

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).

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 be 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.

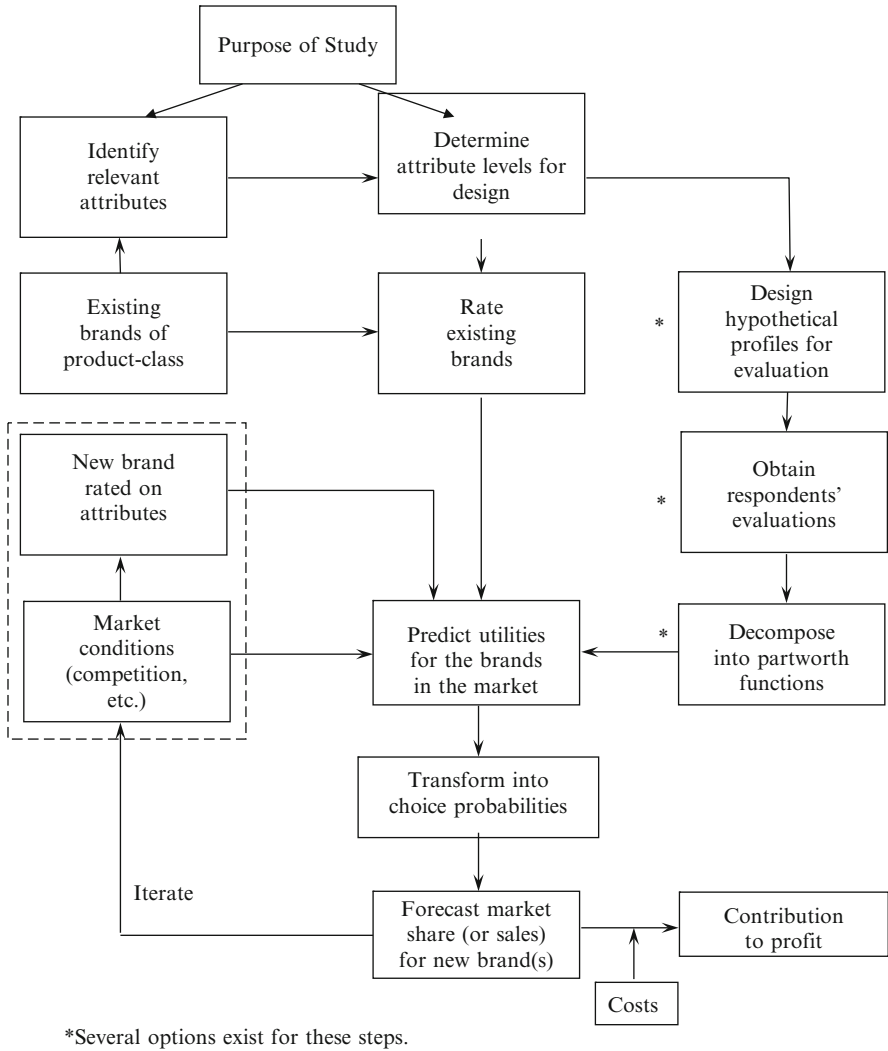


Fig. 2.1 A flowchart for applying conjoint analysis for product design and forecasting sales

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 value¹ 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.

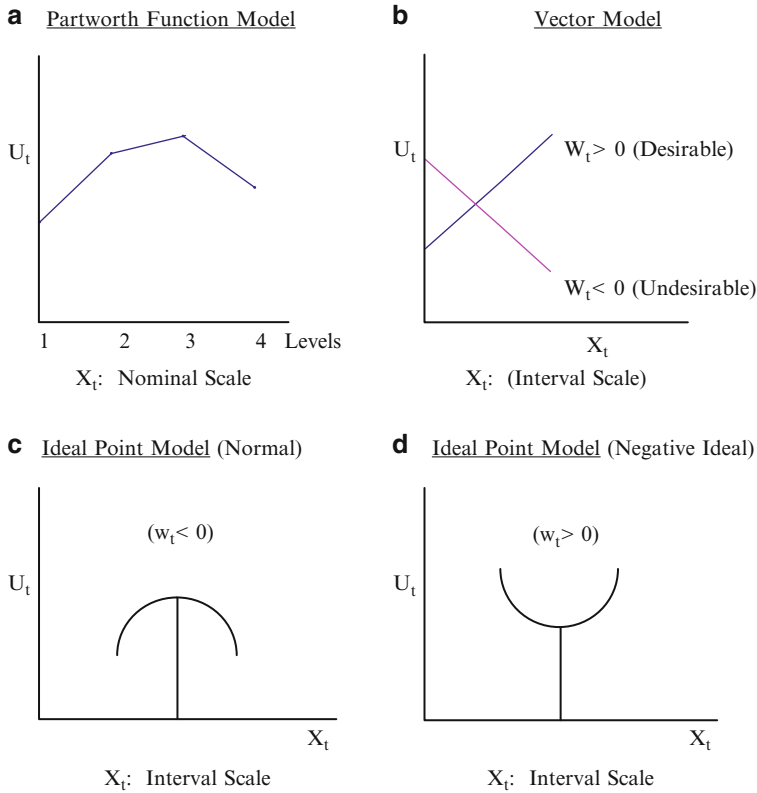


Fig. 2.2 Three forms of component utility functions

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:

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

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:

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

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:

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

The unknowns in this function are U_{t1}, U_{t2}, \dots , 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,

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

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)	$\sum_{k=1}^{r_i} U_{ik} D_{ik}$	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)	$w_t (x_{jt} - x_{0t})^2$	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 result³ 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

³This 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 $\frac{1}{2}$ 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 OPTEX⁴) 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 3⁴ 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 2⁹ 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 × 3 × 2⁷ 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

Stimulus	Factor							
	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:

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

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: $n = 9$, $k = 5$, $r = 10$, $b = 18$, $\ell = 5$

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: $n = 16$, $k = 6$, $r = 9$, $b = 24$, $\ell = 3$

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) data⁵ 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 or 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

Tire Brand	Tread Life		
	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

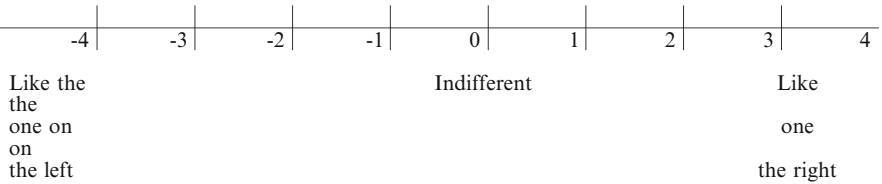
*1 denotes the best-liked combination and 12 denotes the least-liked combination for a hypothetical respondent.

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.



Profile #5		Profile #3	
A. Time taken to ship order after receipt.	2 days	A. Time taken to ship order after receipt.	1 day
B. Ratio of jewelry and fashion items to the rest.	65:35	B. Ratio of jewelry and fashion items to the rest.	40:60
C. Frequency of publication.	4 times a year	C. Frequency of publication.	8 times a year
D. Sponsor of catalog.	Q	D. Sponsor of catalog.	R

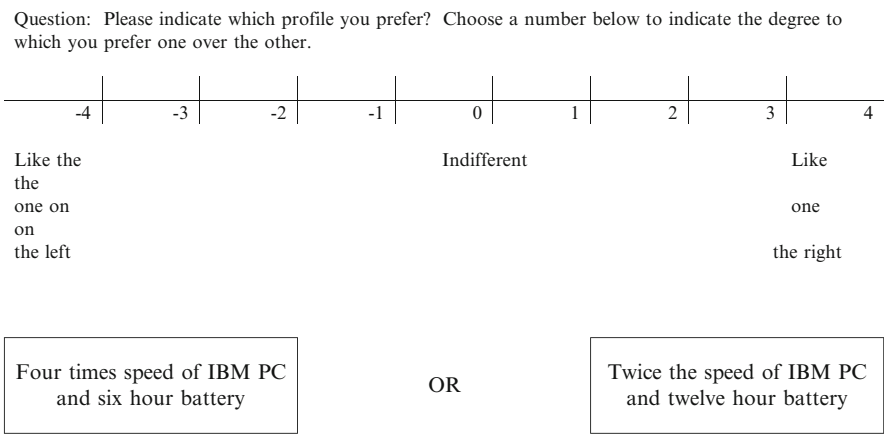
Attributes:					
Fixed set:		Type of paper, number of pages, mode of ordering and payment, Target audience			
Variable set: (Design attributes)					
A. Time taken to ship order after receipt (3 levels)	1.	Within 1 day	C. Frequency of publication	1.	3 times a year
	2.	Within 2 days		2.	4 times a year
	3.	Within 4 days		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	D. Sponsor of catalog (4 levels)	1.	P
	2.	65:35		2.	Q
	3.	50:50		3.	R
	4.	40:60		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.



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

I. Overall Size/Interior Layout

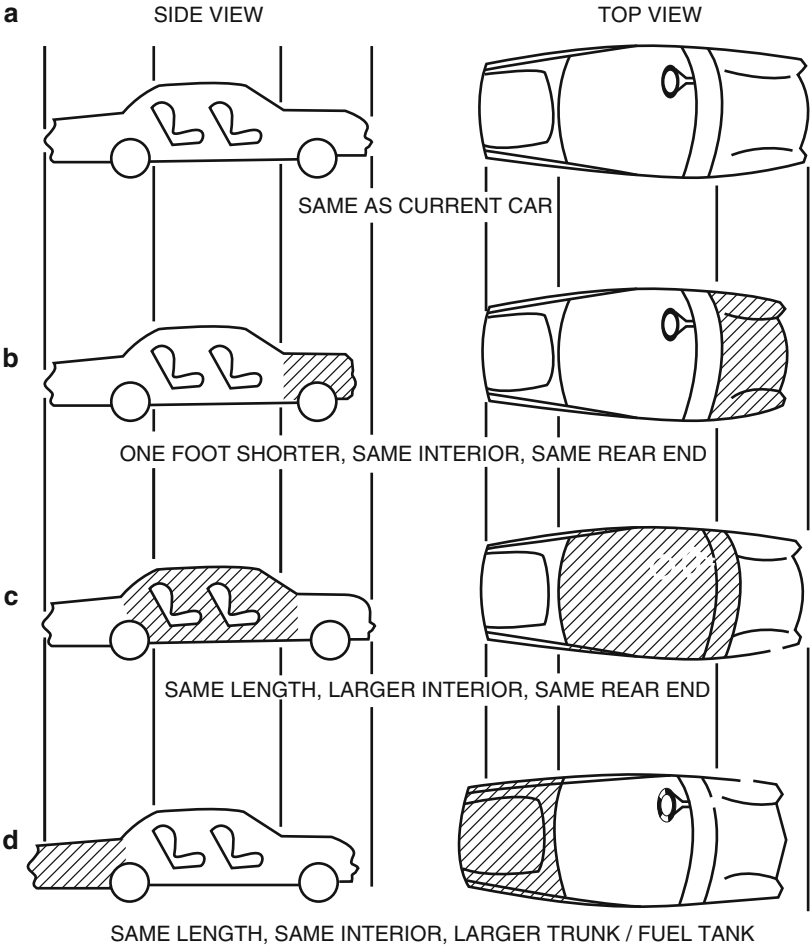


Fig. 2.8 (continued)

Akaah and Korgaonkar (1983) for a comparison of predictive validity of several 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

II. Interior Spaciousness/Visibility of a Car

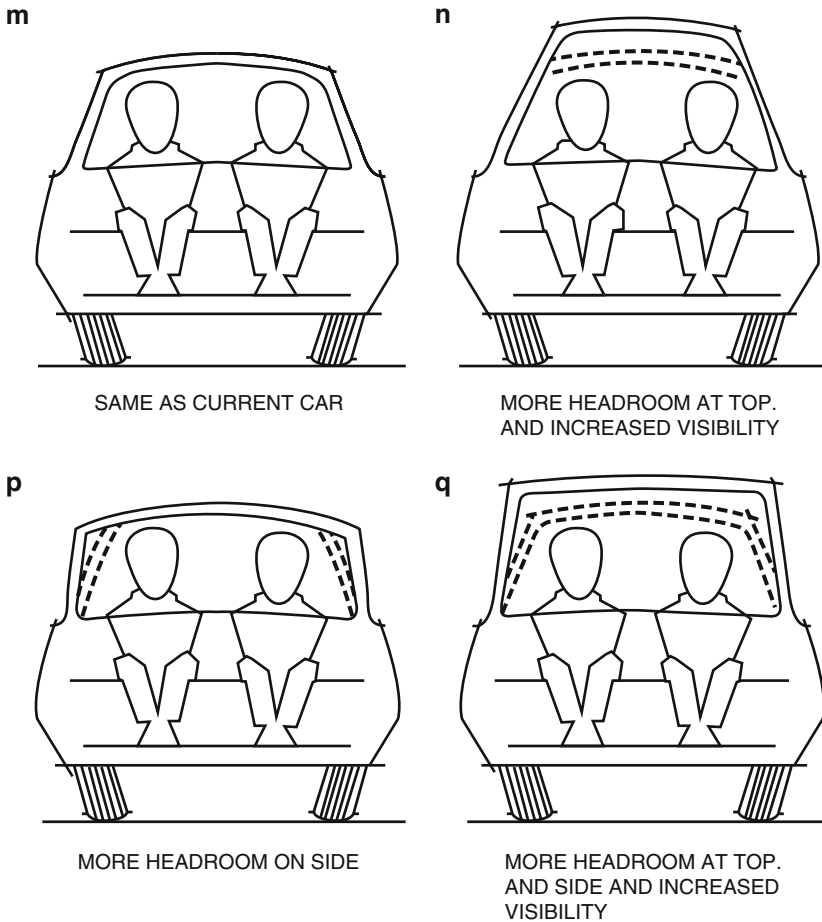
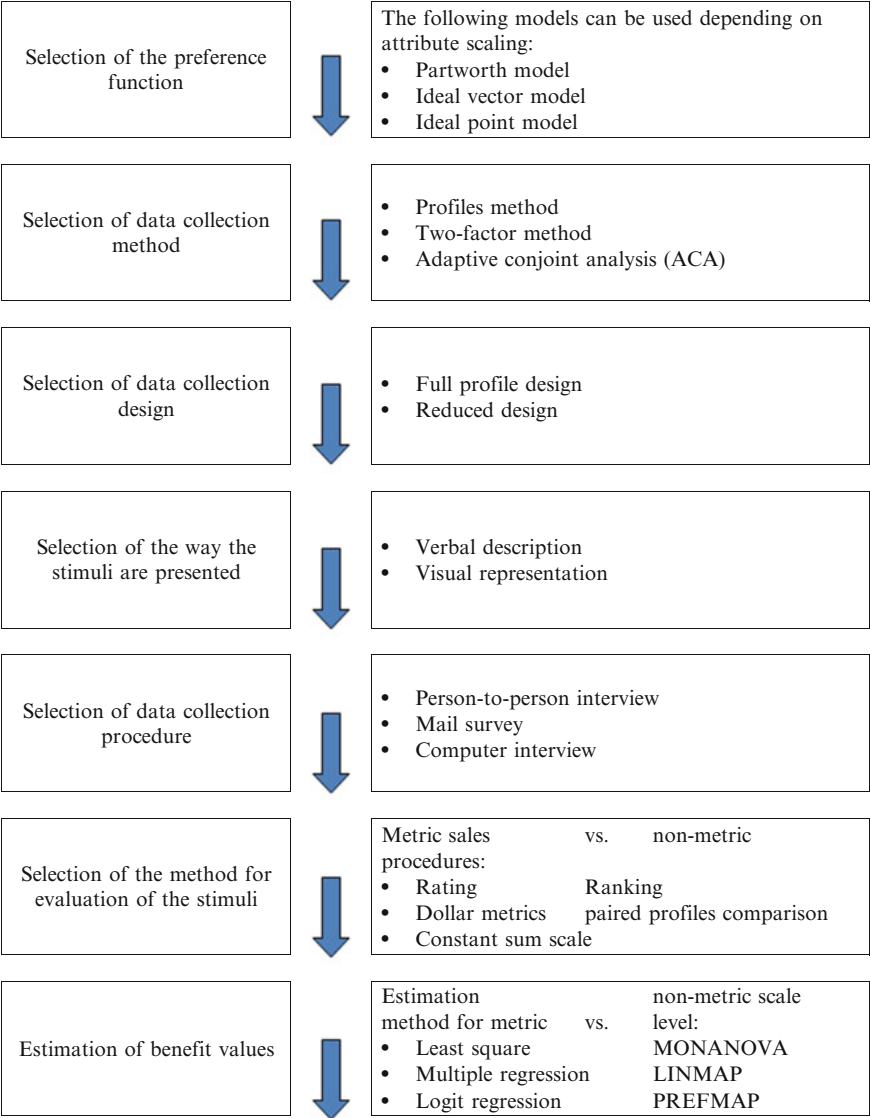


Fig. 2.8 Examples of use of visual props for attributes of a car

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

0102030405060708090100

Definitely not acceptDefinitely accept

PROPOSAL #1		
COST:	\$55,000	Your Rating <div></div>
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	4 months	
METHODOLOGY:	Basic	
PROPOSAL #2		
COST:	\$70,000	Your Rating <div></div>
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	2 months	
METHODOLOGY:	Sophisticated	
PROPOSAL #3		
COST:	\$70,000	Your Rating <div></div>
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	4 months	
METHODOLOGY:	Sophisticated	
PROPOSAL #4		
COST:	\$55,000	Your Rating <div></div>
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	2 months	
METHODOLOGY:	Basic	
PROPOSAL #5		
COST:	\$70,000	Your Rating <div></div>
SUPPLIER REPUTATION:	Established	
DELIVERY TIME:	2 months	
METHODOLOGY:	Basic	
PROPOSAL #6		
COST:	\$85,000	Your Rating <div></div>
SUPPLIER REPUTATION:	New	
DELIVERY TIME:	2 months	
METHODOLOGY:	Sophisticated	

Illustration of a Conjoint Questionnaire

0102030405060708090100

Definitely not accept

Definitely accept

<u>PROPOSAL #7</u>			
<u>COST:</u>	\$85,000	Your Rating	<input type="text"/>
<u>SUPPLIER REPUTATION:</u>	Established		
<u>DELIVERY TIME:</u>	2 months		
<u>METHODOLOGY:</u>	Basic		
<u>PROPOSAL #8</u>			
<u>COST:</u>	\$85,000	Your Rating	<input type="text"/>
<u>SUPPLIER REPUTATION:</u>	Established		
<u>DELIVERY TIME:</u>	4 months		
<u>METHODOLOGY:</u>	Sophisticated		
<u>PROPOSAL #9</u>			
<u>COST:</u>	\$55,000	Your Rating	<input type="text"/>
<u>SUPPLIER REPUTATION:</u>	New		
<u>DELIVERY TIME:</u>	2 months		
<u>METHODOLOGY:</u>	Sophisticated		
<u>PROPOSAL #10</u>			
<u>COST:</u>	\$70,000	Your Rating	<input type="text"/>
<u>SUPPLIER REPUTATION:</u>	New		
<u>DELIVERY TIME:</u>	4 months		
<u>METHODOLOGY:</u>	Basic		
<u>PROPOSAL #11</u>			
<u>COST:</u>	\$85,000	Your Rating	<input type="text"/>
<u>SUPPLIER REPUTATION:</u>	New		
<u>DELIVERY TIME:</u>	4 months		
<u>METHODOLOGY:</u>	Basic		
<u>PROPOSAL #12</u>			
<u>COST:</u>	\$55,000	Your Rating	<input type="text"/>
<u>SUPPLIER REPUTATION:</u>	Established		
<u>DELIVERY TIME:</u>	4 months		
<u>METHODOLOGY:</u>	Sophisticated		

Illustration of a Conjoint Questionnaire

0102030405060708090100

Definitely not acceptDefinitely accept

<u>PROPOSAL #13</u>			
<u>COST:</u>	\$85,000	Your Rating	<div></div>
<u>SUPPLIER REPUTATION:</u>	New		
<u>DELIVERY TIME:</u>	4 months		
<u>METHODOLOGY:</u>	Sophisticated		
<u>PROPOSAL #14</u>			
<u>COST:</u>	\$70,000	Your Rating	<div></div>
<u>SUPPLIER REPUTATION:</u>	Established		
<u>DELIVERY TIME:</u>	2 months		
<u>METHODOLOGY:</u>	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.

	<u>Rank</u>
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 | <input type="checkbox"/> |
| Client | <input type="checkbox"/> |
| Other | <input type="checkbox"/> |
- (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 $n \times p$ 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: $1/(n \text{ trace } ((X'X)^{-1}/p)$;

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 fractional 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 2²3³ 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

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Appendix 3

Several Orthogonal Plans

Source: Addelman, Technometrics; Reproduced with permission

Basic Plan: 1; 4; 3; 2⁷; 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; 3⁴; 2⁴; 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; 4⁵; 3⁵; 2¹⁵; 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; 3⁷; 2⁷; 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; 5⁶; 4⁶; 3⁶; 2⁶; 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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