alternative in the choice set) can be specified for the sample as a whole or for each segment assuming that segments exist in the sample. In the latter case, the parameters of the conjoint choice model are specific to segments, but the segments themselves are latent. Assuming that the sample consists of a prespecified number of segments (which we may call "latent segments"), the analysis algorithm then estimates the segment-specific parameters of the probability model and identifies the corresponding segments. The algorithm iterates over the number of latent segments and the analyst chooses an appropriate number of latent segments using criteria such as the Akaike Information Criterion (or related criteria of fit of the model to data). Thus, choice-based conjoint analysis forms segments in one step rather than two steps as in the ratings-based conjoint approach. An alternative method is to cluster the choice data directly and identify segments and estimate the choice model for each of the identified segments; one may consider both these approaches as post hoc segmentation methods because they use response (outcome) data rather than information on respondent background variables. We describe an application of market segmentation with choice-based conjoint data in a later section of this chapter.

7.3 Applications for Product Positioning

In this section, we describe an application for product positioning of a pharmaceutical product (an antidepressant drug).

7.3.1 Application: Positioning of an Antidepressant Drug

This application is based on a study conducted for a pharmaceutical company; given its confidentiality, some details will be disguised. The problem was one of determining ways in which a prescription drug's benefits could be communicated to psychiatrists. The drug in question was used for treating depression. While the Federal Food and Drug Administration approved the product's chemical characteristics, the firm had some options in varying dosage and other aspects in order to achieve a superior positioning versus the competing products intended to treat the same disease. The firm commissioned a conjoint analysis study to determine the specific profile it wished to communicate to the psychiatrists who prescribe the drug. For this positioning study, the firm identified five attributes respectively at 3, 2, 2, 2, and 2 levels, as shown in Table 7.1. A fractional factorial design was used in developing 12 profiles out of the possible 48 profiles. Ninety psychiatrists, selected

Table 7.1 Attributes and levels in the antidepressant positioning study

Attribute	Level	Description
Sedating effect	1	Balanced effect—more sedating during night but not during day
	2	Marked effect both daytime and night time
	3	Less sedating during night and day
Side effects	1	Significantly lower
	2	Similar to current products
Rapidity of action	1	About 2 days or less
	2	Within a week
Rapidity of true antidepressant action	1	1–2 weeks
	2	3 weeks or more
Dosage level	1	Therapeutic dose
	2	Dose requires titration

among those attending a convention, were interviewed for seeking their evaluations of the profiles; the specific question asked was their likelihood of prescribing an antidepressant with the attributes described in each profile.

In addition, profiles of four patients who were typical for such a drug were developed using information from prior studies. In order to obtain additional insight into how the drug could be positioned, the doctors were asked to evaluate the degree of suitability of each drug profile for each of the patient profiles. In a way, these ratings were patient type-specific evaluations, similar to the overall evaluations of each drug profile. The ratings of the positioning profiles were analyzed in the usual manner with dummy variable regressions for the sample as a whole and for segments of doctors with prespecified characteristics (a priori segments). Similar analyses were done for the patient profile-specific ratings of suitability.

The results indicated that the best positioning was a drug that gave balanced effects with no or fewer side effects and one that acts in 2 days or less with true antidepressant effect in 2–3 weeks. Having decided on its product positioning, the firm used the results from the patient-specific ratings to identify the best profile of the target consumer for the positioning of this drug. Subsequently, the firm utilized this positioning theme to develop a communication strategy with beneficial results.

7.4 Market Segmentation Applications

7.4.1 Application 1: Segments of Camera Buyers

We will describe a small-scale study on a choice-based conjoint analysis of pocket cameras. The study used four product features, a built-in exposure meter, focus adjustment, shutter speed adjustment, and built-in electronic flash; each feature was either included or not in a basic pocket camera. Each respondent was presented with 16 product concepts and were asked to either chooser not choose each one. It so happened that 13 of the respondents opted not to choose any of the 16 product concepts and were treated as a separate segment. The choice data from the remaining 32 respondents for the 16 product combinations were analyzed to obtain coefficients for the four features for each respondent along with a constant term (intercept). The data of the 32 by 5 coefficients (including the intercept) were cluster analyzed using a k-means cluster method to identify segments in this sample. The criterion for clustering was minimizing within group sum of squares. This criterion reduced for 2–5 clusters as follows:

		Size of cluster numbered				
Number of clusters	Percent reduction	1	2	3	4	5
2	46	24	8			
3	58	12	12	8		
4	66	12	11	7	2	
5	71	11	7	7	5	2

The researchers selected a 3-cluster solution to identify segments because of the small marginal reduction in the criterion from a 3-cluster solution to a 4-cluster solution and the small sizes of the clusters beyond 3 clusters. The means and standard errors of the beta coefficients (or weights given to the four product features) are shown in Table 7.2. Here, Segment 1 is uniformly positive for all of the four product features while Segment 2 is positive toward the first three features and negative to the fourth design feature (flash). Segment 3 is moderately responsive to exposure meter but negative toward the other three features. It is worth noting that this analysis revealed segments that differed quite dramatically in terms of their responsiveness toward the product design features studied.

Interestingly, these segments also differed in terms of their background characteristics (photography interest, film usage, readership of photography magazines etc.), as shown in Table 7.3. While this application is for a small sample, the same methods would apply to studies with almost any sample size.

7.4.2 Application 2: Segments of Food Processor Buyers

The reader will recall the detailed discussion of the food processor conjoint study, described in Chap. 6 (see Page and Rosenbaum 1989). In this study, analysis was done at the individual level to obtain partworths for the 12 attributes (7 at 3 levels each and 5 at 2 levels each) for each person. The number of parameters estimated is 19 (=$7 \times 2 + 5 \times 1$). The resulting matrix of 500 respondents by 19 was submitted to a hierarchical clustering program in SAS and a four-cluster solution was selected because it produced a set of clusters which showed face validity and seemed useful for market planning (no statistical details from SAS output were published). These four clusters revealed market segments of food processor buyers who differ in terms of the importance they attached to specific features. Accordingly, these segments desired different combinations of features and benefits of food processors. The four segments were profiled in terms of the attributes used in

Table 7.2 Average response coefficients for camera features for the market segments

	Mean and standard error of beta coefficient for				
Segment	Constant	Exposure meter	Focus	Shutter	Flash
1	−22.84 (1.75)	6.36 (0.86)	8.85 (1.20)	6.34 (1.54)	8.88 (0.78)
2	−18.61 (0.84)	8.28 (0.77)	8.97 (1.42)	8.84 (1.09)	−3.06 (1.27)
3	−2.64 (2.65)	1.03 (2.28)	−1.10 (2.41)	−5.34 (2.06)	−1.30 (3.01)
4	−∞	.0	.0	.0	.0

Source: Reprinted with permission from Rao and Winter (1978), published by the American Marketing Association

Table 7.3 Profiles of the four market segments for camera study

	Market segments						
Characteristics	1	2	3	4	4A[a]	4B[a]	All responses
Size of segment	12	12	8	13	6	7	45
Camera ownership (%):							
Any camera	75	83	62	69	67	71	73
Single lens reflex	42	50	16	38	17	57	40
Film usage (rolls/year)	7.8	7.1	2.9	14.3	3.5	23.6	8.6
% practicing photography as an art form	42	42	25	31	0	58	33
% doing own film or print processing	25	8	25	15	0	28	20
Readership (issues/year)							
Modern photography	0.75	0.75	0.12	0.5	0.	1.0	0.6
Popular photography	1.2	0.4	0.12	0.5	0.	0.9	0.5
New Yorker	3.8	4.3	0.8	0.8	1.2	0.4	2.5

Source: Reprinted with permission from Rao and Winter (1978), published by the American Marketing Association

[a]These two clusters are partitions of cluster 4 (negative response to all 16 concept descriptions) based on intention to buy either a simple camera (cluster 4A) or a single lens reflex camera (cluster 4B)

the study as well as demographic characteristics. Two of these segments are compared in Table 7.4.

These two segments, called *Cheap and Large* segment and *Multiple Speeds and Uses* segment, differed substantially from each other in terms of their most desired attributes in a food processor and the importances they attach to various attributes. They also differed in terms of demographic characteristics. Specifically, the Cheap and Large segment most strongly desired a $49.99 price and a 4-quart bowl while the Multispeeds and Uses segment wanted a $99.99 price and a 2.5-quart bowl size in a food processor. It is unlikely that members of both these segments will buy the same food processor. Depending upon the offerings of competition, the Sunbeam Company could design a new product to command a good share of these two segments. Similar comments apply to the other two segments identified in the study.

Table 7.4 A comparison of two food processor market segments

	The cheap and large segment	The multispeeds and uses segment
Very important features	$49.99 price 4-quart bowl	Seven speeds can be used as a blender and a mixer
Moderately important features	Two speeds seven processing blades heavy duty or professional power motor cylindrical bowl pouring spout	$99.99 price 2-quart bowl cylindrical bowl regular discharge bowl
Features of minor importance	Side discharge bowl three-part feed tube pusher machine that is only a food processor large feed tube under-cabinet design	Three-part feed tube pusher regular size feed tube heavy duty or professional power motor seven processing blades bowl over the motor design
Other demographic and psychographic features of the segment	Least likely segment to already own a food processor have higher than average ownership of Oster and Sears brands most likely segment to give a food processor as a gift older in page have midrange incomes comprise 22 % of the food processor market	Most likely to own a GE brand food processor younger in age have lower incomes comprise 28 % of the food processor market

Source: Compiled from Page and Rosenbaum (1987) with permission of the publisher

7.4.3 Application 3: Segments of Buyers of an Antifungal Medication

This application involves a pharmaceutical firm called Gamma (a disguised name) that markets antifungal medication for treatment of female disorders (Green and Krieger 1991a). To protect confidentiality, the researchers disguised product name and attribute descriptions. The market shares of the major firms in this category were Alpha 6 %, Beta 10 %, Gamma 14 %, and Delta 70 %. Delta was the reference brand given its superior market share.

The Gamma managers commissioned a market survey using conjoint techniques with the objective of determining the demand effects of product improvements in Gamma so as to better compete with the market leader, Delta. Eight attributes were used in the study; their descriptions and their levels are shown in Table 7.5. There were five attributes at 4 levels each and three attributes at 3 levels. A total of 320 physicians were interviewed and appropriate data were collected to enable estimation of partworths at the individual physician level (an honorarium was given to the respondents to compensate for their effort in answering the survey questions). In addition to conjoint data, background data on physicians were collected.

Given the versatility of the data, this study enabled Green and Krieger to determine optimal product design strategies for Gamma under various segmentation methods and compare them in terms of contribution to the overheads of the firm. We turn to a discussion of these results from this analysis.

Table 7.5 Attribute levels used in conjoint survey of antifungal medication

Clinical cure rate in comparison with delta	10 % below	Equal to delta	10 % above	20 % above
Rapidity of symptom relief in comparison with delta	1 day slower	Equal to delta	1 day faster	2 days faster
Recurrence rate in comparison with delta	15 % above	Equal to delta	15 % below	30 % below
Incidence of burning/itching side effects	17 %	10 %	5 %	2 %
Duration of side effects	3 days	2 days	1 day	
Severity of burning/itching side effects	Severe	Moderate	Mild	
Dosage regimen: one dose per day for	14 days	10 days	5 days	2 days
Drug cost per completed therapy	$65.20	$58.85	$44.60	$32.40

Source: Reprinted with permission from the Green and Krieger (1991a), published by the American Marketing Association

Table 7.6 Current drug profiles of four competitors

Attribute	Alpha	Beta	Gamma	Delta
Clinical cure rate in comparison with delta	10 % below	10 % above	10 % above	Equal
Rapidity of symptom relief in comparison with delta	1 day slower	1 day faster	1 day faster	Equal
Recurrence rate in comparison with delta	15 % above	Equal	15% below	Equal
Incidence of side effects	17 %	10 %	5 %	2 %
Duration of side effects	2 days	3 days	2 days	1 day
Severity of side effects	Severe	Moderate	Moderate	Mild
Dosage regimen: one dose per day for	14 days	10 days	5 days	2 days
Drug cost per completed therapy	$44.60	$44.60	$58.85	$58.85
Current market share	6 %	10 %	14 %	70 %

Source: Reprinted with permission from the Green and Krieger (1991a), published by the American Marketing Association

First, Table 7.6 shows the attributes of the four major competing brands in this market. It is quite clear from these data that, while the Gamma brand is priced at the same level as Delta and is better on the first two attributes, it is inferior on other attributes.

The researchers developed segments using four[1] segmentation methods:

1. A priori segmentation of physicians using only type of practice as the variable for segmenting;
2. Post hoc segmentation[2] of physicians using three background variables (type of practice, specialty of physician gynecology, internal medicine, general practice,

[1] The researchers also used a fifth method, called "stepwise segmentation", which is not a method for segmenting physicians but another way to identify optimal products in a sequential manner. We will show the result of the contribution for this method as well.

[2] This approach can also be thought of as an a priori segmentation because variables used in this approach are background variables. But, because some analysis is done for forming segments, it is called post hoc segmentation of physicians.

Table 7.7 Profiles of new gamma products from optimization program (five attributes)

Segmentation strategy	Clinical cure rate	Rapidity of relief	Recurrence rate	Incidence of burning/itching	Dosage: 1 dose per
Buyer: a priori					
Product 1	20 % above	2 days faster	Equal to delta	17 %	10 days
Product 2	20 % above	2 days faster	Equal to delta	17 %	10 days
Gamma share			74.9 %		
Return (index)			100		
Buyer: post hoc					
Product 1	10 % above	2 days faster	Equal to delta	2 %	10 days
Product 2	20 % above	2 days faster	15 % above	17 %	14 days
Gamma share			80.6 %		
Return (index)			109		
Partworth: post hoc					
Product 1	Equal to delta	2 days faster	Equal to delta	2 %	10 days
Product 2	20 % above	2 days faster	Equal to delta	17 %	10 days
Gamma share			81.8 %		
Return (index)			109		
Importances: post hoc					
Product 1	20 % above	2 days faster	Equal to delta	17 %	10 days
Product 2	20 % above	Equal to delta	Equal to delta	2 %	10 days
Gamma share			79.2 %		
Return (index)			103		
Stepwise segmentation					
Product 1	20 % above	2 days faster	Equal to delta	17 %	10 days
Product 2	Equal to delta	Equal to delta	Equal to delta	2 %	10 days
Gamma share			83.1 %		
Return (index)			111		

Source: Reprinted with permission from the Green and Krieger (1991a), published by the American Marketing Association

and 24 psychographic variables) (they first conducted a multiple correspondence analysis before a nonhierarchical clustering method to form segments);

3. Post hoc segmentation of physicians based on partworths (using a nonhierarchical clustering method after centering the data around respondents' mean values); and
4. Post hoc attribute-importance based segmentation of physicians (using a nonhierarchical clustering method).

These methods yielded two segments of physicians used in further analysis. Two new products (one for each segment) were selected for Gamma so as to maximize return (contribution) of the whole product line taking into account the potential for cannibalization. Values for three of the product attributes (duration of side effects at one day, mild severity of side effects, and $65.20 for the cost per completed therapy) were the same for the identified products. The values for the remaining attributes and the return index for the corresponding strategies are shown in Table 7.7. Interestingly, the stepwise method of identifying new products fared better than the

Table 7.8 Average price and choice share for the choice-based conjoint study (application 4)

Brand	Mean price	Choice share
Alpha 1-R (regular)	\$1.34	8.1 %
Alpha 1-D (diet)	\$1.44	9.6
Beta 1-R (regular)	\$1.34	7.7
Beta 1-D (diet)	\$1.44	13.7
Alpha 2-R (regular)	\$1.34	7.3
Alpha 2-D (diet)	\$1.44	11.9
Local-R (regular)	\$1.19	6.2
Beta N-D (new diet concept)	\$1.44	35.6

Source: Reprinted with permission of the publisher from DeSarbo et al. (1995)

four segmentation approaches identified above. (This need not be the case in general). Also, the identified products differed on some or all of the remaining five attributes among these five methods.

7.4.4 *Application 4: Segments from a Choice-Based Conjoint Study*

We now describe an applied choice-based conjoint study and show how market segments are identified with such data (DeSarbo et al. 1995). While the product category was disguised, it contained diet and regular versions of a product marketed by two major firms (Alpha and Beta). At the time of the study, there were seven brands on the market: four brands of Alpha (Alpha 1-R, Alpha 1-D, Alpha 2-R, Alpha 2-D), two brands of Beta (Beta1-R and Beta 1-D) and a local brand (Local-R). The choice-based conjoint study was conducted to determine the prospects of a new brand of Beta under a different name, Beta N-D. For this purpose, 16 choice sets, each consisting of all 8 brands at different prices, were presented to each respondent. The prices were assigned to each brand using an orthogonal design. The choice task for each person was to pick a brand in each choice set presumed to mimic a set of brands on a store shelf. The sample consisted of 600 individuals who qualified as category users, who were recruited at shopping malls. Thus, the data consisted of 9,600 choices over the whole sample. The average prices and shares of the eight brands are shown in Table 7.8.

The authors specified the following choice model for S latent segments. The probability of choice for a particular brand for any person within a segment takes a multinomial logit and the probability of choice of a particular brand for any person is a weighted combination of these probabilities weighted by the probabilities of belonging to each segment. The model estimates the segment-specific coefficients for the eight brands (β_{oj}s) and segment-specific price sensitivity coefficients (β_1s), as well as the probabilities of segment membership (α_s).

The complete model can be described with the following notation. Let:

$i = 1, \ldots, I$ respondents;

$j = 1, \ldots, J$ conjoint profiles and brands;

$k = 1, \ldots, K$ conjoint attributes and dummy variables;

$n = 1, \ldots, N$ choice sets (such as from a 2^J design);

$C_n =$ the specific brands in the n-th choice set;

$X_{jk} =$ k-th dummy variable for the j-th conjoint profile;

$s = 1, \ldots, S$ market segments;

$\beta_{ks} =$ the impact coefficient for the k-th attribute for market segment s;

$Y_{ijn} = 1$ if respondent i chooses brand j in the n-th choice set among C_n; 0 otherwise.

Then, the probability of choice of an item j in the choice set C_n in segment s is the familiar multinomial logit model:

$$P_s(j \in C_n) = \frac{\exp\left(\beta_{0js} + \sum_{k=1}^{K} X_{jk}\beta_{ks}\right)}{\sum_{a \in C_n} \exp\left(\beta_{0as} + \sum_{k=1}^{K} X_{ak}\beta_{ks}\right)},$$

where β_{0js} is the intrinsic utility of brand j to segment s and β_{ks} is the impact coefficient for attribute k in segment s. Then, the unconditional choice probability that a respondent chooses alternative j can be computed as

$$P(j \in C_n) = \sum_{s=1}^{S} \alpha_s P_s(j \in C_n),$$

where α_s, the size of segment s, may be construed as the a priori (or initial) probability of finding a respondent in segment s.

Given a sample of I respondents, the likelihood of the observed conjoint choice data can be formulated as

$$L = \prod_{i=1}^{I} \sum_{s=1}^{S} \alpha_s \prod_{n=1}^{N} \prod_{j \in C_n} \left[\frac{\exp\left(\beta_{0js} + \sum_{k=1}^{K} X_{jk}\beta_{ks}\right)}{\sum_{a \in C_n} \exp\left(\beta_{0as} + \sum_{k=1}^{K} X_{ak}\beta_{ks}\right)} \right]^{Y_{ijn}},$$

where Y_{ijn} reflects the observed choice of respondent i for brand j in choice set n ($Y_{ijn} = 1$ if a choice is observed; 0 otherwise). The goal of the estimation is to

Table 7.9 Choice-based conjoint estimates: aggregate versus post hoc segmentation

	Segment-level analysis				
	Aggregate	Beta segment (24.2 %)	Diet segment (34.5 %)	Regular segment (34.5 %)	Local segment (6.8 %)
Intrinsic brand utilities (β_{0j}):					
Beta N-D	2.129	3.791	3.468	1.733	−0.936
Beta 1-D	1.150	3.026	2.264	0.621	−2.939
Alpha 2-D	1.003	-0.191^{ns}	2.991	0.794	−2.946
Alpha 1-D	0.779	0.546	2.582	0.752	−2.196
Alpha 1-R	0.476	−1.640	−1.093	1.692	−2.063
Beta 1-R	0.426	1.398	-0.120^{ns}	1.417	−3.620
Alpha 2-R	0.371	−1.449	−0.212	1.529	−2.145
Local-R	0.000	0.000	0.000	0.000	0.000
Price sensitivity (β_1)	−1.322	−0.630	−1.334	−1.768	−2.831
Segment size (α_s)		0.242	0.345	0.345	0.068

Source: Reprinted with permission of the publisher from DeSarbo et al. (1995)

Note: All estimates are statistically significant at the 0.01 level, except for those denoted as ns

maximize this likelihood (or equivalently the log likelihood) with respect to the segment-specific parameters $\mathbf{B} = ((\beta_{0js}, \beta_{ks}))$ and the S segment proportions $\mathbf{A} = (\alpha_s)$, subject to the constraint that $\sum_{r=1}^{S} \alpha_r = 1$.

Maximum likelihood methods were used to estimate the parameters for a varying number of segments. The four-segment solution was considered as the best to fit the data using the criterion of Consistent Akaike Information Criterion (CAIC). The estimated parameters for this solution are shown in Table 7.9. Based on the magnitude and signs of the brand-specific coefficients, these four segments were labeled as Beta, Diet, Regular and Local. The first three segments were quite large (24.2 %, 34.5 %, and 34.5 %) and the last segment was under 7 %. The segments differed considerably in terms of price sensitivity, with the local segment being most highly price sensitive.

Some interesting differences among the segments found by the authors are;

1. The new concept (Beta N-D) appears to have least appeal to the regular and local segments but has greatest appeal to the Beta and Diet segments;
2. The diet segment members are willing to pay a price premium for a diet product; and
3. There seems to be a high degree of loyalty for the Beta products among the Beta segment.

These conclusions seem quite meaningful and do provide face validity.

The authors also formed segments using the choice frequencies (another form of post hoc segmentation) but these results were not as clear-cut as the approach of developing latent segments presented here.

7.5 Comparison of Different Conjoint Segmentation Approaches

Segmentation methods developed during in the last few years using mixture models promise to be useful. We described in this chapter several of these procedures for market segmentation, which are largely based on traditional methods of cluster analysis. One large scale simulation study (Vriens et al. 1996) compared nine conjoint segmentation methods using simulated metric conjoint data (or ratings-based conjoint) data with various measures to assess parameter recovery, goodness-of-fit, and predictive accuracy. The simulation involved developing data sets according to known partworths for individuals and adding errors drawn according to a normal distribution. The authors varied six factors in the simulation; these were:

(a) Number of simulated respondents (100 or 200);
(b) Number of profiles (18 or 25 for six attributes each at three levels);
(c) Number of segments (2 or 4);
(d) Percentage of error variances on preferences (5 % or 35 %);
(e) Homogeneous or diffuse segments (variance of error terms of 0.05 or 0.10); and
(f) Similarity between segments (similar or dissimilar).

The simulation involved developing data sets for individuals according to specific partworths in the range of -1.7 and $+\ 1.7$ and adding errors drawn according to a normal distribution with the error terms specified according to the factor D in the simulation. In all 64 data sets (a full factorial of six factors at two levels) were developed and analyzed according to nine methods of forming segments. Some of these methods are traditional and others have been developed recently. The nine methods were:

1. TTSWA: the traditional two-stage approach using Ward's hierarchical clustering algorithm; this involves estimating individual-level conjoint models and then clustering the estimated partworths to form segments of individuals.
2. TTSKM: the traditional two-stage approach using a nonhierarchical clustering (K-means) procedure; it is essentially the same as TTSWA but uses a different clustering algorithm.
3. ATSWA: the alterative two-stage approach using Ward's clustering algorithm; this method involves clustering individuals on the basis of preference ratings and estimating separate conjoint models for each of the identified segments.
4. ATKSM: this alternative two-stage approach is the same as ATSWA but uses the k-means clustering algorithm.
5. OW: optimal weighting method forms segments developed by Hagerty (1985); this method involves a partitioning of the sample using factor analysis of the correlation matrix of preferences. The weights are derived from the factor analysis.
6. OWKM: OW followed by a k-means clustering procedure to identify segments.
7. CR: the clusterwise regression procedure developed by Wedel and Kistemaker (1989); this method yields nonoverlapping clusters developed by a

nonhierarchical procedure in the estimation of conjoint models for a prespecified number of segments (or clusters).

8. FCR: the fuzzy clusterwise regression procedure developed by Wedel and Steenkamp (1989); this method is similar to CR but allows for individuals to have partial membership in several segments.
9. LCN: the latent class normal distribution model proposed by DeSarbo and colleagues (1992); this method involves estimating segments and conjoint model parameters simultaneously for each segment under the assumption that a preference rating for any individual arises from a mixture of multivariate conditional normal distributions.[3]

In Table 7.10, we show some advantages and limitations of these methods. Overall, the traditional methods have the disadvantage of lacking a theoretical basis, but they are easy to implement. While the newer methods are theoretically sound, they are quite difficult to implement because of the need for specialized algorithms (and software).

The authors evaluated the nine methods using six criteria; these are:

1. The percentage of variance explained by the conjoint methods: R-square
2. The root mean-squared error between the true and estimated partworth values computed across attributes, individuals and segments: RMSE (b)
3. The root mean-squared error between the actual and estimated cluster memberships: RMSE (P)
4. The percentage of individuals correctly classified into their true segments: CORRCLS
5. The root mean-squared error between the observed and predicted preferences for the holdout profiles: RMSE (y)
6. The percentage of individuals for whom the holdout first choice in the holdout profiles is predicted correctly: percent first choices.

The measures 5 and 6 were computed by withholding one-eighth of the data.

The empirical results for the simulation as reported by the authors are shown in Table 7.11.

These results indicate that the methods LCN, FCR, and CR generally perform better than the other procedures with respect to coefficient and segment recovery. The differences are quite small among the methods with regard to the criterion of predictive accuracy. Although not shown here, the authors analyzed the criteria of comparison with respect to the six factors of the simulation. As could be expected, the predictive accuracy of the methods deteriorates for a greater number of segments, a higher error level, and diffuse and more similar segments. In general, no single method of market segmentation could be designated as universally preferable, based on this simulation.

[3] The latent class model has been also applied to “pick any/n” type data as well as rank order and choice conjoint data.

Table 7.10 A comparison of the advantages and limitations of the nine segmentation methods

Method of segmentation	Advantages	Limitations
1. TTSWA: traditional two-stage approach with Ward's method	Easy to use	Depends on possibly unreliable estimates of partworths at the individual level In some cases, individual level estimates cannot be obtained Optimization criteria at the two stages are different
2. TTSKM: traditional two-stage approach with K-Means method	Easy to use	Same as for TTSWA
3. ATSWA: alternative approach with Ward's method	Easy to use	Some cases, individual level estimates cannot be obtained due to over-parameterization Optimization criteria at the two stages are different
4. ATSKM: alternative approach with K-Means method	Easy to use	Same as for ATSWA
5. OW: optimal weighting method	Theoretically appropriate	Difficult to use Can result in loss of predictive accuracy
6. OWKM: optimal weighting followed by K-Means method	Theoretically appropriate	Same as for OW
7. CR: clusterwise regression method	Theoretically appropriate Uses a common criterion for finding segments and partworth estimates	Complicated algorithm
8. FCR: fuzzy clusterwise regression method	Same as for CR	Same as for CR
9. LCN: latent class normal distribution model	Posits a theoretical structure for deriving segments	Algorithm intensive

Source: Reprinted with permission from the Vriens et al. (1996), published by the American Marketing Association
Note: This table is developed using the paper by Vriens et al. (1996) and other materials

Table 7.11 Performance measures for the nine methods of conjoint segmentation based on ratings data

	Performance measures (mean values)					
Method	R-Square	RMSE (b)	RMSE (P)	%CORRCLS	RMSE (y)	%1stCH
1. TTSWA	0.7119	0.3479	0.2119	0.9572	1.4677	0.6940
2. TTSKM	0.7094	0.3553	0.2509	0.9472	1.4731	0.6838
3. ATSWA	0.7126	0.3521	0.2427	0.9459	1.4666	0.6840
4. ATSKM	0.7093	0.3641	0.2841	0.9335	1.4723	0.6838
5. OW	0.7554	0.3354	NC	NC	1.5714	0.6683
6. OWKM	0.7016	0.2531	0.2078	0.9063	1.4875	0.6834
7. CR	0.7090	0.1627	0.1234	0.9622	1.4703	0.6817
8. FCR	0.6913	0.1500	0.1524	0.9616	1.4706	0.6797
9. LCN	0.6948	0.1175	0.1013	0.9649	1.4559	0.6823

Source: Reprinted with permission from the Vriens et al. (1996), published by the American Marketing Association, NC = Not Computed

7.6 Conclusion

This chapter delved into two important applications of conjoint analysis, namely, product positioning and market segmentation. We first discussed two conjoint applications for product positioning that deal with pharmaceutical products. Four conjoint applications for market segmentation, also described in this chapter deal with cameras, food processors, antidepressants, and a disguised product category. The chapter also described a simulation study that compared nine different methods of segmentation based on rating data. The general conclusion of this simulation was that no single method is universally preferable for segmenting individuals in a conjoint study.

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Chapter 8
Applications for Pricing Decisions

8.1 Introduction

One significant application of conjoint analysis is in helping the manager with pricing decisions. Determination of optimal price for a new product (or brand) is a typical application. One way to determine the best price is to estimate the market obtainable from the new product at different feasible prices for the new product profile. We described the use of conjoint simulators in Chap. 3. Additional information on cost functions can be integrated into the estimates of market share to yield estimates of profit from the new product at various prices. The price at which the computed profit is highest can be deemed to be the best price for the new product. This approach can also yield a generic estimate of price elasticity for the product category as a whole.

While the simulation approach is feasible, it does not fully utilize economic theories of price determination. According to these theories, optimal price for a product is the resultant of the three forces of cost, demand and competition. The optimal price per unit of a product (P^*) that maximizes the profit to a firm (Simon 1969, p. 82) is:

$$P^* = \frac{\varepsilon + r\eta}{1 + \varepsilon + r\eta} \bullet MC \tag{8.1}$$

where

ε = self-price elasticity;
η = cross-price elasticity (for an average competitor);
r = competitive reaction elasticity; and
MC = marginal cost of the product per unit.

Application of this equation requires estimates of cost, self- and cross-elasticities for the product and competitor reaction elasticity. The marginal cost of a product depends upon the product attributes and needs to be estimated separately by the

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firm's cost department; this activity happens to be a function internal to the firm. Thus, conjoint analysis has little role in the calculation of costs.

If historical data on sales and prices are available for an existing product, it is possible through econometric methods to estimate the elasticity quantities needed in the equation for the optimal price. But, such estimation is not feasible for a new product. It is that here conjoint analysis has been successfully applied. This variation is sometimes called the Brand/Price Trade-off method. We will discuss details in this chapter. See Mohn (1995) for a discussion of pricing research methods in practice.

An alternate approach in determining optimal prices for a new product is by using the concept of reservation price of a potential buyer for the new product directly. Reservation price[1] is the maximum price a buyer/consumer is willing to pay for the new product taking into account its attributes. Naturally, the reservation price will be unique to each buyer (or consumer). Given knowledge of costs, optimal price of a new product can be determined once the distribution of reservation price is obtained. Conjoint analysis has been successfully used in estimating these reservation price distributions. We will discuss this approach also.

Because consumers may infer quality of a new product from its price, the effect of price as estimated from conjoint methodology will be a combination of informational and allocative effects. It may be necessary to separate these effects while computing elasticities because self- and cross-elasticities are derived from the allocative effects. We will discuss how these effects can be separated using conjoint analysis.

Against this background, the rest of this chapter will describe appropriate conjoint methods to estimate self-, cross- and reaction elasticities and reservation prices and how they can be used in computing optimal prices for new products. Details of how to estimate informational and allocative effects of price separately will also be covered. We will also describe an application of a conjoint method to determine competitive bids by an industrial supplier for a new account.

8.2 Conjoint Method for Determining Price Elasticities (Brand/Price Trade-off)

The full profile approach of conjoint analysis can be easily adapted to the problem of determining self- and cross-price elasticities for a set of brands in a product category.[2] The method involves creating price variations experimentally to "simulate" historical variation among prices. For this purpose, we treat brands in a category as "attributes" and vary each brand's price according to an experimental

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[1] While we use the notion of maximum price for a reservation price here (i.e. the probability of buying a product beyond the price is zero), other concepts using other probabilities can be employed. See Wang et al. (2007).

[2] See Mahajan et al. (1982)

design (as described in Chap. 2). This means that the levels of an attribute correspond to different prices varied for a brand and each profile will correspond to a market situation in which each brand will be at a different price. The respondents are presented a profile (or a market situation) and are asked to indicate the relative likelihood of buying each brand at the prices posted; or to allocate 100 points to each brand to reflect the likelihood of buying it. Typically, a logit model is estimated for the odds ratio of the responses (or relative likelihood of buying) in terms of prices of the brands.[3] The self- and cross-price elasticities are determined from the resulting parameter estimates. The reader will recognize the similarity of this approach with that of the choice-based conjoint methods discussed in Chap. 4.

Alternatively, the respondent is asked to indicate which brand he or she will buy under the hypothetical market situation. In this case, the responses can be aggregated to yield "sales estimates" for each market situation. Then a constant elasticity demand model (log-linear model) can be estimated directly to obtain self- and cross-price elasticities.

Likelihood of Buying Responses: Appendix 1 describes the details in mathematical terms. We illustrate this method where the likelihood of buying responses are elicited using the application reported by Mahajan et al. (1982). They consider a 4-brand market for a consumer non-durable good with brands A, B, C, and D (the study sponsor's brand) and current prices of $10.78, $10.93, $11.04 and $15.10 respectively. Each brand's price was varied at 4 levels as follows:

Brand	Levels ($)
A	9.00, 9.90, 10.80, 12.00
B	9.20, 10.10, 11.00, 12.20
C	9.30, 10.20, 11.10, 12.30
D	12.00, 12.60, 13.80, 18.60

A main-effects orthogonal array was used to generate profiles of market situations. Data were collected from 420 respondents who, in an initial screening interview, were classified by the last brand purchased into one of four groups: A, B, C, and D. The interviews were personally administered in a central facility. Each respondent was shown color photographs of brands A, B, C, and D—each priced at the current market conditions and the 16 experimental conditions and was asked to allocate 100 points to reflect the subjective likelihood of selecting the brand at the next purchase.

Average responses for each experimental price condition become the starting point of analysis. For example, for the market situation of prices $9.00, $9.20,

[3] This procedure can also incorporate dynamics of the market, if desired. For this purpose, a brand-switching matrix can be constructed for each experimental price condition by forming subgroups of respondents according to the brand last purchased and the matrix of average of responses for each subgroup or brand constitutes the brand-switching matrix. Using the initial market shares as the base, this brand-switching matrix can be powered to obtain market shares for subsequent (hypothetical) periods of time. The market shares for a future time period can be the starting point for logit analysis

Table 8.1 Estimated price effects (logit parameters)

Price level	Brand D prices	Brand A prices	Brand B prices	Brand C prices
1 (lowest)	0.97[a]	−0.13	−0.06	−0.16[a]
2 (second lowest)	0.84[a]	−0.14	−0.02	−0.05
3 (third lowest)	0.72[a]	−0.09	≈0.0	≈0.0
4 (highest)	0	0	0	0
Intercept = 0.46				

Source: Reprinted with permission from the Mahajan et al. (1982), published by the American Marketing Association

[a]Regression coefficient is significantly different from zero (at the 0.05 level)

Table 8.2 Illustration of brand/price trade-offs: estimated changes in market shares

	Effect on			
	Brand A	Brand B	Brand C	Brand D
Effect of 25 % price increase for:				
Brand A	−5.2	+0.4	+1.8	+3.2
Brand B	+1.2	−11.2	+8.4	+1.6
Brand C	+0.3	+2.0	−2.9	+0.6
Brand D	+8.1	+0.8	+2.6	−11.5
Basic share	22.4 %	36.6 %	13.3 %	27.7 %

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$12.30 and $18.60 respectively for brands A, B, C, and D, the average responses (or market shares) were 0.25, 0.28, 0.25 and 0.22. The price effects estimated for the four brands are shown in Table 8.1. These are the logit parameters for brand D in relation to brand C (the reference brand). These estimates can be used in predicting the market shares for sets of future prices for the brands.

Choice Responses: Table 8.2 shows the results of another study in which "choice" responses are elicited. In this example, the self-elasticity for brand A is $\frac{-5.2}{22.4} * \frac{1}{0.25} = -0.93$. The cross-elasticity for brand A with respect to brand B is $\frac{1.2}{22.4} * \frac{1}{0.25} = 0.21$.

8.3 Conjoint Method for Competitor Reaction Elasticities

Our focus here is to determine how a firm would respond to a competitor's price change by changing its own price. This response is captured by the competitor reaction elasticity, defined as:

$$\frac{\partial P}{\partial P_c} \bullet \frac{P_c}{P} = \frac{\%\text{ change in own price}}{\%\text{ change in competitor's price}}, \tag{8.2}$$

where P and P_c denote the firm's own price and competitor's price.

The conjoint method can be applied to estimate this reaction elasticity as follows. First, the analyst identifies reasons why a firm would change its price; these include changes in competitor's prices, changes in internal costs; and other factors in the environment (e.g., regulation). These factors are then defined as attributes, each with different levels expressed as percentage changes. A set of profiles is developed for these attributes according to a fractional factorial (orthogonal) design. The corresponding profiles are presented to a manager (or a number of managers) of the firm from whose perspective the reaction elasticity is being estimated and judgments on percent changes in firm's price are elicited (this procedure is in some sense similar to the method of decision calculus developed by Little (1970)). It enables capturing the managers' experience in determining the competitor reaction elasticity.

The corresponding conjoint model will be as follows:

$$y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \tag{8.3}$$

where

y = Percent change in firm's price (as judged by the manager);
X_1 = Percent change in competitor's price;
X_2 = Percent change in firm's internal cost;
X_3 = Percent change in other environment factor; and
ε = random error.

The parameter β_1 in this model will be the competitor's reaction elasticity. It is likely that reaction elasticities will be different for increases versus decreases. This fact can be accommodated in the above model by replacing each of the terms β_1X_1, β_2X_2 and β_3X_3 by two terms. For example, β_1X_1 will be replaced by $\beta_{11}D_1X_1 + \beta_{12}(1-D_1)X_1$ where $D_1 = 1$ if the change is positive and 0 otherwise and similarly for other terms. Then, β_{11} will be the reaction elasticity for increases in competitor price and β_{12} for decreases.

An application of this method is found in Rao and Steckel (1995). Focusing on two factors of changes in internal cost and competitor's price change, they conducted a study to determine managers' price responses. A sample of 152 managers in both U.S. and Europe were contacted by mail to elicit their price responses to various scenarios of cost and competitor price changes. See Fig. 8.1 for an example of a scenario used in this study.

The scenarios were constructed specific to each manager.

The model estimated was:

$$\begin{aligned} \mathrm{PCP} = {} & a_0 + e_{pi}(\mathrm{DP} * \mathrm{PC}) + e_{pd}((1 - \mathrm{DP}) * \mathrm{PC}) \\ & + e_{ci}(\mathrm{DC} * \mathrm{CC}) + e_{cd}((1 - \mathrm{DC}) * \mathrm{CC}) \\ & + \mathrm{Error} \end{aligned} \tag{8.4}$$

The Scenarios in Part I are combinations of price changes by your MAJOR COMPETITOR and changes in variable costs of your product or service. Accompanying each scenario is a list of questions which ask how you would react to these scenarios. Remember, PUT YOURSELF IN THE POSITION OF YOUR FIRM WITH ITS CURRENT PLANNING OBJECTIVES. Note that you could adjust none, one, or many of the marketing variables in varying degrees.

SCENARIO 1

Your competitor has increased prices by ____ percent. Your costs have increased by ____ percent. In response to this scenario and considering your current planning objectives.

(a) Which of the following would you consider changing? (Check as many as applicable).

	Price	Advertising Budget	Sales Promotion Budget	Sales Force Budget	Distribution Channels
(b)	If so, Raise ◯ or Lower ◯	If so, Increase ◯ or Decrease ◯	If so, Increase ◯ or Decrease ◯	If so, Increase ◯ or Decrease ◯	What new channels would you seek? ____ ____ ____
(c)	By what percent? ____	By what percent? ____	By what percent? ____	By what percent? ____	

(Please respond to each question.)

Source: This is drawn from the questionnaire used in Rao and Steckel (1995)

Fig. 8.1 An example of a scenario to determine managers' price responses

where

PCP = Percent change in a firm's price conjectured in a given scenario.
DP = A dummy variable which is equal to 1 if the scenario has a price increase and 0 otherwise.
DC = A dummy variable which is equal to 1 if the scenario has a cost increase and 0 otherwise.
PC = Percent change in the competitor's price in a given scenario.
CC = Percent change in the firm's costs in a given scenario.

The parameters e_{pi} and e_{pd} are elasticities for a firm's price change (as conjectured by the managers) for an increase and a decrease in competitor's price. Similarly, the parameters, e_{ci} and e_{cd} are elasticities for increase and decrease in firm's cost.

Based on this analysis, they estimated the reaction elasticity to be 0.41 for increases in competitor's price and 0.38 for decreases in competitor's price. Further, the corresponding elasticities for costs were 0.32 and 0.13. These results indicated that managers make only a partial adjustment in price for the two environmental variables examined in this study. A more detailed analysis of price responses revealed that managers' response elasticities were less than one over the entire range of prices presented in the conjoint profiles.

8.4 Method Based on Reservation Prices

In this method, the goal is to determine the distribution of reservation prices for a new product profile using the partworth functions estimated in a conjoint study.[4] We will first show the optimal price for the new product assuming that we know the distribution of reservation prices and then show how to estimate this distribution.

The reservation price reflects the marginal value of the new product (denoted by n) over the most preferred offering (one of the existing brands in the product category). The reservation prices for the new product n are computed for all individuals in the sample. Let $h(p_n)$ denote the distribution of these reservation prices. (This distribution is normalized to sum to 1.0.) If the sample of individuals is representative, then $h(p_n)$ is also the probability distribution for the population of consumers. Let $H(p_n)$ denote the cumulative density function of $h(p_n)$. Then, $[1 - H(p_n)]$ is the probability that a randomly chosen consumer from the population will have a reservation price less than p_n and will prefer the new product n at price p_n over all products in the evoked set. Therefore, if the new product is priced at p_n, the market share for the new product will be $[1 - H(p_n)]$. If m denotes the total number of consumers in the target market, the number of consumers who will buy the new product n at price p_n is:

$$D(p_n) = m[1 - H(p_n)]. \tag{8.5}$$

If each consumer buys one unit of the product, (8.5) describes the demand function for the new product, n. Let f_n denote the fixed costs associated with the new product and c_n the constant[5] variable costs per unit for the new product. Then, the expected profit from selling the new product n at price p_n is:

$$Z(p_n) = m[1 - H(p_n)](p_n - c_n) - f_n. \tag{8.6}$$

The price at which the expected profit is maximized is the optimal price for the new product. Taking the derivative[6] of $Z(p_n)$ with respect to p_t and setting it equal to zero and solving the equation, we get the optimal price $p_{n,opt}$ to be:

[4] This discussion is adapted from Kohli and Mahajan (1991)

[5] This is a convenient assumption. It can be relaxed, if needed.

[6] Ignoring the constant m, the derivative is: $-h(p_n)(p_n - c_n) - (1 - H(p_n))$ and when this is set equal to zero, we get the solution in (8.7).

$$p_{n,opt} = \frac{1 - H(p_n)}{h(p_n)} + c_n \tag{8.7}$$

Note that there is a direct relationship between costs per unit and optimal price per unit. This equation can be rewritten as: $H(p_n) = 1 - h(p_n)(p_n - c_n)$.

All of this depends upon the availability of the distribution of reservation prices for n. Conjoint methods are used in estimating this distribution.

To facilitate this estimation, we need the following information[7] developed from a suitably designed conjoint study: (1) partworth functions for the product attributes and price for each individual in the sample; (2) the evoked set of brands for each individual; (3) attribute profiles and prices of all brands in the product category; and (4) attribute profile for the new product whose price needs to be determined. Further, we need to assume that the partworth functions for price are downward sloped; this may be accomplished by placing a constraint on this function in the estimation process.[8] Let the range of prices used in the conjoint study be (p_{min}, p_{max}).

Once these data are available, we can estimate the utility values for all brands in his/her evoked set for each individual. Let the maximum of these be u_i^* for the ith individual.

Further, we can estimate the utility values for the new product (without including price) for each individual. Let this value be $u_{in|\sim p}$ for the ith person in the sample to indicate that price is not included in the utility calculation. Let $u_i(p_{min})$ and $u_i(p_{max})$ be the utility values for the minimum and maximum price according to the estimated partworth function for price for the ith consumer. With this information, we can estimate the reservation price for the new product for the ith consumer by solving the equation:

$$u_{in|\sim p} + u_i(p) = u_i^*. \tag{8.8}$$

We compute the difference $u_i^* - u_{in|\sim p}$ and look for the value of p for which the ith person's partworth function for price will be equal to this difference. In some cases, this equation cannot be solved. Then, we can only infer whether the reservation price is below p_{min} or above p_{max}. It is below p_{min} if $u_{in|\sim p} + u_i(p_{\min}) < u_i^* + \varepsilon$ and it is above p_{max} if $u_{in|\sim p} + u_i(p_{\max}) > u_i^* + \varepsilon$, where ε is a very small positive number. In these situations, we can compute the proportion of the sample whose reservation prices are below p_{min} or above p_{max}. Let q_{1n} and q_{2n} denote these fractions. That is to say, $(1 - q_{1n} - q_{2n})$ fraction has reservation prices between p_{min} and p_{max}.

[7] Reservation prices can also be elicited directly for product concepts. Kalish and Nelson (1991) found that the method of direct elicitation of reservation prices has worse predictive validity than the conjoint methods using ranking or rating.

[8] We will return to this issue in the section on separating the informational and allocative effects of price.

Table 8.3 Attributes and concepts for the apartment study. Attributes and levels

Attribute	Number of levels	Levels
Rent	8	\$225, \$270, \$315, \$360, \$405, \$450, \$495, \$540
Walking time to class	4	10, 15, 20, 30 min
Noise level of apartment	4	Very quiet, average, noisier than average, very noisy
Safety of apartment location	4	Very safe, average, less safe than average, very unsafe
Condition of apartment	4	Newly renovated throughout, renovated kitchen only, fair condition, poor condition
Size of living/dining area	4	$24' \times 30'$, $15' \times 24'$, $12' \times 15'$, $9' \times 12'$

Table 8.4 Attributes and concepts for the apartment study. Concepts

Attribute	Concept 1	Concept 2	Concept 3	Concept 4
Walking time	10 min	30 min	10 min	30 min
Noise level	Average	Very quiet	Average	Average
Safety	Average	Very safe	Average	Average
Condition	Poor	Renovated kitchen	Renovated throughout	Renovated throughout
Size of living/dining area	$9' \times 12'$	$12' \times 15'$	$9' \times 12'$	$24' \times 30'$

Source: Kohli and Mahajan, *JMR*, (1991)

Based on the above analysis, we have the following information:

(a) Estimates of reservation prices for each person for a fraction $(1 - q_{1n} - q_{2n})$ of the sample;
(b) q_{1n} fraction and q_{2n} fraction of the sample have reservation prices below p_{min} and above p_{max} respectively.

We can now estimate the whole distribution using the theory of truncated distributions, assuming that the reservation price distribution is normal. Details are described in Appendix 2.

Illustrative Application: Kohli and Mahajan (1991) applied this approach to a set of conjoint data on apartments in a university town collected from 177 students using the rating-based conjoint approach. The respondents rated 32 profiles of apartments drawn according to a fractional factorial design. The six attributes on which the apartments were described are shown in Table 8.3.

The authors used these data in determining optimal prices for the following four concepts 1, 2, 3 or 4 (not used in the design), descriptions of which are also shown in Table 8.4. The analysis was done under the assumption that the real estate developer would offer only one of the apartments described by concepts. There were clear differences in these concepts. Concept 1 apartment is small, close to campus, in poor condition, and average in terms of noise level and safety. Concept 3 apartment was similar to that of Concept 1 but was renovated throughout and has a larger living/dining area. There was a clear tradeoff between apartments described by Concepts 2 and 4; a student had to make a tradeoff between the larger size and better condition of the latter and the lesser noise and greater safety of the former.

It was assumed that all students had the same status quo apartment (or evoked set) with the characteristics of 20 min walking time to class, average in noise level and safety, and had a renovated kitchen only with $12' \times 15'$ living/dining area and was priced at \$360. Using this status quo, the reservation prices were estimated for all the four concept apartments. The authors found that the normal distribution provided a good fit to the estimated reservation prices. The estimated mean and standard deviation of the reservation prices for the four concept apartments are given below. Using these distributions, we can compute the optimal prices for the apartment concepts using (8.8) above. Assuming a cost of \$400 per month for these apartment concepts, the optimal prices, the authors estimated the following optimal prices.

	Estimated distribution of reservation prices		
Concept	Mean (\$)	Standard deviation (\$)	Optimal price (\$)
1	418.33	161.18	539
2	423.72	209.83	585
3	582.25	188.67	722
4	521.38	203.21	680

8.5 Measurement of Price Effects

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 making a 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 when using data on brand preferences or choices becomes confounded owing to the difficulties of modeling the two effects of price distinctly. In practice, only the net effect of price is estimated in any brand choice or preference model.

In a study of price elasticity that covered 367 published papers Tellis (1988) uncovered about 50 studies 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 in these 50 studies, the informational effect may have dominated the allocative effect. Further, the price elasticity was between 0 and -1 for an additional 40 studies possibly indicating that the magnitude of the allocative effect exceeded that of the informational effect.

8.5.1 Using Ratings-Based Approach

Gautschi and Rao (1990) proposed a methodology to estimate separate effects of price in the conjoint setting. It requires collecting data on two preference measurements on the set of choice alternatives—called unconstrained and constrained preferences—respectively obtained under no budget constraint and obtained under the budget constraint. Denoting the unconstrained and constrained preferences by $U(b^*)$ and $U(b)$, they estimate two relationships between $U(b^*)$ and the product attributes and price as well as between the difference, $U(b) - U(b^*)$ as the allocative effect.

The procedure to estimate the informational and allocative effects of price may be illustrated for the situation with one product feature, Z_1, and price, P, and linear functions for the two preferences. Denoting the unconstrained and constrained preference functions as:

$$\boldsymbol{U(b^*) = \alpha_0 + \alpha_1 Z_1 + \alpha_2 P + \varepsilon_{b^*}} \textit{ and}$$
$$\boldsymbol{U(b) = \beta_0 + \beta_1 Z_1 + \beta_2 P + \varepsilon_b}$$

Where the αs and βs are parameters to be estimated and ε's are random components. The difference equation, becomes

$$U(\mathbf{b}) - U(\mathbf{b}*) = (\beta_0 - \alpha_0) + (\beta_1 - \alpha_1)Z_1 + (\beta_2 - \alpha_2)P + \varepsilon_b - \varepsilon_{b^*}.$$

One needs only to estimate the equations for $U(\mathbf{b}*)$ and for the difference, $U(\mathbf{b}) - U(\mathbf{b}*)$ constraining $(\beta_1 - \alpha_1)$ to zero. The main allocative effect of price is then revealed by the estimate of $(\beta_2 - \alpha_2)$. The informational or signaling effect is reflected in the estimate of α_2.

Gautschi and Rao (1990) illustrated this approach using a small-scale conjoint study on laptop computers, each described on three attributes at two levels each among 45 subjects and found that these two effects are quite pronounced for the sample as a whole as well as for subgroups.

A more comprehensive study on this problem was conducted by Rao and Sattler (2000)[9] with a sample of 180 "MBA" and doctoral students at a German University. Two products—marmalade and alarm clocks—were used in the study.

They estimated the two effects of price for each individual in the sample. The average effects are as follows:

Product category	Informational effect	Allocative effect	Net effect
Marmalade	6.07	−36.89	−30.7
Alarm clock	22.01	−46.80	−24.79

While the net effect of price is negative in both cases, the informational effect is *not* small relative to the allocative effect. Further, at the individual level a large number of the allocative and informational effects are in the direction expected. The net price effect was positive in only 4 out of 82 cases for marmalade and 7 out

[9] Both preferences were measured on a zero to 100 scale. The authors explicitly tested the assumption of equality of effects of attributes (excluding price) in the unconstrained and constrained preferences at the individual level and found that this assumption is justified for over 82 % of the respondents at a 0.10 significance level. Thus, the estimation method employed seems appropriate.

of 98 for alarm clocks products. This indicates that a negative price effect estimated in a conjoint study does not enable a researcher to infer the magnitude of the two price effects.

It may be advantageous for conjoint analysts to test in a pilot study whether or not the informational effect is large relative to the allocative effect. If it is small, the current practice may continue to be followed. Otherwise, attempts should be made to separate the two effects by a suitable design.

8.5.2 Using Choice-Based Approach

Völckner and Sattler (2005) have extended the above measurement procedure to separate the informational and allocative effects of price to the case of choice-based conjoint methods. They collected choice data from 355 respondents for two different scenarios: full-price-to-pay (constrained choices) and gift (no budget constraint). The context was the choice of strawberry jam and each product was described on brand (3 levels) and price (3 levels); other information on product characteristics (e.g. fruit content) was also provided but kept identical for each brand and each scenario. In all 27 choice sets were designed each set consisting of 3 profiles, and each brand presented once in each profile; these choice sets cover all combinations of brands and prices and allow for repetition of prices in the same choice set. The "no choice" option was included in each choice set.

The choice data were analyzed using a hierarchical Bayes method[10] that yielded individual-level estimates of parameters for brand and price. These estimates were subsequently transformed into choice shares using the standard logit model for a choice set that represented a realistic market setting. By varying prices of a brand within this setting, the authors computed price elasticities for the two scenarios. The price elasticity for the gift scenarios was deemed to be the informational effect of price and the difference in the price elasticities between the full-price-to-pay and gift scenario as the allocative effect. The main results are shown in Tables 8.5 and 8.6.

The partworth estimates for the brand in the gift scenario indicate that Brand C is the most preferred brand followed by Brands A and B. Further, the partworth values differ by the scenario implies that people prefer Brand C under the gift scenario. The partworth values for price are in the expected direction for the gift scenario and not in the full-price scenario with some values positive and some negative. When the two effects of price are separated, the results look meaningful.

[10] The data were also analyzed using a latent class model and the results were about the same in terms of fit and predictive ability for the two procedures. Both methods account for heterogeneity among the sample individuals. The paper contains predictive validity results as well.

Table 8.5 Partworth estimates and price effects from choice-based conjoint analysis. Panel 1: Attribute partworths

Attribute	Level	Scenario	
		Full-price-to-pay	Gift
Brand	A	0.41 (1.67)[a]	−2.29 (5.91)
	B	−2.42 (1.69)	−3.49 (3.97)
	C	−2.01 (2.37)	5.78 (7.50)
Price (Euros)	1.59	4.11 (1.50)	−5.88 (3.71)
	1.99	0.84 (0.54)	1.26 (0.40)
	2.39	−4.95 (1.79)	4.62 (3.60)

Source: Reprinted from Völckner and Sattler (2005) with permission of the authors
[a]The entries are mean and standard deviation of the partworths

Table 8.6 Partworth estimates and price effects from choice-based conjoint analysis. Panel 2: Price elasticities

Elasticity	Scenario	Brand A	Brand B	Brand C
Total	(a) Full-price-to-pay	−1.60	−4.23	−3.65
Informational	(b) Gift	1.33	2.09	0.83
Allocative	(a)–(b)	−2.93	−6.33	−4.48

Source: Reprinted from Völckner and Sattler (2005) with permission of the authors

The decomposition of the price elasticity by brand for informational and allocative effects shows that the total elasticity can be misleading.

8.6 More Applications

We now describe three applications of conjoint analysis to pricing problems faced by firms. The first of these is the formulation of bids in an industrial marketing situation for a catering company and the second application is for setting prices in a product line of print and PDF formats of various titles published by a national press. The third application is on multipart pricing.

See also Green and Savitz (1994) for an application in the retailing context, Goldberg et al. (1984) for on application to the pricing of hotel amenities. Simon (1992) offers a general discussion of pricing opportunities and Mohn (1995) offers a pragmatic view of several quantitative methods for pricing decisions.

8.6.1 Application 1: Bidding for a Contract

This case is that of the Alpha-catering firm in Scandinavia, which was experiencing a decline in market share. The Alpha firm faces competition from four other firms in this market; we call these Beta, Gamma, Delta and Phi; all but one of these is a large firm and the fifth one (Phi) is an entrepreneurial firm (small).

The catering firm (any one of the five competing firms) sets up cafeteria on customers' (or client companies') premises and runs those cafeterias. It sets prices for each item sold in the form of normal meals[11] in the standard company facility and the client firms offer some subsidy to employees for lunch.

Pricing mechanisms in this catering supplier market are very complicated. Potential suppliers submit competitive bids that propose a fixed (one time) payment. In order to understand the clients' trade-offs, the firm conducted marketing research using conjoint analysis as the main technique.

The conjoint study was aimed at understanding of the various trade-offs involved among the bid price variables. For this purpose, an index was used to describe the set up costs (excluding the costs of catering and banquets) of each catering firm. These indexes varied from a low of 85 to high of 120; the levels varied depending upon the researcher's knowledge of the five firms. Using an orthogonal fractional factorial design from a 5^5 full factorial design, the researchers constructed 25 profiles of bid costs for each of the five competing firms and two profiles drawn at random from the remaining set were added resulting in a total of 27 profiles; these were divided into three rotation sets A, B, and C, each containing 9 profiles. Each respondent received one of these rotation sets selected randomly; the nine profiles within the rotation set were also administered in a random order. The design used is shown in Table 8.7.

For each choice set, a respondent in a client company indicated the catering firm he or she would offer the contract to for the cafeteria business.

The researchers in this study first conducted preliminary interviews and focus groups to identify the factors that decision makers in the customer companies paid attention to. These variables fall into three groups: (1): customer's characteristics (size, percent managerial and white collar personnel etc. preferences for menu and frequency of repetition); (2): restaurant factors (food quality, ambiance and service offered); and (3): pricing variables (lunch price and company subsidy). These data were collected from each client company in addition to the choice data. In all, 207 respondents were contacted in the study; each respondent was chosen to represent his or her company and was responsible for making the decision on the choice of a catering firm for his company.

An aggregated logit model was developed to describe the choices made by the respondents. In this model the bid price indexes and other variables were used as predictors. The model was estimated using maximum likelihood methods. The fit was quite good (model chi square was 286.44 with 34 degrees of freedom and the P-value close to zero); several of the variables turned out to be significant as expected. Due to the confidential nature of this project, we will not offer any details on the estimated coefficients for the bidding indexes and other variables. However, we show in Table 8.8 the impact on the probability of winning a contract for the Alpha-Company for changes in the three sets of variables noted above.

[11] The catering company also sets fixed fees for setting up the catering arrangement and arranging special banquets; but these were beyond the scope this study.

Table 8.7 Bid profiles for the five competing catering firms

Bid profile	Alpha	Beta	Gamma	Delta	Phi
1	100	100	100	100	100
2	100	115	110	95	95
3	90	100	85	85	80
4	120	105	90	105	100
5	110	100	95	105	95
6	110	95	100	110	90
7	95	115	85	110	100
8	95	85	95	100	105
9	90	105	110	100	95
----------------	----------------	----------------	----------------	----------------	----
10	100	100	100	100	100
11	100	105	95	110	80
12	120	100	110	110	105
13	120	95	85	100	95
14	110	115	90	100	80
15	110	85	110	85	100
16	95	105	100	85	95
17	100	85	85	105	90
18	90	95	95	95	100
----------------	----------------	----------------	----------------	----------------	----
19	100	100	100	100	100
20	100	95	90	85	105
21	120	115	95	85	90
22	120	85	100	95	80
23	110	105	85	95	105
24	95	100	90	95	90
25	95	95	110	105	80
26	90	115	100	105	105
27	90	85	90	110	95

Rotation sets A, B, and C are respectively profiles 1–9, 10–18, and 19–27

A decision support system was developed using the estimated logit model to predict the probability of winning a contract for the Alpha-company for a potential client under the assumptions of potential bids by the competing firms. The Alpha-Company manager simply had to input the characteristics of the potential client and his or her assumptions of the possible competitive bids. The following table is an example of such a prediction for one Client Company, Omega. In this example, it is clear that the entrepreneurial firm (Phi) will not be able to win the contract unless it drastically reduces its costs. Also, the chances of the Alpha-Company winning fall when its bid goes up and rise when its bid goes down.

Table 8.8 Impact of selected variables on the probability of choosing alpha company

Variable	Impact on the probability of choosing alpha company (%)
Group A: Customer characteristics and preferences	
Number of employees in units of 100	1.7
Number of managers and white collar workers in units of 10	−1.5[a]
Percentage of women in the client company	−0.4
Rating of dining environment preference	−11.2[a]
Rating on service style preference	−14.4[a]
Rating on food preference	4.7[a]
Group B: Restaurant factors	
Number of warm entries	8.8
A la carte entrée available	24.9
Salad table available	−3.5
Sandwiches available	7.1
Hot cereals available	−40.0[a]
Dessert available	−23.8[a]
Repetition of weekly menu	5.3[a]
Group C: Pricing variables	
Lunch price in Marks	1.8[a]
Company subsidy in Marks	0.6

[a]Statistically significant

	Competitive bid profile set 1		Competitive bid profile set 2		Competitive bid profile set 3	
Catering company	Bid index	Predicted probability of winning the contract	Bid index	Predicted probability of winning the contract	Bid index	Predicted probability of winning the contract
Alpha	110	0.10	115	0.04	105	0.15
Beta	100	0.78	95	0.81	100	0.75
Gamma	95	0.005	95	0.005	95	0.005
Delta	102	0	100	0	102	0
Phi	100	0.115	100	0.145	100	0.095

The Alpha-Company used this decision support system in its bids and experienced a great success in landing new contracts.

8.6.2 *Application 2: Pricing Digital Content Product Lines*

Kannan et al. (2009) applied a set of methods including conjoint analysis to tackle the problem of pricing two different forms of products (print and PDF) sold online by the National Academies Press (NAP). NAP publishes about 200 titles a year—mainly scholarly monographs, study reports, and reference materials in all areas of science, education, engineering, health and medicine. These titles are specialized and focus and cater to niche markets of researchers and practitioners with well-defined needs.

While selling the books online, NAP started offering the full text of books in page-by-page fax quality format free to anyone in the world through its website in 1994. Given that PDF formats are easy to produce and distribute online, NAP contemplated the idea of selling PDF formats online in 2001.

There was also pressure from NAP's stakeholders (e.g. scientists who produced the content NAP sold) to use the Web to disseminate scientific knowledge around the world. The push was for distributing complete text of the titles in PDF format free of charge. The premise was that the two formats (PDF and print) would be strong complements and distributing the PDF format would not impinge on the online sales of printed titles.

Against this background, the authors designed a choice experiment to determine the utility function of customers for combinations of alternative formats (PDF, print, or both). The experiment involved about 500 titles that the publisher was selling in print format for at least 2 months at their website. The prices for the print versions were not varied in the experiment because they were common knowledge to frequent visitors to the website. The content of these books was also available for free browsing in its entirety at the website. The PDF versions of the 500 titles were made available only to the participants in the choice experiment.

Two groups of people were sampled to become respondents in the experiment; these were Group A: those who had books in their shopping cart and Group B: those browsing books with PDF formats. Customers in Group A were observed to make a choice between no purchase and printed book and then intercepted to make a choice among three alternatives: (a) stick with the print title, (b) switch to a PDF format, or (c) purchase the bundle of PDF and print format. Similarly, Group B customers were first offered to make a purchase of a PDF format title at a specific price level. If they chose a PDF title, the price of a PDF title was reduced and they were asked to choose among the three options as before or make "no purchase". The study included six price levels for PDF titles (110 %, 100 %, 75 %, 50 %, 25 %, and 0 % of the price of the printed version). After their choice, a short survey was administered for additional discounts for people choosing the PDF format or free shipping for those choosing print format (with or without PDF). The prices were randomized in the experiment. The experiment ensured that there were at least two choice observations from each respondent in both the A and B groups.

The utility for a customer i from purchasing a title in product form j (print or PDF) is modeled as: $U_{ij} = \beta_{ij}X_i - \beta_{pi}p_j + \varepsilon_{ij}$; j = 1 for print and 2 for PDF format, and p_j is the price of the j-th format, X_i is a measure of individual i's degree of fit of the content to his or her needs, the βs are parameters to be estimated, and ε_{ij} is the error term.

The utility of a customer buying a bundle (Print and PDF) is modeled as: $U_{ib} = (\beta_{i1} + \beta_{i2} + \Delta\beta_i)X_i - \beta_{pi}p_b + \varepsilon_{ib}$, where p_b is the price of the bundle (larger than the minimum of the two prices of the print and PDF formats), and β_{i1} is the value the customer places on the print format, β_{i2} is the value the customer places on the PDF format, and $\Delta\beta_i$ is a parameter that represents how the customer i values the bundle over and beyond the effects of two formats. Further, this parameter is a measure of the substitution or complementarity of the two formats as compared to the two effects β_{i1} and β_{i2}. To pursue this further, the authors indicate that if $\Delta\beta_i = -\min(\beta_{i1}, \beta_{i2})$, the customer perceives the two formats to be substitutes and if $\Delta\beta_i > -\min(\beta_{i1}, \beta_{i2})$, then the customer derives additional utility from the second format (or from the bundle) if he has already decided to purchase one format. A positive value for $\Delta\beta_i$ shows complementarity between the two formats.

The variable X_i is not measured but is assumed vary across the population according to a distribution with finite mixtures; this assumption is similar to that in a latent class model (described in Chap. 7). This distribution is integrated out to obtain market share of any alternative. Once this is done, the researchers derived an expression for market share for each segment and for the sample (or market) as a whole. Using this they a set up an optimization problem to determine the optimal prices, p_1, p_2, and p_b so as to maximize the total profit from the three formats for any title. In their implementation, they did not utilize any discount for the bundle. The problem therefore becomes:

Choose p_1, p_2 and p_b so as to maximize $\Pi = \Pi_1 + \Pi_2 + \Pi_b$ subject to $p_b = p_1 + p_2$.

The expressions for the profit functions are: $\Pi_1 = (p_1 - c_1)*MS_1$; $\Pi_2 = (p_2 - c_2)*MS_2$; and $\Pi_b = (p_b - c_1 - c_2)*MS_b$ and c_1 and c_2 are the costs per unit for the print and PDF formats. The terms MS_1, MS_2, and MS_b are the market shares of the print format, digital format and the bundle of print and digital formats. Because there are no closed-form solutions to prices, the researchers used an adaptive search algorithm along with fine grid search[12] methods to find optimal prices.

In the experiment, the researchers collected data from 1,027 valid customer responses over a 3-week period, out of which 312 were from Group A and the rest from Group B. They developed a 4-segment solution[13] deemed optimal on the basis of information criteria (AIC and BIC) for choice data considering the three alternatives of print, PDF and the bundle. The estimated parameters are shown in Table 8.9. These estimates showed that the values placed on the two formats were statistically significant for all segments. Further, the parameter ($\Delta\beta$) that shows the value of bundle was significant and negative, implying that the two formats were deemed as substitutes.

[12] This method involves dividing the range for each parameter into a number of intervals and computing the value of the objective function for various combinations of the intervals across parameters.

[13] The authors also developed a two-segment solution for choice data that excludes the bundle option. But, for our purpose, the choice data with bundle is more appropriate.

Table 8.9 Estimates from the four segments solution for choice data with bundles

	Estimates (standard errors)			
Parameters	Segment 1	Segment 2	Segment 3	Segment 4
β_{Print}	0.2417 (0.0519)	0.2367 (0.0343)	0.1562 (0.0292)	0.0627 (0.0137)
β_{PDF}	0.0329 (0.0062)	0.0841 (0.0198)	0.1046 (0.0217)	0.1441 (0.0309)
$\Delta\beta$	−0.0298 (0.0017)	−0.0367 (0.0087)	−0.0542 (0.0103)	−0.0253 (0.0064)
β_{price}	−0.0712 (0.0079)	−0.0922 (0.0064)	−0.0991 (0.0048)	−0.1127 (0.0121)
Segment size (%)	40.1	36.3	13.1	10.5
	Log Likelihood[a] (LL)	AIC (LL-p)	BIC (LL-pln(N)/2)	
Model Fit	−2,514.17	−2,533.17	−2,590.30	

Source: Adapted with permission from Kannan et al. (2009), Copyright (2009), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

[a]p is the number of parameters estimated and N is the number of observations. LL is the log likelihood; AIC is the Aikake information criterion and BIC is the Bayesian information criterion

One example of optimal prices from this work for the case when the bundle choice was available and the marginal cost of the PDF version was assumed to be zero is shown in Table 8.10. These computations were made for four typical marginal costs of the print format. It is easy to see the variation in optimal prices as marginal costs of the print version increased; they moved in the expected direction. Further, as one would expect, the prices were higher if there was no constraint on the current price for the print format. It is also interesting to note that the PDF format by itself commanded a reasonable price under all the situations. Further, the bundle price was lower than the sum of the prices of the two formats when discount was allowed (because of the estimated substitutability between them) and the reduction of profit was quite small. When no discount was allowed for the bundle, profits decreased.

The case shown with print format prices as fixed shows the possibilities for NAP to vary prices for print format across the titles (NAP was not considering such a change prior to this study). Obviously profits would be lower because of the constraint placed.

In summary, this application shows how choice-based conjoint methods can be employed for product line pricing decisions. Among other things, estimating the $\Delta\beta$-parameter using the choice model provided the basis for this optimization analysis.

8.6.3 Application 3: Multipart Pricing

Iyengar et al. (2008) applied choice-based conjoint methods to the problem of determining optimal plans for multipart pricing.[14] The context of this application is that of cell phone pricing plans, which used three-part pricing schemes consisting

[14] In an unpublished paper, Iyengar and Jedidi (2012) applied choice-based conjoint methods for determining quantity discounts.

Table 8.10 An illustration of optimal prices of print and PDF versions

Marginal cost of title c_1 ($)	Index	Optimal prices without any constraint ($)	Optimal prices with print price fixed at current levels	Optimal prices with no bundle discount
6.36	p_1	29.55	23 (fixed)	24.97
	p_2	20.63	20.30	16.05
	p_3	29.65	29.03	41.02
	Π	8.49	8.23	7.85
9.79	p_1	32.08	25 (fixed)	27.61
	p_2	19.63	19.40	16.04
	p_3	32.15	31.55	43.65
	Π	7.64	7.37	7.10
12.73	p_1	34.44	29 (fixed)	29.66
	p_2	19.05	18.90	16.02
	p_3	34.55	34.11	45.98
	Π	7.00	6.88	6.55
19.58	p_1	39.97	39 (fixed)	35.66
	p_2	17.91	17.95	16.00
	p_3	40.25	40.88	51.66
	Π	5.85	5.84	5.53

Source: Adapted with permission from Kannan et al. (2009), Copyright (2009), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

of base (access) fee, a free usage allowance, and a per unit (variable) usage charge for the use of the service in excess of the allowance. Obviously consumers need to consider the uncertainty of usage in choosing a cell phone service plan and therefore there is simultaneity between consumption and pricing. The authors developed a utility model that took this feature into account; this translated into conditions on the optimal use depending on the actual number of minutes allowed by the plan. First, the authors specified the utility as a quadratic function of actual consumption of n_{ij} (i.e. include n_{ij} and n_{ij}^2) and a composite good (z_{ij}). The uncertainty in the consumption (on n_{ij}) was modeled as an error distributed as normal with zero mean and variance of θ_i^2 (in the estimation log (θ_i) is assumed to be normal with mean μ_θ and variance τ_θ^2). Then, they optimized the utility under the conditions of an actual plan. The resulting utility model as derived by the authors was:

$$U_{ijt} = E\left[u_{it}\left(n_{ijt}, z_{ijt}\right)\right] + \varepsilon_{ijt},$$

Where $E[u_{it}(n_{ijt},z_{ijt})] = v_{ij} + \beta_{i1}E(n_{ij}) + \beta_{i2}E(n_{ij}^2) + \beta_{i3}E(z_{ij})$. Here, v_{ij} is the deterministic part of the utility due to the other aspects of the service plan (e.g., the firm, length of contract, prices etc.). In their derivations, they come up with the following relationships between the composite good consumption (z_{ij}) and the features of the service plan and the unobserved consumption level:

$z_{ij} = w_i - f_j$ if $0 \leq n_{ij} - A_j$ and $z_{ij} = w_i - f_j - p_j(n_{ij} - A_j)$ if $n_{ij} \geq A_j$, where A_j is the pre-specified limit of number of minutes under the plan, f_j is the base fee, and w_i is the budget for the consumer for the service.

Using the random utility model framework, one can derive the probability that a consumer will choose a particular plan among a set of possible plans or for the no choice option. Note that this analysis depends on the particulars of the service plan (f_j, A_j, p_j, and any other descriptors) and the budget of the consumer (w_i).

The authors conducted a conjoint study to estimate the parameters of the model. Based on a pretest, attributes and levels they selected were: Service provider; Access fee; Plan minutes; Per-minute rate; Internet access; and Roll-over unused minutes. The service provider was one of Verizon, Cingular, or T-Mobile. Internet access was either yes or no. Other attributes were varied with reasonable ranges based on pretest results; they were \$15–\$90 for access fee; \$15–\$60 for per-minute charge and yes or no for rollover minutes. Using randomly selected values for each attribute, they designed 18 choice sets of 3 plans each using the utility-balance approach described in Chap. 4. The "no choice" option was included in each choice set. Service plans with higher access fees have more free minutes (plan minutes). The authors designed the choice sets to reflect reality by first computing the cost of free minute in the existing plans in the marketplace and used it in the value of plan minutes for the choice alternatives.

The choice data were collected from a sample of 72 undergraduate students in two U.S. universities in the Northeast. Several choice models were estimated with these data using MCMC methods. We will focus on two of these—proposed model with no uncertainty and a model with interactions among the attributes. The estimates obtained for these two models are shown in Table 8.11. The equations for these models are implicitly shown in this table; note that the choice set attributes were included as dummy variables in these equations.

All parameters, except for the uncertainty, in the uncertainty model were significant in the sense that the 95 % posterior confidence interval did not contain zero. Even though the uncertainty estimate was not significant, the authors demonstrated that the estimate of monthly uncertainty was 167 min which was close to 181 min estimated for a wireless company in another study. The parameters for the interaction conjoint model generally followed the same pattern as that of the uncertainty model but with a lower degree of its fit.

Given these results, the authors developed optimal plans for T-Mobile by evaluating all possible combinations of the deign factors at discrete points. These optimal plans are shown below:

	Uncertainty model	Interaction conjoint model
Access fee	\$59	\$90
Per-minute rate	\$0.04	\$0.50
Free minutes	369	100
Rollover	Yes	Yes
Internet access	Yes	Yes
Choice probability	0.38	0.17
Expected profit per customer	\$13.40	\$48

Table 8.11 Parameter estimates for two models for the multipart conjoint study (posterior means and 95 % confidence intervals)

Variable	Variable label	Parameter	Uncertainty model	Interaction conjoint model
Quantity	N_{ij}	β_1	**2.59** (2.44, 2.73)	—
Quantity^2	n_{ij}^2	β_2	−0.**29** (−0.32, −0.25)	—
Income effect	z_{ij}	β_3	**0.07** (0.05, 0.08)	—
Cingular	CING	β_4	−0.**19** (−0.30, −0.06)	−0.**34** (−0.59, −0.10)
T-Mobile	TMOB	β_5	−0.**12** (−0.21, −0.02)	−0.21 (−0.46, 0.03)
Verizon	VER		0	0
Rollover	ROLL	β_6	**0.38** (0.26, 0.49)	**0.42** (0.20, 0.66)
Internet	INT	β_7	**0.27** (0.09, 0.46)	0.24 (−0.03, 0.52)
Intercept		β_0	−**0.78** (−1.16, −0.39)	0.77 (−0.43, 1.80)
Uncertainty	Θ	μ_θ	0.06 (−0.07, 0.19)	—
Access fee	F_j	γ_1	—	−0.40 (−2.80, 1.70)
Per-minute rate	P_j	γ_2	—	−1.12 (−3.23, 0.62)
Free minutes	A_j	γ_3	—	**92.90** (72.80, 117.01)
Access x minutes	F_j x A_j	γ_4	—	−**135.02** (−170.01, −109.50)
Access x rate	F_j x p_j	γ_5	—	−0.50 (−5.40, 3.90)
Rate x minutes	Pj X A_j	γ_6	—	15.10 (−6.21, 41.10)
Log Marginal Likelihood	LML	—	932.65	977.82
Hit Rate	HR	—	68.2 %	67.3 %

Source: Compiled with permission from Iyengar et al. (2008), Copyright (2008), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

The two optimal plans are quite different and show that ignoring uncertainty can lead to an optimal plan which may fare poorly in the marketplace. This illustration shows how conjoint methods can be extended to a practical problem with some advantage. In this case, inclusion of uncertainty is a critical factor.

8.7 Summary

This chapter delved into ways in which conjoint methods are utilized for pricing decision for a product or service. Application of the formula for optimal price for an established product requires knowledge of self- and cross-price elasticities as well competitive reaction elasticities. This chapter showed ways in which conjoint methods can be used to determine these elasticities for a given a context. In a similar manner, knowledge of reservation prices is essential for determining the optimal price for a new product or service. The discussion showed how conjoint models can be employed for this purpose as well.

Further, a normal conjoint research generally confounds the two distinct roles of price, namely, the allocative and information roles of price. We have shown how a researcher can disentangle these two roles (which are of opposite sign) with a simple modification of a conjoint research design. In one application to ratings-based methods, these effects are quite distinct although the net effect of price is negative. Similar results are shown for the choice-based methods in the context of estimating price elasticities. While in most cases this may not matter, it is useful for a researcher to test whether this distinction is needed for conjoint applications in practice. One of these applications is in estimating willingness to pay for an attribute change.

Finally, we described three applied projects in which conjoint methods were used to determine bids in a competitive context for a catering firm with significant advantage. The second application showed how choice-based conjoint methods were used for pricing product lines of print and PDF formats for titles published by NAP. The third application dealt with multipart pricing for a wireless carrier in which a utility model was developed to deal with uncertainty of actual usage relative to what a plan offers. The model was compared with an interaction conjoint model to show that the optimal plans can be worse if the uncertainty is ignored.

Appendix 1

Technical Details for Estimating Self- and Cross-Price/Demand Relationships

Let m_j be the market share of brand j under the scenario of prices ($x_1, x_2, \ldots, x_J$) for a set of J brands. (Note that $\sum_{j=1}^{J} m_j = 1 \text{ } and \text{ } m_j \geq 0$). We can specify two models for these data: a logit model and a log-linear model.

Logit Model

Under the logit model, we can write m_j as:

$$m_j = \frac{\exp\left[\beta_{0j} + \sum_{b=1}^{J} \beta_{bj} x_b\right]}{\sum_{k=1}^{J} \exp\left[\beta_{ok} + \sum_{b=1}^{J} \beta_{bj} x_k\right]}$$

This model can be estimated using a log transformation of the odds ratios of m_k relative to base brand J (for example). Then we will have:

$$\ln\left(\frac{m_j}{m_J}\right) = \left(\beta_{0j} - \beta_{0J}\right) + \sum_{b=1}^{J}\left(\beta_{bj} - \beta_{bJ}\right) x_b$$

These equations are estimated using data for all the scenarios using maximum likelihood methods. The result will be estimates of differences $(\beta_{0j} - \beta_{0J})$, $(\beta_{1j} - \beta_{1J})$, ... $(\beta_{Jj} - \beta_{JJ})$, all relative to the base brand, J. We can show that

$$\beta_{j\ell} - \beta_{jn} = \frac{\eta_{\ell j} - \eta_{nj}}{x_j}$$

where η_{lj} is the cross-elasticity for the brand l with regard to the price of brand j. Note that the elasticities are *not* constant in a logit model.

When the prices are described as levels and converted to dummy variables, we will get the (price) effects for discrete jumps.

Constant Elasticity Model (Log-Linear Model)

Under the log-linear model, we can write m_j as:

$$m_j = \beta_{0j} x_1^{\eta_{1j}} x_2^{\eta_{2j}} \ldots x_J^{\eta_{Jj}}$$

where η's are cross-price elasticities (η_{jj} will be the self price elasticity). This equation becomes linear by taking logarithms on either side. The linearized equation and can be estimated using ordinary least squares to yield estimates of the complete matrix of (J × J) elasticities.

Appendix 2

Estimation of Mean and Variance from Truncated Normal Distribution

Let μ_t and σ_t^2 be the mean and variance of the full distribution (normal) of reservation prices for the new product. Let $\bar{p}_t$ and s_t^2 be the mean variance of the truncated distribution (truncated below p_{min} and above p_{max}); this distribution applies to the fraction of $(1 - q_{1t} - q_{2t})$ of the sample. Then, we can use the following formulae to estimate μ_t and σ_t^2. Let the estimates be denoted by $\hat{\mu}_t$ and $\hat{\sigma}_t^2$. Then:

$$\hat{\mu}_t = \bar{p}_t - R\hat{\sigma}_t^2$$

$$\hat{\sigma}_t^2 = \frac{s_t^2}{c}$$

where:

$$R = \frac{f\left(z_{t,min}\right) - f\left(z_{t,max}\right)}{F\left(z_{t,max}\right) - F\left(z_{t,min}\right)}$$

and

$$C = 1 + \frac{z_{t,min} f\left(z_{t,min}\right) - z_{t,max} f\left(z_{t,max}\right)}{F\left(z_{t,max}\right) - F\left(z_{t,min}\right)} - R^2$$

Here, $F\left(z_{t,min}\right) = q_{1t}$ and $F\left(z_{t,max}\right) = 1 - q_{2t}$, which arise due to truncation. The corresponding $z_{t,min}$ and $z_{t,max}$ can be determined from standard normal tables or with the help of Excel. The terms $f\left(z_{t,min}\right)$ and $f\left(z_{t,max}\right)$ are the corresponding values of the unit normal variates $f(z_t) = \frac{1}{\sqrt{2\pi}} \exp\left(-z_t^2/2\right)$; these can be directly computed.

Once the values of $\hat{\mu}_t$ and $\hat{\sigma}_t^2$ are estimated, the distribution of reservation prices for the new product is known. Note that we are assuming this distribution to be normal. If an alternate distribution is to be used, the theory of corresponding truncated distribution is called for.

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Chapter 9
Applications to a Miscellany of Marketing Problems

9.1 Introduction

We have seen applications of conjoint analysis to marketing problems such as product design, market segmentation, product positioning and pricing. We have also seen that conjoint simulators have been quite helpful in dealing with these questions. In this process, we have tangentially dealt with the design of appropriate competitive strategies. The objective of this chapter is to present an overview of several other applications to demonstrate the versatility of the methodology of conjoint analysis for general research in marketing.

We describe a variety of applications of conjoint analysis to other marketing problems. The applications will include competitive strategies, store location, setting of sales quotas, allocating resources, choice of a distribution channel, and measuring brand equity from a customer perspective, and customer satisfaction. Most of these applications are drawn from the literature.[1]

9.2 Competitive Strategy Decisions

Conjoint-based simulators have been typically used to answer what-if questions, such as "what is my firm's best move if my competitor does X?", and to arrive at possible action for the firm. An example of such a simulator is SIMOPT, which we discussed in Chap. 8. This simulation is basically a static optimization model where competitor's product profiles and consumer tastes (partworths) are assumed to remain *fixed* over the firm's planning horizon. To be able to evaluate competitive actions, the conjoint simulators need to be run in a repetitive, cyclical fashion for each competitor in the market to obtain the firm's "best" competitive response against the other players in the market. The cycle needs to be repeated several times

[1] For an application on strategic decision making procedures, see Priem (1992).

V.R. Rao, *Applied Conjoint Analysis*, DOI 10.1007/978-3-540-87753-0_9,

until a stable or convergent solution is found. Also, the convergence properties of these methods are not known. Thus, procedures to determine best competitive actions based on simulators are typically ad hoc.

When a firm faces competition, an appropriate theoretical concept to determine the "best" competitive strategy is the concept of Nash equilibrium. This concept can be best explained as follows. Suppose a firm faces two or more competitors, each trying to formulate its competitive strategy to maximize its own profits, given a specific set of competitive products, market strategies, and consume preferences. Since the market shares of competing products would usually be affected by a given firm's strategy, we could expect their competitive strategies (defined either in terms of product attributes, price, or some other marketing mix valuable) to change in response to the initiating firm's actions. The Nash equilibrium represents a market situation where no individual firm can make further gains for it by unilaterally changing its strategy from the equilibrium outcomes. This equilibrium is probably unattainable in reality. Further, the existence and uniqueness of equilibrium is difficult to establish in a general case. But, simulation procedures can be used to find a local equilibrium. See Choi and DeSarbo (1993) for the algorithmic details of finding such a local Nash equilibrium.

In practice, a Nash equilibrium is determined by one of two iterative procedures: simultaneous and sequential. In the latter case, the competitors select strategies, in turn, in a predetermined order. This option is more realistic than the simultaneous option because it portrays the actions and reaction sequences. Green and Krieger (1997) describe a simulation procedure, called SYMDYN, to determine Nash equilibrium for conjoint data with the sequential option. We illustrate this method below with the case of cellular phones.

Application: This application was reported by Green and Krieger (1995). The management of the Alpha company (a fictitious name for a real company) is considering how to change its current cellular phone products. It anticipates that its rivals, Beta and Gamma, will respond and it needs to incorporate their reactions in the design of its product strategy. For this purpose, Alpha commissioned a hybrid conjoint study among potential cellular telephone buyers in the southwestern United States. The sample consisted of prospective buyers who expressed an interest in purchasing a cellular phone in the next 6-month period. Interviews were conducted via a telephone-mail-telephone procedure. Potential respondents, initially screened by telephone, were mailed a questionnaire and conjoint materials; the materials included color photographs and detailed descriptions of each telephone feature. They were subsequently interviewed by telephone to obtain conjoint and related data. The final sample consisted of 600 respondents.

The conjoint task consisted of 15 attributes, four at three levels and nine at two levels. Attributes and their levels are shown in Table 9.1. The hybrid conjoint procedure consisted of a self-explication task, an evaluation of eight profiles (drawn from a master orthogonal design array of 32 profiles) and other

Table 9.1 Attributes and levels and cost structure for the cellular telephone study

Attribute	Levels[a]	Cost structure for alpha	Cost structure for beta	Cost structure for gamma
1. Initial price (3)	\$125; \$175; \$250	75; 105; 150	75; 105; 150	65; 95; 140
2. Brand (3)	Alpha; beta; gamma	0; 0; 0	0; 0; 0	0; 0; 0
3. Warranty (2)	3 years; 1 year	−10; 0	−15; 0	−5; 0
4. Weight (3)	7.5; 8.5; 9.5 oz	−20; −10; 0	−30; −15; 0	−15; −5; 0
5. High battery strength of 15 h (2)	Present; Absent	0; −2	0; −2	0; −2
6. 9-number speed dialing (2)	Present; Absent	0; −2	0; −2	0; −2
7. Programmable for two different numbers (2)	Present; Absent	0; −4	0; −2	0; −2
8. Cigarette lighter battery charger (2)	Present; Absent	0; −5	0; −2	0; −4
9. Large size (100 number) memory (2)	Present; Absent	0; −5	0; −5	0; −5
10. Portable car roof antenna (2)	Present; Absent	0; −8	0; −7	0; −5
11. Low-battery warning beep (2)	Present; Absent	0; −5	0; −7	0; −5
12. Electronic lock (2)	Present; Absent	0; −5	0; −7	0; −10
13. Missed call counter (2)	Present; Absent	0; −9	0; −8	0; −10
14. Mute function (2)	Present; Absent	0; −5	0; −2	0; −10
15. Extra (rechargeable) battery included (2)	Present; Absent	0; −10	0; −5	0; −15

Source: This table is adapted from Green, P.E. & Krieger, A. in George S. Day and David Reibstein (eds.) *Wharton on Dynamic Competitive Strategy*, 1997, with permission of the Publisher, John Wiley & Sons, Inc.

[a]The levels are 1, 2, and 3 and 1 and 2 for the 3-level and 2-level attributes respectively

background/demographic questions. The main conjoint response was to sort the eight profiles into three graded categories of less desirable, neutral, and most desirable profiles, and then rate each profile in each category on a 0–100 likelihood-of-purchase scale. The analysis was done to determine individual partworths. The average partworths for the 15 attributes displayed an expected pattern and there were no surprises. The general pattern was: the presence of additional features was deemed more attractive; lighter phones were preferred over heavier ones; lower price was preferred over higher prices.

We now describe how these data were used to design competitive strategies. For this purpose, a competitive strategy is the attribute profile of a new product each company can design to compete best in the marketplace. The costs involved in changing the levels of the attributes needs to be considered in evaluating any competitive strategy of the three firms. These costs are also shown in Table 9.1.

The authors used the SYMDIN simulation to find the Nash equilibrium for this market, focusing on two key variables: the cost structure of the competitors and their participation in the market. For each of these variables, they made two different assumptions:

Table 9.2 Equilibrium solutions for the cellular telephone study

Solution	Brand	Profile: first five attributes[a]	Number of moves for reaching equilibrium[b]	Market shares %	Returns $	Sum $
A: Initial conditions	Alpha	1,1,2,3,1	NA	20.4	6.73	37.56
	Beta	2,2,1,1,2		33.7	17.52	
	Gamma	1,3,2,3,1		45.9	13.31	
B: Equilibrium under equal costs	Alpha	3,1,1,1,2	7	33.0	19.81	65.83
	Beta	3,2,1,1,2	8	37.8	22.67	
	Gamma	3,3,1,3,2	11	29.2	23.35	
C: Initial conditions for unequal costs	Alpha	1,1,2,3,1	NA	20.4	6.73	30.16
	Beta	2,2,1,1,2		33.7	15.17	
	Gamma	1,3,2,3,1		45.9	8.26	
D: Equilibrium under unequal costs	Alpha	3,1,1,1,2	6	38.6	23.13	66.14
	Beta	3,2,1,3,2	6	25.0	21.49	
	Gamma	3,3,1,2,2	6	36.5	21.52	
E: Equilibrium under unequal costs and gamma passive	Alpha	3,1,1,1,2	4	41.5	29.04	65.54
	Beta	3,2,1,2,2	4	38.2	32.84	
	Gamma	1,3,2,3,1[c]	NA	20.3	3.66	

Source: This table is adapted from Green, P.E. & Krieger, A. in George S. Day and David Reibstein (eds.) *Wharton on Dynamic Competitive Strategy*, 1997, with permission of the Publisher, John Wiley & Sons, Inc.

NA not applicable

[a]These five attributes respectively are price, brand, warranty, weight, and battery. Optimal values for the attributes 6 through 15 are at level 2 in all cases

[b]Shown are the numbers of moves required when the corresponding firm is the initiator of competitive actions

[c]This strategy for Gamma is the same as that under initial conditions for unequal costs

1. Cost structure is the same or different for the three firms; and
2. Active or passive participation of the firms: all are assumed to be active; and one of the three is assumed to be passive.

Passive participation means that the firm does not change its product profile in response to the actions of the other firms. We show three equilibrium solutions in Table 9.2. The first row, labeled A shows the initial conditions. The second row, B shows the equilibrium solution when all firms are assumed to have equal costs, the same as those of the firm Alpha. The third row, C shows the initial conditions when the three firms have unequal costs (as shown in Table 9.1). The fourth row, D shows the equilibrium solution under unequal costs and all firms are active participants. The fifth row, E shows the equilibrium solution under unequal costs (as shown in Table 9.1) when the Gamma firm is passive.

These results reveal interesting dynamics in the market as discussed below:

1. In general, an equilibrium was achieved in a smaller number of moves for the unequal costs case than the equal costs case (4–6 versus 7–11).
2. The Nash equilibrium solution is quite different from the initial conditions. For Alpha, for example, the market share under equilibrium is 33.0 % as compared to 20.4 % under the initial conditions. Also, when only the Alpha profile is optimized, its share jumps to 61.1 % (this result is not shown the table).

3. In equilibrium under equal costs, all three firms are charging the highest price ($150) and offer a 3 year warranty. But, their weights differ; Alpha's and Beta's weight is 7.5 oz. while Gamma's optimal weight is 9.5 oz. Their returns are much less varied under equilibrium compared to the initial conditions.
4. Under unequal conditions also, there is much less variability in the returns for the three firms, although their market shares differ quite a bit. The optimal product profile differs in the weight of the cellular telephone.
5. Under unequal costs and Gamma being passive, the equilibrium solution again differs on the weight attribute.
6. Finally, the total return for all three firms (or the total profit in the market) is much larger under the Nash equilibrium; this implies that when firms do not act optimally, they can be worse off.

This illustration shows how conjoint analysis can be employed to gauge the effect of potential competitor actions and reactions. Although this was done in the context of a product design, the same principles can be used for other types of competitor actions. We must note however that product design context is one of the most popular applications of conjoint analysis.

9.3 Distribution and Personal Selling Decisions

9.3.1 Store Location Decisions

When a firm wishes to locate a retail store in a given geographic area, it generally evaluates the potential sales (and profits) from several alternative (and feasible) locations. For each location, it needs to assess the total market potential as well as the strength of competing stores in the area. Based on these data, it estimates the potential market share and sales for each location. Several models exist for this purpose.

One such model (Ghosh and Craig 1991) considered both the potential to take market share from existing competitors and the market expansion potential in the geographic area due to the new store. One such model is due to Durvasula et al. (1992). These authors estimate of market share for a new store or the $(n + 1)$-th store, MS_{n+1} in a geographic area with n existing stores as: $MS_{n+1} = \left[\sum_{i=1}^{n} PMS_i * M_i + k_{n+1} * ME\right] \Big/ (1 + ME)$
Where PMS_i is the proportion of current market share of i-th store (M_i) captured by the new store, k_{n+1} is the proportion of the market expansion (ME) captured by the new store. The revised market shares of the existing stores can also be formulated as: $MS_i = (M_i - PMS * M_i + k_i * ME)/(1 + ME)$. Here, k_i is the proportion of the market expansion potential captured by i-th store. Further, the k-values (all non-negative) should satisfy the constraint, $\sum_{i=1}^{i=n+1} k_i = 1$. In this model, market shares of

Table 9.3 Attributes, levels, and partworths for competitor strength for the store location study

	Partworths for attribute levels for managers			
Attributes and levels	M1	M2	M3	M4
1. Competitor's current market share				
a. Less than ABC's average	0.00	0.00	0.00	0.00
b. About the same as ABC's average	0.06	0.70	1.13	0.86
c. More than ABC's average	0.82	1.40	2.96	0.13
2. Growth rate of competitor's deposits				
a. Less than ABC's average	0.00	0.00	0.00	0.00
b. About the same as ABC's average	0.99	0.69	1.87	0.88
c. More than ABC's average	2.00	1.41	3.74	0.12
3. Aggressiveness of competitor in attracting deposits				
a. Less than that of ABC	0.00	0.00	0.00	0.00
b. About the same as ABC	1.92	2.58	1.09	1.08
c. More than that of ABC	3.83	4.69	0.22	1.80
4. Age of competitor's branch				
a. Relatively new	0.00	0.00	0.00	0.00
b. Relatively established	1.15	0.00	0.00	0.07
5. Type of competitor's bank				
a. Statewide	0.00	0.04	0.13	0.00
b. Local	2.28	0.00	0.00	4.57

Source: Reprinted from Durvasula et al. (1992) with permission of the publisher
Note: The partworths are expressed in utiles and they are rounded to two decimal places

the n existing stores are typically known and the other quantities (PMSs, ks , and ME) need to be estimated by another model or judged by the decision makers. One model used for estimating the PMS quantities is: $\text{PMS}_i = \text{PMIN} + (\text{PMAX} - \text{PMIN})\,(1 - f\,(S_i))$; $i = 1, \ldots, n$, where S_i is the relative strength of the existing stores in the area and PMAX and PMIN are respectively the maximum and minimum market shares any store can get. Typically, f (S_i) is modeled as a logistic function in S_i.

The relative strength construct depends on various attributes of a store and can be modeled using conjoint analysis. We describe an application of this model to financial institutions, reported by Durvasula et al. (1992) (herein after called DJA) and show how conjoint analysis was used in estimation. The context was that of a firm, called ABC Commerce evaluating the potential for four locations, L1, L2, L3, and L4 in a certain geographic region. The firm currently had 16 branches in the region. In order to evaluate relative strength, the authors identified five attributes by an exploratory study. The attributes were: competitor's market share, growth of competitor's deposits, aggressiveness of the competitor in attracting deposits, age of the competitor's branch, and type of financial institution.; these were varied respectively at 3, 3, 3, 2, and 2 levels as shown in Table 9.3.

Sixteen descriptions of the competitive situation were developed using a fractional factorial design and four experienced managers (M1, M2, M3 and M4) rank ordered the profiles on the relative competitor strength. Based on these judgments, partworths were computed for each of the five attributes. The derived partworths for the four managers are also shown in Table 9.3. It is worth noting that the four managers differed somewhat in their evaluations of the attribute levels, but these differences were not very large.

DJA used these results to evaluate the market potential for the four locations using the models described earlier; the conjoint results for competitor's strength were the major input into the analysis. Managers also provided additional inputs (e.g. PMIN, PMAX etc.) judgmentally. The logistic functions, f(S) were estimated individually from the estimates of competitive strength obtained for the competitive branches in each location calculated using the partworth values. There was reasonable agreement among the managers in their site evaluations. The results are shown below:

	Market share potential for the proposed branches (in percent of deposits)			
Location	Manager M1	Manager M2	Manager M3	Manager M4
L1	28.42	23.00	29.00	28.79
L2	10.81	12.83	10.66	10.11
L3	17.78	13.58	18.50	18.37
L4	32.25	22.75	27.45	11.79

Source: Reprinted from Durvasula et al. (1992) with permission of the publisher

Based on these, it appeared that location L1, followed by L4, were the most attractive locations for the ABC Commerce bank. One should caution that these results need validation. Nevertheless, this illustration shows how conjoint analysis can be employed for location decisions.

9.3.2 Setting Sales Quotas

Sales quotas procedures generally attempt to integrate several relevant variables such as sales potential, competition, territory's response to various marketing mix elements, and the salespeople's experience and abilities. Sales quotas serve as a challenge to a salesperson and also as a managerial device for setting rewards for achievement. The reward system offered to a salesperson is usually in the form of bonuses. It is possible to give options for salespeople to devote more time to handle a larger quota and consequently receive higher bonus. From the sales person's perspective there is a clear tradeoff between a quota and a bonus; for example, some salespeople may be satisfied with a lower quota and lower bonus while some other may like to work for toward a larger quota and a larger bonus. From the firm's perspective, achievement of a larger quota will yield higher gross margin but the firm will also incur a larger bonus. Thus, the problem of setting sales quotas involves tradeoffs for both firms and salespeople.

Conjoint methods are useful in ascertaining the level of satisfaction for quotas and bonuses (or a utility function in quota and bonus) for salespersons. The knowledge of such functions will enable a firm in setting individual-specific quotas so that net profit to the firm is maximized. Using this logic, Darmon (1979) developed a procedure based on conjoint analysis. We describe the details in this section.

Mathematically, let Q and B be sales quota (in dollars) and bonus (in dollars) respectively, U(Q, B) represent the utility function for a salesperson and *m* represent the gross margin per every sales dollar. Further, assume that the utility level for a salesperson at the current time is U_0. Then, the problem of setting a sales quota and bonus level for the salesperson can be formulated as:

Max (m*Q − B)
Subject to U(Q, B) = U_0.
The solution is obtained by solving simultaneously the following equations:

$$\frac{\partial U/\partial Q}{\partial U/\partial B} = -m; \text{ and}$$

$$U(Q,\ B) = U_0.$$

The solution depends on the knowledge of the functional from of U(Q, B). Conjoint analysis is helpful in determining this function specific for each salesperson. For this purpose, the analyst will present a number of quota-bonus combinations to a salesperson and seek judgments on his/her satisfaction with each option either on a rating scale or on a ranking scale. These judgments are then processed to obtain the functional form of the U- function. In order to avoid corner solutions, a function with linear and squared terms will be necessary.

Illustration: We use a hypothetical example patterned after the data given in Darmon (1979). Table 9.4 shows the preference data for one salesperson for 35 combinations of sales quota and bonus; these are ratings on a 1–100 scale.

We first fit the following function utility function to these data: $U(Q,B) = a_0 + a_1Q + a_2B + a_3B^2$. Here, a_1 and a_2 are positive and a_3 is negative so that the function exhibits the kind of properties generally present in such a utility function; it is increasing in quota and concave in the bonus. It represents the fact that a salesperson that is given a higher sales quota needs to be compensated by a higher bonus. The equations to be solved for the optimal values of sales quota and bonus to maintain the current level of utility are:

$a_1/(a_2 + 2a_3B) = -m$, and U(B, Q) = U_0. Then the optimal values of quota (Q*) and bonus (B*) are:

$$Q^* = U_0 - a_0 - a_2B^* - a_3B^{*2}, \text{ and } B^* = -(a_1 + a_2m)/2a_3m.$$

The estimated utility function for the data in Table 9.4 is: U(Q, B) = −34.3 − 3.18*Q + 12.05*B − 0.21*B^2, where Q is measured in $100,000 and bonus in $1,000.

Let us assume that the current sales quota and bonus for the salesperson are $1,400,000 and $20,000 respectively. Further we assume that the firm's gross margin is 4 % of sales in dollars. With these data, the current level of utility for the salesperson is 77.29. With the estimated utility function, the optimal quota and

Table 9.4 Preference ratings for sales quota and bonus combinations (hypothetical)

	Sales quota ($000s)						
Bonus level ($)	1,200	1,300	1,400	1,500	1,600	1,800	2,000
10,000	27	21	17	14	9	5	0
12,000	50	43	39	36	32	28	23
15,000	60	55	51	47	43	38	34
20,000	87	80	76	74	69	65	60
30,000	100	95	90	88	82	80	75

bonus are $1,868,383 and $28,371. If this optimal policy of quota and bonus is implemented, both the firm and the salesperson will benefit. A comparison of the current situation and the optimal policy is given below:

	Sales quota	Bonus	Profit to the firm
Current	$1,400,000	$20,000	$36,000
Optimal	$1,868,383	$28,371	$46,364
Ratio (Optimal to Current)	1.334	1.418	1.287

This illustration shows the advantage of tailoring sales quota policies specific to each salesperson using conjoint methods.

9.3.3 *Choice of a Distribution Channel*

We now describe an application of choice-based conjoint analysis to an individual's choice of a distribution channel to purchase a durable good. This is based on an empirical study conducted by Foutz et al. (2002); while the authors' purpose was to test some behavioral decision theories, we use it simply to show an application of choice-based conjoint analysis to the problem of an individual choosing an outlet (conventional bricks & mortar, catalog, and an Internet store) for purchasing a computer monitor. The choice context given to respondents of the study was as follows:

> Place yourself in a situation where you have just settled down in a new city, and you are thinking of purchasing a new 17'' computer monitor for yourself, since you sold the old one when you moved. You have a budget of *three hundred U.S. dollars* for this purchase, and you have other uses for any funds left over. You also wish to get the monitor soon due to the need of some work at hand. After some initial information search, you have narrowed down to your most favorite model. Your search has also identified three retailers, each of which is the best in each of the three channels, from which you may consider purchasing the monitor, *bricks & mortar*, *print catalog*, and the *Internet/online*. Fortunately, all of them carry the model you want.

All three retailers are described on five attributes of average price, product trial/evaluation, sales assistance, speed of acquiring purchased monitor, and convenience of acquisition and return, described on 3, 2, 3, 3, and 3 levels respectively. The definitions of the levels were as follows:

Attribute	Levels
Average price	1. Around $230
	2. Around $250
	3. Around $270
Product trial/evaluation	1. Display only
	2. Display AND physical/virtual trial
Sales assistance	1. Not available
	2. Only minimal technical support
	3. Very helpful with rich technical information
Speed of acquiring purchased monitor	1. Same day
	2. Within 2–7 days
	3. Longer than 7 days
Acquisition and return	1. In store only
	2. Mail only
	3. In store OR mail

This study was conducted among 146 graduate and senior undergraduate students (78 males and 68 females) in a major Northeastern university; respondents were compensated for their participation of the study. Each survey took about half an hour and consisted of 11 conjoint choice tasks on channel choices for the purchase of a computer monitor and respondents were asked to choose the one option from which he/she would actually purchase a monitor.

An example of a purchase situation is as shown below:

	Bricks & mortar	Print catalog	Internet/online
Average price	Around $270	Around $250	Around $230
Product trial/evaluation	Display AND physical/virtual trial	Display AND physical/virtual trial	Display AND physical/virtual trial
Sales assistance	Very helpful with rich technical information	Very helpful with rich technical information	Only minimal technical support
Speed of acquiring purchased monitor	Same day	Within 2–7 days	Same day
Acquisition & return	Mail only	In store only	Mail only

A short questionnaire was used to collect information on demographics and other important individual characteristics. The majority of the respondents had more than 3 years of online experience (93.8 % of the 146 respondents) and spent less than 20 hours per week online (72.4 %). One third (32.4 %) of the respondents spent less than $200 per year online; another third (37.9 %) spent between $200 and $1,000 annually online; the rest of them spent more than $1,000. 64.8 % of the

Table 9.5 MNL estimates for the choice-based conjoint study of channel choice

Attribute and levels	Coefficient	Standard error	t-value	P-level
Channel:				
Bricks and mortar	0.112	0.882	1.27	0.20
Catalog	−0.221	0.096	−2.29	0.02
Internet	0			
Price:				
$230	2.702	0.138	19.57	0.00
$250	1.598	0.129	12.37	0.00
$270	0			
Trial and evaluation:				
Display only	−0.730	0.095	−7.70	0.00
Display & physical trial	0			
Sales assistance:				
Not available	−1.692	0.119	−14.23	0.00
Only minimal technical support	−0.763	0.113	−6.71	0.00
Very helpful rich technical information	0			
Speed of acquisition:				
Same day	2.000	0.121	16.48	0.00
Within 2–7 days	1.564	0.125	12.46	0.00
Longer than 7 days	0			
Acquisition and return:				
In store only	−0.136	0.106	−1.28	0.20
Mail only	−0.873	0.113	−7.70	0.00
In store or mail	0			
Likelihood of the model	−901.15			
Rho-square	0.37			
Number of observations	1,305			

respondents purchased computer monitors before, however only 20.7 % claimed that they had adequate technical knowledge about computer monitors. In addition, 71 % of the respondents had purchased from catalogs before.

The choice data were analyzed using a multinomial logit model. The fit of the model as described by the Rho-square (a measure analogous to R-square for the multinomial logit analysis) was 0.38; this indicates heterogeneity among the respondents. The estimates for the sample as a whole, shown in Table 9.5, represent average partworths for the attributes used in the study; there were few surprises in the partworths. After appropriate validation, they can be employed in identifying the attribute levels deemed important in a new store on any one of the three distribution channels. We should note that the attribute levels implied different resource commitments in the design of a store.

Table 9.6 The five design factors and levels (web site design study)

Factor	Level 1	Level 2
1 Background color	Pale blue background color	White background color
2 White space	More white space: no gray border present	Less white space: gray border present
3 Thumbnail image location	To the left of the product description	To the right of the product description
4 Thumbnail image size	Large thumbnail image	Small thumbnail image
5 Thumbnail order	First thumbnail image in the list of products	Second thumbnail image in the list of products

Source: Agarwal A. (2007) reprinted with permission of the author

9.3.4 Web Page Design

We will discuss the study Anshu Agarwal conducted for her master's thesis in the Design and Environmental Analysis Department at Cornell University as an illustration of application of ratings-based conjoint methods for determining importances of various factors in creating a web page (Agarwal 2007). It evaluated the aesthetic aspects of a web site, E-Retailer associated with the web site, and purchase intention of products from it. She utilized the literature in ergonomic design to develop elements varied in the hypothetical web sites. We will briefly discuss the attributes and selected results from this work.

Based on an initial analysis of various existing web pages, Agarwal selected five attributes each at two levels for the conjoint study: background color[2] (white or pale blue); amount of white space (more white space and no gray border present or less white space with gray order present); thumbnail image location (to the right or left of the product description); thumbnail image size (large or small) and thumbnail order (first thumbnail image in the list of products or second); these are also shown in Table 9.6. She constructed an orthogonal design of 16 profiles (or half-factorial design) using the SAS OPTEX procedure. Using a generic e-commerce web page design patterned upon model websites such as Amazon.com, Buy.com, and BarnesandNobles.com, 16 hypothetical web pages were designed according to the profiles. Responses to an initial survey indicated that the prototype design had no apparent similarities to any recognizable e-retailer. The 16 distinct web page prototypes were created in Adobe Illustrator according to the factor combinations of the experimental design. Once complete, the 16 prototype files were saved as jpeg images and placed into individual web pages on the CUErgo web server.

The study included several questions on the aesthetic aspects of the web site (e.g. easy to read, like the look, like the location of the image, easy to see the product

[2] Luminance values were measured using a luminance contrast meter in a room with dim lighting; the pale blue background had a luminance of 123 cd/m^2 and the white background color had a luminance value of 172 cd/m^2. Based upon the luminance values measured, the white background color was thus approximately 28.5 % brighter than the pale blue background color.

Table 9.7 Selected results from the web site design study

Evaluation	Selected measures	Web site design factors		
		Background color	Thumbnail image location	Thumbnail image size
Aesthetics	Easy to read	[a]	[a]	
	Like look	[a]	[a]	
	Not cluttered	[a]	[a]	
	Like image location	[a]	[a]	
	Easy to find product	[a]	[a]	
E-retailer	Professional	[a]	[a]	
	Quality company	[a]	[a]	
	High budget	[a]	[a]	
	Trust buying product	[a]	[a]	
Purchase intention	Likely to purchase	[a]	[a]	
	Image size picked	[a]	[a]	[a]

Source: Compiled from Agarwal A. (2007) with permission of the author
[a]Indicates significant partworth values (Level 1 as compared to Level 2 of the attribute)

description) and inferences of E-Retailers (e.g., professional, quality company, trust etc.), measured on a six-point scale. The purchase intention was measured for two product categories: (1) ergonomic office products and (2) electronic products (selected using the criteria of perceived price differences, purchase frequency, and consumer involvement). In general, electronics products were perceived to be higher priced, purchased less often, and higher-involvement than ergonomic office products. Two main questions were a choice question on purchase intention and a question for qualitative feedback for the choice as shown below:

1. “Assuming the products on this web page suit your needs, which of these two products displayed would you be more likely to purchase: the First or the Second product shown on the above web page?” and
2. “Why? Briefly explain why you’d be more likely to purchase the product you selected in the previous question”.

In addition, there were a few questions on background characteristics (age, gender, Internet usage and online shopping experience) of the respondents. In all 229 student respondents (drawn from two U.S. universities in the Northeast) completed the study.

Agarwal analyzed the response data for the aesthetic evaluations, E-Retailer evaluations, and purchase intentions using a mixed model that controlled for respondent differences. The coefficients are like partworth values. One should note that she measured the aesthetics and E-Retailer evaluations with several measures and only selected ones are shown in Table 9.7.

Aesthetic Evaluations: (1) White background color was preferred over the pale blue background color, (2) Thumbnail image location to the left of the product description preferred to right location; and (3) white space did not matter. Further, she found a significant interaction between background color and the amount of white space. Other design variables were not significant.

E-Retailer Evaluations: These results were similar to that for the aesthetic evaluations.

Purchase Intentions: Thumbnail image location and background color turned out to be significant.

9.4 Legal Decisions

9.4.1 Measuring Damage Due to Patent Infringement

It is not uncommon for a firm (knowingly or otherwise) to infringe patents assigned to another firm. Such an action usually leads to a lawsuit by the patent owner to claim damages incurred due to infringement. When the claim has to be settled, it is necessary to measure the monetary loss incurred by the patent owner (using such measures as market share, revenues, profits, and loss of reputation). Typically, the actions of both the firms will involve business/marketing decisions such as price, advertising etc. other than the product quality (which is the key variable affected by the patent). Therefore, an analysis of market shares alone will not enable the analyst to disentangle the effect of patent infringement on the marketplace outcomes of the firms. Conjoint analysis is quite well suited to determine the effect of change in product attributes (as affected by the patents) on the market shares. Legal proceedings have begun to use conjoint methods to resolve such patent disputes.

As an example, consider the case of Firm Q (name disguised) which received a U.S. patent on the elastic waistband for disposable diapers and introduced a product with it and an additional product attribute of improved absorbency. But a competitor, Firm B (name disguised) imitated the modification. Given that the imitation was illegal, Firm Q claimed damages. In order to determine the extent of damages, a conjoint study was conducted among a large sample of household decision makers to evaluate their tradeoffs among various product attributes of disposable diapers; the attributes and levels were: brand name (Q, B, or other); degree of absorbency (low medium, or high); elastic band (present or absent); weight (light, medium or heavy); and fit (good or poor); and price per diaper. A conjoint choice simulation was performed to determine what the market share would be if the Firm B did not have the attribute of elastic band for its product; in this estimation, suitable weights were used to project the sample to the population of purchasers of disposable diapers. Using this estimate, damages to be paid to the Firm Q were computed. It was reported that the law suit was settled out of court and that Firm B paid an undisclosed amount of damages to Firm Q.

In the next section, we will describe details of measuring the value of an attribute improvement; this method can be valuable in such patent infringement cases.

9.4.2 An Application to a Class Action Suit

Conjoint analysis methods provided major support for the arguments (pro and con) in a class action suit[3] filed in the U.S. District Court for the Eastern District of New York in 2006 by Barbara Schwab et al., individually and on behalf of all others similarly paced (Plaintiffs) against the Defendants (Philip Morris USA Inc., and other cigarette manufacturers—R.J. Reynolds Tobacco Company, Brown & Williamson Tobacco Corporation, Liggett Group Inc. and the British American Tobacco, p.l.c.). The issue under contention was the degree to which health concerns played a role in smokers' choice of "light" cigarettes and whether the "light" cigarette consumers were led to believe that a light cigarette was healthier product. The Plaintiffs sought the consulting services of D. John Hauser of MIT and he conducted a conjoint study to determine the value and importance of health risks to "light" cigarette consumers in their decision to purchase a "light" cigarette. The details of this conjoint analysis study and comments by the Defendants' counsel and their consultants on selected aspects of the study and the rebuttal to the comments the Plaintiffs' consultant are described below.

9.4.2.1 Conjoint Study

The consultant (Dr. John Hauser of M.I.T.) began his work by identifying the features that drive "light" cigarette consumers' purchases of cigarettes using 14 in-depth interviews with current "light" cigarette consumers. This information was used in developing a choice-based conjoint study (CBC) and a questionnaire that used words and phrases consumers use to describe the features of cigarettes. A pre-test with nine respondents was conducted to ensure that the descriptions, instructions, and questions were understood.

Four features respectively at 2, 5, 3, and 5 levels were chosen for this study. These are shown in Table 9.8.

The study involved showing sixteen (16) choice sets (shown as screen shots in a computerized data collection) containing four cigarette options that were described by the combinations of the levels of the above features. The design of the choice

[3] This is the Civil Action No. 04-CV-1945 (JGW) (SMG). This section is based on various exhibits in the publicly available documents for this case.

Table 9.8 Features and levels in the cigarette conjoint study

Feature	Number of levels	Description of levels
Pack type	2	Soft or hard
Perceived health risks	5	Health risks are greater than regular cigarettes
		Health risks are the same as regular cigarettes
		Health risks are the same as “light” cigarettes
		Health risks are the same as “ultra-light” cigarettes
		Health risks are less than “ultra light” cigarettes
Taste	3	Tastes like a regular cigarette
		Tastes like your brand of “light” cigarette
		Tastes like an “ultra-light” cigarette
Price per pack	5	50 % less than what you pay now
		20 % less than what you pay now
		Same price as what you pay now
		20 % more than what you pay now
		50 % more than what you pay now per pack

sets was highly efficient. After collecting choices for the 16 choice sets, respondents were thanked and the interview was concluded.

The main study was conducted among respondents selected at random from Greenfield Online’s database. The respondents were invited to go to a special website to complete the survey. Each invitation included a URL with an embedded password that was then matched against a list of valid passwords that had been already been used. Respondents received an initial e-mail invitation and up to four e-mail reminders. Greenfield Online motivated the respondents to participate in this survey by adding $5 to the Greenfield prize accounts of all who qualified for and completed the survey. In order to qualify, respondents were screened to assure that they were “light” cigarette consumers. A total of 627 respondents completed the survey beginning June 15th, 2005 and ending on June 29th, 2005. The completion rate was 94.9 %.

The data collected from the respondents were analyzed using hierarchical Bayesian methods described in Chap. 4. The testimony of Dr. Hauser was based on the individual estimates of partworths for various levels (15 across all the four attributes). Dr. Steve Gaskin conducted the analysis, on behalf of Applied Marketing Science, Inc., under Dr. Hauser’s direction.

9.4.2.2 Results

The main results of this study conducted by Dr. Hauser are as follows:

1. The fit of the HB estimates to the data was quite good; the average U^2 for 15 of the 16 choice sets was 0.522 and the average U^2 for the hold out task (16th choice set) was 0.459. These values compared well with a model in which the

partworth estimates were the same for every respondent (0.288 and 0.279). (U^2 is a measure of fit in a logit model.)

2. Respondents who placed a higher importance on health risks placed a lower importance on taste; the correlation was -0.22.
3. Using the estimates of HB CBC, 622 of the 627 respondents were found to follow a compensatory model while only five of them were found to be lexicographic in their choices. Further, no one was found to be lexicographic at the top level with respect to taste, health risks, or price. In other words, for 99.2 % of the respondents for features of taste, health risks, and price, improvements in some attributes (from one level to another) can compensate decreases in other features.
4. For 90.1 % of the respondents, the importance for health risks (computed as the difference in the partworth value for "Health risks are less than the ultra-light cigarette" and "health risks are greater than a regular cigarette") was positive. Using a one-tailed *t*-test, for 76.4 % of the respondents, the importance health risks was positive and statistically significant at 0.10 level and for 69.7 % of the respondents the importance was positive and significant at 0.05 level. For only 2.1 % of the respondents the importance of health risks was negative and significant at .10 level and for 1.1 % of the respondents the importance is negative and significantly negative at the 0.10 level.
5. The study also concluded that "health risks" was third or higher in importance for 98.1 % of respondents (all light cigarette purchasers). Overall, on the average, price was most important, health risks second, taste third, and pack type fourth. Thus for 98.1 % of the "light" cigarette consumers, health risks was a significant contributing factor in their purchase decisions.
6. Using the partworth values, Dr. Hauser estimated that more than 75 % of the consumers would be willing to pay more than 50 % of the price per pack of their cigarettes to decrease health risks from greater than regular cigarettes to health risks the same as "light" cigarettes.
7. Based on various methodologies employed (consumer willingness-to-pay and market-based simulations), the market value of the change in perceived health risks from that of a regular cigarette to that of a "light" cigarette was between 39.8 % and 47.3 % of the price per pack.

9.4.2.3 Comments and Responses

As could be expected, the defendants' experts raised several issues with the results reported by Dr. Hauser. We list below a sample of such comments and the responses.

No.	Issue	Comment	Response
1.	Sample representativeness	Greenfield Online panel is opt-in and therefore, not representative	Corporations routinely use opt-in panels and opt-in panels are accepted by courts. Further, the result on the percentage of respondents who value health risk positively in their decision to purchase light cigarettes and in the median willing-to-pay for a change in health risk was basically the same even after weighting the panel on each of the demographic variables (sex, income, age, region, ethnicity, and education) cited by Defendants' experts Further, Greenfield Online panel sample is more representative than a typical convenience sample
2.	Survey taking	Respondents are "professional survey takers"	When the partworth values were computed for the health risks attribute as a function of number of surveys taken by the respondent, the partworth functions looked quite similar. Median willingness to pay calculations and percentage of respondents who valued health risk were quite similar
3.	Sample size	Sample size is to small	In the survey, each of the 627 respondents answered 16 choice questions for a total of 10,032 choice questions among an aggregated total of 40,128 profiles. These responses were more than sufficient to estimate WTP and percent of respondents who placed positive value on health risk
4.	Method of conjoint analysis	Individual choices are not explained perfectly by the estimated partworth values	While the individual respondent partworth values were still "fuzzy" because they were estimated on only 16 observed choices, the population level partworth values were estimated by a large sample of 10,032 choices. This was further demonstrated by the high value of U^2 for the data as a whole
5.	Estimates versus observed choices	Inconsistencies exist between the percentage of respondents who value different levels of the health risk attribute	These inconsistencies were found by the defendants' expert because he did not consider the lack of significance of the estimates (or in other words the "fuzziness" of the estimates). Further, the defendants' expert was

(continued)

No.	Issue	Comment	Response
			cherry-picking the data and not considering all of the data
6.	Price-constrained criticism	Allegation that different results would have been obtained for the WTP estimates if a different statistical model were used	First, the model selected was better at predicting holdout choices. The selected model was robust and less sensitive to "fuzziness" at the individual level. Even if an unconstrained model were used, the results were in the range indicated if more appropriate calculations were employed
7.	Summary measure for the importance of health risk	Defendants' experts argued for using measure based on partworth values for the intermediate values of the health risk attribute	The use of importance measure based on the partworth values for the end-points (levels) of an attribute is a common practice
		They also argued for the use of the difference "between "light" cigarettes and 'regular' cigarettes" as a measure of health risk sensitivity	The second measure was considered less-robust and was more sensitive to fuzziness. Even if used, Dr. Hauser's recomputation showed an estimate of 90.4 % rather than 90.1 %

We hope that the above description of the use of conjoint analysis for studying a legal question was instructive. Further, the readers should note the range of issues that could be raised by "experts" in evaluating the results of a conjoint study. The responses of Dr. Hauser should be valuable in properly directing a researcher in making the innumerable choices needed in the design and implementation of a conjoint analysis study. It is gratifying that the main conclusions were shown to be robust while dealing with the critique of the other experts.

9.5 Resource Allocation Decisions

An important task of any management is to allocate the limited amount of resources among competing demands so as to maximize a pre-specified objective such as total sales. The theoretical solution to the problem of allocation is to allocate the available budget (B) among n alternative demands (X_1, X_2, . . ., X_n) in proportion to the partial elasticities of the different expenditures. But, one needs to know the relationship between the expenditures and the objective to determine these partial elasticities. Such a function can be estimated using regression methods when historical data on objective and expenditures are available.

In the absence of such historical data, conjoint methods can be employed to estimate such a relationship. In this case, several profiles of expenditures will be given to an experienced manager (or a sample of managers) to seek their judgments on the expected outcome for each profile of expenditures. The judgments can then be related to the levels of expenditures in a manner similar to the preference regressions in full profile conjoint experiments. When more than one manger is involved in the study, some form of aggregation is necessary to arrive at a response function. Resource allocation can be made with such a judgmentally-derived response function. We describe an application of conjoint analysis for allocating the push marketing budget for a brand among mix elements.

In another application, we describe how to measure the market value of improvement in an attribute; these measurements will be useful in a firm's decision on the allocation of resources for product improvement.

9.5.1 Allocation of Push Marketing Mix Budget for a Brand

Levy et al. (1983) applied conjoint analysis to the problem of determining a profit function for alternative push strategies for a margarine manufacturer. They described each push strategy in terms of four marketing mix variables: cooperative advertising (3 levels), coupons in local newspapers (3 levels), financial terms of sale (2 levels), and service level defined in terms of percentage of items shipped that were ordered by the retailer (4 levels); details of the levels for the four marketing mix variables are shown in the second column of Table 9.9. While costs for a push strategy could be computed from internal records of the firm, sales response could not be estimated from past data. The authors utilized conjoint analysis to determine the retailers' sales response to different push strategies. For this purpose, nine profiles, developed using a partial factorial orthogonal design, were presented to sample of 68 buyers and merchandising managers. The judgment by the respondent was the expected change from last year's sales due to the push marketing mix defined by each profile. All the retail buyers were classified into small, medium, and large buyers with the respective levels of past purchases of 5,000, 15,000, and 30,000 cases and the sales level used in the questionnaires was changed according to the size of past buying by the retail buyer. The judged sales changes were used in computing the expected sales revenues and profits from each marketing mix. The average partworth values (computed as dollar sales) are shown in Table 9.9.

Based on this analysis, the authors conclude that the least profitable marketing mix is cooperative advertising offered three times a year at 15 cents per pound, coupons in newspapers offered two times a year at 25 cents per pound, terms of sale 2 %/10 days/net 30, and 96 % level of service. The most profitable marketing mix consisted of cooperative advertising six times a year at 7 cents per pound, coupons four times a year at 10 cents per pound, 2 %/30 day terms and a 98 % service level. Although the particular results are specific to the situation considered, the application shows how conjoint analysis can be employed to determine the allocation of a marketing mix budget for a brand.

Table 9.9 Average partworths for the levels of push marketing mix

Attribute of marketing mix	Level	Partworth (sales estimate)
Co-operative advertising	3 times at 15 cents/lb	$2,477
	4 times at 10 cents/lb	873
	6 times at 7 cents/lb	0
Coupons in local newspapers	2 times at 25 cents/lb	0
	4 times at 10 cents/lb	481
	3 times at 15 cents/lb	913
Financial terms of sale	2 %/10 days/net 30	0
	2 %/30 days	1,366
"Service level" Percentage of items that were shipped that were ordered	96 %	0
	98 %	1,283
	99.5 %	1,173

Source: Reprinted with permission from Levy et al. (1983), published by the American Marketing Association

9.5.2 Market Value of an Attribute Improvement (MVAI)

As firms improve the attributes of their products, question arises whether the attribute improvement measured in terms of profitability is worth the cost. This question can be answered with the help of conjoint results as shown by Ofek and Srinivasan (2002). We describe their approach in some detail.

It is possible to derive a mathematical expression for the market value of an attribute improvement. For this purpose, we consider a market consisting of J firms, each offering one product in a category. Each product has K attributes in addition to its price. Let x_{jk} be the value of the k-th attribute for the j-th product and let p_j be the price of the j-th product. Consumers have the choice of buying any one of the J products or not buying at all. Let m_j denote the market share for the j-th product ($j = 1, \ldots, J$) and m_0 be the market share of the no purchase option. Further[4] let c_{jk} be the change in the cost of the j-th product for a unit change in the k-th attribute. The authors considered the ratio of the change in market share due to the improvement (positive change) in an attribute to the ratio of decrease (negative change) in market share due to change in price as the market value of an attribute improvement. Mathematically,

$$\text{MVAI} = -(\partial m_j/\partial x_{jk})\big/(\partial m_j/\partial p_j)$$

It would be worthwhile for the firm to undertake the attribute improvement if this quantity exceeded the cost of attribute improvement (c_{jk}). Naturally, the market share of a brand depends upon the choice set, competitive reactions, heterogeneity of the sample of individuals whose responses are used to calibrate the conjoint

[4] While the authors developed their theory using continuous changes in the attributes, we use discrete changes for the purposes of exposition. See their paper for complete theoretical analysis.

Table 9.10 MVAI values for the camera mount products study

Attribute	Cost of improving the attribute ($)	MVAI computed values ($)		
		UltraPod	Q-Pod	GorillaPod
Weight	4.9	15.9	16.6	15.8
Size	2.3	11.2	12.6	11.5
Set up time	14.1	9.5	9.9	10.0
Stability	3.1	11.0	13.5	12.6
Positioning flexibility	2.6	7.4	8.6	8.90
Product descriptions				
Weight (oz)		2.0	3.5	4.6
Size (1 = small; 3 = large)		0.98	0.84	1.27
Set up time (min)		0.98	0.84	0.50
Stability (1 = low; 3 = large)		1.8	2.5	2.3
Positioning flexibility (1 = low; 3 = high)		1.96	2.17	2.84

Source: Reprinted from Ofek and Srinivasan (2002), Copyright (2002), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA

model, and the particular specification used for the conjoint model, and the rule used to translate utilities into probabilities of choice. If there is no heterogeneity and if a vector model is used to specify the partworths, the model is additive and a logit choice rule is used, then the MVAI will simply be the ratio of the weights for the k-th attribute and price in the conjoint model. But, averaging such ratios across a heterogeneous sample of people will yield a biased estimate of MVAI.

The changes in market share can be estimated using a conjoint study. This is what Ofek and Srinivasan used to empirically evaluate attribute improvements in a product under two scenarios of no reaction by competition and when competitors reacted to the change by making appropriate changes in their own products. They used a logit model to specify the probabilities of choice at the individual level and aggregated them to obtain market shares at the aggregate level. (We refer the reader to the article for more details.)

We use the authors' example to illustrate the approach. The product category for this example is portable camera mount products. The set of competing products consisted of UltraPod, Q-Pod, GorillaPod, Camera Critter, and Half Dome; the third product was a hypothetical one under development. These products were described on five attributes: weight, size, set up time in minutes, stability, and positioning flexibility for adaptation to different terrains and angles. In the conjoint study, each attribute was varied at three levels and 302 subjects ranked 18 full profiles. The authors estimated the MVAI for each of the five attributes when changes were made in each of the three products. Some results are shown in Table 9.10. These results show that the benefits from improving all attributes except set up time exceeded the cost of making the improvement. The authors also compared these MVAI values with those calculated using a commonly used approach of averaging the ratio of weights of attribute and price across the individuals in the sample to be considerably upward biased. Further, the profitability of different attribute improvements was much lower when competitive reactions were considered in the computations (we should also note that such calculations are possible with simulations in conjoint studies).

9.6 Measurements for Marketing Strategies

Two emerging topics in marketing strategy are brand equity and customer satisfaction. In this section, we will describe how conjoint methods can be employed for deriving measures of brand equity and customer satisfaction.

9.6.1 *Measuring Brand Equity*

Customer-based brand equity can be measured several ways (see Agarwal and Rao 1996, for a discussion of ten such methods); one method used by these authors is to determine the total value of a brand using choice-based conjoint methods. We describe it in some detail.

The application involved measuring the brand equity for a set of 13 candy bars shown in the bottom panel of Table 9.11; these items were selected out of 22 brands on the basis of awareness by respondents. The method involved creating 32 choice sets (as shown in Table 9.11), with each of the 13 brands being present or absent in the choice set. These choice sets were shown to a sample of 114 undergraduate student respondents. Respondents were asked to choose one of the available brands (or none) in each choice set. The random utility model of an alternative was modeled as the sum of a deterministic component (or brand value) and a random error. No specific attributes were included in the model as the objective was to estimate the total value of a brand; also prices of the brands were about the same. The choice data were analyzed using the multinomial logit model at the individual level in order to estimate the brand equities for each brand for each respondent. The average values and standard deviations of these estimates are shown in Table 9.12.

These data indicated considerable differences in the way the 13 brands of candy bars were valued by the respondents; the standard deviations were also quite different among the brands. Further, the authors showed that these brand values were good predictors of choices made by the respondents in an experimental laboratory context; see Agarwal and Rao (1996) for more details. This procedure can be valuable in measuring brand equity from consumers' perspective.

9.6.2 *Customer Satisfaction*

Customer satisfaction has recently become an important topic both for managers and researchers. The main objective here is to design new products and services or reposition existing products and services of a firm so as to increase the satisfaction of its current customers as well as customers of its competitors. Conjoint methods are quite well suited to achieve this objective; in this context, one has to measure the degree of current satisfaction of various products/services bought by a sample of

Table 9.11 Choice sets used in the study for determining brand equities of 13 candy bars

	Brand													
Choice Set	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1	0	0	1	0	0	0	1	1	0	1	1	0	1
2	1	1	1	0	1	0	1	1	0	0	1	0	0	1
3	0	1	1	1	1	0	1	1	0	0	0	1	0	1
4	0	1	1	1	0	0	0	0	0	1	0	1	0	1
5	1	1	1	1	0	0	0	0	0	1	0	1	0	1
6	1	0	0	0	1	0	1	1	0	1	0	1	0	1
7	0	0	0	1	1	0	1	0	1	1	1	0	0	1
8	1	0	1	0	0	1	1	1	0	0	1	0	0	1
9	0	0	1	1	0	1	1	0	1	0	0	1	0	1
10	0	1	0	0	1	1	0	1	1	0	0	0	0	1
11	1	1	0	1	1	1	0	0	0	0	1	1	0	1
12	1	1	0	0	0	1	0	1	1	1	0	1	0	1
13	0	1	0	1	0	1	1	1	0	1	1	0	0	1
14	0	0	1	0	1	1	0	0	0	1	1	1	0	1
15	1	0	1	1	1	1	0	1	1	1	0	0	0	1
16	0	1	0	0	0	0	1	0	0	0	1	1	1	1
17	1	1	0	1	0	0	1	0	1	0	0	0	1	1
18	1	0	1	0	1	0	0	0	1	0	0	1	1	1
19	0	0	1	1	1	0	0	1	0	0	1	0	1	1
20	0	0	1	0	0	0	1	1	1	1	0	0	1	1
21	1	0	1	1	0	0	1	0	0	1	1	1	1	1
22	1	1	0	0	1	0	0	1	0	1	1	0	1	1
23	0	1	0	1	1	0	0	0	1	1	0	1	1	1
24	1	1	1	0	0	1	0	1	0	0	0	1	1	1
25	0	1	1	1	0	1	0	0	1	0	1	0	1	1
26	0	0	0	0	1	1	1	1	1	0	1	1	1	1
27	1	0	0	1	1	1	1	0	0	0	0	0	1	1
28	1	0	0	0	0	1	0	0	1	1	1	0	1	1
29	0	0	0	1	0	1	0	1	0	1	0	1	1	1
30	0	1	1	0	1	1	1	0	0	1	0	0	1	1
31	0	0	0	0	1	0	1	0	1	1	0	0	1	1
32	1	0	0	1	1	1	1	0	1	1	1	0	0	1

Brands: 1: 3 Musketeers; 2: Baby Ruth; 3: Butterfinger; 4: Hershey's Almonds; 5: Kit Kat; 6: M&M's Plain; 7: M&M's Peanut; 8: Mars Almond Bar; 9: Milky Way; 10: Nestle Crunch; 11: Reese's Peanut Butter Cups; 12: Snickers; 13: Twix Caramel; 14: None of these (Would buy another brand)

individuals and develop satisfaction functions and estimate the corresponding partworths of attributes that define the product/service. Once such functions are estimated, the conjoint simulation methods can be employed to identify attributes of new product offerings or modifications of existing products so that customer satisfaction can be maximized subject to any constraints. In principle, this research is quite similar to that on product design.

Table 9.12 Estimates of brand-specific coefficients for 13 candy bars

Brand	Mean coefficient	Standard deviation
1: 3 Musketeers	−3.42	0.80
2: Baby Ruth	−4.52	0.89
3: Butterfinger	−5.33	0.90
4: Hershey's Almonds	−2.97	0.89
5: Kit Kat	2.55	0.51
6: M&M's Plain	1.37	0.59
7: M&M's Peanut	0.82	0.61
8: Mars Almond Bar	−6.74	0.92
9: Milky Way	−2.49	0.81
10: Nestle Crunch	1.62	0.57
11: Reese's Peanut Butter Cups	0.75	0.66
12: Snickers	1.00	0.79
13: Twix Caramel	−0.45	0.76

Source: Based on unpublished analysis for Agarwal, M. K. and Rao, V. R. (1996)

Several marketing research companies have developed products to analyze customer satisfaction data. Most of these use regression analysis as a main analytical tool. But, Green and Krieger (1995) have developed an analytical and predictive product called, VOICE for analyzing customer satisfaction data obtained from two or more competing suppliers. The Voice model is typically used to measure customer satisfaction regarding products and services. Its strategic purpose is to select those product/service attributes that will maximize the firm's share/return, conditional upon competitive firms' offerings.

VOICE analyzes data from a typical customer satisfaction study or product ratings studies; these data include: product/service attribute importances, product/service attribute performances, first choice supplier/brand, constant sum values on the likelihood of choosing each competitive supplier/brand, and background variables (e.g., respondent demographics, attitudes, brand usage etc.). VOICE models these data designed to answer such questions as:

What is each brand's current market share?
How important is each attribute?
How does each supplier/brand perform on each attribute?
How loyal is each respondent to each supplier/brand?
How sensitive is the market share of the firm (supplier/brand) to potential changes in attribute importances, performances, and customer loyalties?
How do market shares change when two or more firms (suppliers/brands) change their attribute performances independently?
What are the corresponding predictions for selected market segments, composable from the background variable data?
How should a firm's total budget for service/brand improvement be best allocated across attribute performances?

We illustrate the use of VOICE with data collected from a sample of customers on four suppliers in the package delivery market; the suppliers are denoted as

Alpha, Beta, Gamma, and Delta. This demonstration study used 15 attributes; these are:

A1. Less expensive than most suppliers
A2. Uses advanced technology in package pickup and delivery
A3. Highly knowledgeable employees
A4. Friendly employees
A5. Wide variety of service delivery options
A6. Really interested in customer's welfare
A7. Quickly responsive to customer inquiries
A8. Flexible contract negotiator
A9. Outstanding record of on-time delivery
A10. Easy to trace lost packages
A11. Easy to obtain status of current shipments
A12. Settles customers' claims quickly and efficiently
A13. Will make special trips to pick up packages
A14. Easy-to-calculate shipping costs
A15. Relatively little paper work needed in preparing shipping information.

The initial market shares for the four suppliers based on the survey data were: Alpha 23 %, Beta 28 %, Gamma 22 %, and Delta 26 %. The VOICE model was used to conduct simulation to determine the effects of three changes in the marketing of the Alpha firm's services; these are: (1) improving the attribute importances for two attributes of advanced technology (A2) from 0.04 to 0.06 and on-time delivery (A9) from 0.26 to 0.33; (2) improving the attribute performances on advanced technology from 0.62 to 0.96 and on-time delivery from 0.73 to 0.97; and (3) loyalty from 0.16 to 0.75. (Note the attribute importances and performances are measured on constant sum scales adding to 1.)

The analysis showed that these three changes would improve Alpha's market share from 23 % to 37 %. Obviously, the management of Alpha would need to consider if the changes suggested were feasible and were cost-effective relative to the projected market share increase. This illustration shows only a fraction of the capability of the VOICE approach.

9.7 Summary

This chapter described several applications of conjoint analysis (both ratings-based and choice-based) to a variety of marketing problems. These included competitive strategy analysis, different distribution and personal selling decisions (e.g. store location, sales quota setting, design of a new distribution channel and a web site design), legal decisions (measuring damage due to patent infringement, class action suit), resource allocation, and measurements of marketing strategy such as brand equity and customer satisfaction. This discussion should clearly show that the methods of conjoint analysis are quite versatile. It reinforces the essential elements of conjoint methodology for application to any marketing problem (e.g. identification of relevant underlying attributes and levels, suitable data collection, and identification and estimation of a suitable utility model or a choice model). The research design for collecting necessary data will follow quite naturally according to the methods described in Chaps. 2 and 4.

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Chapter 10
Recent Developments and Future Outlook

10.1 Introduction

The previous chapters described several approaches employed for determining partworths of attributes and tradeoffs among them. The chapters dealt with various methods for both of ratings-based and choice-based conjoint methods. In addition, we described several applications of conjoint methodology to different marketing problems such as product design, product positioning, pricing, market segmentation, and several miscellaneous problems. During the last thirty plus years since these methods were introduced to marketing research, researchers have tackled various problems that are encountered in applying these methods in practice. As Hauser and Rao (2004) have noted, conjoint analysis is alive and well. In fact there have been several developments in the last 5–10 years that place this methodology as one of the most vibrant techniques in marketing research.

In this concluding chapter, we focus on some selected developments (mostly of recent origin), mainly in three areas: (1) Experimental designs that combine mixture and mixture-amount useful in a service context; (2) Conjoint approaches such as the Barter Conjoint, Conjoint Poker, Best-Worst Scaling, and methods for measuring peer influence, for incorporating non-compensatory processes, and for combining preference and choice data; and (3) Applications for self-designed products and bundle choice problems.

Finally, we present an assessment of the developments and applications of the methodology and will identify some directions for future research. We must note that this chapter will not be exhaustive of all the developments but will give a flavor of some recent work.

V.R. Rao, *Applied Conjoint Analysis*, DOI 10.1007/978-3-540-87753-0_10,

10.2 Experimental Designs for Mixture and Mixture-Amount

We described in previous chapters experimental designs for designing profiles for the ratings based approach and for designing choice sets for the choice-based conjoint methods. Some developments in this area are also described in the previous Chaps. 2 and 4. We wish to mention a text by Raghavarao et al. (2011)[1] specifically devoted to designs for choice experiments. While this book reviews several designs, the set of designs for mixtures and mixture-amount will be of significant interest to conjoint researchers. These designs occur in such settings as product/service development, where the total cost of a product or service is the amount, and mixture refers to the proportion of discretionary cost allocated to various components of the product and design of insurance policies where amounts correspond to premiums and mixtures correspond to coverage allowed for various types of risk exposures.

The context for one of their illustrations is that of a restaurant owner who wishes to arrange a lunch plate with a fixed cost and who has to decide on how much of that fixed cost goes to each of the four menu items: drink, appetizer, main course, and dessert. Suppose that total cost is \$15.00 and after overhead, a budget of \$9.00 is available for the four items. Further, the manager wants a minimum of \$0.75 for drink, \$0.50 for appetizer, \$1.50 for main course, and \$0.65 for dessert. This leaves a discretionary amount of \$5.60 to be used for the four items, and the objective is to allocate the \$5.60 to the four items. They use a simplex-lattice design for this problem with 13 profiles which enable estimation of 4 main effects and 6 pair-wise interactions. The specific design is shown in Table 10.1 with average response on a 1–10 scale (10 = most preferred) across a sample of 100 respondents.

The fitted response equation (or utility function) for this problem is:

$$\begin{aligned} Y = {} & .61x_1 - .59x_2 - 1.34x_3 + .48x_4 - .61x_1x_2 + .61x_1x_3 + .19x_1x_4 + 1.54x_2x_3 \\ & - .51x_2x_4 + .36x_3x_4. \end{aligned}$$

The optimal values of x_1,x_2,x_3, and x_4 can be obtained by differentiating Y with respect to these four parameters with the constraint $\Sigma\, x_i = 1$. The optimal solution for x_1*, x_2*, x_3*and x_4*is 0 %, 55 %, 45 %, and 0 %. The optimum allocations preferred by the respondents are drink (\$0.75 + 5.60 x_1*), appetizer (\$0.50 + \$5.69 x_2*), main course (\$1.50 + 5.60 x_3*), dessert (\$0.65 + \$5.60 x_4*), for a total of \$9.00. It is easy to see how valuable such mixture-amount designs will be for various allocation problems in marketing.

We have discussed another recent development in design of choice sets due to Street and Burgess in Chap. 4.

[1] See also Raghavarao and Wiley (2009).

Table 10.1 Illustration of an experimental design for mixtures-amounts

	Mixture				Amount				
Profile	Drink (%)	Appetizer (%)	Main course (%)	Dessert (%)	Drink	Appetizer	Main course	Dessert	Average response
1	100	0	0	0	$6.35	$0.50	$1.50	$0.65	8.00
2	0	100	0	0	$0.75	$6.10	$1.50	$0.65	6.00
3	0	0	100	0	$0.75	$0.50	$7.10	$0.65	1.00
4	0	0	0	100	$0.75	$0.50	$1.50	$6.25	5.00
5	50	25	25	0	$3.55	$1.90	$2.90	$0.65	9.00
6	0	50	25	25	$0.75	$3.30	$2.90	$2.05	9.00
7	25	0	50	25	$2.15	$0.50	$4.30	$2.05	8.00
8	25	25	0	50	$2.15	$1.90	$1.50	$3.45	4.00
9	25	50	25	0	$2.15	$3.30	$2.90	$0.65	10.00
10	0	25	50	25	$0.75	$1.90	$4.30	$2.05	10.00
11	25	0	25	50	$2.15	$0.50	$2.90	$3.45	8.00
12	50	25	0	25	$3.55	$1.90	$1.50	$2.05	4.00
13	25	25	25	25	$2.15	$1.90	$2.90	$2.05	8.00

Source: Reprinted from Raghavarao et al. (2011) with permission of the publisher.

10.3 Conjoint Approaches

In this section, we will cover four items: Barter Conjoint method, Conjoint Poker, Best-Worst Scaling, peer influence measurement, incorporating non-compensatory choice processes, combining preference and choice data, and an extension for adoption decisions.

10.3.1 Barter Conjoint Method

Ding et al. (2009) developed an interesting method for collecting conjoint data from individuals that enables reduction of "wear-out" and uses a natural way people trade with each other.[2] This approach called "Barter Conjoint Method" collects a large amount of data from any individual and enables exchange of information among participants in a natural environment. The authors conducted experiments to demonstrate this method and to compare its predictive validity relative to the incentive-aligned Choice-Based Conjoint (CBC) Method.

As designed by the authors, a Barter Conjoint Study is implemented on Internet-connected computers. The number of markets and number of rounds are the design parameters of the study. First, a market is constructed to consist of a small number of individuals or subjects (e.g. 4, 6, or 8); there could be several such independent

[2] This material is based on Ding et al. (2009).

markets in a study. For a specific product category under study, a number of profiles are developed according to some experimental design and each subject in the market is endowed with one of the profiles and a prespecified amount of cash. In one round of the barter exchanges, the steps are:

1. Each subject is allowed to make an offer to exchange his/her product profile with the other person's product profile; a subject may decide not to make an offer to exchange. Thus, there will be at most 2*(N−1) offers for any pair of subjects in a market of N people;
2. The market pauses until all offers (or no offers) are made by the N individuals;
3. The next step is to show to each individual the offers made to him/her to select a pair of individuals and to ask each person as to which offers he/she will accept. The market pauses for a while until all people have responded to the offers;
4. The computer interface randomly pairs two participants in the same market (say, A and B) and then randomly picks one possible barter (A→B or B→A) to determine the outcome for the pair. This is done for everybody in the barter market. If no offer is made, or an offer is made but rejected in this randomly picked possible barter, both persons keep their endowed products and cash. On the other hand, if an offer is made and accepted, they will exchange products, and their cash balance will be adjusted based on the cash amount stated in the offer. These steps will complete one round; and
5. Each participant is shown the complete round information (offers made, responses to offers, and final product) for everybody in the same market.

The above steps are repeated with a new set of profiles (that are different from the previous sets) for this market, until all rounds have been completed. Finally, the computer randomly picks a round and the product and cash a participant owned at the end of the Step (5) above are given to the participant[3] (and participants know this, and hence they are incentive-aligned).

There are several benefits of this method: (1) it allows for diffusion of information among participants in the same market, which will help some people better assess product options by incorporating other people's valuations; (2) the method provides the researcher a lot information to infer the participants' tradeoffs among product options with specific monetary valuations; (3) the method is adaptive and controlled by the participants; and (4) the method is realistic and highly involving for the participants.

The authors conducted two studies to demonstrate the relative performance of barter conjoint method against CBC; they used the context of a weekend trip to Ocean City Maryland (beach) in the first study and two product categories (Bahamas Cruise and Camcorder) in the second study. These studies offer some generality for the application of the barter conjoint method. Relevant information on attributes and their levels and the number of subjects and the procedure for

[3] For expensive products, a lottery mechanism may be used to determine which participant will end up receiving the final product and cash.

Table 10.2 Details of the studies for Barter conjoint method

Study on →	Ocean city beach	Bahamas cruise	Camcorder
Number of attributes	6	5	6
Attributes (levels)	Hotel (6) Restaurant (4) Entertainment (6) Type of visitors (3) Average temperature (3) Price (3)	Time of the trip (3) Activities at port of call — Freeport (3) Ground tours at Nassau (4) Wet activities at Nassau (4) Price (4)	Storage format (3) LCD screen size (2) Optical zoom (3) Resolution (2) Low light sensitivity (3) Price (3)
Number of product profiles generated[a]	72	48	36
Number of "markets"	18	12	9
Number of subjects	122	169	169
Methods compared (no. of subjects)	Conventional CBC (66) Barter conjoint (56)	Conventional CBC (53) Incentive-aligned CBC (56) Barter conjoint (60)	Conventional CBC (53) Incentive-aligned CBC (56) Barter conjoint (60)
Holdout tasks	Select 1 out 10 profiles in the data collection phase and a second hold out task which the subjects responded to after receiving a e-mail (2 weeks later)	Select 1 out 10 profiles in the data collection phase and a second hold out task which the subjects responded to after receiving a e-mail (2 weeks later)	Select 1 out 10 profiles in the data collection phase and a second hold out task which the subjects responded to after receiving a e-mail (2 weeks later)

Source: Compiled with permission from Ding et al. (2009), Copyright (2009), the Institute for Operations Research and the Management Science, Catonsville, MD 21228, USA
[a]D-efficiency of 100 %

validation etc. is shown in Table 10.2. The parameter estimates are made using Hierarchical Bayesian methods[4] as described in the discussion of the upgrading method (see Chap. 5).

[4] Specifically, the probability that the i-th subject chooses the k-th alternative from the j-th choice set is given by

$$p_{ij}^{k} = \frac{\exp\left\{\beta_i^T x_{ij}^k\right\}}{\sum_l \exp\left\{\beta_i^T x_{ij}^l\right\}}$$

where x_{ij}^k describes the k-th alternative evaluated by the i-th subject from the j-th choice set, and βi is a vector of partworths for the i-th subject. They assume a hierarchical shrinkage specification for the individual partworths, where a priori, $\beta_i \sim N(\beta, \Lambda)$.

In the first study, the hit rates (i.e., matches between the actual choice and the top predicted option) are 33 % for the first holdout task (the same day) and 31 % for the second holdout task (two weeks later) under the barter market, versus 19 % and 17 % under the CBC, respectively; the improvement in prediction over the hypothetical CBC is significant at the 1 % level in both holdout tasks. The improvements in prediction were similar for the second study.

10.3.2 Conjoint Poker

Toubia et al. (2012) developed a new procedure for preference measurement that increases respondent involvement and attention while maintaining incentive compatibility. They call this the "Conjoint Poker" game, inspired by regular poker. While this method can involve multiple people (as in the Barter conjoint method), the initial application was implemented against a computer.

This method is like a poker game and the game is played in a set of rounds. In one round, each player (or respondent) is presented with a set of profiles, each profile described on a number of attributes as in a choice-based conjoint method, as per the particulars of the study. Subsequently, the round consists of two stages: a hand selection stage and a card selection stage. In the hand selection stage, each player is asked to select three cards (out of the profiles presented) for the game; presumably the player selects the three best cards in the set. The winner in each round is the player with the strongest hand[5].

In the card selection stage, each player is asked to indicate the most preferred card from the hand. At the end of the experiment, by random selection, one player and one round for that player are selected. If the player wins that round, he or she wins the product on the preferred card; this method makes the process incentive-compatible. Refer to the article for further details on estimation methods employed with the conjoint poker data.

The authors implemented a study that compared the conjoint poker (CP) method with choice-based conjoint method (CBC) for the context of laptop computers (with six attributes including price) and found that the individual hit rates for the incentive-compatible CP method and the incentive-compatible CBC method were not significantly different. But, the CBC method showed better aggregate market share predictions than the CP method. The authors also tested the CP method against CBC method with eye-tracking data and inferred that respondents under the CP condition considered a significantly larger number of cells across the rounds.

[5] The hand strength is determined in a manner similar to that of the poker. The authors consider six types of hands. The weakest hand will be a pair, with two cards having the same level on an attribute and the strongest hand having all three cards have the same level on two attributes (called double flush). Probabilities of hand strength are computed from a random set of cards (possibly four) drawn without replacement. These probabilities are used to determine the probability of winning with each hand against the computer.

While the CP method seems technically more complicated, it is promising as a data collection method for future conjoint studies.

10.3.3 Best-Worst Scaling

Best-worst scaling (BWS) is an approach developed by Jordan Louviere to measure attribute importance ratings that is akin to conjoint analysis. It involves presenting to a sample of respondents a list of attributes (which may in fact contain levels of the attributes as well) and asking respondents to indicate the best of the list and the worst of the list. Based on these ratings, a score is constructed which is the difference between the count of the best and the count of the worst for each attribute. The differences between these two scores are then regressed on the X- variables (1 or 0) that describe the design of the questions; the analysis method is usually weighted least squares.[6] The method can be used to compute importance values for almost any type of stimuli. If the set of attributes is large, experimental designs can be employed to come up with subsets of items to be administered to respondents. These methods are quite similar to the discrete choice experiments described in Chap. 4.

The theoretical basis for this method is described in Marley and Louviere (2005). One can think of this method as an extension of Thurstone Case V method (Torgerson 1958).

There have been several studies that utilized this technique (see Finn and Louviere 1993). One study compared the importance weights and willingness-to-pay measures derive from this method and choice-based conjoint method and constant sum scaling technique (Louviere and Islam 2008). The BWS method and constant sum scaling method are direct methods for estimating attribute importances while choice-based methods are indirect. Two indirect methods used are: (1) the willingness-to-pay[7] for differences in attribute levels[8] based on the compensating variation in price and (2) the partial log likelihood value (which is the log-likelihood difference between full model and model with the attribute omitted). In this study, the researchers estimated importance weights using the four methods

[6] This method is part of the Sawtooth Software under the name MAXDiff. It offers several features such as the MAXDiff Experimental Designer for developing questions and MAXDiff Analyzer for analyzing the data collected.

[7] A recent paper (Miller et al. 2011) compares four separate measures for measuring willing-to-pay for an attribute. The main result in this paper is that incentive-aligned methods pass statistical and decision-oriented tests.

[8] These measures are obtained as compensating variation in price for a change in the attribute levels so as to keep the utility the same. For a utility function $U(A, P) = a_0 + a_1XA1 + a_2XA2 + a_3XA3 - bP$, for one attribute, A with four levels, A1, A2, A3, and A4 (coded as dummy variables XA1, XA2, XA3) and price (P), the willingness-to-pay for a change in attribute level from A2 to A1 will be $(a_2\text{-}a_1)/b$.

for two product categories (Juice products and pizza) and found high agreement within indirect and direct methods, but less agreement between direct and indirect methods.

10.3.4 Peer Influence Measurement

In a recent paper, Narayan et al. (2011) developed a two-stage choice-based conjoint method to measure the effects of peer influence on multi-attribute product choices of individuals. Given the increase in the emergence and use of social networks, this measurement is important for especially for word-of-mouth marketing. The first stage of their method involved collecting choice data for sets of multi-attributed items and information on the degree to which an individual interacted with his/her peers. In the second stage, actual choices made by one's peers were inputted as an additional attribute in the profiles of choice sets and individuals were asked to indicate their choices given the additional information. With these data, these authors developed models to determine which of three underlying behavioral mechanisms of peer influence on the choices. The mechanisms are: (1) Bayesian updating of attribute importances as influenced by peers' choices; (2) a general updating of attribute importances as influenced by peers' choices; and (3) no updating at all due to peers' choices. Mathematically, these mechanisms can be described as follows. Let β_i^R is the K-dimensional vector of the *revised* attribute importance weights and β_i^I is the K-dimensional vector of initial attribute importance weights of individual *i*. Let $w_{ii'}$ (of the sociomatrix W) represent the extent to which consumer *i*' influences consumer *I* and label individual *i*' an influencing individual *i* if $w_{ii'} > 0$. The three formulations of updating then are:

Mechanism 1

$$\beta_{ik}^R = \rho_{ik}\beta_{ik}^I + (1-\rho_{ik})\frac{\sum_{i'=1,i'\neq i}^{N} w_{ii'}\beta_{i'k}^I}{\max\left[\left(\sum_{i'=1,i'\neq i}^{N} w_{ii'}\right),1\right]} \text{ where } 0 \le \rho_{ik} \le 1\text{; and}$$

Mechanism 2

$$\beta_{ik}^R = \rho_k\beta_{ik}^I + (1-\rho_k)\frac{\sum_{i'=1,i'\neq i}^{N} w_{ii'}\beta_{i'k}^I}{\max\left[\left(\sum_{i'=1,i'\neq i}^{N} w_{ii'}\right),1\right]}\text{; and}$$

Mechanism 3 No change in the attribute importance weights (β_{ik}^I) but a general increase in the utility of an item due to peers' choices of the same item.

The difference between the Mechanisms 1 and 2 is that the peer influence parameter ρ_{ik} is specified according the Bayes revision rule in the Mechanism 1 and left unspecified in Mechanism 2. The peer influence parameters then relate to the uncertainties of the attribute weights of the focal consumer and influencers: $\rho_{ik} = \frac{\frac{1}{\sigma^{2I}_{ik}}}{\frac{1}{\sigma^{2I}_{ik}} + \frac{1}{\phi_k}\left[\sum_{i'=1, i' \neq i}^{N} \left(\frac{w_{ii'}}{\sigma^{2I}_{i'k}}\right)\right]}$

Further, the estimate of the importance of a parameter can be estimated (computed) as: $\beta^R_{ik} = \rho_k \beta^I_{ik} + (1 - \rho_k) \frac{\sum_{i'=1, i' \neq i}^{N} w_{ii'} \beta^I_{i'k}}{\max\left[\left(\sum_{i'=1, i' \neq i}^{N} w_{ii'}\right), 1\right]}$

Given these mechanisms, the authors specified the utility functions for an item and estimated the parameters using MCMC methods with data on choices pre-influence and post-influence of peers. The underlying choice model is the multinomial probit model.[9] For details see Narayan et al. (2011).

In order to determine the most suitable mechanism, they implemented a study using the electronic book readers at the category. Based on a pretest, they selected six product attributes each at four levels in the conjoint study; the attributes and levels were: weight with levels of 6, 8, 10, 12 oz.; screen resolution with levels of 8, 12, 16, and 20; number of books available for download in thousands with levels of 10, 90, 170, 250; storage capacity in GB with levels of 0.5, 1.0, 1.5 and 2.0; brand with levels of Amazon Kindle, HP, Sony and iRex; and price in dollars with levels of 279, 319, 359, and 399. The two-stage study was conducted among a sample of 70 MBA students of a large Northeast University with 25 choice sets designed using the OPTEX procedure. Using the peer influence data, the authors estimated the parameters for the three mechanisms to determine how individuals update their attribute preferences in light of information on peers' choices.

Their main results were: (1) the Bayesian updating model (Mechanism 1) fitted the data better than the other two mechanisms; (2) the Bayesian updating mechanism, the extent of preference revision diminishes with increasing number of influencers; the weight ρ_{ik} an individual placed was estimated to be 0.96 if the individual had 1 influencer, 0.77 for 9 influencers, and 0.37 for 69 influencers; and (3) the preference revision varied across attributes; and (4) the predictive validity

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[9] In this model for the pre-influence stage, the individual i's utility for the j-th profile for the p-th choice set in the first stage (pre-influence) is specified as: $U^I_{ijp} = X_{jp}\beta^I_i + \varepsilon^I_{ijp}$ where X_{jp} is the K-dimensional vector of attributes (suitably coded and including brand dummy variables) for profile p ($p = 1, \ldots,$ P) in choice set j ($j = 1, \ldots,$ J); β^I_i is the K-dimensional vector of initial attribute importance weights of individual i; and ε^I_{ijp} follows an IID standard normal distribution. Each choice set contains P profiles. Under the assumption that the individual chooses one out of P profiles by maximizing one's utility, i.e. $Y^I_{ijp} = 1$ if $U^I_{ijp} = \max[U^I_{ij1}, .., U^I_{ijP}]$; otherwise $Y^I_{ijp} = 0$, where Y^I_{ijp} is the choice in the first stage, the implied choice model will be the multinomial probit model. The model is similar for the post-influence stage.

was highest when the choices of influencers were taken into account. This study is an illustration of how conjoint methods can be employed for measuring peer influence.

10.3.5 Incorporating Non-compensatory Choice Processes

While the models described in this monograph are compensatory among attributes in nature, some recent research has focused on the issue of non-compensatory decision rules (See Payne et al. 1993 for a review). Gilbride and Allenby (2004), who utilize data augmentation methods to estimate thresholds and discontinuities in the conjoint preference function. Jedidi and Kohli (2005), Kohli and Jedidi (2007) have focused on using dynamic programming methods to estimate nonlinear preference structures. Yee et al. (2007) test greedoid methods for deducing lexicographic processes from observed preference data which is also applicable to rating, ranking and choice and they analyzed the rules of elimination by aspects, acceptance by aspects, lexicographic by features; they use dynamic programming that makes estimation practical for moderately sized data sets.

10.3.6 Combining Preference and Choice Data

While we discussed stated preferences (using ratings-based conjoint methods) and stated choices (using choice-based conjoint methods) separately for estimating a preference/utility function for an item, it is possible to combine these two types of data. The general method involves relating the errors in the two utility functions for stated preference and stated choice (assuming that the one chosen is the most preferred) and maximizing the likelihood of the two data sets. As an example, Morikawa et al. (1991) applied this method for forecasting intercity rail ridership with good results due to good parameter estimates when the two data sets are combined. While this problem is not new, opportunities exist for further work in this area as described in Ben-Akiva et al. (1994).

10.4 Applications

This monograph covered a large variety of applications. Nevertheless, we describe two recent developments to illustrate the current progress in conjoint methods. The first is some work on self-designed products using online Configurators. The second is a model that describes the choice of a bundle of items from heterogeneous product categories. The bundling models generalize the single item choice problem handled with conjoint methods.

10.4.1 Self-designed Products

In the discussion of various conjoint methods described in this book implicitly assume that consumers/individuals have enduring preferences and that they can be measured (tapped) using either ratings-based on choice-based procedures of data collection and estimation. Implicitly, consumers are "passive" in the traditional data collection.

But, in the wake of mass customization companies recently are offering consumers (usually online) a menu of choices for each product feature for configuring their own products and services. Online Configurators have become popular in enabling consumers to design their own products; examples include www.dell.com. (See also www.Configurator-database.com for more than 800 entries of Configurators.)

The Online Configurators enable a firm to collect data on preferences for each level of an attribute (or product feature) at the individual level and these data can be used to calibrate preference functions to compute attribute partworths. In a recent paper, Liechty et al. (2001) developed a menu-based experimental approach that offers consumers menus of product attributes with separate prices for each level of the attributes. This approach is quite similar to choice-based conjoint method but with a twist of separate prices for attribute levels. They implemented this approach using Web-based data collection in the context of developing customized services on the Internet such as Internet Yellow Pages; the details of the application are disguised however. They formulated a multivariate probit model (MVP) and analyzed the data with hierarchical Bayesian methods to allow for individual heterogeneity. Their random effects MVP model performed better than alternative models such as random effects multinomial probit model (MNP) where choices were derived from the menu options data. These menu-based data collection and analysis approaches are fruitful areas for further research.

The process of an individual designing own products is akin to constructed preferences rather than endured preferences[10]; the latter is presumably the process in conjoint analysis. There is research that shows that these two views of preferences (enduring or constructed) are not mutually exclusive; see Bettman et al. (2008), Simonson (2008a, b). The issue then is to determine the conditions when each type of preference is more relevant in the final choices.[11] See also Franke and Schreier (2010).

Deng and Hutchinson (2010) proposed a model in two phases to discern how enduring and constructed preferences are incorporated into the process of people self-designing products and how they influence the evaluation of the self-designed product. The authors called the degree of preference for a self-designed product

[10] There is growing evidence in the behavioral research that consumers construct preferences when the need arises via context-sensitive processes (Bettman et al. 1998; Simonson 2005).

[11] Research in this theme is limited. But, see Cooke et al. (2004), Kivetz et al. (2004), Srinivasan and Park (1997) for some work in this area.

over commercially available products the *self-design effect*. They identified three psychological factors (product fit, believed authorship, and process affect) contributing to the self-design effect. Using the NIKEiD Configurator as the context, subjects in their experiments designed Nike Shox shoe. They showed that the products designed using the online configurator to be superior on all the three psychological dimensions than those products designed using a paper-and-pencil configurator. This research bodes well for the use of online configuartors.

10.4.2 Bundle Choice Models

A bundle consists of a number of products (components) offered for sale by a supplier. Bundle choices by consumers can be modeled in two main ways: using the components directly or using the attributes of the components. A bundle choice model in terms of attributes will be more useful from a bundle design perspective. The balance model of Farquhar and Rao (1976) is suitable for describing the utility of a bundle of items drawn from a homogeneous product category (e.g., bundle of magazines); this model includes means and dispersions among the items in the bundle for each of the attributes.

Chung and Rao (2003) developed a general choice model that extends the balance model to accommodate different types of bundles drawn from either homogeneous products or heterogeneous product categories (e.g. a bundle of computer, printer and monitor). Their COBA Model (COmparability-based BAlance model) is a generalization of the balance model applicable to the case of bundles drawn from heterogeneous product categories; it uses the construct of "comparability" of attributes. The utility function for the bundle in the COBA model consists of terms for "fully comparable" attributes, "partially comparable" attributes and "noncomparable" attributes. It incorporates heterogeneity among individual weights for the attribute terms (means and dispersions) and price of the bundle. Their basic model for the bundle value for an individual is:

$$BV_b = \alpha_0 + \sum_{p_1 \in A^1} \left[\beta_{p_1} S^b_{p_{1i}} + \gamma_{p_1} D^b_{p_1} \right] + \sum_{p_2 \in A^2} \left[\beta_{p_2} S^b_{p_2} + \gamma_{p_2} D^b_{p_2} \right] + \sum_{p_3 \in A^3} \alpha_{p_3} C^b_{p_3}$$

where A^1, A^2, and A^3 are the sets of fully comparable, partially comparable and noncomparable attributes; S and D are sum and dispersion measures for the fully and partially comparable attributes, and C is a component score for the noncomparable attributes. The parameters in the model are the αs, βs, and γs. The bundle utility, V_b is written as:

$$V_b = BV_b + \alpha_{BP} BP_b$$

Where BP_b is the bundle price and α_{BP} is the coefficient of price in the utility for the bundle. The choice of a bundle is modeled as a nested logit function with the inclusion of the "no purchase" option.

They implemented this model using a set of choice data collected from a sample of students for choices made among computer systems (consisting of computer, printer and monitor) using a mixed logit model and estimate it using Hierarchical Bayesian methods. They showed that the mixed logit model for two segments case is superior to other bundle choice models (mostly special cases of the COBA model) in terms of both in-sample and out-of-sample fit. Further, they showed how their model can be employed to determine reservation prices for bundles.

10.4.2.1 An Assessment of Trends in Conjoint Analysis

At the risk of omitting some, the following eight developments[12] in conjoint analysis seem significant:

1. *Shift from ratings-based methods to choice-based conjoint methods*: It is becoming quite common to utilize choice-based conjoint analysis in most situations; this is due to various reasons including the appeal of dealing with choice rather than preference. Even when one deals with preference data, it becomes necessary to convert utility estimates into probability of choice. This step is essentially eliminated in the choice-based methods. However, the choice-based methods may not have the same flexibility as ratings-based methods.
2. *Shift from regression methods to hierarchical Bayesian regression methods*: Independent of which approach is used for collecting conjoint data (ratings or choices), there is a trend to utilize Hierarchical Bayesian methods for estimation. As we have seen, the HB methods enable incorporating heterogeneity and yield individual-level estimates of partworths.
3. *Tendency to utilize adaptive conjoint analysis methods*: Given the availability of commercial software for implementing conjoint analysis, applied studies in industry seem to utilize adaptive conjoint methods.[13] Such software is available from Sawtooth Software (http://www.sawtoothsoftware.com).
4. *Beginnings of multi-period (dynamic) conjoint studies*: As conjoint analysis is used for a diversity of problems, the issue of understanding dynamics of

[12] This section draws from Rao (2008).

[13] The adaptive conjoint analysis (ACA) approach involves presenting two profiles that are as nearly equal as possible in estimated utility measured on a metric scale and developing new pairs of profiles sequentially as a respondent provides response to previous questions. There has been considerable amount of research on this approach. In a recent paper, Hauser and Toubia (2005) found that the result of the metric utility balance used in ACA leads to partworth estimates to be biased due to endogeneity. The authors also found that these biases are of the order of response errors and suggest alternatives to metric utility balance to deal with this issue. See also, Liu, Otter, and Allenby (2007) who suggest using the likelihood principle in estimation to deal with the endogeneity bias in general.

consumer choice behavior will become significant. The idea of estimating demand for new products even before they diffuse in the marketplace becomes important for both practice and research. The concepts of information acceleration can be utilized for such estimation problems. It is at least in this context we think that dynamic conjoint studies will become extremely essential.[14]

5. *Shift from focus on prediction to focus on understanding of choice process*: The primary focus in conjoint analysis has so far been on developing models and procedures that enhance predictive ability. As noted in the discussion on partial profiles, there is some shift toward incorporating some postulates of choice process. We expect that this will become more significant as conjoint modelers begin to incorporate learnings from behavioral research on information processing and choice. I also think that such a shift will be highly worthwhile.
6. *Pragmatic approaches to theoretically sound methods (e.g. incentive-aligned)*: Despite the fact that the origins of conjoint analysis were in the axiomatic development of conjoint measurement, current practice seems to have largely been on developing pragmatic approaches for data collection and estimation. However, recent trends indicate that conjoint researchers are concerned about theoretical bases of the data collected in conjoint studies. An example of this is the development of incentive-aligned methods for data collection. We expect that this trend to continue and that future data collection efforts will begin to incorporate assumptions normally made to develop consumer utility functions (e.g., budget constraints and separability).
7. *Simpler models to richer methods and models*: The trend toward technically advanced methods of estimation and data collection is here to stay. In particular, the Hierarchical Bayesian methods will continue to be part of standard arsenal of a conjoint analyst.
8. *Mainly product design domain to varied domains*: A general application of conjoint analysis has been product/service design. The methods are now being applied to a varied set of domains such as tourism, healthcare, corporate acquisitions and the like. This trend is likely to continue.

10.5 Future Outlook

In one sentence, it is fair to say that conjoint analysis is alive, well, and growing. The preceding discussion of recent developments is an indication of the potential future for conjoint analysis. Theory and practice have exploded to address a myriad of issues. As this field continues to be vibrant for many years to come, new challenges will appear. Several researchers in conjoint analysis have identified

[14] A study that looks at the dynamics of partworths during the data collection process for conjoint data is due to Liechty et al. (2005).

Table 10.3 Selected research directions in conjoint analysis

Type of issues	Research directions
Pragmatic issues	1. Meta-analysis of various conjoint studies conducted for a variety of managerial problems with the goal to seek generalizations on methods of data collection, stimulus (profile or choice set) presentation and analysis methods. One may consider generalizations on trade-offs using "meta attributes" (e.g. performance, quality, user convenience etc.) that transcend specific studies
	2. Conjoint studies using product configuartors for self-designed products
Conceptual issues	1. Studies that relate behavior of the firm and its competitors to the choice behavior of consumers as elicited in conjoint research
	2. Studies on the effects of attribute information diffusion on the derived importances and willing-to-pay measures in conjoint research
	3. Studies on the way price attribute affects the conclusions drawn in conjoint research
	4. Research on the effects of learning, wear-out, self-perception biases and other phenomenon on the data collection tasks
Methodological issues	1. Improved models and methods of analysis for combining data from multiple data sources
	2. Models and analysis methods for estimating trade-offs from aggregate market share data
	3. Studies to evaluate extant methods of analysis of conjoint data

new research directions in this vibrant methodology of conjoint analysis.[15] Hauser and Rao (2004) identified a set of research challenges under three categories—pragmatic issues, conceptual issues, and methodological issues.

Pragmatic issues involve an analysis of tradeoffs between complexity of method, cost, and managerial application. Conceptual issues relate to the development of suitable conjoint models that include roles of price, diffusion of information on attributes, and competition, while methodological issues involve the development of newer methods of data collection and estimation. Further, we expect future conjoint studies to go beyond individual or organizational consumers and be employed for other stakeholder groups, such as stockholders, employees, suppliers, and governmental organizations.

While there exist numerous research possibilities in this area, Table 10.3 lays out selected research directions. The review paper developed from the Choice Symposium included in this book as Chap. 11 identifies several further research opportunities.

[15] Eric Bradlow (2005) presents a wish list for conjoint analysis such as within task learning/variation, embedded prices, massive number of attributes, non-compensatory decision rules, Integration of conjoint data with other sources, experimental design (from education literature), getting the right attributes and levels, mix and match, and product-bundle conjoint. There is a considerable overlap between this list and mine described below. Recently, Agarwal et al. (2012) have developed a review of the current state of conjoint research.

10.6 Summary

This concluding chapter reviewed recent developments in conjoint analysis in three sections. The first section reviewed new experimental designs that combine mixture and mixture-amount, particularly useful in a service context. The second described some newer approaches for design and analysis of conjoint data; these included Barter Conjoint and Conjoint Poker and the technique of Best-Worst Scaling (BWS) and a comparison of results from BWS with established conjoint methods. The second section also described some newer methods based on conjoint analysis for measuring peer influence as well as methods for incorporating non-compensatory processes, and methods for combining preference and choice data,. The third section described applications for self-designed products and bundle choice problems.

Finally, we presented an assessment of the developments and applications of the methodology and will identify some directions for future research. We must note that this chapter will not be exhaustive of all the developments but will give a flavor of some recent work. The Chap. 11 (a paper based on Choice Symposium) will give additional insights in the future outlook of conjoint analysis.

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Chapter 11
Beyond Conjoint Analysis: Advances in Preference Measurement

11.1 Introduction: Beyond Conjoint Analysis

Researchers and practitioners often equate preference measurement with conjoint analysis. Indeed, since its introduction (Green and Rao 1971), conjoint analysis (and its variants) has become the method of choice for quantitative preference measurement, and is considered among the major contributions of marketing science to marketing practice. However, conjoint analysis is only a special case of the broader field of preference measurement (Gustafsson et al. 2007). While academic research in conjoint analysis may be viewed by some as mature, the field of preference measurement remains very active, important, and growing.

In this paper, we review recent developments in preference measurement that go beyond the "traditional" set of tools that are familiar to many practitioners and academics, and offer directions for future research. We propose viewing preference measurement as comprising three main components (see Fig. 11.1): (1) the problem that the study is ultimately intended to address; (2) the design of the preference measurement task and the data collection approach; (3) the specification and estimation of a preference model, and the conversion into action. In the context of conjoint analysis, these three components typically take the following form: (1) the problem is to help (profit-maximizing) firms design products and/or predict market shares; (2) data collection involves consumers rating, ranking, or choosing among hypothetical profiles designed according to traditional statistical efficiency measures; and (3) the output consists of individual-level partworths estimated assuming additive and normative utility model specifications.

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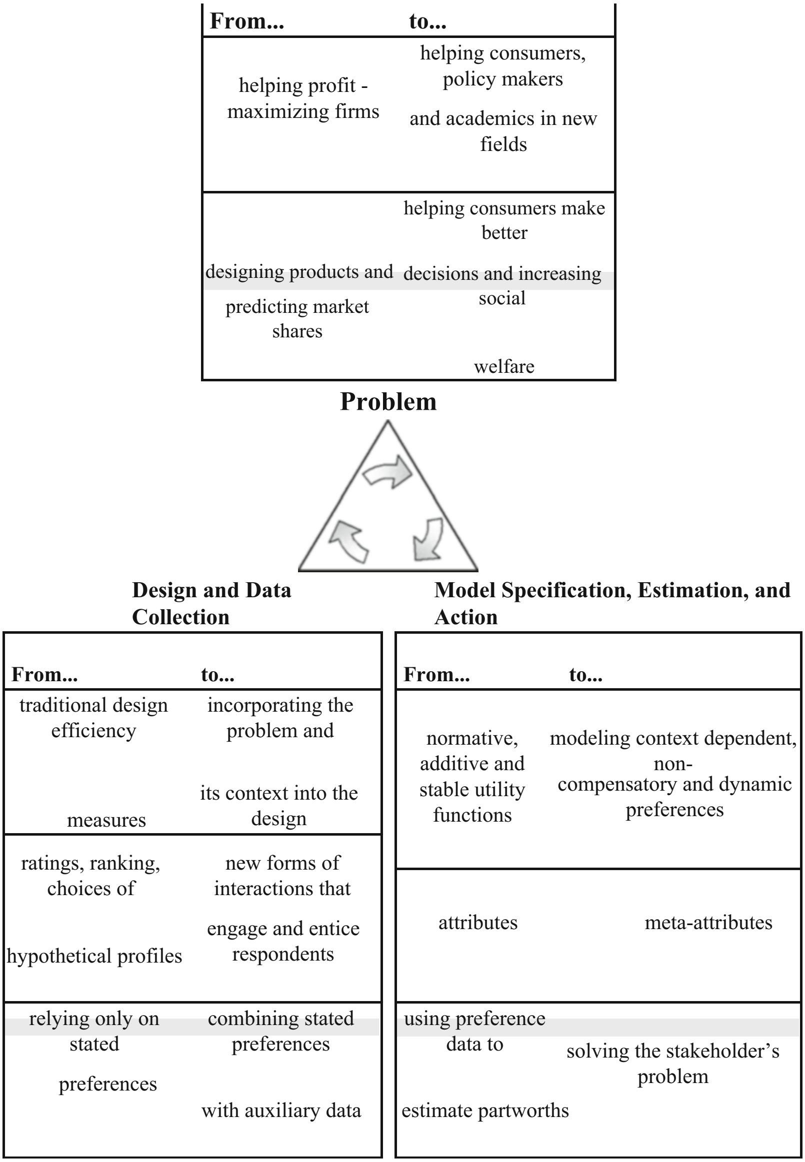

Fig. 11.1 The changing landscape of preference measurement

In the past few decades, many of the advances in the area of preference measurement have revolved around proposing better methods for designing conjoint analysis questionnaires and estimating individual-level partworths using relatively sparse data. However, in recent years, preference measurement researchers have contributed to all three components of the proposed preference measurement framework. Specifically, users of preference measurement studies now include, in addition to firms, consumers (e.g., using recommendation agents), policy makers, and researchers from various fields. Accordingly, the problems being addressed extend well beyond opportunistic profit maximization to altruistic consumer and social welfare objectives. Researchers have developed novel data collection methods based on interactions between consumers and firms as well as among consumers, making the preference measurement task more engaging and appealing. In addition, incentive-compatible mechanisms have substantially improved the quality of preference measurement data. Finally, researchers have started incorporating behavioral context effects, non-compensatory processes, and dynamic effects into preference models. Thus, as a field, we are moving toward better, faster, easier-to-collect, and truer data.

We hope to see more research in the future that will continue to investigate alternatives to traditional conjoint analysis along the three components of our proposed framework. Moreover, we argue that these three components are interrelated; thus the optimal decisions in each component are influenced by the other components. For example, the problem being addressed by the preference measurement study should be taken into account in all stages of the study, from the design of the task through model estimation, to the conversion of the estimated preferences into action.

11.2 Problem

The types of problems being addressed by preference measurement studies are evolving. Companies have started using preference measurement in new ways that go beyond partworth estimation, and users increasingly include consumers, policy makers, and health care professionals, as well as academic researchers from fields where preference measurement is less ubiquitous.

11.2.1 Helping Companies

Conjoint analysis has helped a large number of companies make decisions in areas such as new product development, pricing, segmentation, positioning, and advertising (Cattin and Wittink 1982; Wittink and Cattin 1989). Such decisions have relied primarily on the estimation of partworths. Given the growing diversity and complexity of the shopping environment, companies are increasingly interested in modeling and understanding the actual process through which consumers choose products, in addition to consumers' partworths. For example, Erdem et al. (2005) estimated a choice model that captures the role of active information search and learning in consumer decision making in the context of high-involvement consumer durables. Iyengar et al. (2008) built a structural model of consumer preferences for non-linear contracts (e.g., two- or three-part tariff cell phone plans). Gilbride and

Allenby (2004) and Jedidi and Kohli (2005) went beyond partworth estimation and utilized preference measurement techniques to study the formation of consideration sets. Preference measurement could also be used more extensively by companies to guide project selection and investment decisions.

11.2.2 Helping Consumers

The last few years have seen a great increase in the number of preference measurement methods designed to help consumers make better choices. The most prevalent example is that of recommendation agents. Recommenders have been and continue to be a popular research topic in various fields, such as information systems, computer science and machine learning (Adomavicius and Tuzhilin 2005; Srebro et al. 2005), psychology (Häubl and Murray 2003) and marketing (Ansari et al. 2000; Arora et al. 2008; Häubl and Trifts 2000; Liechty et al. 2001; Ying et al. 2006). A good example of the revived interest in this topic is the "Netflix Prize" (www.netflixprize.com). The use of preference measurement methods in recommendation systems requires researchers to modify current methodologies in ways that substantially shorten the preference measurement task, and, in some cases, allow practitioners to estimate and utilize partworths in real time (De Bruyn et al. 2008).

11.2.3 Helping Policy Makers and Health Care Professionals

Policy makers and health care professionals (e.g., doctors, pharmaceutical companies, hospitals) have become increasingly interested in preference measurement techniques. Their objective may be opportunistic (e.g., maximize profit, maximize chances of winning an election) or altruistic. For example, in medical decision analysis, Bleichrodt and Pinto (2000) developed a non-parametric method to elicit the probability weighting function in the context of choices between medical treatments. Saigal et al. (2007) used conjoint analysis to optimize treatment for prostate cancer based on each patient's unique tradeoffs between various outcomes and side effects. Parker and Srinivasan (1976) used preference measurement techniques to incorpo-rate patients' preferences in planning a rural primary health care delivery system.

11.2.4 Helping Academic Researchers

Preference measurement is inherently an interdisciplinary field. For example, some of its origins may be traced back to mathematical psychology and transportation. While most of the active work on the topic is currently linked to marketing, we expect the preference measurement community to expand to new fields in the coming years. For example, behavioral economists are increasingly interested in individual-level estimates of the parameters of the value function and the probability weighting function (Kahneman and Tversky 1979; Prelec 1998; Gonzalez and Wu 1999) in the context of cumulative prospect theory (Tversky and Kahneman 1992). Such estimates allow studying the relationship among parameters that represent loss aversion or risk aversion and individual characteristics such as age, income, or education (Tanaka et al. 2007), or between such parameters and behavior (Fehr and Goette 2007; Jarnebrant et al. 2009). We believe that advances in preference measurement, such as adaptive questionnaire design and Bayesian estimation, may benefit this community of researchers. In like manner, researchers in preference measurement may greatly benefit from collaborating with colleagues in fields such as computer science (Evgeniou et al. 2005), education (Bradlow 2005), engineering (Michalek et al. 2005), and psychology (Otter et al. 2008).

11.3 Design and Data Collection

11.3.1 Optimal Experimental Design: Beyond A-Efficiency and D-Efficiency

The design of conjoint experiments has traditionally focused on maximizing design efficiency measures such as D-efficiency or A-efficiency (Addelman 1962; Kuhfeld et al. 1994). These measures of efficiency are based on matrix norms defined on the covariance matrix of the estimates of the partworths. In other words, in the context of an individual-level regression, D-efficient or A-efficient designs (such as the well-known orthogonal designs) produce partworth estimates that have minimal variance and intercorrelation.

However, those traditional efficiency measures overlook the managerial objective of the preference measurement study. In particular, while traditional measures of efficiency focus on the covariance matrix of the partworths, managers typically take actions that are based on some functions of these partworths (e.g., willingness to pay for a specific feature), and put more weight on some decisions than others. Toubia and Hauser (2007) proposed M-efficiency measures that account for such managerial considerations. Future research may incorporate other aspects of the environment, such as engineering constraints (Michalek et al. 2005) or prior knowledge of consumers' preferences, into the design stage of preference measurement studies. For example, Gensler et al. (2007) consider acceptable ranges of willingness to pay in the design of an adaptive choice-based conjoint analysis. Along similar lines, the existence of unacceptable product features or combinations of features may have an impact on the criteria used to evaluate possible designs. Note, however, that one should be cautious in asking consumers directly which attribute levels are unacceptable (Green et al. 1988).

More generally, we believe that experimental design may be greatly enhanced by being systematically approached using Bayesian Decision Theory (Chaloner and Verdinelli 1995). Bayesian experimental designs minimize an expected loss function over the posterior distribution of the parameter estimates. For example, Sandor and Wedel (2001) proposed a method for eliciting managers' prior beliefs about attribute preferences and used this prior information to design Bayesian D-efficient choice experiments. Sandor and Wedel (2005) showed how taking prior information about heterogeneity across consumer preferences into account affects design optimality. In particular, they show how the use of a small set of different conjoint designs improves efficiency over a single design administered to all participants. However, A-efficiency and D-efficiency are just special cases corresponding to two particular loss functions. The specific context of the study may give rise to alternative loss functions and/or prior distributions on the parameters that more accurately reflect the objectives and beliefs of the user. In summary, when designing a preference measurement task, we encourage researchers to incorporate aspects such as managerial objectives, prior beliefs, constraints and characteristics of the task into the criteria used to evaluate the design.

11.3.2 New Forms of Interactions

Preference measurement data have been traditionally collected using pencil and paper questionnaires or one-on-one or mail–telephone–mail interviews involving sorting or rating tasks. Since the early 1990s, many respondent interactions have been relegated to computer and web interfaces. The use of web-based questionnaires triggered the development of adaptive methods that allow collecting more information per question. Adaptive methods include the commercially available adaptive conjoint analysis (ACA, Johnson 1987), the Fast Polyhedral approach (Toubia et al. 2003, 2004, 2007b; Vadali et al. 2007), the Adaptive Self-Explicated approach (Netzer and Srinivasan 2008).

However, the technological advances and easier accessibility to respondents afforded by the web come at the cost of decreased respondent patience and attentiveness. Thus, it is becoming more important than ever to keep respondents engaged with the task. Dahan and Hauser (2002) surveyed several virtual interactive web-based interfaces that have been proposed in the past few years to address that issue. For example, the user design approach collects preference data by allowing respondents to design their ideal virtual product (von Hippel and Katz 2002). The Information Pump (Prelec 2001) and the Securities Trading of Concepts (STOC; Dahan et al. 2007a, b) collect preference data by allowing respondents to interact with one another in game-like mechanisms, making the task more engaging and fun. Note that, when designing data collection methods that are based on interactions among consumers, one needs to be aware of biases that such interactions may induce (Johnson et al. 2005). Keeping respondents engaged may also be achieved by showing them physical prototypes to increase the realism of the task (Luo et al. 2008; Srinivasan et al. 1997). Dahan and Srinivasan (2000) took this approach even further and reduced its cost by developing a web interface to measure preferences using static or dynamic virtual prototypes.

Another method to increase consumer involvement is to replace the commonly used hypothetical data collection exercises with incentive-aligned tasks, in which respondents have to "live with" their decisions (Ding 2007; Ding et al. 2005; Park et al. 2008; Prelec 2001). A recent study by Ding (2007) suggested that incentive-aligned mechanisms may be used even when not all the product profiles exist in the market. Incentive-aligned mechanisms were empirically found to increase not only respondents' engagement but also out-of-sample predictive validity. For example, the incentive-aligned mechanism proposed by Ding et al. (2005) increased hit rates (correct prediction of the first choice out of 21 options) by almost a factor of two (from 26 % to 48 %). Incentive-aligned mechanisms have been shown to be very effective also in economic experiments for market design such as matching and public goods problems (Amaldoss et al. 2008).

In summary, when building a data collection mechanism, it is important to keep in mind the experience of the consumer completing the task. To be specific, since the ultimate goal is usually to predict actual behavior, engaging and incentive-compatible mechanisms should be favored over hypothetical tasks.

11.3.3 Dealing with a Large Number of Attributes and Products

As products become more complex, consumer preferences need to be measured over a larger number of product attributes and levels. Applications of conjoint analysis have been conducted on products involving as many as 50 product attributes (Wind et al. 1989). Several methods have been proposed to handle the demand for complex problems. The traditional self-explicated approach (Srinivasan 1988) can deal with a large number of attributes and levels. However, this approach carries several limitations (Green and Srinivasan 1990), which have been partially overcome by hybrid estimation methods that combine self-explicated data with preference data from full or partial profile tasks (Green et al. 1981; Johnson 1987; Marshall and Bradlow 2002; Ter Hofstede et al. 2002). Utilizing the concept of complexity control from machine learning, Cui and Curry (2005) and Evgeniou et al. (2005) used a support vector machine approach to handle complex preference measurement problems.

Researchers recently proposed to address the problem of large product dimensionality by developing innovative data collection mechanisms. For example, the Conjoint Adaptive Ranking Database System (CARDS) method proposed by Dahan (2007) simplifies the conjoint analysis task by asking respondents to choose only among the very limited number of sets that are perfectly mapped to specific utility functions proposed in advance by the researcher. Park et al. (2008) proposed an auction-based approach in which respondents can auction a large number of product feature upgrades. Taking a different approach, Netzer and

Srinivasan (2008) developed an adaptive self-explicated approach to solve the self-explicated constant sum question problem when the number of product attributes becomes large, demonstrating significant improvement in predictive validity. We expect that many of the advances in our ability to study complex problems will come from the development of such innovative data collection techniques and from the use of auxiliary information.

11.3.4 Combining Multiple Sources of Data

Traditionally, preference measurement studies have relied on data provided explicitly and consciously by consumers during the preference measurement task. Marketers recently started identifying new sources of data and supplementing stated preference data with auxiliary revealed preference data to: (1) improve predictive ability; (2) ask fewer questions; (3) correct biases related to the preference measurement task.[1] Such auxiliary data may be either internal or external to the preference measurement task.

11.3.4.1 Internal Sources of Data

Examples of data that are internal to the task include response latencies, eye movement, and mouse movement. Haaijer et al. (2000) demonstrated that response time is related to preference by means of choice uncertainty, whereby shorter response times represent more certain choices. Otter et al. (2008) proposed a Poisson race model to capture response time in conjoint analysis. Netzer et al. (2008) modeled and exploited the relation between response time and choice conflict. Liechty et al. (2003) utilized eye movement data to identify the attention state of respondents when evaluating stimuli. In the future, we expect that more decision process data such as mouse movement, click-stream data and brain images will be utilized in preference measurement.

11.3.4.2 External Sources of Data

Examples of auxiliary data that are external to the task include, but are not limited to, sales and market share data. Feit et al. (2007) developed a method for melding experimental choice data and data on market purchases to leverage the best properties of both. Along the same lines, Horsky et al. (2006) demonstrated the

[1] We refer the reader to the previous Choice Symposium papers by Ben-Akiva et al. (1994) and Louviere et al. (1999) for a summary of the benefits and difficulties of combining stated and revealed preference data

benefits of combining scanner-based data with survey-based preference data. Gilbride et al. (2006) proposed a loss function approach to incorporate market share information as constraints in the estimation of choice-based conjoint analysis partworths. De Bruyn et al. (2008) combined preference measurement data with intended product use and customer characteristics data, in the context of recommendation agents. Some less traditional sources of auxiliary data have also been investigated recently. For example, Hui et al. (2009) measured consumer preferences by combining shopping path data (collected using RFID technology) with transaction data. Another promising external source of data includes readily available data posted on the internet, such as product reviews (Lee and Bradlow 2008).

With the advantages offered by combining multiple sources of information comes the difficulty and complexity of combining data sets that are often not fully aligned with one another. Several approaches have been suggested including data fusion (Gilula et al. 2006), common individual characteristics (Feit et al. 2007) and common latent constructs underlying the multiple data sets (Hui et al. 2008a).

We encourage researchers to identify unique sources of data that could improve our ability to measure consumers' preferences and to develop methods to overcome the difficulties involved in combining multiple sources of data.

11.4 Model Specification, Estimation, and Action

11.4.1 Taking Social Interactions into Account

Preference measurement models have almost exclusively assumed that consumers make choices independently of one another. Some noteworthy exceptions include Rao and Steckel (1991) who studied the polarizing effects of group decision making, Arora and Allenby (1999) who modeled decisions made jointly by husbands and wives, and Ding and Eliashberg (2007) who proposed formal models of multi-party decision-making and applied them to choices of pharmaceutical prescriptions by doctors and patients. Recent research in marketing has continued to highlight and illustrate the importance of social interactions in consumption and choices (e.g., Godes and Mayzlin 2004; Goldenberg et al. 2002). We believe that capturing such interactions more systematically in preference measurement is an important area for future research.

11.4.2 Meta-attributes

Preferences are often modeled and estimated in the space defined by product attributes and levels. Working in this space makes the translation of consumer preferences into engineering terms easier. However, consumers often think in terms of “meta-attributes” such as needs, motivations, and goals, which may correspond to bundles of physical product attributes. There are several advantages to working in meta-attribute spaces. First, if consumers indeed evaluate products according to meta-attributes, the preference measurement task may become more natural. Second, using dimensions like goals and needs, which are the true drivers of decision making, is likely to lead to better preference measurement. Finally, needs, motivation, and goals are likely to be more stable over time than preferences for specific product attributes (e.g., consumers may have stable preference for faster computers, but their preference for a specific processor may change over time as technology evolves). While working with meta-attributes may be beneficial, identifying and constructing meta-attributes can prove to be difficult. Methods such as factor analysis may provide some insights but lack the fundamental ability to create maps between physical attributes and meta-attributes. The challenge of finding these maps is confounded with issues of language that could be used to describe meta-attributes. Text mining of consumer-written product reviews (Lee and Bradlow 2008) is a potentially valuable tool for automating the process of identifying the language consumers use to describe products. Furthermore, the translation between meta-attributes defined in consumer language and engineering specifications used in product design may not be straightforward.

A few successful attempts to integrate meta-attributes in preference measurement include Luo et al. (2008) who incorporated meta-attributes such as “comfort” and “power” along with more objective characteristics. In the context of recommendation agents, De Bruyn et al. (2008) used tree-based methods combined with higher level “ask-once” questions to group consumers, suggesting that meta-attributes may be related to and identified with “ask-once” questions in online or offline recommendations. Ghose and Rao (2007) tackled directly the topic of how one could construct and utilize meta-attributes in the context of conjoint analysis. We hope to see more work along these lines in the future.

11.4.3 More Flexible Utility Functions

Preference measurement has typically assumed linear and additive utility functions. An increasing number of papers have explored utility functions that deviate from these assumptions. For example, Kim et al. (2007) modeled preferences using Bayesian splines with endogenous knot configurations, finding hold-out choice prediction improvement in the 10–20 % range. Ben-Akiva et al. (2002) proposed a hybrid choice model that integrates many types of discrete choice modeling methods, draws on different types of data, and allows the explicit modeling of latent psychological explanatory variables. Other researchers have explored non-compensatory utility functions. Yee et al. (2008) and Kohli and Jedidi (2007) proposed dynamic programming methods to estimate lexicographic preference structures. Non-compensatory processes seem particularly relevant in the context of consideration sets. Gilbride and Allenby (2004) modeled a two stage process in which the first stage consists of a (potentially) non-compensatory screening of alternatives and the second stage of a compensatory choice among the remaining alternatives. They estimated their model using hierarchical Bayes methods, augmenting the latent consideration sets within their MCMC approach. Jedidi and Kohli (2005) introduced subset-conjunctive screening rules, which generalize disjunctive and conjunctive rules. Non-compensatory decision process may be viewed as the result of simplifying heuristics used by boundedly rational consumers during the preference measurement task. For example, Kim (2004) used a Bayesian hidden Markov model to describe changes in individual consumers' latent choice heuristics over time.

We hope that future work in this area will enhance the ecological rationality of preference measurement models, i.e., will improve the fit between the structural properties of the model and the structure of the environment to which it is applied.

11.4.4 Incorporating Behavioral Effects

The process of data collection in preference measurement often involves a sequence of choices, ranking, ratings, or tradeoffs between attributes and/or products. Much of the research in Behavioral Decision Theory has been focused on studying context and other behavioral effects that may be prevalent when consumers are making such decisions. Therefore, it is surprising that only a handful of studies have attempted to test and apply the battery of robust and significant behavioral effects documented in the consumer behavior literature to preference measurement.

Some of the early work on incorporating behavioral effects into preference measurement explored the effect of the number of attribute levels on the perceived attribute importances (Wittink et al. 1989). The authors suggested that researchers should try to keep the number of attribute levels similar across attributes to avoid biases. Bradlow et al. (2004) investigated and modeled the behavioral effects caused by omitting product attributes in partial profile designs. A few studies have also attempted to model context effects in preference measurement. Kivetz et al. (2004a) proposed several choice models that could capture the well-known compromise effects given a set of partworths collected using alternative preference measurement tasks. In a follow-up paper, the authors suggested that their models could capture additional context effects such as asymmetric dominance, attraction, and detraction (Kivetz et al. 2004b). Haaijer et al. (1998) proposed a flexible covariance matrix that could potentially capture context effects in choice-based conjoint analysis. The paper by Adamowicz et al. (2008), appearing in the current issue of the journal, provides a detailed overview of behavioral effects in choice modeling.

One of the difficulties involved with studying behavioral effects in preference measurement is that one cannot claim that a model describes behavior better than another model based on superior fit or predictive ability only. In particular, more complex models naturally tend to fit better and can often predict worse (due to potential overfitting). Therefore, many factors may influence fit and predictive ability, beyond the accuracy of the behavioral assumptions made by the model. Claiming that a model is isomorphic to the true underlying decision process (i.e., it actually captures the underlying behavior) seems to require exogenous manipulations and/or a set of process measures. Otherwise, a model may only be shown to be paramorphic to the true underlying decision process (i.e., it gives rise to similar outcomes).

Nevertheless, we believe that with the increase in the number of contact points between firms and consumers, and therefore in the number of ways in which practitioners may influence the choice process, consumer psychology is more relevant than ever to preference measurement from a managerial perspective. From an academic perspective, we hope to see a two-way exchange between the preference measurement and consumer psychology community. Psychologists can suggest behavioral effects that may improve the accuracy of preference measurement while preference measurement researchers in turn can develop new methods for measuring and testing alternative behavioral effects.

11.4.5 Modeling Learning, Dynamics and Preference Formation

Most preference measurement models assume that consumers have well-defined and stable preferences. The above discussion suggests that preferences may not be well formed and may be influenced by the task itself and by its context. Furthermore, if preferences are not well formed we are likely to observe dynamics throughout the preference measurement task as a result of preference formation, learning or fatigue. DeSarbo et al. (2005) and Liechty et al. (2005) proposed models that allow the partworth estimates to vary throughout the preference measurement task using a dynamic random effects model. Su and Rao (2007) studied the evolution of willingness to pay for different types of attributes and how such changes affect new product adoption. Many of the flexible models developed to capture dynamics in repeated choice (e.g., Kim et al. 2005; Lachaab et al. 2006) could be applied to preference measurement. Bradlow et al. (2004) take a first step in understanding the antecedents of dynamics by studying consumer learning about preferences for missing attribute levels in a partial profile design. We join Bradlow (2005) in the call for more work attempting to disentangle the different sources of dynamic effects in preference measurement.

11.4.6 Recent Tools for Estimation

The standard estimation method for conjoint analysis has become hierarchical Bayes (Lenk et al. 1996; Rossi and Allenby 2003). Although this estimation method has been researched extensively, it continues to be an exciting research area. For example, Sonnier et al. (2007) showed that specifying a normal heterogeneity distribution on the parameters of the multinomial logit model implies a distribution on willingness-to-pay that has substantial mass in the tail, leading to extreme behavior for some individuals. This suggests that prior or heterogeneity distributions should be specified on meaningful quantities (e.g., willingness-to-pay) instead of on latent constructs, like partworths.

An alternative approach to conjoint estimation is based on optimization. This approach has a long history, starting with the Linmap method of Srinivasan and Shocker (1973a, b). More recently, Toubia et al. (2003, 2004) proposed polyhedral methods for conjoint estimation and questionnaire designs. These methods are based on interpreting the answer to each conjoint question as a constraint on the respondent's partworths. Toubia et al. (2007b) and Vadali et al. (2007) generalized the polyhedral methods to capture response error and informative priors on the parameters. Evgeniou et al. (2005, 2007) and Cui and Curry (2005) proposed conjoint estimation methods based on machine learning and statistical learning theory. The method of Evgeniou et al. (2007) has been shown to outperform, in some cases, hierarchical Bayes in estimation accuracy and predictive ability. The two methods are comparable conceptually, with the fundamental difference that all parameters are endogenous in the machine learning method of Evgeniou et al. (2007) while some parameters are typically set exogenously in hierarchical Bayes (e.g., the hyperparameters). Finally, Toubia et al. (2007a) showed that many optimization methods for conjoint estimation may be integrated within the framework of statistical learning theory.

One of the current limitations of optimization-based methods is that they produce point estimates, whereas likelihood-based methods such as hierarchical Bayes provide full distributions on the parameter estimates. While Evgeniou et al. (2007) illustrated a bootstrapping approach to obtaining confidence intervals for their method, we believe that future research may explore alternative approaches to allow statistical inference and hypothesis testing for optimization-based methods. More generally, a fundamental challenge that we hope will be addressed in future research is linking optimization-based methods with likelihood-based methods. For example, Toubia et al. (2007b) and Vadali et al. (2007) gave a likelihood interpretation of polyhedral methods. Bridging the likelihood-based and optimization-based approaches may benefit both approaches. For example, Evgeniou et al. (2007) showed an example of how principles from statistical learning theory may be used to significantly improve the estimation accuracy and predictive ability of hierarchical Bayes estimation.

11.4.7 From Model to Action

Parameter estimation is often thought of as the final stage of a preference measurement study. However, at the conclusion of a study, it is imperative to come back to the original problem that motivated the study and ensure that a solution is provided to that problem. Some of the key decisions in marketing are those of optimal product design and product line optimization (Dobson and Kalish 1993; Green and Krieger 1985; Kohli and Sukumar 1990; McBride and Zufryden 1988).

Recently, Luo et al. (2005) proposed an approach that takes into account variations in the conditions under which the product will be used, and introduced the concept of "robust product design," which offers excellent performance under worst-case variations and low sensitivity to variations. Recent models in the area of product line optimization have also emerged from engineering, using detailed physical models to determine which products can be produced (Michalek et al. 2005; Wassenaar et al. 2005). These models combine innovative ways to define feasibility constraints with tailored optimization algorithms. For example, Michalek et al. (2007) used analytical target cascading (ATC) to formally coordinate models from marketing and engineering, and design "optimal" marketing-based products and product lines that are technically feasible.

Beyond product line optimization, we believe that the managerial relevance and impact of preference measurement studies may be enhanced by systematically modeling the Bayesian-decision theoretic loss function of the stakeholder (company, consumers, policy makers, etc.), and providing decision support tools for identifying the action that will minimize this loss function over the entire posterior distribution of the parameters being estimated. Currently, most preference measurement studies are used to produce point estimates of some parameters such as partworths. However, basing decisions on point estimates is suboptimal, as decisions should be based on the expected loss across the entire posterior distribution of the estimates (Chaloner and Verdinelli 1995). For example, Blattberg and George (1992) showed that incorporating the manufacturer's profit-maximizing goal into the Bayesian loss function leads to smaller price-sensitivity estimates and higher optimal prices. Note that in some of the new domains of application identified earlier in this paper, the loss function may take very different forms from that of a profit-maximizing firm. For example, the appropriate loss function for a recommendation agent may include both the utility derived by the consumer from the recommended product and the effort spent by the consumer throughout his or her interactions with the agent. Given the fact that Bayesian Decision Theory involves integrating over posterior distributions, we believe that there is an opportunity to construct decision support tools that will simplify the choice of actions, based on the output of the preference measurement study and all other relevant information.

11.5 In Conclusion…"Every Generation Needs a New Revolution"[2]

Preference measurement is a very exciting and active field that goes well beyond conjoint analysis. We proposed a framework consisting of three interrelated components for approaching this field. We have summarized some cutting edge research and identified fruitful directions for future research pertaining to the

[2] Thomas Jefferson

framework's three components, and to their mutual integration. The past two decades have seen great advances in conjoint analysis through the use of computerized adaptive questionnaires and the development of new estimation methods that account for consumer heterogeneity. Moving forward, we encourage researchers to go beyond conjoint analysis and explore new problems and applications of preference measurement, develop new forms of data collection that engage and entice respondents, take advantage of the availability of new sources of data, model new phenomena such as behavioral effects and dynamics, and combine statistical and optimization methods to improve estimation. Moreover, we encourage researchers to take into account the objectives and context of the preference measurement study throughout each step of the process.

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