CHAPTER **S-2**

Conjoint Analysis

LEARNING OBJECTIVES

Upon completing this chapter, you should be able to do the following:

- Explain the managerial uses of conjoint analysis.
- Know the guidelines for selecting the variables to be examined by conjoint analysis.
- Formulate the experimental plan for a conjoint analysis.
- Understand how to create factorial designs.
- Explain the impact of choosing rank choice versus ratings as the measure of preference.
- Assess the relative importance of the predictor variables and each of their levels in affecting consumer judgments.
- Apply a choice simulator to conjoint results for the prediction of consumer judgments of new attribute combinations.
- Compare a main effects model and a model with interaction terms and show how to evaluate the validity of one model versus the other.
- Recognize the limitations of traditional conjoint analysis and select the appropriate alternative methodology (e.g., choice-based or adaptive conjoint) when necessary.

CHAPTER PREVIEW

Since the mid-1970s, conjoint analysis has attracted considerable attention as a method that portrays consumers' decisions realistically as trade-offs among multi-attribute products or services [35]. Conjoint analysis gained widespread acceptance and use in many industries, with usage rates increasing up to tenfold in the 1980s [114]. During the 1990s, the application of conjoint analysis increased even further, spreading to almost every field of study. Marketing's widespread utilization of conjoint analysis in new product development for consumers led to its adoption in many other areas, such as segmentation, industrial marketing, pricing, and advertising [31, 61]. This rise in usage in the United States has been similar in other parts of the world as well, particularly in Europe [119].

Coincident with this continued growth was the development of alternative methods of constructing the choice tasks for consumers and estimating the conjoint models. Most of the multivariate techniques we discuss in this text are established in the statistical field. Conjoint analysis, however, will continue to develop in terms of its design, estimation, and applications within many areas of research [14].

The use of conjoint analysis accelerated with the widespread introduction of computer programs that integrate the entire process, from generating the combinations of independent variable values to be evaluated to creating choice simulators for predicting consumer choices across a wide number of alternative product and service formulations. Today, several widely employed packages can be accessed by any researcher with a personal computer [9, 10, 11, 41, 86, 87, 88, 92, 96, 97]. Moreover, the conversion of even the most advanced research developments into the PC-based programs is continuing [14], and interest in these software programs is increasing [13, 69, 70].

In terms of the basic dependence model discussed in Chapter 1, conjoint analysis can be expressed as

$$\underset{\text{(nonmetric or metric)}}{Y_1} = \underset{\text{(nonmetric)}}{X_1 + X_2 + X_3 + \ldots + X_N}$$

With the use of nonmetric independent variables, conjoint analysis closely resembles analysis of variance (ANOVA), which has a foundation in the analysis of experiments. As such, conjoint analysis is closely related to traditional experimentation. Let's compare a traditional experiment with a conjoint analysis.

The use of experiments in studying individuals typically involves designing a series of stimuli and then asking respondents to evaluate a single stimulus (or sometimes multiple stimuli in a repeated-measures design). The results are then analyzed with ANOVA (analysis of variance) procedures, such as those discussed in Chapter 7. Conjoint analysis follows this same approach through the design of stimuli (known as *profiles*). It differs in that respondents are always shown multiple profiles (most often 15 or more profiles) to allow for model estimates to be made for each respondent because each respondent provides multiple observations by evaluating multiple profiles.

In both situations, the researcher has a limited number of attributes that can be systematically varied in amount or character. Although we might try to utilize the traditional experimental format to understand consumers' preferences, it requires large numbers of respondents and only makes comparisons between groups (refer back to Chapter 7 for design considerations). Conjoint analysis affords the researcher a technique that can be applied to a single individual or group of individuals and provide insights into not only the preferences for each attribute (e.g., fragrance), but also the amount of the attribute (slightly or highly) [28, 30].

Conjoint analysis is actually a family of techniques and methods specifically developed to understand individual preferences that share a theoretical foundation based on the models of information integration and functional measurement [58]. It is best suited for understanding consumers' reactions to and evaluations of predetermined attribute combinations that represent potential products or services. The flexibility and uniqueness of conjoint analysis arise primarily from the following:

- An ability to accommodate either a metric or a nonmetric dependent variable
- The use of only categorical predictor variables
- Quite general assumptions about the relationships of independent variables with the dependent

variable

As we will see in the following sections, conjoint analysis provides the researcher with substantial insight into the composition of consumer preferences while maintaining a high degree of realism.

KEY TERMS

Before starting the chapter, review the key terms to develop an understanding of the concepts and terminology to be used. Throughout the chapter the key terms appear in **boldface.** Other points of emphasis in the chapter and key term cross-references are *italicized.*

Adaptive conjoint method Methodology for conducting a conjoint analysis that relies on respondents providing additional information not in the actual *conjoint task* (e.g., importance of attributes). This information is then used to adapt and simplify the *conjoint task*. Examples are the *self-explicated* and *adaptive,* or *hybrid,* models.

Adaptive model Technique for simplifying conjoint analysis by combining the *self-explicated model* and *traditional conjoint analysis*. The most widely known example is Adaptive Conjoint Analysis (ACA) from Sawtooth Software.

Additive model Model based on the additive *composition rule,* which assumes that individuals just "add up" the *part-worths* to calculate an overall or total worth score indicating *utility* or preference. It is also known as a *main effects model* and is the simplest conjoint model in terms of the number of evaluations and the estimation procedure required.

Balanced design Profile *design* in which each *level* within a *factor* appears an equal number of times across the profiles in the *conjoint task*.

Bayesian analysis Alternative estimation procedure relying on probability estimates derived from both the individual cases as well as the sample population that are combined to estimate the conjoint model.

Bridging design Profile *design* for a large number of *factors* (attributes) in which the attributes are broken into a number of smaller groups. Each attribute group has some attributes contained in other groups enabling the results from each group to be combined, or bridged.

Choice-based conjoint approach Alternative form of *conjoint task* for collecting responses and estimating the conjoint model. The primary difference is that respondents select a single *full profile* from a set of profiles (known as a *choice set*) instead of rating or ranking each profile separately.

Choice set Set of profiles constructed through experimental design principles and used in the *choice-based conjoint approach*.

Choice simulator Procedure that enables the researcher to assess many "what-if" scenarios. Once the conjoint *part-worths* have been estimated for each respondent, the choice simulator analyzes a set of *profiles* and predicts both individual and aggregate choices for each profile in the set. Multiple sets of profiles can be analyzed to represent any scenario (e.g., preferences for hypothetical product or service configurations or the competitive interactions among profiles assumed to constitute a market).

Composition rule Rule used to represent how respondents combine attributes to produce a judgment of relative value, or *utility,* for a product or service. For illustration, let us suppose a person is asked to evaluate four objects. The person is assumed to evaluate the attributes of the four objects and to create some overall relative value for each. The rule may be as simple as creating a mental weight for each perceived attribute and adding the weights for an overall score (*additive model*), or it may be a more complex procedure involving *interaction effects*.

Compositional model Class of multivariate models that estimates the dependence relationship based on respondent observations regarding both the dependent and the independent variables. Such models calculate, or "compose," the dependent variable from the respondent-supplied values for all of the independent variables. Principal among such methods are regression analysis and discriminant analysis. These models are in direct contrast to *decompositional models.*

Conjoint task The procedure for gathering judgments on each profile in the conjoint *design* using one of the three types of presentation method (i.e., *full-profile, pairwise comparison,* or *trade-off*).

Conjoint variate Combination of independent variables (known as *factors*) specified by the researcher that constitute the total worth or *utility* of the profile.

Decompositional model Class of multivariate models that decompose the individual's responses to estimate the dependence relationship. This class of models presents the respondent with a predefined set of objects (e.g., a hypothetical or actual product or service) and then asks for an overall evaluation or preference of the object. Once given, the evaluation/preference is decomposed by relating the known attributes of the object (which become the independent variables) to the evaluation (dependent variable). Principal among such models is conjoint analysis and some forms of multidimensional scaling (see Chapter 10).

Design Specific set of conjoint *profiles* created to exhibit the statistical properties of *orthogonality* and *balance.*

Design efficiency Degree to which a *design* matches an *orthogonal* design. This measure is primarily used to evaluate and compare *nearly orthogonal* designs. Design efficiency values range from 0 to 100, which denotes an *optimal design.*

Environmental correlation See *interattribute correlation.*

Factor Independent variable the researcher manipulates that represents a specific attribute. In conjoint analysis, the factors are nonmetric. Factors must be represented by two or more values (known as *levels*), which are also specified by the researcher.

Factorial design Method of designing *profiles* by generating all possible combinations of *levels.* For example, a three-factor conjoint analysis with three levels per factor ($3 \times 3 \times 3$) would result in 27 combinations that would act as profiles in the *conjoint task.*

Fractional factorial design Method of designing profiles (i.e., an alternative to *factorial design*) that uses only a subset of the possible profiles needed to estimate the results based on the assumed composition rule. Its primary objective is to reduce the number of evaluations collected while still maintaining *orthogonality* among the levels and subsequent *part-worth* estimates. It achieves this objective by designing profiles that can estimate only a subset of the total possible effects. The simplest design is an *additive model,* in which only *main effects* are estimated. If selected *interaction terms* are included, then additional profiles are created. The design can be created either by referring to published sources or by using computer programs that accompany most conjoint analysis packages.

Full-profile method Method of gathering respondent evaluations by presenting *profiles* that are described in terms of all *factors*. For example, let us assume that a candy was described by three factors with two levels each: price (15 cents or 25 cents), flavor (citrus or butterscotch), and color (white or red). A full profile would be defined by one level of each factor. One such profile would be a red butterscotch candy costing 15 cents.

Holdout profiles See *validation profiles.*

Hybrid model See *adaptive model.*

Interaction effects Effects of a combination of related features (independent variables), also known as *interaction terms*. In assessing value, a person may assign a unique value to specific combinations of features that runs counter to the additive *composition rule*. For example, let us assume a person is evaluating mouthwash products described by the two factors (attributes) of color and brand. Let us further assume that this person has an average preference for the attributes red and brand X when considered separately. Thus, when this specific combination of levels (red and brand X) is evaluated with the additive composition rule, the red brand X product would have an expected overall preference rating somewhere in the middle of all possible profiles. If, however, the person actually prefers the red brand X mouthwash more than any other profiles, even above other combinations of attributes (color and brand) that had higher evaluations of the individual features, then an interaction is found to exist. This unique evaluation of a combination that is greater (or could be less) than expected based on the separate judgments indicates a two-way interaction. Higher-order (three-way or more) interactions can occur among more combinations of levels.

Interattribute correlation Also known as *environmental correlation,* it is the correlation among attributes that makes combinations of attributes unbelievable or redundant. A negative correlation depicts the situation in which two attributes are naturally assumed to operate in different directions, such as horsepower and gas mileage. As one increases, the other is naturally assumed to decrease. Thus, because of this correlation, all combinations of these two attributes (e.g., high gas mileage and high horsepower) are not believable. The same effects can be seen for positive correlations, where perhaps price and quality are assumed to be positively correlated. It may not be believable to find a high-price, low-quality product in such a situation. The presence of strong interattribute correlations requires that the researcher closely examine the profiles presented to respondents and avoid unbelievable combinations that are not useful in estimating the *part-worths*.

Level Specific nonmetric value describing a *factor*. Each factor must be represented by two or more levels, but the number of levels typically never exceeds four or five. If the factor is originally metric, it must be reduced to a small number of nonmetric levels. For example, the many possible values of size and price may be represented by a small number of levels: size (10, 12, or 16 ounces) or price ($1.19, $1.39, or $1.99). If the factor is nonmetric, the original values can be used as in these examples: color (red or blue), brand (X, Y, or Z), or fabric softener additive (present or absent).

Main effects Direct effect of each *factor* (independent variable) on the dependent variable. May be complemented by *interaction effects* in specific situations.

Monotonic relationship The assumption by the researcher that a preference order among *levels* should apply to the *part-worth* estimates. Examples may include objective factors (closer distance preferred over farther distance traveled) or more subjective factors (more quality preferred over lower quality). The implication is that the estimated part-worths should have some ordering in the values, and violations (known as *reversals*) should be addressed.

Nearly orthogonal Characteristic of a profiles design that is not *orthogonal,* but the deviations from orthogonality are slight and carefully controlled in the generation of the profiles. This type of design can be compared with other profiles designs with measures of *design efficiency*.

Optimal design Profiles design that is *orthogonal* and *balanced.*

Orthogonality Mathematical constraint requiring that the *part-worth* estimates be independent of each other. In conjoint analysis, orthogonality refers to the ability to measure the effect of changing each attribute level and to separate it from the effects of changing other attribute levels and from experimental error.

Pairwise comparison method Method of presenting a pair of *profiles* to a respondent for evaluation, with the respondent selecting one profile as preferred.

Part-worth Estimate from conjoint analysis of the overall preference or *utility* associated with each *level* of each *factor* used to define the product or service.

Preference structure Representation of both the relative importance or worth of each *factor* and the impact of individual *levels* in affecting *utility*.

Profile By taking one *level* from each *factor,* the researcher creates a specific "object" (also known as a *treatment*) that can be evaluated by respondents. For example, if a soft drink was being defined by three factors, each with two levels (diet versus regular, cola versus non-cola, and caffeine-free or not), then a profile would be one of the combinations with levels from each factor. Some of the possible profiles would be a caffeine-free diet cola, a regular caffeine-free cola, or a diet caffeine-free non-cola. There can be as many profiles as there are unique combinations of levels. One method of defining profiles is the *factorial design,* which creates a separate profile for each combination of all levels. For example, three factors with two levels each would create eight (2 × 2 × 2) profiles. However, in many conjoint analyses, the total number of combinations is too large for a respondent to evaluate them all. In these instances, some subsets of profiles are created according to a systematic plan, most often a *fractional factorial design.*

Prohibited pair A specific combination of *levels* from two *factors* that is prohibited from occurring in the creation of profiles. The most common cause is *interattribute correlation* among the factors.

Respondent heterogeneity The variation in *part-worths* across unique individuals found in disaggregate models. When aggregate models are estimated, modifications in the estimation process can approximate this expected variation in part-worths.

Reversal A violation of a *monotonic relationship,* where the estimated *part-worth* for a level is greater/lower than it should be in relation to another level. For example, in distance traveled to a store, closer stores would always be expected to have more *utility* than those farther away. A reversal would be when a farther distance has a larger part-worth than a closer distance.

Self-explicated model *Compositional model* for performing conjoint analysis in which the respondent provides the *part-worth* estimates directly without making choices.

Stimulus See *profile.*

Trade-off analysis Method of presenting profiles to respondents in which *factors* (attributes) are depicted two at a time and respondents rank all combinations of the *levels* in terms of preference.

Traditional conjoint analysis Methodology that employs the classic principles of conjoint analysis in the *conjoint task,* using an *additive model* of consumer preference and *pairwise comparison* or *full-profile methods* of presentation.

Utility An individual's subjective preference judgment representing the holistic value or worth of a specific object. In conjoint analysis, utility is assumed to be formed by the combination of *part-*

worth estimates for any specified set of levels with the use of an *additive model,* perhaps in conjunction with *interaction effects.*

Validation profiles Set of *profiles* that are not used in the estimation of *part-worths.* Estimated part-worths are then used to predict preference for the validation profiles to assess validity and reliability of the original estimates. Similar in concept to the validation sample of respondents in discriminant analysis.

WHAT IS CONJOINT ANALYSIS?

Conjoint analysis is a multivariate technique developed specifically to understand how respondents develop preferences for any type of object (products, services, or ideas). It is based on the simple premise that consumers evaluate the value of an object (real or hypothetical) by combining the separate amounts of value provided by each attribute. Moreover, consumers can best provide their estimates of preference by judging objects formed by combinations of attributes.

Utility, a subjective judgment of preference unique to each individual, is the most fundamental concept in conjoint analysis and the conceptual basis for measuring value. The researcher using conjoint analysis to study what things determine utility should consider several key issues:

- Utility encompasses all features of the object, both tangible and intangible, and as such is a measure of an individual's overall preference.
- Utility is assumed to be based on the value placed on each of the levels of the attributes. In doing so, respondents react to varying combinations of attribute levels (e.g., different prices, features, or brands) with varying levels of preference.
- Utility is expressed by a relationship reflecting the manner in which the utility is formulated for any combination of attributes. For example, we might sum the utility values associated with each feature of a product or service to arrive at an overall utility. Then we would assume that

products or services with higher utility values are more preferred and have a better chance of choice.

To be successful in defining utility, the researcher must be able to describe the object in terms of both its attributes and all relevant values for each attribute. To do so, the researcher develops a **conjoint task,** which not only identifies the relevant attributes, but defines those attributes so hypothetical choice situations can be constructed. In doing so, the researcher faces four specific questions:

1. *What are the important attributes that could affect preference?* In order to accurately measure preference, the researcher must be able to identify all of the attributes, known as **factors,** that provide utility and form the basis for preference and choice. Factors represent the specific attributes or other characteristics of the product or service.
2. *How will respondents know the meaning of each factor?* In addition to specifying the factors, the researcher must also define each factor in terms of **levels,** which are the possible values for that factor. These values enable the researcher to then describe an object in terms of its levels on the set of factors characterizing it. For example, brand name and price might be two factors in a conjoint analysis. Brand name might have two levels (brand X and brand Y), whereas price might have four levels (39 cents, 49 cents, 59 cents, and 69 cents).
3. *What do the respondents actually evaluate?* After the researcher selects the factors and the levels to describe an object, they are combined (one level from each factor) into a **profile,** which is similar to a **stimulus** in a traditional experiment. Therefore, a profile for our simple example might be brand X at 49 cents.
4. *How many profiles are evaluated?* Conjoint analysis is unique among the multivariate methods, as will be discussed later, in that respondents provide multiple evaluations. In terms of the conjoint task, a respondent will evaluate a number of profiles in order to provide a basis for under-

standing their preferences. The process of deciding on the actual number of profiles and their composition is contained in the **design.**

These four questions are focused on ensuring that the respondent is able to perform a realistic task—choosing among a set of objects (profiles). Respondents need not tell the researcher anything else, such as how important an individual attribute is to them or how well the object performs on any specific attribute. Because the researcher constructed the hypothetical objects in a specific manner, the influence of each attribute and each value of each attribute on the utility judgment of a respondent can be determined from the respondents' overall ratings.

HYPOTHETICAL EXAMPLE OF CONJOINT ANALYSIS

As an illustration, we examine a simple conjoint analysis for a hypothetical product with three attributes. We first describe the process of defining utility in terms of attributes (factors) and the possible values of each attribute (levels). With the factors specified, the process of collecting preference data through evaluations of profiles is discussed, followed by an overview of the process of estimating the utility associated with each factor and level.

Specifying Utility, Factors, Levels, and Profiles

The first task is to define the attributes that constitute utility for the product being studied. A key issue involves defining the attributes that truly affect preferences and then establishing the most appropriate values for the levels.

Assume that HBAT is trying to develop a new industrial cleanser. After discussions with sales representatives and focus groups, management decides that three attributes are important: cleaning ingredients, form, and brand name. To operationalize these attributes, the researchers create three factors with two levels each:

	Levels	
Factor	*1*	*2*
1. Ingredients	Phosphate-Free	Phosphate-Based
2. Form	Liquid	Powder
3. Brand Name	HBAT	Generic Brand

A profile of a hypothetical cleaning product can be constructed by selecting one level of each attribute. For the three attributes (factors) with two values (levels), eight (2 × 2 × 2) combinations can be formed. Three examples of the eight possible combinations (profiles) are:

- Profile 1: HBAT phosphate-free powder
- Profile 2: Generic phosphate-based liquid
- Profile 3: Generic phosphate-free liquid

By constructing specific combinations (profiles), the researcher attempts to understand a respondent's **preference structure.** The preference structure depicts not only how important each factor is in the overall decision, but also how the differing levels within a factor influence the formation of an overall preference (utility).

Gathering Preferences from Respondents

With the profiles defined in terms of the attributes giving rise to utility, the next step is to gather preference evaluations from respondents. This process shows why conjoint analysis is also called **trade-off analysis,** because in making a judgment on a hypothetical product respondents must consider both the "good" and "bad" characteristics of the product in forming a preference. Thus, respondents must weigh all attributes simultaneously in making their judgments. Respondents can either rank-order the profiles in terms of preference or rate each combination on a preference scale (perhaps a 1–10 scale).

In our example, conjoint analysis assesses the relative impact of each brand name (HBAT versus generic), each form (powder versus liquid), and the different cleaning ingredients (phosphate-free versus phosphate-based) in determining a person's utility by evaluating the eight profiles. Each respondent was presented with eight descriptions of cleanser products (profiles) and asked to rank them in order of preference for purchase (1 = most preferred, 8 = least preferred). The eight profiles are described in Table S2-1, along with the rank orders given by two respondents.

This utility, which represents the total worth or overall preference of an object, can be thought of as the sum of what the product parts are worth, or **part-worths.** The general form of a conjoint model can be shown as

$$
\begin{aligned}
(\text{Total worth for product})_{ij\,.\,.\,.\,n_{ij}} = {} & \text{Part worth of level } i \text{ for factor } 1 \\
& + \text{Part worth of level } j \text{ for factor } 2 + \ldots \\
& + \text{Part worth of level } n \text{ for factor } m
\end{aligned}
$$

where the product or service has m attributes, each having n levels. The product consists of level i of factor 2, level j of factor 2, and so forth, up to level n for factor m.

In our example, the simplest model would represent the preference structure for the industrial cleanser determined by adding the three factors (utility = brand effect + ingredient effect + form effect). This format is known as an *additive model* and will be discussed in more detail in a later section. The preference for a specific cleanser product can be directly calculated from the part-worth values. For example, the preference for profile 1 described previously (HBAT phosphate-free powder) is defined as

TABLE S2-1 Profile Descriptions and Respondent Rankings for Conjoint Analysis of Industrial Cleanser Example

PROFILE DESCRIPTIONS	
Levels of:	*Respondent Rankings*

Profile #	Form	Ingredients	Brand	Respondent 1	Respondent 2
1	Liquid	Phosphate-free	HBAT	1	1
2	Liquid	Phosphate-free	Generic	2	2
3	Liquid	Phosphate-based	HBAT	5	3
4	Liquid	Phosphate-based	Generic	6	4
5	Powder	Phosphate-free	HBAT	3	7
6	Powder	Phosphate-free	Generic	4	5
7	Powder	Phosphate-based	HBAT	7	8
8	Powder	Phosphate-based	Generic	8	6

Note: The eight profiles represent all combinations of the three attributes, each with two levels (2 × 2 × 2).

Utility = Part-worth of HBAT brand

+ Part-worth of phosphate-free cleaning ingredient

+ Part-worth of powder

With the part-worth estimates, the preference of an individual can be estimated for any combination of factors. Moreover, the preference structure would reveal the factor(s) most important in determining overall utility and product choice. The choices of multiple respondents could also be combined to represent the real-world competitive environment.

Estimating Part-Worths

How do we estimate the part-worths for each level when we have only rankings or ratings of the profiles? The procedure is analogous to multiple regression with dummy variables or ANOVA, although other estimation techniques are also used, such as multinomial logit models. We should note that these calculations are done for each respondent separately. This approach differs markedly from other techniques where we deal with relationships across all respondents or group differences. More detail on the actual estimation process is provided for interested readers in the Basic Stats appendix on the text's Web sites (accessed through cengagebrain.co.uk or www.mvstats.com).

Table S2-2 provides the estimated part-worths for two respondents in our example. As we can see, each level has a unique part-worth estimate that reflects that level's contribution to utility when contained in a profile. In viewing part-worths for respondent 1, we can see that *Ingredients* seems to be most important because they have the largest impact on utility (part-worths). This differs from respondent 2, where the largest estimated part-worths relate to *Form*.

TABLE S2-2 Estimated Part-Worths and Factor Importance for Respondents 1 and 2

	Respondent 1			**Respondent 2**		
	Estimated Part-Worths	*Calculating Factor Importance*		*Estimated Part-Worths*	*Calculating Factor Importance*	
Factor Level	**Estimated Part-Worth**	**Range of Part-Worths**	**Factor Importance[a]**	**Estimated Part-Worth**	**Range of Part-Worths**	**Factor Importance[a]**
Form						
Liquid	+.756	1.512	28.6%	+1.612	3.224	66.7%
Powder	-.756			-1.612		
Ingredients						
Phosphate free	+1.511	3.022	57.1%	+.604	1.208	25.0%
Phosphate based	-1.511			-.604		

Brand						
HBAT	+.378	.756	14.3%	–.20	.400	8.3%
Generic	–.378			+.20		
Sum of Part-Worth Ranges		5.290			4.832	

[a]Factor importance is equal to the range of a factor divided by the sum of ranges across all factors, multiplied by 100 to get a percentage.

Determining Attribute Importance

Because the part-worth estimates are on a common scale, we can compute the relative importance of each factor directly. The importance of a factor is represented by the range of its levels (i.e., the difference between the highest and lowest values) divided by the sum of the ranges across all factors. This calculation provides a relative impact or importance of each attribute based on the size of the range of its part-worth estimates. Factors with a larger range for their part-worths have a greater impact on the calculated utility values, and thus are deemed of greater importance. The relative importance scores across all attributes will total 100 percent.

For example, for respondent 1, the ranges of the three attributes are 1.512 [.756 − (−.756)], 3.022 [1.511 − (−1.511)], and .756 [.378 − (−.378)]. The sum total of ranges is 5.290. From these, the relative importance for the three factors (form, ingredients, and brand) is calculated as 1.512/5.290, 3.022/5.290, and .756/5.290, or 28.6 percent, 57.1 percent, and 14.3 percent, respectively. We can follow the same procedure for the second respondent and calculate the importance of each factor, with the results of form (66.7%), ingredients (25%), and brand (8.3%). These calculations for respondents 1 and 2 are also shown in Table S2-2.

Assessing Predictive Accuracy

To examine the ability of this model to predict the actual choices of the respondents, we predict preference order by summing the part-worths for the profiles and then rank-ordering the resulting scores. Comparing the predicted preference order to the respondent's actual preference order assesses predictive accuracy. Note that the total part-worth values have no real meaning except as a means of developing the preference order and, as such, are not compared across respondents.

The calculations for both respondents for all eight profiles are shown in Table S2-3, along with the predicted and actual preference orders. Let's examine the results for these respondents to understand how well their preferences were represented by the part-worth estimates:

- *Respondent 1.* The estimated part-worths predict the preference order perfectly for this respondent. This result indicates that the preference structure was successfully represented in the part-worth estimates and that the respondent made choices consistent with the preference structure.
- *Respondent 2.* The inconsistency in rankings for respondent 2 prohibits a full representation of the preference structure. For example, the average rank for profiles with the generic brand is lower than those profiles with the HBAT brand (refer to Table S2-3). This result indicates that, all things being equal, the profiles with the generic brand will be more preferred. Yet, examining the actual rank orders, this response is not always seen. Profiles 1 and 2 are equal except for brand name, yet HBAT is more preferred. The same thing occurs for profiles 3 and 4. However, the correct ordering (generic preferred over HBAT) is seen for the profile pairs of 5–6 and 7–8. Thus, the preference structure of the part-worths will have a difficult time predicting this choice pattern. When we compare the actual and predicted rank orders (see Table 8-3), we see that respondent 2's choices are often incorrectly predicted, but most often miss by one position due to what is termed an *interaction effect* (discussed in a later section).

As you can see, the results of a conjoint analysis provide a complete understanding of the respondent's preference structure. Estimates are made not only of the utility of each level (e.g., Brand X versus Brand Y) but of the relative importance of factors as well (e.g., Ingredients versus Brand). This provides a unique insight into the choice process and the role of important factors.

TABLE S2-3 Predicted Part-Worth Totals for Each Profile and a Comparison of Actual and Estimated Preference Rankings

	Profile Description			*Part-Worth Estimates*				*Preference Rankings*	
Profile	**Form**	**Ingredients**	**Brand**	**Form**	**Ingredients**	**Brand**	**Total**	**Estimated**	**Actual**
Respondent 1									
1	Liquid	Phosphate-free	HBAT	.756	1.511	.378	2.645	1	1
2	Liquid	Phosphate-free	Generic	.756	1.511	−.378	1.889	2	2
3	Liquid	Phosphate-based	HBAT	.756	−1.511	.378	−.377	5	5
4	Liquid	Phosphate-based	Generic	.756	−1.511	−.378	−1.133	6	6
5	Powder	Phosphate-free	HBAT	−.756	1.511	.378	1.133	3	3
6	Powder	Phosphate-free	Generic	−.756	1.511	−.378	.377	4	4
7	Powder	Phosphate-based	HBAT	−.756	−1.511	.378	−1.889	7	7
8	Powder	Phosphate-based	Generic	−.756	−1.511	−.378	−2.645	8	8
Respondent 2									
1	Liquid	Phosphate-free	HBAT	1.612	.604	−.200	2.016	2	1
2	Liquid	Phosphate-free	Generic	1.612	.604	.200	2.416	1	2

3	Liquid	Phosphate-based	HBAT	1.612	−.604	−.200	.808	4	3
4	Liquid	Phosphate-based	Generic	1.612	−.604	.200	1.208	3	4
5	Powder	Phosphate-free	HBAT	−1.612	.604	−.200	−1.208	6	7
6	Powder	Phosphate-free	Generic	−1.612	.604	.200	−.808	5	5
7	Powder	Phosphate-based	HBAT	−1.612	−.604	−.200	−2.416	8	8
8	Powder	Phosphate-based	Generic	−1.612	−.604	.200	−2.016	7	6

THE MANAGERIAL USES OF CONJOINT ANALYSIS

Before discussing the statistical basis of conjoint analysis, we should understand the technique in terms of its role in understanding consumer decision making and providing a basis for strategy development [98]. The simple example we just discussed presents some of the basic benefits of conjoint analysis. The flexibility of conjoint analysis gives rise to its application in almost any area in which decisions are studied. Conjoint analysis assumes that any set of objects (e.g., brands, companies) or concepts (e.g., positioning, benefits, images) is evaluated as a bundle of attributes. Having determined the contribution of each factor to the consumer's overall evaluation, the researcher could then proceed with the following:

1. Define the object or concept with the optimum combination of features.
2. Show the relative contributions of each attribute and each level to the overall evaluation of the object.
3. Use estimates of purchaser or customer judgments to predict preferences among objects with differing sets of features (other things held constant).
4. Isolate groups of potential customers who place differing importance on the features to define high and low potential segments.
5. Identify marketing opportunities by exploring the market potential for feature combinations not currently available.

The knowledge of the preference structure for each individual allows the researcher almost unlimited flexibility in examining both individual and aggregate reactions to a wide range of product- or service-related issues. We examine some of the most popular applications later in this chapter.

COMPARING CONJOINT ANALYSIS WITH OTHER MULTIVARIATE METHODS

Conjoint analysis represents a hybrid type of multivariate technique for estimating dependence relationships. In one sense it combines traditional methods (i.e., regression and ANOVA), yet it is unique in that it is decompositional in nature and results can be estimated for each respondent separately. It offers the researcher an analysis tool developed specifically to understand consumer decisions and their preference structures. Conjoint analysis differs from other multivariate techniques in four distinct areas: (1) its decompositional nature, (2) specification of the variate, (3) the fact that estimates can be made at the individual level, and (4) its flexibility in terms of relationships between dependent and independent variables.

Compositional Versus Decompositional Techniques

Many of the dependence multivariate techniques we examined in previous chapters are termed **compositional models** (e.g., discriminant analysis and many regression applications). With these techniques, the researcher collects ratings from the respondent on many product characteristics (e.g., favorability toward color, style, specific features) and then relates these ratings to some overall preference rating to develop a predictive model. The researcher does not know beforehand the ratings on the product characteristics, but collects them from the respondent. With regression and discriminant analysis, the respondent's ratings and overall preferences are analyzed to "compose" the overall preference from the respondent's evaluations of the product on each attribute.

Conjoint analysis, a type of **decompositional model,** differs in that the researcher needs to know only a respondent's overall preference for a profile. The values of each attribute (levels act as the values of the independent variables) were already specified by the researcher when the profile was created. In this way, conjoint analysis can determine (decompose) the value of each attribute using only the overall preference measure. It should be noted that conjoint analysis does share one characteristic with compositional models in that the researcher does define the set of attributes to be included in the analysis. Thus, it differs in this regard with other decompositional models such as MDS (see Chapter S-3) which do not require specification of the attributes.

Specifying the Conjoint Variate

Conjoint analysis employs a variate quite similar in form to what is used in other multivariate techniques. The **conjoint variate** is a linear combination of effects of the independent variables (levels of each factor) on a dependent variable. The important difference is that in the conjoint variate the researcher specifies both the independent variables (factors) *and* their values (levels). The only information provided by the respondent is the dependent measure. The levels specified by the researcher are then used by conjoint analysis to decompose the respondent's response into effects for each level, much as is done in regression analysis for each independent variable.

This feature illustrates the common characteristics shared by conjoint analysis and experimentation, whereby designing the project is a critical step to success. For example, if a variable or effect was not anticipated in the research design, then it will not be available for analysis. For this reason, a researcher may be tempted to include a number of variables that might be relevant. However, conjoint analysis is limited in the number of variables it can include, so the researcher cannot just include additional questions to compensate for a lack of clear conceptualization of the problem.

Separate Models for Each Individual

Conjoint analysis differs from almost all other multivariate methods in that it can be carried out at the individual level, meaning that the researcher generates a separate model for predicting the preference structure of each respondent. Most other multivariate methods use each respondent's measures as a single observation and then perform the analysis using all respondents simultaneously. In fact, many methods require that a respondent provide only a single observation (the assumption of independence) and then develop a common model for all respondents, fitting each respondent with varying degrees of accuracy (represented by the errors of prediction for each observation, such as residuals in regression).

The ability to estimate models for each individual comes with the requirement, however, that consumers provide multiple evaluations of differing profiles. And as the number of factors and levels increase, the required number of profiles increases as well (see later section for more detailed discussion). But even the simplest situation, such as the cleanser example earlier, requires a substantial number of responses that quickly increase the difficulty of the conjoint task.

Although we have focused on estimates for the individual (disaggregate), estimates can also be made for groups of individuals representing a market segment or the entire market (aggregate). Each approach has distinct benefits. At the disaggregate level, each respondent must rate enough profiles for the analysis to be performed separately for each person. Predictive accuracy is calculated for each person, rather than only for the total sample. The individual results can then be aggregated to portray an overall (aggregate) model as well.

Many times, however, the researcher selects an aggregate analysis method that performs the estimation of part-worths for the group of respondents as a whole. Aggregate analysis can provide several advantages. First, it is a means for reducing the data collection task so that the number of evaluations per person is reduced (discussed in later sections). Second, methods for estimating interactions between factors (e.g., choice-based conjoint) are easily estimated with aggregate models. Third, greater statistical efficiency is gained by using more observations in the estimation process.

In selecting between aggregate and disaggregate conjoint analyses, the researcher must balance the benefits gained by aggregate methods versus the insights provided by the separate models for each respondent obtained by disaggregate methods.

Flexibility in Types of Relationships

Conjoint analysis is not limited at all in the types of relationships required between the dependent and independent variables. As discussed in earlier chapters, most dependence methods assume that a linear relationship exists when the dependent variable increases (or decreases) in equal amounts for each unit change in the independent variable. If any type of nonlinear relationship is to be represented, either the model form must be modified or specialized variables must be created (e.g., polynomials).

Conjoint analysis, however, can make separate predictions for the effects of each level of the independent variable and does not assume the levels are related at all. Conjoint analysis can easily handle nonlinear relationships—even the complex curvilinear relationship, in which one value is positive, the next negative, and the third positive again. Moreover, the types of relationships can vary between attributes. As we discuss later, however, the simplicity and flexibility of conjoint analysis compared with the other multivariate methods are based on a number of assumptions made by the researcher.

DESIGNING A CONJOINT ANALYSIS EXPERIMENT

The researcher applying conjoint analysis must make a number of key decisions in designing the experiment and analyzing its results. Figure S2-1 (stages 1–3) on pages 421–422 and Figure S2-4 (stages 4–7) show the general steps followed in the design and execution of a conjoint analysis experiment. The discussion follows the model-building paradigm introduced in Chapter 1.

The decision process is initiated with a specification of the objectives of conjoint analysis. Because conjoint analysis is similar to an experiment, the conceptualization of the research is critical to its success. After the defining the objectives, addressing the issues related to the actual research design, and evaluating the assumptions, the discussion looks at how the decision process then considers the actual estimation of the conjoint results, the interpretation of the results, and the methods used to validate the results. The discussion ends with an examination of the use of conjoint analysis results in further analyses, such as market segmentation and choice simulators.

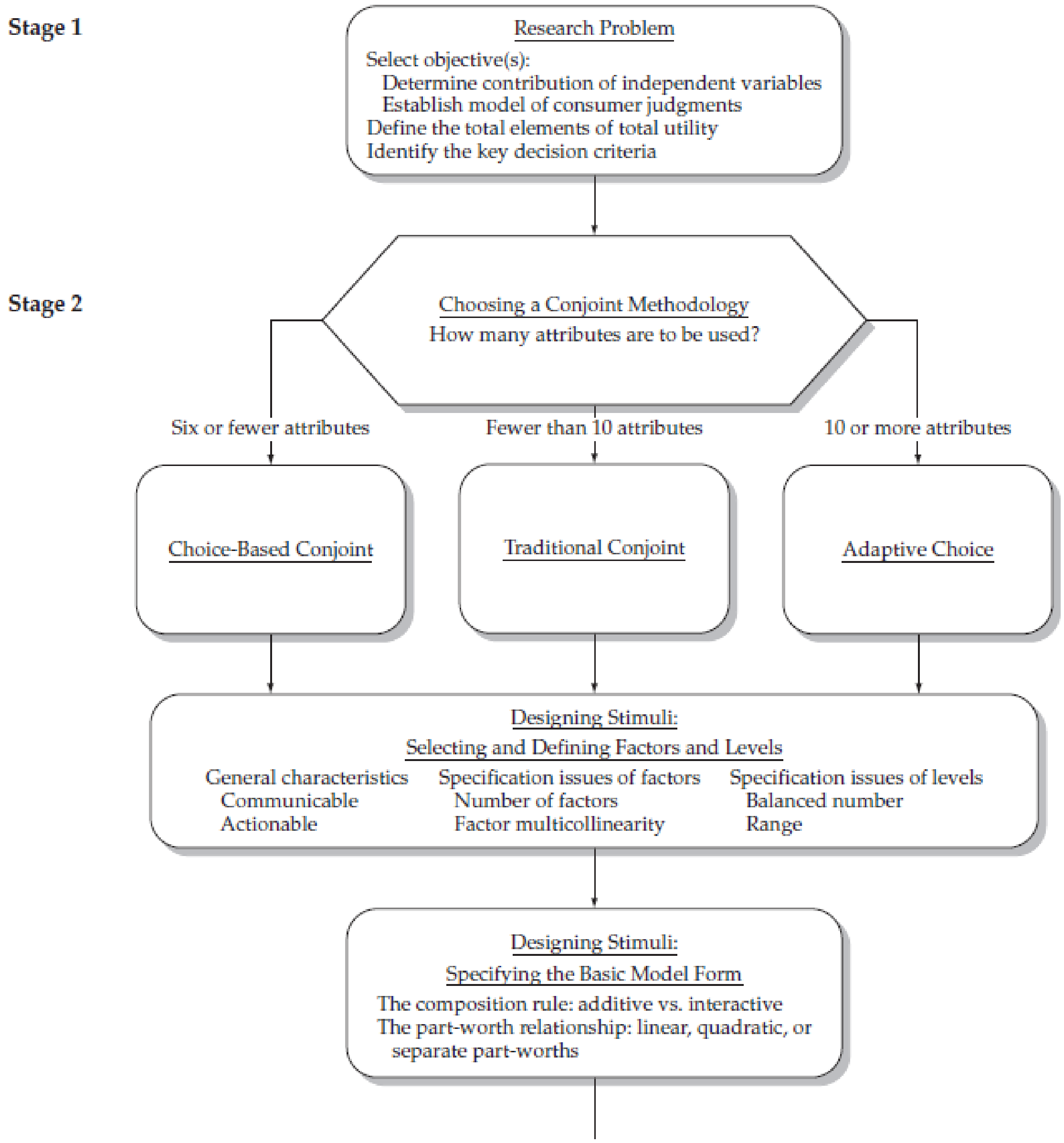

FIGURE S2-1 Stages 1–3 of the Conjoint Analysis Decision Diagram

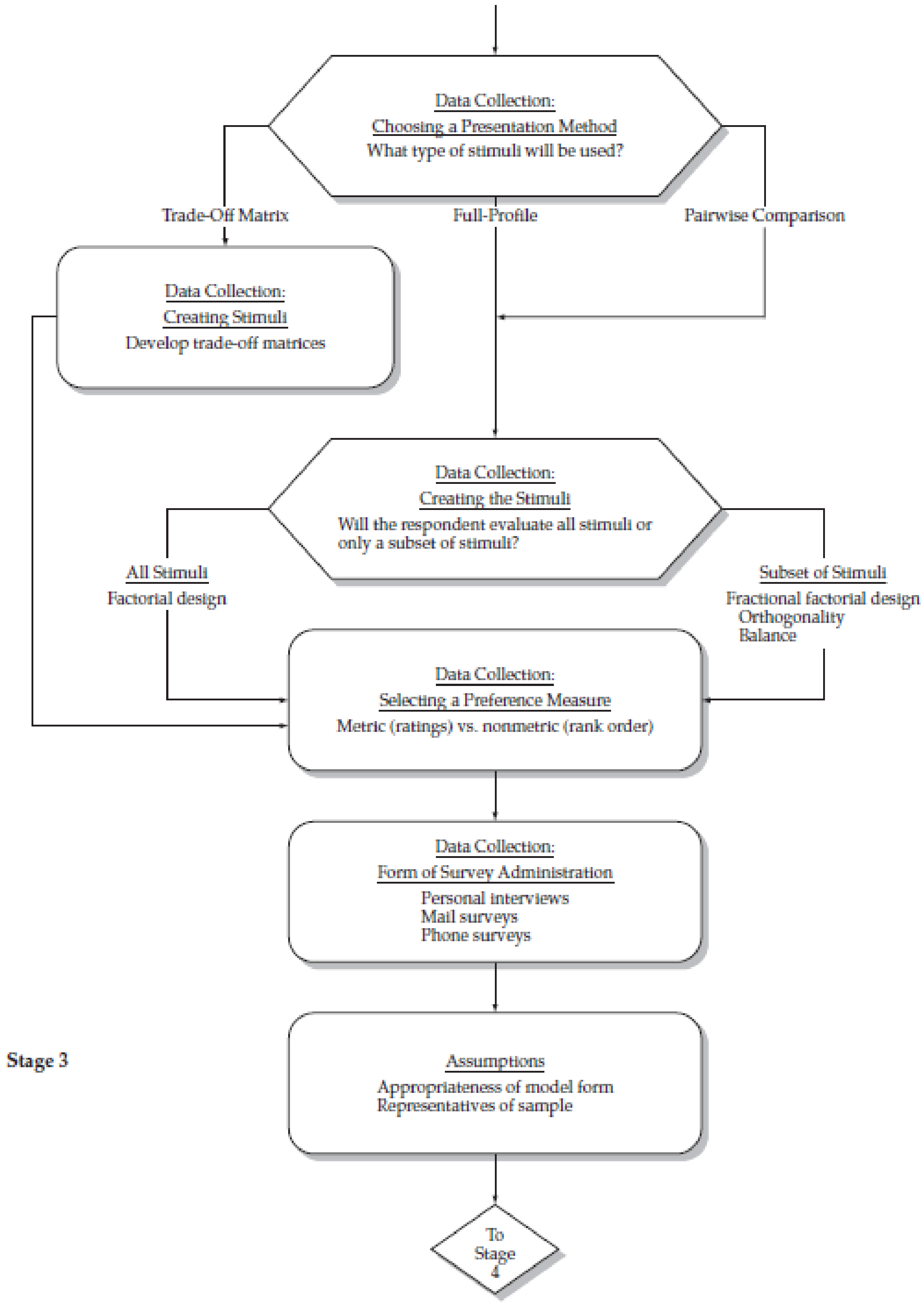

FIGURE S2-1 (continued)

Each of these decisions stems from the research question and the use of conjoint analysis as a tool in understanding the respondent's preferences and judgment process. We follow this discussion of the model-building approach by examining two alternative conjoint methodologies (choice-based and adaptive conjoint), which are then compared to the issues addressed here for traditional conjoint analysis.

STAGE 1: THE OBJECTIVES OF CONJOINT ANALYSIS

As with any statistical analysis, the starting point is the research question. In understanding consumer decisions, conjoint analysis meets two basic objectives:

1. *To determine the contributions of predictor variables and their levels in the determination of consumer preferences.* For example, how much does price contribute to the willingness to buy a product? Which price level is the best? How much change in the willingness to buy soap can be accounted for by differences between the levels of price?
2. *To establish a valid model of consumer judgments.* Valid models enable us to predict the consumer acceptance of any combination of attributes, even those not originally evaluated by consumers. In doing so, the issues addressed include the following: Do the respondents' choices indicate a simple linear relationship between the predictor variables and choices? Is a simple model of adding up the value of each attribute sufficient, or do we need to include more complex evaluations of preference to mirror the judgment process adequately?

The respondent reacts only to what the researcher provides in terms of profiles (attribute combinations). Are these the actual attributes used in making a decision? Are other attributes, particularly attributes of a more qualitative nature, such as emotional reactions, important as well? These and other considerations require the research question to be framed around two major issues:

- Is it possible to describe all the attributes that give utility or value to the product or service being studied?
- What are the key attributes involved in the choice process for this type of product or service?

These questions need to be resolved before proceeding into the design phase of a conjoint analysis because they provide critical guidance for key decisions in each stage.

Defining the Total Utility of the Object

The researcher must first be sure to define the total utility of the object. To represent the respondent's judgment process accurately, all attributes that potentially *create* or *detract* from the overall utility of the product or service should be included. It is essential that both positive and negative factors be considered. First, by focusing on only positive factors the research may seriously distort the respondents' judgments. A realistic choice task requires that the "good and bad" attributes be considered. Second, even if the researcher omits the negative factors, respondents can subconsciously employ them, either explicitly or through association with attributes that are included. In either instance, the researcher has an incomplete view of the factors that influenced the choice process.

Fortunately, the omission of a single factor typically can have only a minimal impact on the estimates for other factors when using an additive model [84], but the omission of a key attribute may still seriously distort the representation of the preference structure and diminish predictive accuracy.

Specifying the Determinant Factors

In addition, the researcher must be sure to include all determinant factors (drawn from the concept of determinant attributes [5]). The goal is to include the factors that best *differentiate* between the objects. Many attributes considered to be important may not differentiate in making choices because they do not vary substantially between objects.

RULES OF THUMB S2-1

Objectives of Conjoint Analysis

- Conjoint analysis is unique from other multivariate techniques in that:
  - It is a form of decompositional model that has many elements of an experiment
  - Consumers only provide overall preference rating for objects (stimuli) created by the researcher

- Stimuli are created by combining one level (value) from each factor (attribute)
- Each respondent evaluates enough stimuli so that conjoint results are estimated for each individual

- A "successful" conjoint analysis requires that the researcher:
  - Accurately define all of the attributes (factors) that have a positive and negative impact on preference
  - Apply the appropriate model of how consumers combine the values of individual attributes into overall evaluations of an object
- Conjoint analysis results can be used to:
  - Provide estimates of the "utility" of each level within each attribute
  - Define the total utility of any stimuli so that it can be compared to other stimuli to predict consumer choices (e.g., market share)

For example, safety in automobiles is an important attribute, but it may not be determinant in most cases because all cars meet strict government standards and thus are considered safe, at least at an acceptable level. However, other features, such as gas mileage, performance, or price, are important and much more likely to be used to decide among different car models. The researcher should always strive to identify the key *determinant* variables because they are pivotal in the actual judgment decision.

STAGE 2: THE DESIGN OF A CONJOINT ANALYSIS

Having resolved the issues stemming from the research objectives, the researcher shifts attention to the particular issues involved in designing and executing the conjoint analysis experiment. As described in the introductory section, four issues face a researcher in terms of research design:

1. Which of several alternative conjoint methods should be chosen? Conjoint analysis has three differing approaches to collecting and analyzing data, each with specific benefits and limitations.
2. With the conjoint method selected, the next issue centers on the composition and design of the profiles. What are the factors and levels to be used in defining utility? How are they to be combined into profiles?
3. A key benefit of conjoint analysis is its ability to represent many types of relationships in the conjoint variate. A crucial consideration is the type of effects that are to be included because they require modifications in the research design. **Main effects,** representing the direct impact of each attribute, can be augmented by **interaction effects,** which represent the unique impact of various combinations of attributes.
4. The last issue relates to data collection, specifically the type of preference measure to be used and the actual conjoint task faced by the respondent.

Note that the design issues are perhaps the most important phase in conjoint analysis. A poorly designed study cannot be “fixed” after administration if design flaws are discovered. Thus, the researcher must pay particular attention to the issues surrounding construction and administration of the conjoint experiment.

Selecting a Conjoint Analysis Methodology

After the researcher determines the basic attributes that constitute the utility of the product or service (object), a fundamental question must be resolved: Which of the three basic conjoint methodologies (traditional conjoint, adaptive conjoint, or choice-based conjoint) should be used [74]?

The choice of conjoint methodologies revolves around the basic characteristics of the proposed research: number of attributes handled, level of analysis, choice task, and the permitted model form. Table S2-4 compares the three methodologies on these considerations. As portrayed in the earlier example, **traditional conjoint analysis** is characterized by a simple additive model generally containing up to nine factors estimated for each individual. A respondent evaluates profiles constructed with selected levels from each attribute. Although this format has been the mainstay of conjoint studies for many years, two additional methodologies have been developed in an attempt to deal with certain design issues. The **adaptive conjoint method** was developed specifically to accommodate a large number of factors (many times up to 30), which would not be feasible in traditional conjoint analysis. It employs a computerized process that adapts the profiles shown to a respondent as the choice task proceeds. Moreover, the profiles can be composed of subsets of attributes, thus allowing for many more attributes. The **choice-based conjoint approach** employs a unique form of presenting profiles in sets (choose one profile from a set of profiles) rather than one by one. Due to the more complicated task, the number of factors included is more limited, but the approach does allow for inclusion of interactions and can be estimated at the aggregate or individual level.

Many times the research objectives create situations not handled well by traditional conjoint analysis, thus the use of these alternative methodologies. The issues of establishing the number of attributes and selecting the model form are discussed in greater detail in the following section, focusing on traditional conjoint analysis. Then, the unique characteristics of the two other methodologies are addressed in subsequent sections. The researcher should note that the basic issues discussed in this section apply to the two other methodologies as well.

Designing Profiles: Selecting and Defining Factors and Levels

The experimental foundations of conjoint analysis place great importance on the design of the profiles evaluated by respondents. The design involves specifying the conjoint variate by selecting the factors and levels to be included in constructing the profiles. Other issues relate to the general character of both factors, and levels as well as considerations are specific to each. These design issues are important, because they affect the effectiveness of the profiles in the task, the accuracy of the results, and ultimately their managerial relevance.

TABLE S2-4 A Comparison of Alternative Conjoint Methodologies

	Conjoint Methodology		
Characteristic	**Traditional Conjoint**	**Adaptive/Hybrid Conjoint**	**Choice-Based Conjoint**
Upper Limit on Number of Attributes	9	30	6
Level of Analysis	Individual	Individual	Aggregate or Individual
Model Form	Additive	Additive	Additive + Interaction
Choice Task	Evaluating Full-Profiles One at a Time	Rating Profile Containing Subsets of Attributes	Choice Between Sets of Profiles
Data Collection Format	Any Format	Generally Computer-Based	Any Format

GENERAL CHARACTERISTICS OF FACTORS AND LEVELS Before discussing the specific issues relating to factors or levels, characteristics applicable to the specification of factors and levels should be addressed. When operationalizing factors or levels, the researcher should ensure that the measures are both communicable and actionable.

Communicable Measures. First, the factors and levels must be easily communicated for a realistic evaluation. Traditional methods of administration (pencil and paper or computer) limit the types of factors that can be included. For example, it is difficult to describe the actual fragrance of a perfume or the "feel" of a hand lotion. Written descriptions do not capture sensory effects well unless the respondent sees the product firsthand, smells the fragrance, or uses the lotion. If respondents are unsure as to the nature of the attributes being used, then the results are not a true reflection of their preference structure.

One attempt to bring a more realistic portrayal of sensory characteristics that may have been excluded in the past involves specific forms of conjoint developed to employ virtual reality [83] or to engage the entire range of sensory and multimedia effects in describing the product or service [43, 57, 94]. Regardless of whether these approaches are used, the researcher must always be concerned about the communicability of the attributes and levels used.

Actionable Measures. The factors and levels also must be capable of being put into practice, meaning the attributes must be distinct and represent a concept that can be implemented precisely. Researchers should avoid using attributes that are hard to specify or quantify, such as overall quality or convenience. A fundamental aspect of conjoint analysis is that respondents trade off between attributes in evaluating a profile. If they are uncertain as to how one attribute compares to another attribute (e.g., one more precisely defined than the other), then the task cannot reflect the actual preference structure. Likewise, levels should not be specified in imprecise terms, such as low, moderate, or high. These specifications are imprecise because of the perceptual differences among individuals as to what they actually mean (as compared with actual differences as to how they feel about them).

If factors cannot be defined more precisely, the researcher may use a two-stage process. A preliminary conjoint study defines profiles in terms of more global or imprecise factors (quality or convenience). Then the factors identified as important in the preliminary study are included in the larger study in more precise terms.

SPECIFICATION ISSUES REGARDING FACTORS Having selected the attributes to be included as factors and ensured that the measures will be communicable and actionable, the researcher still must address three issues specific to defining factors: the number of factors to be included, multicollinearity among the factors, and the unique role of price as a factor. Specification of factors is a critical phase of research design because once a factor is included in a conjoint analysis choice task, it cannot be removed from the analysis. Respondents always evaluate sets of attributes collectively. Removal of an attribute in the estimation of the part-worths will invalidate the conjoint analysis.

Number of Factors. The number of factors included in the analysis affects the statistical efficiency and reliability of the results. Two limits come into play when considering the number of factors to be included in the study.

First, adding factors to a conjoint study always increases the minimum number of profiles in the conjoint design. This requirement is similar to those encountered in regression where the number of observations must exceed the number of estimated coefficients. A conjoint design with only a couple of factors is fairly simple, but the addition of factors can quickly make it a quite complex and arduous task for the respondent. The minimum number of profiles that must be evaluated by each respondent is:

$$\text{Minimum number of profiles} = \text{Total number of levels across all factors} \\ - \text{Number of factors} + 1$$

For example, a conjoint analysis with five factors with three levels each (a total of 15 levels) would need a minimum of 11 (15 − 5 + 1) profiles.

Even though it might seem that increasing the number of factors would reduce the number of profiles required (i.e., the number of factors is subtracted in the preceding equation), remember that each factor must have at least two levels (and many times more), such that an additional factor will always increase the number of profiles. Thus, in the previous example, adding one additional factor with three levels would necessitate at least two additional profiles. Some evidence indicates that traditional conjoint analysis techniques can employ a larger number of attributes (20 or so) than originally thought [82]. As we will discuss later, some techniques have been developed to specifically handle large numbers of attributes with specialized designs. Even in these situations, the researcher is cautioned to ensure that no matter how many attributes are included, it does not present too complex a task for the respondent.

Second, the number of profiles also must increase when modeling a more complex relationship, such as the case of adding interaction terms. Some reductions in profiles are possible by specialized conjoint designs, but the increased number of parameters to be estimated requires either a larger number of profiles or a reduction in the reliability of parameters.

It is especially important to note that conjoint analysis differs from other multivariate analyses in that the need for more profiles described above cannot be fixed by adding more respondents. In conjoint analysis, each respondent generates the required number of observations, and therefore the required number of stimuli is constant no matter how many respondents are analyzed. Specialized forms of estimation estimate aggregate models across individuals, thus requiring fewer stimuli per respondent, but in these cases the fundamental concept of obtaining conjoint estimates for each respondent is eliminated. We will discuss these options in greater detail in a later section.

Interattribute Correlation. A critical issue that many times goes undetected unless the researcher carefully examines all of the profiles in the conjoint design is the correlation among factors (known as **interattribute** or **environmental correlation**). In practical terms, the presence of correlated factors denotes a lack of conceptual independence among the factors. We first examine the effects of interattribute correlation on the conjoint design and then discuss several remedies.

When two or more factors are correlated, two direct outcomes occur. First, as in many other multivariate techniques, particularly multiple regression, the parameter estimates are affected (Chapter 4 contains a discussion of multicollinearity and its impact). Among the more problematic effects is the inability to obtain reliable estimates due to the lack of uniqueness for each level.

Perhaps the more important effect is the creation of unbelievable combinations of two or more factors that can distort the conjoint design. This issue typically occurs in two situations. The first is when two attributes are negatively correlated, such that consumers expect that high levels of one factor should be matched with low levels of another factor. Yet when levels from each are combined in the conjoint task, the profiles are not realistic. The problem lies not in the levels themselves but in the fact that they cannot realistically be paired in all combinations, which is required for parameter estimation. A simple example of unbelievable combinations is for horsepower and gas mileage. Although both attributes are quite valid when considered separately, many combinations of their levels are not believable. What is the realism of an automobile with the highest levels of both horsepower and gas mileage? Moreover, why would anyone consider an automobile with the lowest levels of horsepower and gas mileage?

The second situation where unbelievable combinations are formed occurs when one factor indicates presence/absence of a feature and another attribute indicates amount. In this situation the conjoint task includes profiles denoting that a feature is available/unavailable, with a second factor indicating the amount. Again, each factor is plausible when considered separately, yet when combined create profiles that are not possible and cannot be used in the analysis. An example of the problems caused by a presence/absence factor is when one factor indicates the presence/absence of a price discount and the second factor indicates the amount of the discount. The problem comes whenever profiles are constructed that indicate the absence of a price discount, yet the second factor specifies an amount. Including a level with the amount of zero only increases the problem, because now included profiles may indicate a price discount with the amount of zero. The result in each situation is an implausible profile.

Even though a researcher would always like to avoid an environmental correlation among factors, in some cases the attributes are essential to the conjoint analysis and must be included. When the correlated factors are retained, the researcher has three basic remedies to overcome the unrealistic profiles included in the conjoint design.

The most direct remedy is to create *superattributes* that combine the aspects of correlated attributes. Here the researcher takes the two factors and creates new levels that represent realistic amounts of both attributes. It is important to note that when these superattributes are added they should be made as actionable and specific as possible. If it is not possible to define the broader factor with the necessary level of specificity, then the researchers may be forced to eliminate one of the original factors from the design.

In our example of horsepower and gas mileage, perhaps a factor of "performance" could be substituted. In this instance levels of performance can be defined in terms of horsepower and gas mileage, but as realistic combinations in a single factor. As an example of positively correlated attributes, factors of store layout, lighting, and decor may be better addressed by a single concept, such as "store atmosphere." This factor designation avoids the unrealistic profiles of high levels of layout and lighting, but low levels of décor (along with other equally unbelievable combinations). When a presence/absence factor is utilized with another factor indicating amount, the most direct approach is to combine them into a single factor, with the levels including zero to indicate the absence of the attribute.

A second approach involves refined experimental designs and estimation techniques that create nearly orthogonal profiles, which can be used to eliminate any unbelievable profiles resulting from interattribute correlation [102]. Here the researcher can specify which combinations of levels (known as **prohibited pairs**) or even profiles of the orthogonal design are to be eliminated from the conjoint design, thus presenting respondents only with believable profiles. However, the danger in this approach is that poorly designed profiles will result in so large a number of unacceptable profiles that one or more of the correlated factors are effectively eliminated from the study, which then affects the part-worth estimates for that and all other factors.

The third remedy is to constrain the estimation of part-worths to conform to a prespecified relationship. These constraints can be between factors as well as pertaining to the levels within any single factor [100, 106]. Again, however, the researcher is placing restrictions on the estimation process, which may produce poor estimates of the preference structures.

Of the three remedies discussed, the creation of superattributes is the conceptually superior approach because it preserves the basic structure of the conjoint analysis. The other two remedies, which add significant complexity to the design and estimation of the conjoint analysis, should be considered only after the more direct remedy has been attempted.

The Unique Role of Price as a Factor. Price is a factor included in many conjoint studies because it represents a distinct component of value for many products or services being studied. Price, however, is not like other factors in its relationship to other factors [50]. We will first discuss the unique features of price and then address the approaches for the inclusion of price into a conjoint analysis.

Price is a principal element in any assessment of value and thus an attribute ideally suited to the trade-off nature of conjoint analysis. However, it is this basic nature of being an inherent trade-off that creates several issues with its inclusion. The most basic issue is that in many, if not most instances, price has a high degree of interattribute correlation with other factors. For many attributes, an increase in the amount of the attribute is associated with an increase in price, and a decreasing price level may be unrealistic (e.g., the price-quality relationship). The result is one or more profiles that are inappropriate for inclusion in the conjoint design (see earlier discussion of interattribute correlation for possible remedies).

Secondly, many times price is included in the attempt to represent value—the trade-off between the utility you get (the positive factors of quality, reliability, etc.) versus what you must give up; that is, price. Most times utility is defined by many factors whereas price is defined by only one factor. As a result, just due to the disparate number of factors there may be a decrease in the importance of price [77].

Finally, price may interact (i.e., have different effects for differing levels) when combined with other factors, particularly more intangible factors, such as brand name. An example is that a certain price level has different meanings for different brands [50, 77], one that applies to a premium brand and another for a discount brand. We discuss the concept of interactions later in this chapter.

All of these unique features of price as a factor should not cause a researcher to avoid the use of price, but instead to anticipate the impacts and adjust the design and interpretation as required. First, explicit forms of conjoint analysis, such as conjoint value analysis (CVA), have been developed for occasions in which the focus is on price [92]. Moreover, if interactions of price and other factors are considered important, methods such as choice-based conjoint or multistage analyses [77, 81, 112] provide quantitative estimates of these relationships. Even if no specific adjustment is made, the researcher should consider these issues in the definition of the price levels and in the interpretation of the results.

SPECIFICATION ISSUES REGARDING LEVELS The specification of levels is a critical aspect of conjoint analysis because the levels are the actual measures used to form the profiles. Thus, in addition to being actionable and communicable, research has shown that the number of levels, the balance in number of levels between factors, and the range of the levels within a factor all have distinct effects on the evaluations.

Number and Balance of Levels. The estimated relative importance of a variable tends to increase as the number of levels increases, even if the end points stay the same [52, 71, 110, 117, 118]. Known as the "number of levels effect," the refined categorization calls attention to the attribute and causes consumers to focus on that factor more than on others. Thus, researchers should attempt as best as possible to balance or equalize the number of levels across factors so as to not bias the conjoint task in favor of factors with more levels. If the relative importance of factors is known a priori, then the researcher may wish to expand the levels of the more important factors to avoid a dilution of importance and to capture additional information on the more important factors [116].

Range of Levels. The range (low to high) of the levels should be set somewhat outside existing values but not at an unbelievable level. This range should include all levels of interest because the results should never be extrapolated beyond the levels defined for an attribute [77]. Although this practice helps to reduce interattribute correlation, it also can reduce believability if the levels are set too extreme. Levels that are impractical, unbelievable, or that would never be used in realistic situations can artificially affect the results and should be eliminated.

Before excluding a level, however, the researcher must ensure that it is truly unacceptable, because many times people select products or services that have what they term unacceptable levels. If an unacceptable level is found after the experiment has been administered, the recommended solutions are either to eliminate all profiles that have unacceptable levels or to reduce part-worth estimates of the offending level to such a low level that any objects containing that level will not be chosen.

For example, assume that in the normal course of business activity, the range of prices varies about 10 percent around the average market price. If a price level 50 percent lower was included, but would not realistically be offered, its inclusion would markedly distort the results. Respondents would logically be most favorable to such a price level. When the part-worth estimates are made and the importance of price is calculated, price will artificially appear more important than it would actually be in day-to-day decisions.

Specifying the Basic Model Form

For conjoint analysis to explain a respondent's preference structure based only on overall evaluations of a set of profiles, the researcher must make two key decisions regarding the underlying conjoint model: specifying the composition rule to be used and selecting the type of relationships between part-worth estimates. These decisions affect both the design of the profiles and the analysis of respondent evaluations.

THE COMPOSITION RULE: SELECTING AN ADDITIVE VERSUS AN INTERACTIVE MODEL The most wide-ranging decision by the researcher involves the specification of the respondent's **composition rule.** The composition rule describes how the researcher postulates that the respondent combines the part-worths of the factors to obtain overall worth or utility. It is a critical decision because it defines the basic nature of the preference structure that will be estimated. In the following section, we discuss the basic elements of the most common composition rule—the additive model—and then address the issues involved in the addition of other forms of part-worth relationships known as interaction terms.

RULES OF THUMB S2-2

Designing the Conjoint Task

- Researchers must select one of three methodologies based on number of attributes, choice task requirements, and assumed consumer model of choice:
  - Traditional methods are best suited when the number of attributes is less than 10, results are desired for each individual, and the simplest model of consumer choice is applicable
  - Adaptive methods are best suited when larger numbers of attributes are involved (up to 30), but require computer-based interviews
  - Choice-based methods are considered the most realistic, can model more complex models of consumer choice, and have become the most popular, but are generally limited to six or fewer attributes
- The researcher faces a fundamental trade-off in the number of factors included:
  - Increase them to better reflect the "utility" of the object

    - Minimize them to reduce the complexity of the respondent's conjoint task and allow use of any of the three methods

- Specifying factors (attributes) and levels (values) of each factor must ensure that:
    - Factors and levels are distinct influences on preference defined in objective terms with minimal ambiguity, thereby generally eliminating emotional or aesthetic elements
    - Factors generally have the same number of levels
    - Interattribute correlations (e.g., acceleration and gas mileage) may be present at minimal levels (.20 or less) for realism, but higher levels must be accommodated by:
        - Creating a superattribute (e.g., performance)
        - Specifying prohibited pairs in the analysis to eliminate unrealistic stimuli (e.g., fast acceleration and outstanding gas mileage)
        - Constraining the model estimation to conform to prespecified relationships
    - Price requires special attention because:
    - It generally has interattribute correlations with most other attributes (e.g., price–quality relationship)
        - It uniquely represents in many situations what is traded off in cost for the object
        - Substantial interactions with other variables may require choice-based conjoint or multistage conjoint methods

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The Additive Model. The most common and basic composition rule is an **additive model.** It assumes the respondent simply adds the values for each attribute (i.e., the part-worths of the levels) to get the total value for a profile. Thus, the total utility of any defined profile is simply the sum of the part-worths.

For example, let us assume that a product has two factors (1 and 2), each with two levels each (A, B and C, D). The part-worths of factor 1 have been estimated at 2 and 4 (levels A and B), and factor 2 has part-worth values of 3 and 5 (levels C and D). We can then calculate the total utility of the four possible profiles as follows:

Profile	Levels Defining Profile	Additive Model Part-Worths	Total Utility
1	A and C	2 + 3	5
2	A and D	2 + 5	7
3	B and C	4 + 3	7
4	B and D	4 + 5	9

The additive model typically accounts for the majority (up to 80% or 90%) of the variation in preference in almost all cases, and it suffices for most applications. It is also the basic model underlying both traditional and adaptive conjoint analysis (see Table S2-4).

Adding Interaction Effects. The composition rule using interaction effects is similar to the additive form in that it assumes the consumer sums the part-worths to get an overall total across the set of attributes. It differs in that it allows for certain combinations of levels to be more or less than just their sum. The interactive composition rule corresponds to the statement, “The whole is greater (or less) than the sum of its parts.” Let’s revisit one of our earlier examples to see how interaction effects impact utility scores.

In our industrial cleanser example, let us examine the results for respondent 2 (refer back to Table S2-3). In the estimated part-worths, the Generic brand was preferred over HBAT, phosphate-free over phosphate-based ingredients, and liquid over powder form. But the respondent’s results are not always this consistent. As discussed earlier, for profiles 5 through 8 the respondent always preferred profiles with the Generic brand over profiles with the HBAT brand, all other things held constant. But the reverse is true with profiles 1 through 4. What differs between these two sets of profiles? Looking at Table S2-3 we see that profiles 1–4 contain the liquid form, whereas profiles 5–8 contain the powder form. Thus, it looks like respondent 2’s preferences for brand differ depending whether the profile contains a liquid or powder form. In this case, we say that the factors of Brand and Form interact, such that one or more combinations of these factors result in much higher or lower ratings than expected. Without including this interaction effect the estimated and actual preference rankings will not match.

With the ability of interaction terms to add generalizability to the composition rule, why not use the interactive model in all cases? The addition of interaction terms does have some drawbacks that must be considered. First, each interaction term requires an additional part-worth estimate with at least one additional profile for each respondent to evaluate. Unless the researcher knows exactly which interaction terms to estimate, the number of profiles rises dramatically. Moreover, if respondents do not utilize an interactive model, estimating the additional interaction terms in the conjoint variate reduces the statistical efficiency (more part-worth estimates) of the estimation process as well as making the conjoint task more arduous. Second, from a practical perspective, interactions (when present) predict substantially less variance than the additive effects, most often not exceeding a 5- to 10-percent increase in explained variance. Interaction terms are most likely to be substantial in cases for which attributes are less tangible, particularly when aesthetic or emotional reactions play a large role. Thus, in many instances the increased predictive power will be minimal.

The researcher must balance the potential for increased explanation from interaction terms with the negative consequences from adding interaction terms. The interaction term is most effective when the researcher can hypothesize that "unexplained" portions of utility are associated with only certain levels of an attribute. Interested readers are referred to the text's Web sites (accessed through cengagebrain.co.uk or www.mvstats.com) for a more detailed examination of how to identify interactions terms and their impact on part-worth estimates and predictive accuracy.

Selecting the Model Type. The choice of a composition rule (additive only or with interaction effects) determines the types and number of treatments or profiles that the respondent must evaluate, along with the form of estimation method used. As discussed earlier, trade-offs between the two approaches need to be considered. An additive form requires fewer evaluations from the respondent, and it is easier to obtain estimates for the part-worths. However, the interactive form is a more accurate representation when respondents utilize more complex decision rules in evaluating a product or service. This choice must be made before the data is collected in order to design the set of profiles correctly.

SELECTING THE PART-WORTH RELATIONSHIP: LINEAR, QUADRATIC, OR SEPARATE PART-WORTHS The flexibility of conjoint analysis in handling different types of variables comes from the assumptions the researcher makes regarding the relationships of the part-worths within a factor. In making decisions about the composition rule, the researcher decides how factors relate to one another in the respondent's preference structure. In defining the type of part-worth relationship, the researcher focuses on how the levels of a factor are related.

Types of Part-Worth Relationships. Conjoint analysis gives the researcher three alternatives, ranging from the most restrictive (a linear relationship) to the least restrictive (separate part-worths), with the ideal point, or quadratic model, falling in between. Figure S2-2 illustrates the differences among the three types of relationships.

The *linear model* is the simplest yet most restricted form, because we estimate only a single part-worth (similar to a regression coefficient), which is multiplied by the level's value to arrive at a part-worth value for each level. In the *quadratic form,* also known as the *ideal model,* the assumption of strict linearity is relaxed, so that we have a simple curvilinear relationship. The curve can turn either upward or downward. Finally, the *separate part-worth form* (often referred to simply as the *part-worth form*) is the most general, allowing for separate estimates for each level. When using separate part-worths, the number of estimated values is the highest because a separate parameter is estimated for each level.

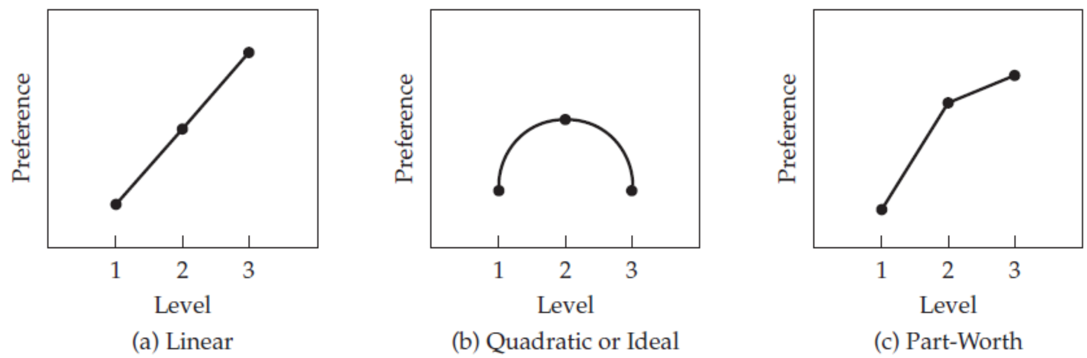

FIGURE S2-2 Three Basic Types of Relationships Between Factor Levels in Conjoint Analysis

The form of part-worth relationship can be specified for each factor separately such that each factor takes on a different part-worth relationship. This choice does not affect how the profiles are created and part-worth values are still calculated for each level. It does, however, affect how and what types of part-worths are estimated by conjoint analysis. If we can reduce the number of parameters estimated for any given set of profiles by using a more restricted part-worth relationship (e.g., linear or quadratic form), the calculations will be more efficient and reliable from a statistical estimation perspective.

Selecting a Part-Worth Relationship. The researcher must consider the trade-off between the gains in statistical efficiency by using the linear or quadratic forms versus the potentially more accurate representation of how the consumer actually forms overall preference if we employ less restrictive part-worth relationships. The researcher has several approaches to deciding on the type of relationship for each factor.

The primary support for any part-worth relationship should be from prior research or conceptual models. In this way, a researcher may be able to specify a linear or quadratic relationship to achieve not only statistical efficiency, but also consistency with the research question. If adequate conceptual support is not available, the researcher may follow a more empirical approach. Here the conjoint model is estimated first as a part-worth model. Then the different part-worth estimates are examined visually to detect whether a linear or a quadratic form is appropriate. In many instances, the general form is apparent, and the model can be reestimated with relationships specified for each variable as justified. When different relationships seem reasonable and with support, then the relationship type maximizing predictive ability would be chosen. An empirical approach is not recommended without at least some theoretical or empirical evidence for the possible type of relationship considered. Without such support, the results may have high predictive ability but be of little use in decision making.

Analyzing and Interpreting the Separate Part-Worth Relationship. The separate part-worth relationship may seem like the logical option in all instances, but the researcher must realize that this flexibility in the form of the relationship may also create difficulties in estimation or interpretation. These problems occur whenever the researcher expects some form of **monotonic relationship** to exist among the levels (i.e., some form of ordered preference is present among the levels) without specifying the actual form of this relationship (e.g., linear or quadratic). Let us look at an example to see where these problems might occur.

Assume that we have a simple conjoint analysis addressing store patronage with two factors (store type and travel distance to store). We can estimate both sets of part-worths with the separate part-worth relationship. For the store type factor, the part-worth estimates represent the relative utility of each type of store with no predefined ordering of which store must be preferred over another. With distance, the most likely assumption is that closer distance would be preferred over a farther distance. At the very least, farther distances should not be more preferred than short distances. Yet when we employ a separate part-worth relationship, the part-worths method lacks the predefined pattern of the linear or quadratic relationship. We may find that the estimated part-worths do not follow the prescribed pattern for one or more levels, due most likely to inconsistencies in the responses. Three miles away, for example, may have a higher part-worth utility than 1 mile away, which seems illogical.

The researcher must always be aware of the possibility of these violations of the monotonic relationship (known as *reversals*) and examine the results to ascertain the severity of any occurrences. We discuss this issue in more detail when discussing estimation (where remedies are possible) and in the interpretation of the part-worths themselves.

Data Collection

Having specified the factors and levels, plus the basic model form and the relationships among part-worth estimates, the researcher must next make three decisions involving data collection: type of presentation method for the factors (trade-off, full-profile, or pairwise comparison), type of response variable, and the method of data collection. The overriding objective is to present the attribute combinations to the respondent in the most realistic and efficient manner possible. Most often they are presented in written descriptions, although physical or pictorial models can be quite useful for aesthetic or sensory attributes.

RULES OF THUMB S2-3

Specifying Model Form and Part-Worth Relationships

- Researchers can choose between two basic model forms based on the assumed composition rule for individuals:
  - Additive model: Assumes the simplest type of composition rule (utility for each attribute is simply added up to get overall utility) and requires the simplest choice task and estimation procedures
  - Interactive model: Adds interaction terms between attributes to more realistically portray the composition rule, but requires a more complex choice task for the respondent and estimation procedure

- Additive models generally suffice for most situations and are the most widely used

- Estimating the utility of each level (known as part-worths) can follow one of three relationships:
  - Linear: Requires that the part-worths be linearly related, but may be unrealistic to expect for specific types of attributes
  - Quadratic: Most appropriate when an "ideal point" in the attribute levels is expected
  - Separate: Makes each part-worth estimate independently of other levels, but is most likely to encounter reversals (violations of the hypothesized relationship)

CHOOSING A PRESENTATION METHOD Three methods of profile presentation are most widely associated with conjoint analysis. Although they differ markedly in the form and amount of information presented to the respondent (see Figure S2-3), they all are acceptable within the traditional conjoint model. The choice between presentation methods focuses on the assumptions as to the extent of consumer processing being performed during the conjoint task and the type of estimation process being employed.

Full-Profile Method. The most popular presentation method is the **full-profile method** principally because of its perceived realism as well as its ability to reduce the number of comparisons through the use of fractional factorial designs. In this approach, each profile is described separately, most often using a profile card (see Figure S2-3b). This approach elicits fewer judgments, but each is more complex, and the judgments can be either ranked or rated. Its advantages include a more realistic description achieved by defining a profile in terms of a level for each factor and a more explicit portrayal of the trade-offs among all factors and the existing environmental correlations among the attributes. It is also possible to use more types of preference judgments, such as intentions to buy, likelihood of trial, and chances of switching—all difficult to answer with the other methods.

The full-profile method is not flawless and faces two major limitations based on the respondents' ability and capacity to make reasoned decisions. First, as the number of factors increases, so does the possibility of information overload. The respondent is tempted to simplify the process by focusing on only a few factors, when in an actual situation all factors would be considered. Second, the order in which factors are listed on the profile card may have an impact on the evaluation. Thus, the researcher needs to rotate the factors across respondents when possible to minimize order effects.

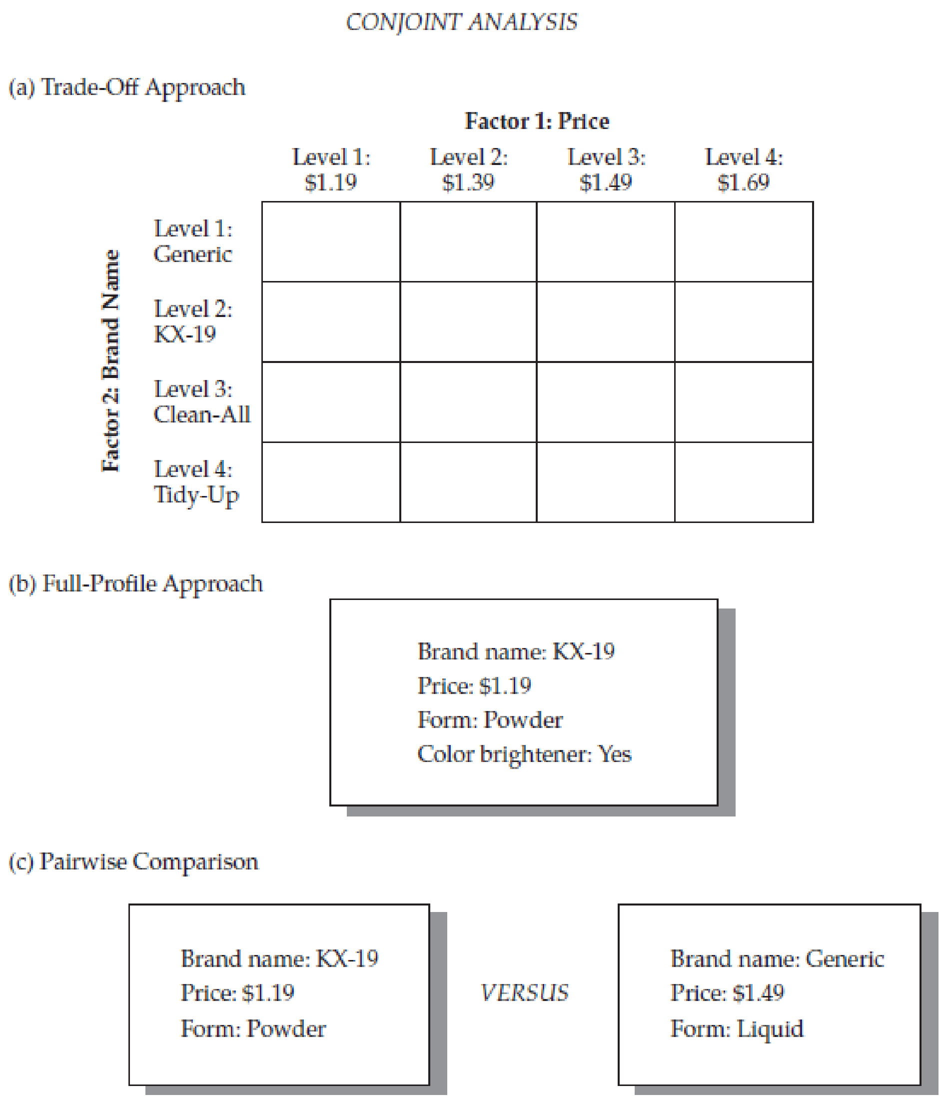

FIGURE S2-3 Examples of the Trade-Off and Full-Profile Methods of Presenting Stimuli

number of factors ranges from 7 to 10, the trade-off approach becomes a possible option to the full-profile method. If the number of factors exceeds 10, then alternative methods (adaptive conjoint) are suggested [29].

The Pairwise Combination Presentation. The second presentation method, the **pairwise comparison method,** involves a comparison of two profiles (see Figure S2-3c), with the respondent most often using a rating scale to indicate strength of preference for one profile over the other [46]. The distinguishing characteristic of the pairwise comparison is that the profile typically does not contain all the attributes, as does the full-profile method. Instead only a few attributes at a time are selected in constructing profiles in order to simplify the task if the number of attributes is large. The researcher must be careful to not take this characteristic to the extreme and portray profiles with too few attributes to realistically portray the objects.

The pairwise comparison method is also instrumental in many specialized conjoint designs, such as Adaptive Conjoint Analysis (ACA) [87], which is used in conjunction with a large number of attributes (a more detailed discussion of dealing with a large number of attributes appears later in this chapter).

Trade-Off Presentation. The final method is the trade-off approach, which compares attributes two at a time by ranking all combinations of levels (see Figure 8-3a). It has the advantages of being simple for the respondent and easy to administer, and it avoids information overload by presenting only two attributes at a time. It was the most widely used form of presentation in the early years of conjoint analysis. Usage of this method has decreased dramatically in recent years, however, owing to several limitations. Most limiting is the sacrifice in realism by using only two factors at a time, which also makes a large number of judgments necessary for even a small number of levels. Respondents have a tendency to get confused or follow a routinized response pattern because of fatigue. It is also limited to only nonmetric responses and cannot use fractional factorial designs to reduce the number of comparisons necessary. It is rarely used in conjoint studies except in specialized designs [118].

CREATING THE PROFILES Once the factors and levels have been selected and the presentation method chosen, the researcher turns to the task of creating the profiles for evaluation by the respondents. For any presentation method, the researcher always faces increasing the burden on the respondent as the number of profiles increases to handle more factors or levels. The researcher must weigh the benefits of increased task effort versus the additional information gained. The following discussion focuses on creating profiles for the full-profile or pairwise comparison approaches. The trade-off approach is not addressed due to its limited use.

These two approaches involve the evaluation of one profile at a time (full-profile) or pairs of profiles (pairwise comparison). In a simple conjoint analysis with a small number of factors and levels (such as those discussed earlier for which three factors with two levels each resulted in eight combinations), the respondent evaluates all possible profiles. This format is known as a **factorial design.**

As the number of factors and levels increases, this design can quickly become impractical. For example, if the conjoint task involves four variables with four levels for each variable, 256 profiles (4 levels × 4 levels × 4 levels × 4 levels) would be created in a full factorial design. Even if the number of levels decreases, a moderate number of factors can create a difficult task. For a situation with six factors and two levels each, 64 profiles would be needed. If the number of levels increased just to three for the six factors, then the number of profiles would increase to 729. These situations obviously include too many profiles for one respondent to evaluate and still give consistent, meaningful answers. An even greater number of pairs of profiles would be created for the pairwise combinations of profiles with differing numbers of attributes.

In addition to the limitations of the respondent, the number of profiles must also be large enough to derive stable part-worth estimates. The minimum number of profiles equals the number of parameters to be estimated, calculated as:

Number of estimated parameters = Total number of levels − Number of attributes + 1

It is suggested that the respondent evaluate a set of profiles equal to a multiple of (two or three times) the number of parameters. Yet as the number of levels and attributes increases, the respondent burden increases quickly. Research has shown that respondents can complete up to 30 choice tasks, but after that point the quality of the data may come into question [92]. The researcher then faces a dilemma: Increasing the complexity of the choice tasks by adding more levels and/or factors increases the number of estimated parameters and the recommended number of choice tasks. Against this the researcher must consider the limit on the number of choice tasks that can be completed by a respondent, which vary by type of presentation method and complexity of the profiles.

DEFINING SUBSETS OF PROFILES Many times, as discussed above, the number of profiles in the full factorial design becomes too large and must be reduced. The process of selecting a subset of all possible profiles must be done in a manner to preserve the **orthogonality** (no correlation among levels of an attribute) and **balanced design** aspect (each level in a factor appears the same number of times). Two approaches are available for selecting the subset of profiles that still meet these criteria.

Fractional Factorial. A **fractional factorial design** is the most common method for defining a subset of profiles for evaluation. The process designs a sample of possible profiles, with the number of profiles depending on the type of composition rule assumed to be used by respondents. Using the additive model, which assumes only main effects with no interactions, the full-profile method with four factors at four levels requires only 16 profiles to estimate the main effects. Table 8-5 shows two possible sets of 16 profiles. The sets of profiles must be carefully constructed to ensure the correct estimation of the main effects. The two designs in Table S2-5 are **optimal designs,** meaning they are orthogonal and balanced.

The remaining 240 possible profiles in our example that are not in the selected fractional factorial design are used to estimate interaction terms if desired. If the researcher decides that selected interactions are important and should be included in the model estimation, the fractional factorial design must include additional profiles to accommodate the interactions. Published guides for fractional factorial designs or conjoint program components will design the subsets of profiles to maintain orthogonality, making the generation of full-profile profiles quite easy [1, 17, 33, 65].

Bridging Design. If the number of factors becomes too large and the adaptive conjoint methodology is not acceptable, a **bridging design** can be employed [8]. In this design, the factors are divided in subsets of appropriate size, with some attributes overlapping between the sets so that each set has a factor(s) in common with other sets of factors. The profiles are then constructed for each subset so that the respondents never see the original number of factors in a single profile. When the part-worths are estimated, the separate sets of profiles are combined, and a single set of estimates is provided. Computer programs handle the division of the attributes, creation of profiles, and their recombination for estimation [12]. When using pairwise comparisons, the number may be quite large and complex, so that most often interactive computer programs are used that select the optimal sets of pairs as the questioning proceeds.

TABLE S2-5 Two Alternative Fractional Factorial Designs for an Additive Model (Main Effects Only) with Four Factors at Four Levels Each

	Design 1: Levels for . . . [a]				*Design 2: Levels for . . .* [a]			
Profile	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
1	3	2	3	1	2	3	1	4
2	3	1	2	4	4	1	2	4
3	2	2	1	2	3	3	2	1
4	4	2	2	3	2	2	4	1
5	1	1	1	1	1	1	1	1
6	4	3	4	1	1	4	4	4
7	1	3	2	2	4	2	1	3
8	2	1	4	3	2	4	2	3
9	2	4	2	1	3	2	3	4
10	3	3	1	3	3	4	1	2
11	1	4	3	3	4	3	4	2
12	3	4	4	2	1	3	3	3
13	1	2	4	4	2	1	3	2
14	2	3	3	4	3	1	4	3
15	4	4	1	4	1	2	2	2
16	4	1	3	2	4	4	3	1

[a]The numbers in the columns under factor 1 though factor 4 are the levels of each factor. For example, the first profile in design 1 consists of level 3 for factor 1, level 2 for factor 2, level 3 for factor 3, and level 1 for factor 4.

UNACCEPTABLE PROFILES The creation of any design, even those with orthogonality and balance, does not mean, however, that all of the profiles in that design will be acceptable for evaluation. We will first discuss the most common reasons for the occurrence of unacceptable profiles and then address the potential remedies.

The most common reason for unacceptable profiles is the creation of "obvious" profiles—profiles whose evaluation is obvious because of their combination of levels. Typical examples of unacceptable profiles are those with all levels at either the highest or lowest values. These profiles really provide little information about choice and can create a perception of unbelievability on the part of the respondent. The second reason is interattribute correlation, which can create profiles with combinations of levels (high gas mileage, high acceleration) that are not realistic. Finally, external constraints may be placed on the combinations of attributes. The research setting may preclude certain combinations as unacceptable (i.e., certain attributes cannot be combined) or inappropriate (e.g., certain levels cannot be combined). In either instance, the attributes and levels are important to the research question, but certain combinations must be excluded.

In any of these instances, the unacceptable profiles present unrealistic choices to the respondent and should be eliminated to ensure a valid estimation process as well as a perception of credibility of the choice task among the respondents. Several courses of action help eliminate unacceptable profiles. First, the researcher can generate another fractional factorial design and assess the acceptability of its profiles. Because many fractional factorial designs are possible from any larger set of profiles, it may be possible to identify one that does not contain any unacceptable profiles. If all designs contain unacceptable profiles and a better alternative design cannot be found, then the unacceptable profile can be deleted. Although the design will not be totally orthogonal (i.e., it will be somewhat correlated and is termed to be **nearly orthogonal**), it will not violate any assumptions of conjoint analysis. Many conjoint programs also have an option to exclude certain combinations of levels (known as *prohibited pairs*). In these instances, the program attempts to create a set of profiles that is as close as possible to optimal, but it should be noted that this option cannot overcome design flaws in the specification of factors or levels. In instances in which a systemic problem exists, the researcher should not be comforted by a program that can generate a set of profiles, because the resulting fractional factorial design may still have serious biases (low orthogonality or balance) that can impact the part-worth estimation.

All nearly orthogonal designs should be assessed for **design efficiency,** which is a measure of the correspondence of the design in terms of orthogonality and balance to an optimal design [55]. Typically measured on a 100-point scale (optimal designs = 100), alternative nonorthogonal designs can be assessed, and the most efficient design with all acceptable profiles selected. Most conjoint programs for developing nearly orthogonal designs assess the efficiency of the designs [54].

Unacceptable profiles due to interattribute correlations are a unique case and must be accommodated within the development of designs on a conceptual basis. In practical terms, interattribute correlations should be minimized but they do not need to be zero if small correlations (.20 or less) will add to realism. Most problems are found in the case of negative correlations, as between gas mileage and horsepower. Adding uncorrelated factors can reduce the average interattribute correlation, so that with a realistic number of factors (e.g., 6 factors) the average correlation would be close to .20, which has relatively inconsequential effects. The researcher should always assess the believability of the profiles as a measure of practical relevance.

SELECTING A MEASURE OF CONSUMER PREFERENCE The researcher must also select the measure of preference: rank-ordering versus rating (e.g., a 1–10 scale). Both the pairwise comparison and full-profile methods can evaluate preferences either by obtaining a rating of preference of one profile over the other or just a binary measure of which is preferred.

Using a Rank-Order Preference Measure. Each preference measure has certain advantages and limitations. Obtaining a rank-order preference measure (i.e., rank-ordering the profiles from most to least preferred) has two major advantages: (1) it is likely to be more reliable because ranking is easier than rating with a reasonably small number (20 or fewer) of profiles, and (2) it provides more flexibility in estimating different types of composition rules.

It has, however, one major drawback: It is difficult to administer, because the ranking process is most commonly performed by sorting profile cards into the preference order, and this sorting can be done only in a personal interview setting.

Measuring Preference by Ratings. The alternative is to obtain a rating of preference on a metric scale. Metric measures are easily analyzed and administered, even by mail, and enable conjoint estimation to be performed by multivariate regression. However, respondents can be less discriminating in their judgments than when they are rank-ordering. Also, given the large number of profiles evaluated, it is useful to expand the number of response categories over that found in most consumer surveys. A rule of thumb is to have 11 categories (i.e., rating from 0 to 10 or 0 to 100 in increments of 10) for 16 or fewer profiles and expand to 21 categories for more than 16 profiles [58].

Choosing the Preference Measure. The decision on the type of preference measure to be used must be based on practical as well as conceptual issues. Many researchers favor the rank-order measure because it depicts the underlying choice process inherent in conjoint analysis: choosing among objects. From a practical perspective, however, the effort of ranking large numbers of profiles becomes overwhelming, particularly when the data collection is done in a setting other than personal interview.

The ratings measure has the inherent advantage of being easy to administer in any type of data collection context, yet it too has drawbacks. If the respondents are not engaged and involved in the choice task, a ratings measure may provide little differentiation among profiles (e.g., all profiles rated about the same). Moreover, as the choice task becomes more involved with additional profiles, the researcher must be concerned with not only task fatigue, but reliability of the ratings across the profiles.

SAMPLE SIZE Conjoint analysis represents a somewhat unique situation with regard to determining the sample size requirements. First, as mentioned before, improving the accuracy of the part-worth estimates for an individual relates to the number of choice tasks (i.e., profiles rated) performed by each respondent. So theoretically a conjoint analysis can be estimated with one respondent if that respondent provided enough choice tasks (see earlier discussion on number of choice tasks required).

So is sample size irrelevant for conjoint analysis? The answer depends on the research objective being addressed. Although each respondent is estimated separately in a disaggregate approach, the research still must consider the degree to which the respondents are representative of the population of interest. The required sample size needed relates to what the choices reflect (e.g., purchase/no purchase or market share) and how accurate you want that prediction to be. Here the conventional procedures for estimating confidence intervals based on sample size now come into play. If a specific confidence interval is desired (i.e., ± error rate), then estimating the standard error of the estimate provides the necessary sample size. Given the typical applications of conjoint analysis, sample sizes of 200 have been found to provide an acceptable margin of error. We should note that this relates to each group in the population, so if you are expecting to segment the population you should try and have sample sizes of 200 for each group. But small-scale studies with as few as 50 respondents can provide a glimpse into the preferences of respondents and how they might vary in basic ways.

SURVEY ADMINISTRATION In the past, the complexity of the conjoint analysis task led most often to the use of personal interviews to obtain the conjoint responses. Personal interviews enable the interviewer to explain the sometimes more difficult tasks associated with conjoint analysis. Recent developments in interviewing methods, however, make conducting conjoint analyses feasible both through the mail (with pencil-and-paper questionnaires or computer-based surveys) and by telephone. If the survey is designed to ensure that the respondent can assimilate and process the profiles properly, then all of the interviewing methods produce relatively equal predictive accuracy [2]. The use of computerized interviewing has greatly simplified the conjoint task demands on the respondent and made the administration of full-profile designs feasible [79, 113] while also accommodating even adaptive conjoint analysis [87]. Recent research even demonstrated the reliability and validity of full-profile conjoint when administered over the Internet [80].

RULES OF THUMB S2-4

Data Collection

- Data collection by traditional methods of conjoint analysis:
  - Generally is accomplished with some form of full-profile approach using a stimulus defined on all attributes
  - Increasing the number of factors and/or levels above the simplest task (two or three factors with only two or three levels each) requires some form of fractional factorial design that specifies a statistically valid set of stimuli
- Alternative methodologies (adaptive or choice-based methods) discussed in later sections provide options in terms of the complexity and realism of the choice task that can be accommodated
- Respondents should be limited to evaluating no more than 30 stimuli, regardless of the methodology used
- The estimation of an individual's part-worths is related to the number of choice tasks a respondent completes, not the sample size of respondents
- Sample size impacts the ability of the respondents to represent the population. Fifty respondents is suggested as the minimum sample size, and the recommended sample size is at least 200 per group
- If multiple groups are going to be formed from the respondents (e.g., with cluster analysis to iden-

tify segments), then the sample size considerations apply to each group

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One concern in any conjoint study is the burden placed on the respondent due to the number of conjoint profiles evaluated. Obviously, the respondent could not evaluate all 256 profiles in our earlier factorial design, but what is the appropriate number of tasks in a conjoint analysis? A recent review of commercial conjoint studies found that respondents can easily complete up to 20 or even 30 conjoint evaluations [51, 92]. After that many evaluations, the responses start to become less reliable and less representative of the underlying reference structure. The researcher should always strive to use the fewest possible evaluations while maintaining efficiency in the estimation process. Yet, in trying to reduce the effort involved in the choice task, the researcher should not make it too simplistic or unrealistic. Also, nothing substitutes for pretesting a conjoint study to assess the respondent burden, the method of administration, and the acceptability of the profiles.

STAGE 3: ASSUMPTIONS OF CONJOINT ANALYSIS

Conjoint analysis has the least restrictive set of assumptions associated with model estimation. The structured experimental design and the generalized nature of the model make most of the tests performed in other dependence methods unnecessary. Therefore, the statistical tests for normality, homoscedasticity, and independence that were performed with other dependence techniques are not necessary for conjoint analysis. The use of statistically based profiles designs also ensures that the estimation is not confounded and that the results are interpretable under the assumed composition rule.

Yet even with fewer statistical assumptions, the conceptual assumptions are probably greater than with any other multivariate technique. As mentioned earlier, the researcher must specify the general form of the model (main effects versus interactive model) before the research is designed.

The development of the actual conjoint task builds upon this decision and makes it impossible to test alternative models once the research is designed and the data are collected. Conjoint analysis is not like regression, for example, where additional effects (interaction or nonlinear terms) can be easily evaluated after the data are collected. In conjoint analysis, the researcher must make a decision regarding model form and then design the research accordingly. Thus, conjoint analysis, although having few statistical assumptions, is theory-driven in its design, estimation, and interpretation.

STAGE 4: ESTIMATING THE CONJOINT MODEL AND ASSESSING OVERALL FIT

The options available to the researcher in terms of estimation techniques have increased dramatically in recent years. Moreover, the development of techniques in conjunction with specialized methods of profile presentation (e.g., the adaptive or choice-based conjoint) is just one improvement of this type. The researcher, in obtaining the results of a conjoint analysis study, has numerous options available when selecting the estimation method and evaluating the results.

Selecting an Estimation Technique

For many years, the type of estimation process was dictated by the choice of preference measure. Recent research, however, focused on developing an alternative estimation approach appropriate for all types of preference measures while also providing a more robust estimation methodology and improvement in both aggregate and disaggregate results.

TRADITIONAL ESTIMATION APPROACHES Rank-order preference measures were typically estimated using a modified form of analysis of variance specifically designed for ordinal data. Among the most popular and best-known computer programs are MONANOVA (Monotonic Analysis of Variance) [46, 53] and LINMAP [95]. These programs give estimates of attribute part-worths, so that the rank order of their sum (total worth) for each treatment is correlated as closely as possible to the observed rank order.

When a metric measure of preference is used (e.g., ratings rather than rankings), then many methods, even multiple regression, can estimate the part-worths for each level. Most computer programs available today can accommodate either type of evaluation (ratings or rankings), as well as estimate any of the three types of relationships (linear, ideal point, and part-worth). Estimation through the multinomial logit model and its extensions allow for more complicated consumer preference models including interaction terms and cross-attribute effects and the specific model forms discussed below.

EXTENSIONS TO THE BASIC ESTIMATION PROCESS Up to this point, we discussed only estimation of the basic conjoint model with main and perhaps interaction effects. Although this model formulation is the foundation of all conjoint analysis, extensions of this approach may be warranted in some instances. The following sections discuss extensions applicable to disaggregate and aggregate methods.

One of the primary criticisms of aggregate model estimations is the lack of separate part-worth estimates for each individual versus the single aggregate solution. Yet the researcher is not always able to utilize a disaggregate approach due to any number of design considerations (e.g., type of choice format, number of variables, or sample size).

One approach for accounting for heterogeneity is the Bayesian estimation approach discussed in the following section [4, 55]. A second is modification of the traditional estimation to introduce a form of **respondent heterogeneity,** which represents the variation expected across individuals if the model was estimated at the disaggregate level [111]. In both approaches improvements in predictive accuracy have been achieved at levels comparable to those found in disaggregate models [76].

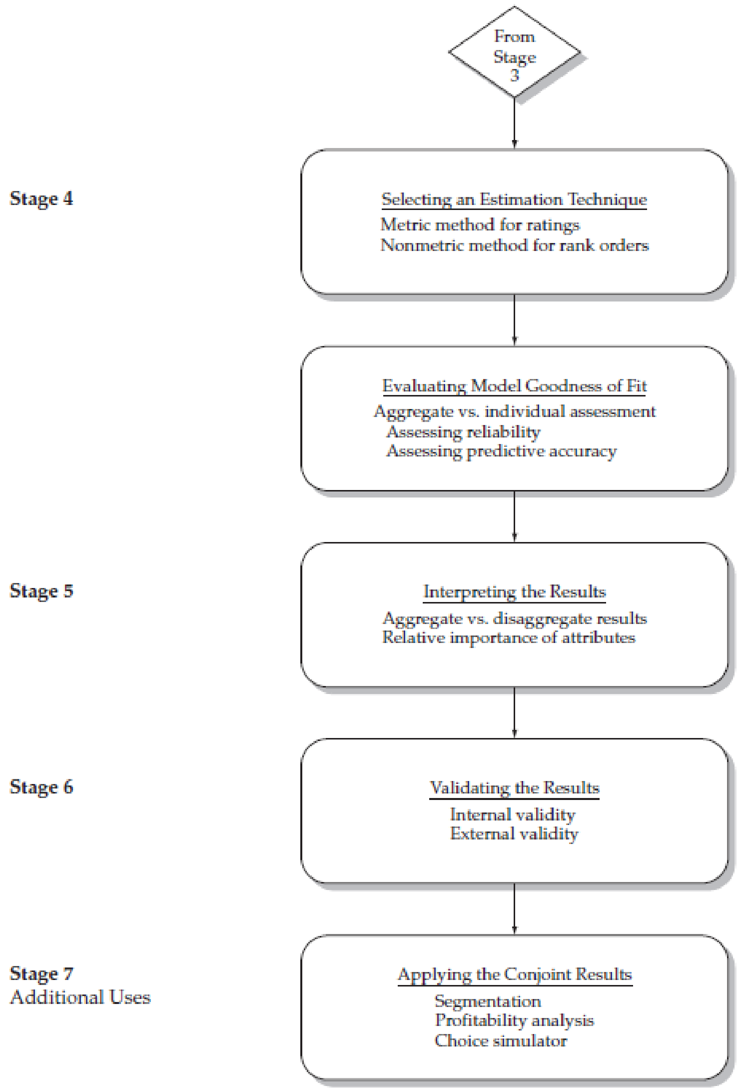

FIGURE S2-4 Canonical Relationship Between Consumer Characteristics and Their Credit Card Usage

Another extension in the basic conjoint model is the incorporation of additional variables in the estimation process, particularly variables reflecting characteristics of the individual or choice context. Up to this point, we assumed that preferences for the profiles are completely expressed in the levels of the various attributes. But what about other less quantifiable measures, such as attitudes, or even socioeconomic characteristics? Even though we may assume that these individual differences will be reflected in the disaggregated part-worth estimates, in some instances it is beneficial to establish the relationship with these types of variables. Recent research has explored techniques for including socioeconomic and choice context variables as well as attitudinal variables and even latent constructs [142]. These techniques are not widely available yet, but they represent potentially useful approaches for quantifying the impacts of variables outside those used in constructing the profiles.

BAYESIAN ESTIMATION: A RADICALLY NEW APPROACH The estimation procedures just described are based on classical statistical theory that is the foundation for all of the multivariate methods discussed in this text. These approaches, however, are being supplanted by a new approach, **Bayesian analysis** [22], that is quite different in its basic method in the estimation of the conjoint model. The application of Bayesian analysis is occurring not only in conjoint analysis [3, 56, 62], but in the more traditional methods such as regression analysis as well [4, 93]. Bayesian estimation represents potentially significant improvements over existing methods in terms of both predictive and explanatory ability. Researchers are encouraged to examine Bayesian estimation options in conjoint analysis where available and continue to follow its progress as the issues of implementation discussed below are addressed.

The Basics of Bayesian Analysis. The underlying premise of Bayesian analysis is Bayes' theorem, which is based on defining two probability values: the prior probability and the likelihood probability. In a general sense, the likelihood probability is the probability derived from the actual data observations. The prior probability is an estimate of how likely this particular set of observations (and the associated prior probability) is to occur in the population. By combining these two probabilities we make some estimate of the actual probability of an event (known as the *joint probability*). Interested readers are referred to the Basic Stats appendix on the text's Web sites accessed through cengagebrain.co.uk or www.mvstats.com for a more detailed look at the fundamental principles underlying Bayesian estimation.

Advantages and Disadvantages of Bayesian Estimation. In using Bayesian analysis for estimation of a conjoint model, the researcher does not need to do anything different; these probability values are estimated by the program from the set of observations. The question to be asked, however, is: What are the advantages and disadvantages of employing this technique? Let's examine them in more detail.

Numerous studies examined Bayesian estimation versus the more traditional methods and in all instances those studies found Bayesian estimation to be comparable or even superior for both part-worth estimation and predictive capability [6]. The advantages go beyond just estimation precision, however. Given the nature of the required probability estimates, Bayesian estimation allows for conjoint models to be estimated at the individual level where previously only aggregate models were possible (i.e., choice-based conjoint and more complex models with interaction terms). To this end, it has been incorporated into all of the basic conjoint models [89, 91].

Bayesian estimation does have some drawbacks. First, it requires a large sample (typically 200 or more respondents) because it is dependent on the sample for the estimates of prior probabilities. This requirement differs from traditional conjoint models that could be estimated solely for one individual. Second, it requires substantially more computing resources because it takes an iterative approach in estimation. Analyses that could be estimated in seconds using traditional means now take several hours [103]. Even though rapid increases in desktop computing power have somewhat mitigated this issue, the researcher must still be aware of the additional resources needed.

Estimated Part-Worths

Once an estimation method is chosen, the responses for each profile are analyzed to estimate the part-worths for each level. The most common method is some form of linear model, depending on whether the dependent measure is metric or nonmetric. As such, the estimated part-worths are essentially regression coefficients estimated with dummy variables, and one level for each attribute is eliminated to avoid singularity (see Chapter 4 for a more detailed discussion of using dummy variables in regression). Thus, the resulting part-worth estimates must be interpreted in a relative sense.

Here is an example of estimated part-worths using ACA [87] for a simple three-attribute design with five and four levels.

Attribute 1		*Attribute 2*		*Attribute 3*	
Level	**Part-Worth**	**Level**	**Part-Worth**	**Level**	**Part-Worth**
1	−.657	1	−.751	1	−.779
2	−.0257	2	−.756	2	−.826
3	−.378	3	.241	3	−.027
4	.098	4	.302	4	.667
5	−.0111				

As we can see, the part-worths must be judged relative to one another, because they have both negative and positive values. For example, for the second attribute, the second level is actually the least desired (most negative at −.756) by a small amount with the fourth level having the highest utility (.302). The levels can also be compared across attributes, but care must be taken to first assess the levels within attribute to establish their relative position.

To assist in interpretation, many programs convert the part-worth estimates to some common scale (e.g., minimum of zero to a maximum of 100 points) to allow for comparison both across attributes for an individual and across individuals. Shown next are the scaled part-worths for the example just discussed. As we can see, they are much easier to interpret, both within attributes as well as across attributes. The relative ordering in the original utility values is preserved, but now the lowest level in each attribute is set to zero and all other levels valued relative to that level.

Attribute 1	*Attribute 2*	*Attribute 3*

Level	Part-Worth	Level	Part-Worth	Level	Part-Worth
1	0.00	1	.23	1	2.15
2	18.29	2	0.00	2	0.00
3	12.76	3	45.59	3	36.59
4	34.53	4	48.38	4	68.28
5	29.54				

Because the part-worth estimates are always interpreted in a relative perspective (one part-worth versus another) rather than an absolute amount (the actual amount of change in the dependent measure), the researcher should focus on a method of portraying the results that best facilitates both application and interpretation. Scaling the part-worth estimates provides a simple yet effective way of presenting the relative positioning of each level. This format is also conducive to graphical portrayal and also provides a means of more easily using the part-worths in other multivariate techniques such as cluster analysis.

Evaluating Model Goodness-of-Fit

Conjoint analysis results are assessed for accuracy at both the individual and aggregate levels. The objective in both situations is to ascertain how consistently the model predicts the set of preference evaluations. Because any measure of goodness-of-fit may be overfitted when evaluating a single respondent, the researcher must take care to complement any empirical process with additional evaluation through examination of the estimated preference structure as discussed in the next section.

ASSESSING INDIVIDUAL-LEVEL CONJOINT MODELS The role of any goodness-of-fit measure is to assess the quality of the estimated model by comparing actual values of the dependent variable(s) with values predicted by the estimated model. For example, in multiple regression we correlate the actual and predicted values of the dependent variable for the coefficient of determination (R^2) across all respondents. In discriminant analysis we compare the actual and predicted group memberships for each member of the sample in the classification matrix. What distinguishes conjoint analysis from the other multivariate techniques is that separate conjoint models are estimated for each individual, requiring that the goodness-of-fit measure provide information on the estimated part-worths for each respondent. As we will see in the following discussions, this process requires special care in the type of goodness-of-fit measure used and how it is interpreted.

Types of Goodness-of-Fit Measures. For an individual-level model, the goodness-of-fit measure is calculated for each individual. As such, it is based on the number and type of choice tasks performed by each respondent. When the choice tasks involve nonmetric rank-order data, correlations based on the actual and the predicted ranks (e.g., Spearman's rho or Kendall's tau) are used. When the choice tasks involve a rating (e.g., preference on a 0–100 scale), then a simple Pearson correlation, just like that used in regression, is appropriate. In both cases, the estimated part-worths are used to generate predicted preference values (ranks or metric ratings) for each profile. The actual and predicted preferences are then correlated for each person and tested for statistical significance. Individuals who have poor predictive fit should be candidates for deletion from the analysis.

Evaluating the Strength of the Goodness-of-Fit Measure. How high should the goodness-of-fit values be? As with most fit measures, higher values indicate a better fit. In most conjoint experiments, however, the number of profiles does not substantially exceed the number of parameters, and the potential for overfitting the data, and thus overestimating the goodness-of-fit, is always present. Goodness-of-fit measures are not corrected for the degrees of freedom in the estimation model.

Thus, as the number of profiles approaches the number of estimated parameters, the researcher must apply a higher threshold for acceptable goodness-of-fit values. For example, multiple regression is many times used in the metric estimation process. In assessing goodness-of-fit with the coefficient of determination (R^2), the researcher should always calculate the adjusted R^2 value, which compensates for lower degrees of freedom. Thus, in many instances, what seem to be acceptable goodness-of-fit values in conjoint analyses may actually reflect markedly lower adjusted values because the number of profiles evaluated is not substantially greater than the number of part-worths (see Chapter 4 for more detailed discussion of the adjustment process). Moreover, values that are exceedingly high (very close to 100%) may not reflect exceedingly good fit, but rather indicate respondents who may not be following the choice tasks correctly and thus are also candidates for deletion.

Using a Validation Sample. Researchers are also strongly encouraged to measure model accuracy not only on the original profiles but also with a set of **validation** or **holdout profiles.** In a procedure similar to a holdout sample in discriminant analysis, the researcher prepares more profile cards than needed for estimation of the part-worths, and the respondent rates all of them at the same time. Parameters from the estimated conjoint model are then used to predict preference for the new set of profiles, which is compared with actual responses to assess model reliability [48]. The holdout sample also gives the researcher an opportunity for a direct evaluation of profiles of interest to the research study.

RULES OF THUMB S2-5

Estimating a Conjoint Model

- The selection of an estimation method is straightforward:
  - The most common method is a regression-based approach, applicable with all metric preference measures
  - Using rank-order preference data requires more specialized estimation (e.g., MONANOVA)
  - Bayesian methods are emerging that allow for individual-level models to be estimated where not previously possible, but they require larger samples, are more computationally intensive, and are not widely available
- Goodness-of-fit should be assessed with:

- Coefficient of determination (R^2) between actual and predicted preferences
- Measures based on the rank orders of the predicted and actual preferences
- Measures for both the estimation sample and a holdout or validation sample of additional stimuli not used in the estimation process

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In measuring the goodness-of-fit of a holdout sample, however, the researcher must use extreme caution in evaluating the actual values of the goodness-of-fit measure. In most instances the holdout sample may contain a small number of additional profiles (four to six), thus the values are calculated on a small number of observations. Extremely high values may be suspect in that they do not reflect good fit, but rather fundamental problems in the estimated preference structure of the choice process itself.

AGGREGATE-LEVEL ASSESSMENT If an aggregate estimation technique is used, then the same basic procedures apply, only now aggregated across respondents. Researchers also have the option of selecting a holdout sample of respondents in each group to assess predictive accuracy. In these instances, the aggregate model is applied to individuals and then evaluated in terms of predictive accuracy of their choices. This method is not feasible for disaggregate results because no generalized model is available to apply to the holdout sample, and each respondent in the estimation sample has individualized part-worth estimates.

STAGE 5: INTERPRETING THE RESULTS

The customary approach to interpreting conjoint analysis is at the disaggregate level. That is, each respondent is modeled separately, and the results of the model (part-worth estimates and assessments of attribute importance) are examined for each respondent. Interpretation, however, can also take place with aggregate results. Whether the model estimation is made at the individual level and then aggregated or aggregate estimates are made for a set of respondents, the analysis fits one model to the aggregate of the responses. As one might expect, this process generally yields poor results when predicting what any single respondent would do or when interpreting the part-worths for any single respondent. Unless the researcher is dealing with a population definitely exhibiting homogeneous behavior with respect to the attributes, aggregate analysis should not be used as the only method of analysis. However, many times aggregate analysis more accurately predicts aggregate behavior, such as market share. Thus, the researcher must identify the primary purpose of the study and employ the appropriate level of analysis or a combination of the levels of analysis.

Examining the Estimated Part-Worths

One of the unique elements of conjoint analysis is the ability to represent the preference structure of individuals through part-worths, yet many researchers neglect to validate these preference structures. Much insight can be gained from such examination, plus the potential for improving the overall results by correcting for invalid patterns among the part-worths. The most common method of interpretation is an examination of the part-worth estimates for each factor, assessing their magnitude and pattern. Part-worth estimates are typically scaled so that the higher the part-worth (either positive or negative), the more impact it has on overall utility. As noted earlier, many programs will rescale the part-worths to common scale, such as 0–100 points so as to allow easier comparison across and within respondents.

ENSURING PRACTICAL RELEVANCE In evaluating any set of part-worth estimates, the researcher must consider both practical relevance as well as correspondence to any theory-based relationships among levels. In terms of practical relevance, the primary consideration is the degree of differentiation among part-worths within each attribute. For example, part-worth values can be plotted graphically to identify patterns. Relatively flat patterns would indicate a degree of indifference among the levels in that the respondent did not see much difference between the levels as affecting choice. As such, whether it be graphical or empirical comparisons among the levels, it is imperative that the researcher evaluate each set of part-worths to ensure that they are an appropriate representation of the preference structure.

REVERSALS: A CASE OF THEORETICAL INCONSISTENCY Many times an attribute has a theoretically based structure for the relationships between levels. The most common is a monotonic relationship, such that the part-worths of level C should be greater than those of level B, which should in turn be greater than the part-worths of level A. Common situations in which such a relationship is hypothesized include such attributes as price (lower prices always valued more highly), quality (higher quality always better), or convenience (closer stores preferred over more distant stores). With these and many other attributes, the researcher has a theoretically based relationship to which the part-worth values should correspond.

What happens when the part-worths do not follow the theorized pattern? We introduced the concept of a **reversal** in our earlier discussion of model forms as being when the part-worth values violate the assumed monotonic relationship. In a simple sense, we are referring to the seemingly nonsensical situations in which respondents value paying higher prices, having lower quality, or driving further distances. A reversal represents potentially serious distortions in the representation of a preference structure. Not only does it affect the relationship between adjacent levels, but it may affect the part-worths for the entire attribute.

When reversals create a preference structure that cannot be supported theoretically, the researcher should then consider deletion of the respondent. At issue is the size and frequency of reversals, because they represent illogical or inconsistent patterns in the overall preference structure, as measured by the part-worths.

Factors Contributing to Reversals. Given the potentially serious consequences from a reversal, a researcher must be cognizant of factors in the research setting that create the possibility of reversals.

These factors should be considered when judging the extent of reversals and making a conclusion as to the validity/invalidity of a preference structure:

- *Respondent effort.* A critical factor in the success of any conjoint analysis is sustained interest in the conjoint tasks in order to accurately assess preference structure. Many factors, however, can diminish this effort, such as respondent fatigue with the conjoint tasks or other parts of the survey or disinterest in the research task. A simple measure of respondent interest is the time spent on the conjoint tasks. The researcher should always pretest the conjoint tasks and develop a minimum time period considered necessary to reliably complete the task. For individuals falling under this time threshold, special consideration should be given in examining their part-worths for reversals.
- *Data collection method.* The preferred method of administration is through a personal interview because of the possible complexity of the choice tasks, but recent advances make alternative means of data collection (e.g., Web-, mail-, or phone-based methods) feasible. Although studies support the predictive validity of these alternative methods the researcher must consider that such situations may exhibit a higher level of reversals due to such factors as increased respondent effort required, loss of respondent interest, or even the inability to resolve questions or confusion with the research task.

  The researcher should always include some form of debriefing with the respondent, either through a series of questions administered after the conjoint task or through a series of probes by the survey administrator in a personal interview. The purpose should be to assess the respondent's level of understanding of the factors and levels involved as well as the realism of the choice task.
- *Research context.* A final issue that contributes to the potential level of reversals is the object/concept being studied. Low-involvement products or situations (e.g., commodities, lower-

risk ideas or concepts) always run the risk of inconsistencies in the actual choices and resulting part-worths. The researcher must always consider the ability of any set of choice tasks to maintain enough consumer involvement with a decision process when in actuality the consumer may not give the decision the level of thought modeled by the conjoint tasks. Too many times researchers identify too many attributes for consideration, overcomplicating a simple process from the respondent's perspective. When this situation happens, the respondent may view the choice tasks as too complex or unrealistic and provide inconsistent or illogical results.

Identifying Reversals. With the potential influences of the research setting considered, the researcher is still faced with the critical question: What actually is a reversal? Technically, any time a part-worth is hypothesized to be higher than an adjacent level, but isn't, it violates the monotonic relationship and could be considered a reversal. Yet what amount of increase is needed to avoid being considered a reversal? What if the two adjacent levels are equal? What if the decline is miniscule?

The first step is to identify possible reversals. A simple yet effective method is to graphically portray the part-worth patterns for each attribute. Illogical patterns can be quickly identified within each attribute. However, as the number of attributes and respondents increases, the need for some empirical measure becomes apparent. It is a simple process to calculate the differences between adjacent levels, which can then be examined for illogical patterns. A miniscule decline might not constitute a reversal, so how large does the difference have to be? As a practical matter, however, some range of differences, even when contrary to the expected pattern, would probably be considered acceptable. In order to establish this range of acceptability, several options exist:

- One approach is to examine the differences and see where some natural break occurs, denoting those truly different values. Again, the researcher is looking for those truly distinctive values that indicate preferences contrary to the hypothesized relationship.
- A second approach would be to try and establish some estimate of a confidence interval that

takes into account the established distributional characteristics of the differences. One possibility is to determine the standard error of the differences and then use that to construct a confidence interval around zero to denote truly distinctive differences. We should note that technically the confidence interval should be constructed "within subject" but too few observations are provided on any factor to do so. Thus, use of the standard error calculated across subjects is necessary.

Ultimately, to answer this question, the researcher is encouraged to examine the distribution of differences and then identify those deemed outside a reasonable range. The extent of this range should be based not only on the actual differences, but also on the factors discussed earlier (respondent effort, data collection method, and research context), which impact the possibility of reversals.

The objective of any analysis of reversals is to identify consistent patterns of reversals that indicate an invalid representation of a preference structure. Although a researcher would hope for no reversals, reversals can occur occasionally and still provide a valid preference structure. It is the job of the researcher to consider all of the factors discussed, along with the extent of the reversals for each respondent, and identify those respondents with an inappropriate number of reversals.

Remedies for Reversals. Even though the presence of reversals does not necessarily invalidate a set of part-worth estimates, the researcher must strongly consider a series of remedies to ensure both the appropriateness of the results as well as maximize the predictive ability of the part-worths. When faced with a substantial number of reversals, the researcher has several options:

- *Do nothing.* Many times a small number of reversals can be ignored, particularly if the focus is on aggregate results. Many researchers suggest leaving these reversals in as a measure of real-world inconsistency. The reasoning is that the reversals will be compensated for during aggregation.
- *Apply constraints.* Constraints can be applied in the estimation process such that reversals are

prohibited [3, 109]. The specificity of these constraints ranges from simple approaches of creating a "tie" for the levels involved (i.e., give them the same part-worth estimate) to monotonicity constraints both within and across attributes [107]. One can also view the linear or ideal point models of part-worths discussed earlier as a type of constraint.

Even though studies show that the predictive accuracy can be improved with these constraints, the researcher also must assess the degree to which these constraints potentially distort the preferences into predefined relationships. Thus, whereas constraints may be utilized to correct the occasional reversal, it would be inappropriate to utilize constraints to correct for incorrectly specified levels or attributes even if predictive accuracy was improved.

- *Delete respondents.* A final remedy involves the deletion of respondents with substantial numbers of reversals from the analysis. At issue here is the trade-off between reducing representativeness and diversity of the sample through deletion versus the inclusion of invalid preference structures. Again, the researcher must weigh the costs versus benefits in making such a decision.

Care should always be taken any time the researcher directly affects the estimated part-worths. Although the absence of reversals achieves a sense of validity by corresponding to the hypothesized relationships, the researcher must be sure to not impose restrictions that might obscure valid but counterintuitive results. With any remedy for reversals, the researcher also must be cognizant of the implications not only on the individual part-worth estimates, but also on the overall depictions of preference seen in aggregate results or other applications (e.g., segmentation, choice simulators).

Assessing the Relative Importance of Attributes

In addition to portraying the impact of each level with the part-worth estimates, conjoint analysis can assess the relative importance of each factor. Because part-worth estimates are typically converted to a common scale, the greatest contribution to overall utility—and hence the most important factor—is the factor with the greatest range (low to high) of part-worths. The importance values of each factor can be converted to percentages summing to 100 percent by dividing each factor's range by the sum of all range values.

Using our earlier example of estimated part-worths with three attributes, the calculation of importance would be as follows. First, find the range (maximum value minus minimum value) for attribute. Then divide each range value by the total for the importance value.

Attribute	**Minimum**	**Maximum**	**Range**	**Importance**
1	−.657	.098	.755	22.8%
2	−.756	.302	1.058	32.0%
3	−.826	.667	1.493	45.2%
Total			3.306	100.0%

In this case, the third attribute accounted for almost one-half of the variation (1.493 ÷ 3.306 = .452) in the utility scores, even though the other two attributes were lower (32.0% and 22.8%). We could then state that for this respondent, attribute 3 was twice as important as attribute 1 in deriving utility scores and preferences.

This approach allows for comparison across respondents using a common scale as well as giving meaning to the magnitude of the importance score. The researcher must always consider the impact on the importance values of an extreme or practically infeasible level. If such a level is found, it should be deleted from the analysis or the importance values should be reduced to reflect only the range of feasible levels.

STAGE 6: VALIDATION OF THE CONJOINT RESULTS

Conjoint results can be validated both internally and externally. Internal validation involves confirmation that the selected composition rule (i.e., additive versus interactive) is appropriate [19]. The researcher is typically limited to empirically assessing the validity of only the selected model form in a full study, owing to the high demands of collecting data to test both models. This validation process is most efficiently accomplished by comparing alternative models (additive versus interactive) in a pretest study to confirm which model is appropriate. We already discussed the use of holdout profiles to assess the predictive accuracy for each individual or a holdout sample of respondents if the analysis is performed at the aggregate level.

External validation involves in general the ability of conjoint analysis to predict actual choices, and in specific terms the issue of sample representativeness. Although conjoint was employed in numerous studies in the past 20 years, relatively few studies focused on its external validity. One study confirmed that conjoint analysis closely corresponded to the results from traditional concept testing, an accepted methodology for predicting customer preference [105]; other studies demonstrated the predictive accuracy for purchases of consumer electronics and groceries [37, 76]. Although no evaluation is made of sampling error in the individual-level models, the researcher must always ensure that the sample is representative of the population of study [72]. This representativeness becomes especially important when the conjoint results are used for segmentation or choice simulation purposes (see the next section for a more detailed discussion of these uses of conjoint results).

MANAGERIAL APPLICATIONS OF CONJOINT ANALYSIS

Typically, conjoint models estimated at the individual level (separate model per individual) are used in one or more of the following areas: segmentation, profitability analysis, and conjoint simulators. In addition to the individual-level results, aggregate conjoint results can represent groups of individuals and also provide a means of predicting their decisions for any number of situations. The unique advantage of conjoint analysis is the ability to represent the preferences for each individual in an objective manner (e.g., part-worth utilities). In the most fundamental sense, conjoint analysis can help identify customers' needs, prioritize those needs, and then translate those needs into actual strategies [67, 90, 98]. The most common managerial and academic applications of conjoint analysis in conjunction with its portrayal of the consumer's preference structure include segmentation, profitability analysis, and conjoint simulators.

RULES OF THUMB S2-6

Interpreting and Validating Conjoint Results

- Results should be estimated for each individual unless:
  - The conjoint model requires aggregate-level estimates (i.e., some forms of choice-based conjoint)
  - The population is known to be homogeneous, with no variation between individual preference structures
- Part-worth estimates are generally scaled to a common basis to allow for comparison across respondents
- Theoretically inconsistent patterns of part-worths, known as reversals, can give rise to deletion of a respondent unless:
  - Their occurrence is minimal
  - Constraints are applied to prohibit reversals
- Attribute importance must be derived based on the relative ranges of part-worths for each attribute
- Validation must occur at two levels:
  - Internal validation: Testing whether the appropriate composition rule has been selected (i.e., additive or interactive) and is done in a study pretest

- External validation: Assessing the predictive validity of the results in an actual setting in which the researcher must always ensure the sample is representative of the population of study

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Segmentation

One of the most common uses of individual-level conjoint analysis results is to group respondents with similar part-worths or importance values to identify segments. The estimated conjoint part-worth utilities can be used solely or in combination with other variables (e.g., demographics) to derive respondent groupings that are most similar in their preferences [20, 26]. In the industrial cleanser example, we might first group individuals based on their attribute importance scores, finding one group for which brand is the most important feature, whereas another group might value price more highly. Another approach would be to examine the part-worth scores directly, again identifying individuals with similar patterns of scores across each of the levels within one or more attributes.

For the researcher interested in knowing the presence of such groups and their relative magnitude, a number of different approaches to segmentation are available, all with differing strengths and weaknesses [66, 109]. One logical approach would be to apply cluster analysis (see Chapter 9) to the part-worth estimates or the importance scores for each attribute to identify homogeneous subgroups of respondents. Conjoint analysis has also been proposed as a means of validating segmentation analyses formed with other clustering variables, whereby differences in conjoint preference structures are used to demonstrate distinctiveness between the segments [18].

Profitability Analysis

A complement to the product design decision is a marginal profitability analysis of the proposed product design. If the cost of each feature is known, the cost of each product can be combined with the expected market share and sales volume to predict its viability. This process could identify combinations of attributes that would be profitable even with smaller market shares because of the low cost of particular components. An adjunct to profitability analysis is assessing price sensitivity [45], which can be addressed through either specific research designs [81] or specialized programs [92]. Both individual and aggregate results can be used in this analysis.

Conjoint Simulators

At this point, the researcher still understands only the relative importance of the attributes and the impact of specific levels. So how does conjoint analysis achieve its other primary objective of using what-if analyses to predict the share of preferences that a profile (real or hypothetical) is likely to capture in various competitive scenarios of interest to management? This role is played by **choice simulators,** which enable the researcher to simulate any number of competitive scenarios and then estimate how the respondents would react to each scenario.

The researcher is cautioned in any application of the conjoint simulator in assuming that the share of preference in a conjoint simulation directly translates to market share [15]. The conjoint simulation represents only the product and perhaps price aspects of marketing management, omitting all of the other marketing factors (e.g., advertising and promotion, distribution, competitive responses) that ultimately affect market share. The conjoint simulation does, however, present a view of the product market and the dynamics of preferences that may be seen in the sample under study.

CONDUCTING A SIMULATION A conjoint simulation is an attempt to understand how the set of respondents would choose among a specified set of profiles. This process provides the researcher with the ability to utilize the estimated part-worths in evaluating any number of scenarios consisting of differing combinations of profiles. For any given scenario, the researcher follows a three-step process.

Step 1: Specify the Scenario(s). After the conjoint model is estimated, the researcher can specify any number of sets of profiles for simulation of consumer choices. Among the possible scenarios that can be assessed are the following:

- Impacts of adding a product to an existing market
- Increased potential from a multiproduct or multibrand strategy, including estimates of cannibalism
- Impacts of deleting a product or brand from the market
- Optimal product design(s) for a specific market setting

In each case, the researcher provides the set of profiles representing the objects (products, services, etc.) available in the market scenario being examined, and the choices of respondents are then simulated. The unique value of using conjoint analysis in the simulation is that multiple scenarios can be evaluated and the results compiled for each respondent through their preference structure of part-worths.

Step 2: Simulate Choices. Once the scenarios are complete, the part-worths for each individual are used to predict the choices across the profiles in each scenario. Choice simulators afford the researcher the ability to evaluate any number of scenarios, but their real benefit involves the ability of the researcher to specify conditions or relationships among the profiles to represent market conditions more realistically. For example, will all objects compete equally with all others? Does similarity among the objects create differing patterns of preference? Can the unmeasured characteristics of the market be included in the simulation? These questions are just a few of the many that can be addressed through a choice simulator in portraying a realistic market within which respondents make choices [37].

The ability of choice simulators to represent these relationships enables researchers to more realistically portray the forces acting among the set of objects being considered in the scenario. Moreover, predictive accuracy is markedly improved along with a better understanding of the underlying market behavior of the respondents [37, 78].

Step 3: Calculate Share of Preference. The final step in conjoint simulation is to predict preference for each individual and then calculate share of preferences for each profile by aggregating the individual choices. Choice simulators can use a wide range of choice rules [25] in predicting the choice for any individual:

- *Maximum utility (first choice) model.* This model assumes the respondent chooses the profile with the highest predicted utility score. Share of preference is determined by calculating the number of the individuals preferring each profile. This approach is best suited for situations with individuals of widely different preferences and in situations involving sporadic, nonroutine purchases.
- *Preference probability model.* In this model, predictions of choice probability sum to 100 percent over the set of profiles tested, with each person having some probability of purchasing each profile. The overall share of preference is measured by summing the preference probabilities across all respondents. This approach, which can approximate some elements of product similarity, is best suited to repetitive purchasing situations, for which purchases may be more tied to usage situations over time. The two most common methods of making these predictions are the BTL (Bradford-Terry-Luce) and logit models, which make quite similar predictions in almost all situations [36].
- *Randomized first choice.* Developed by Sawtooth Software [73, 78], this method attempts to combine the best of the two prior approaches. It samples each respondent multiple times, each time adding random variation to the utility estimates for each profiles. For each iteration, it applies the first choice rule and then totals the outcomes for each individual to get a share of preference per respondent. It corrects for product similarity and can be fine-tuned by specifying the amount and type of random variation that best approximates known preference shares [37, 75].

The share of preference, determined by any of the three methods described, provides insight into many factors underlying the actual choices of respondents. Multiple product scenarios can be evaluated, giving rise to not only a perspective of any single scenario, but of the dynamics in share of preference as the profiles change.

ALTERNATIVE CONJOINT METHODOLOGIES

Up to this point we have dealt with conjoint analysis applications involving the traditional conjoint methodology. However, real-world applications many times involve 20 to 30 attributes or require a more realistic choice task than used in our earlier discussions. Recent research directed toward overcoming these problems encountered in many conjoint studies is leading to the development of two new conjoint methodologies: (1) an adaptive/self-explicated conjoint for dealing with a large number of attributes and (2) a choice-based conjoint for providing more realistic choice tasks. These areas represent the primary focus of current research in conjoint analysis [14, 29, 63].

Adaptive/Self-Explicated Conjoint: Conjoint with a Large Number of Factors

The full-profile method starts to become unmanageable with more than 10 attributes, yet many conjoint studies need to incorporate 20, 30, or even more attributes. In these cases, some adapted or reduced form of conjoint analysis is used to simplify the data collection effort and still represent a realistic choice decision. The two options are the self-explicated models and adaptive or hybrid models.

SELF-EXPLICATED CONJOINT MODELS In the **self-explicated model,** the respondent provides a rating of the desirability of each level of an attribute and then rates the overall relative importance of the attribute. Part-worths are then calculated by a combination of the two values [99]. In this compositional approach, ratings are made on the components of utility, rather than just overall preference. As a major variant of conjoint analysis that is closer to traditional multi-attribute models, this model raises several concerns.

First, can respondents assess the relative importance of attributes accurately? A common problem with self-ratings is the potential for importance to be underestimated in multi-attribute models because respondents want to give socially desirable answers. In such situations, the resulting conjoint model is also biased. Second, interattribute correlations may play a greater role and cause substantial biases in the results due to double counting of correlated factors. Traditional conjoint models suffer from this problem as well, but the self-explicated approach is particularly affected because respondents must never explicitly consider these attributes in relation to other attributes. Finally, respondents never perform a choice task (rating the set of hypothetical combinations of attributes), and this lack of realism is a critical limitation, particularly in new-product applications.

Recent research demonstrates that this method may offer suitable predictive ability when compared to traditional conjoint methods [27]. This approach is best utilized when aggregate models are preferred, because individual idiosyncrasies can be compensated for in the aggregate results. Thus, if the number of factors cannot be reduced to a manageable level acceptable for any of the other conjoint methods, then a self-explicated model may be a viable alternative method.

ADAPTIVE, OR HYBRID, CONJOINT MODELS A second approach is the **adaptive** or **hybrid model,** so termed because it combines the self-explicated and part-worth conjoint models [23, 24]. This approach utilizes the self-explicated values to create a small subset of profiles selected from a fractional factorial design. The profiles are then evaluated in a manner similar to traditional conjoint analysis. The sets of profiles differ among respondents based on their self-explicated responses, and although each respondent evaluates only a small number, collectively all profiles are evaluated by a portion of the respondents. The approach of integrating information from the respondent to simplify or augment the choice tasks led to a number of recent research efforts aimed at differing aspects of the research design [3, 44, 101, 106].

One of the most popular variants of this approach is ACA, a computer-administered conjoint program developed by Sawtooth Software [87]. ACA employs self-explicated ratings to reduce the factorial design size and make the process more manageable. It is particularly useful when the study includes a large number of attributes not appropriate for the other approaches. Here the program first collects self-explicated ratings of each factor. Then these ratings are used in generating the profiles such that the less important factors are quickly eliminated. Moreover, each profile contains just a small number of factors (three to six) to keep the choice task more manageable. This adaptive process can only be accomplished through the associated software, making this approach inappropriate for any type of noninteractive setting (e.g., written survey). Yet its flexibility in accommodating large numbers of attributes with simple choice tasks has made it one of the most widely used approaches. Moreover, its relative predictive ability has been shown to be comparable to traditional conjoint analysis, thus making it a suitable alternative when the number of attributes is large [27, 47, 105, 115, 119].

CHOOSING BETWEEN SELF-EXPLICATED AND ADAPTIVE/HYBRID MODELS When faced with a number of factors that cannot be accommodated in the conjoint methods discussed to this point, the self-explicated and adaptive/hybrid models preserve at least a portion of the underlying principles of conjoint analysis. In comparing these two extensions, the self-explicated methods have a slightly lower reliability, although recent developments may provide improvement. When the hybrid models and self-explicated methods are compared with full-profile methods, the results are mixed, with slightly better performance by the adaptive/hybrid method, particularly ACA [38]. Although more research is needed to confirm the comparisons across methods, the empirical studies indicate that the adaptive/hybrid methods and the newer forms of self-explicated models both offer viable alternatives to traditional conjoint analysis when dealing with a large number of factors.

Choice-Based Conjoint: Adding Another Touch of Realism

In recent years, many researchers in the area of conjoint analysis have directed their efforts toward a new conjoint methodology that provides increased realism in the choice task. With the overriding objective of understanding the respondent's decision-making process and predicting behavior in the marketplace, traditional conjoint analysis assumes that the judgment task, based on ranking or rating, captures the choices of the respondent. Yet researchers argue that this approach is not the most realistic way of depicting a respondent's actual decision process, and others have pointed to the lack of formal theory linking these measured judgments to choice [59].

What emerged is an alternative conjoint methodology, known as **choice-based conjoint (CBC),** with the inherent face validity of asking the respondent to choose a full profile from a set of alternative profiles known as a **choice set.** This method is much more representative of the actual process of selecting a product from a set of competing products. Moreover, choice-based conjoint provides an option of not choosing any of the presented profiles by including a no-choice option in the choice set. Whereas traditional conjoint analysis assumes respondents' preferences will always be allocated among the set of profiles, the choice-based approach allows for market contraction if all the alternatives in a choice set are unattractive.

The advantages of the choice-based approach are the additional realism and the ability to estimate interaction terms. After each respondent has chosen a profile for each choice set, the data can be analyzed either at the disaggregate level (individual respondents) or aggregated across respondents (segments or some other homogeneous groupings of respondents) to estimate the conjoint part-worths for each level and the interaction terms. From these results, we can assess the contributions of each factor and factor-level interaction and estimate the likely market shares of competing profiles.

A SIMPLE ILLUSTRATION OF FULL-PROFILE VERSUS CHOICE-BASED CONJOINT Before discussing some of the more technical details of choice-based conjoint and how it differs from the other conjoint methodologies we will first examine the differences in creating profiles and then review the actual data collection process.

Creating Profiles. The first difference between full-profile and choice-based conjoint is the type of profiles. Both methods use a form of full-profile profiles, but the choice task is quite different. Let's examine a simple example to illustrate the differences.

A wireless phone company wishes to estimate the market potential for three service options that can be added to the base service fee of $14.95 per month and $0.50 per minute of calling time:

ICA	Itemized call accounting with a $2.75-per-month charge
CW	Call waiting with a $3.50-per-month service charge
TWC	Three-way calling with a $3.50-per-month service charge

Traditional conjoint analysis is performed with full-profile profiles representing the various combinations of service, ranging from just the base service to the base service and all three options. The complete set of profiles (factorial design) is shown in Table S2-6. Profile 1 represents the base service with no options, profile 2 is the base service plus itemized call accounting, and so forth, up to profile 8 being the base service plus all three options (itemized call accounting, call waiting, and three-way calling).

TABLE S2-6 A Comparison of Profile Designs Used in Traditional and Choice-Based Conjoint Analysis

TRADITIONAL CONJOINT ANALYSIS					
	Levels of Factors[a]			*Choice-Based Conjoint*	
Profile	**ICA**	**CW**	**TWC**	**Choice Set**	**Profiles in Choice Set**[b]
1	0	0	0	1	1, 2, 4, 5, 6, and No Choice
2	1	0	0	2	2, 3, 5, 6, 7, and No Choice

3	0	1	0	3	1, 3, 4, 6, 7, 8, and No Choice
4	0	0	1	4	2, 4, 5, 7, 8, and No Choice
5	1	1	0	5	3, 5, 6, 8, and No Choice
6	1	0	1	6	4, 6, 7, and No Choice
7	0	1	1	7	1, 5, 7, 8, and No Choice
8	1	1	1	8	1, 2, 6, 8, and No Choice
				9	1, 2, 3, 7, and No Choice
				10	2, 3, 4, 8, and No Choice
				11	1, 3, 4, 5, and No Choice

[a]Levels: 1 = service option included; 0 = service option not included.

[b]Profiles used in choice sets are those defined in the design for the traditional conjoint analysis.

In a choice-based approach, the respondent is shown a series of choice sets. Each choice set has several full-profile profiles. A choice-based design is also shown in Table S2-6. The first choice set consists of five of the full-profile profiles (profiles 1, 2, 4, 5, and 6) and a "No Choice" option. The respondent then *chooses only one of the profiles in the choice set ("most preferred" or "most liked") or "none of these."* An example choice set task for choice set 6 is shown in Table S2-7. The preparation of profiles and choice sets is based on experimental design principles [44, 59] and is the subject of considerable research effort to refine and improve on the choice task [3, 14, 40, 44, 81].

Data Collection. Given the differing ways in which profiles are formed, the choice tasks facing the respondent are quite different. As we will see, the researcher must select between a simpler choice task in the full-profile method versus the choice-based task that is more realistic.

TABLE S2-7 Example of a Choice Set in Choice-Based Conjoint

Which Calling System Would You Choose?

1	2	3	4
Base system at $14.95/month and $.05/minute plus: • TWC: Three-way calling for $3.50/month	Base system at $14.95/month and $.05/minute plus: • ICA: Itemized call accounting for $2.75/month	Base system at $14.95/month and $.05/minute plus: • CW: Call waiting for $3.50/month and • TWC: Three-way calling for $3.50/month	None of these

For the full-profile approach, the respondent is asked to rate or rank each of the eight profiles. The respondent evaluates each profile separately and provides a preference rating. The task is relatively simple and can be performed quite quickly after a few warm-up tasks. As discussed earlier, as the number of attributes and levels increases (remember our earlier example of four factors with four levels each generating 256 profiles), the task can become very large and require some form of subset of profiles that still may be fairly substantial.

For the choice-based approach, the number of profiles may or may not vary across choice sets [59]. Also, the number of choices made (1 choice for each of 11 choice sets) is actually more in this case than required in this example. As the number of factors and levels increases, however, the choice-based design requires considerably fewer evaluations. But in all situations, the respondent sees multiple full-profiles and selects one profile from the choice set.

UNIQUE CHARACTERISTICS OF CHOICE-BASED CONJOINT The basic nature of choice-based conjoint and its background in the theoretical field of information integration [58] have led to a somewhat more technical perspective than found in the other conjoint methodologies. Even though the other methodologies are based on sound experimental and statistical principles, the additional complexity in both profile designs and estimation has prompted a great deal of developmental efforts in these areas. From these efforts, researchers now have a clearer understanding of the issues involved at each stage. The following sections detail some of the areas and issues in which choice-based conjoint is unique among the conjoint methodologies.

Type of Decision-Making Process Portrayed. Traditional conjoint has always been associated with an information-intensive approach to decision making because it involves examining the profiles composed of levels from each attribute. But in choice-based conjoint, researchers are coming to the conclusion that the choice task may invoke a different type of decision-making process. In making choices among profiles, consumers seem to choose among a smaller subset of factors upon which comparisons, and ultimately choice, are made [39]. This parallels the types of decisions associated with time-constrained or simplifying strategies, each characterized by a lower depth of processing. Thus, each conjoint methodology provides different insights into the decision-making process. Because researchers may not be willing to select only one methodology, an emerging strategy is to employ both methodologies and draw unique perspectives from each [39, 80].

Choice Set Design. Perhaps the greatest advantage of choice-based conjoint is the realistic choice process portrayed by the choice set. Recent developments have further enhanced the choice task, allowing for additional relationships within the choice model to be analyzed while increasing the effectiveness of the choice set design.

A recent effort showed how the choice set can be created to ensure balance not just among factor levels, but also among the utilities of the profiles [40]. The most realistic and informative choice is among closely comparable alternatives, rather than the situation in which one or more profiles are markedly inferior or superior. However, the profile design process is typically focused on achieving orthogonality and balance among the attributes. This approach provides a more realistic task by creating profiles with more comparable utility levels, increasing consumer involvement and providing better results.

Choice-based conjoint also provides the options to include the "No Choice" alternative, in which the respondent has the choice of choosing none of the specified options [32]. This option provides the respondent with an additional level of realism while also providing the researcher with a means of establishing absolute as well as relative effects. Finally, CBC readily accommodates model modifications such as prohibited pairs, level-specific effects, or cross-effects between levels (e.g., brands) that require specially designed choice tasks best accomplished through choice-based conjoint [16, 85]. Moreover, in a method involving additional information from the respondents, choice sets are created that fit the unique preferences of each individual and achieve better predictive accuracy in market-based situations [12].

Estimation Technique. The conceptual foundation of choice-based conjoint is psychology [60, 104], but it was the development of the multinomial logit estimation technique [64] that provided an operational method for estimating these types of choice models. Although considerable efforts have refined and made the technique widely available, it still represents a more complex methodology than those associated with the other conjoint methodologies.

The choice-based approach was originally estimated only at the aggregate level, but developments have allowed for the formation of segment-level models (known as *latent class models*) and even individual models through Bayesian estimation [6, 56, 91, 103]. This development fostered even more widespread adoption of choice-based methods by making disaggregate models more conducive for use in choice simulators and other applications.

One particular aspect that remains problematic in aggregate models or in the use of choice simulators is the property of IIA (independence of irrelevant alternatives), an assumption that makes the prediction of similar alternatives problematic. Although exploring all of the issues underlying IIA is beyond the scope of this discussion, the researcher is cautioned when using aggregate-level models estimated by choice-based conjoint to understand the ramifications of this assumption.

SOME ADVANTAGES AND LIMITATIONS OF CHOICE-BASED CONJOINT The growing popularity of choice-based conjoint analysis among marketing research practitioners is primarily due to the belief that obtaining preferences by having respondents choose a single preferred profile from among a set of profiles is more realistic—and thus a better method—for approximating actual decision processes. Yet the added realism of the choice task is accompanied with a number of trade-offs the researcher must consider before selecting choice-based conjoint.

The Choice Task. Each choice set contains several profiles, and each profile contains all of the factors, similar to the full-profile profiles. Therefore, the respondent must process a considerably greater amount of information than the other conjoint methodologies in making a choice in each choice set. Sawtooth Software, developer of a choice-based conjoint (CBC) system, believes choices involving more than six attributes are likely to confuse and overwhelm the respondent [88]. Although the choice-based method does mimic actual decisions more closely, the inclusion of too many attributes creates a formidable task that results in less information than would have been gained through the rating of each profile individually.

Predictive Accuracy. In practice, all three conjoint methodologies allow for similar types of analyses, simulations, and reporting, even though the estimation processes are different. Choice-based models still have to be subjected to more thorough empirical tests, yet some researchers believe they gain an advantage in predicting choice behavior, particularly when segment-level or aggregate models are desired [108]. However, empirical tests indicate little difference between individual-level ratings-based models adjusted to take the "No Choice" option into account and the generalized multinomial logit choice-based models [68].

In comparing the two approaches (ratings-based or choice-based) in terms of the ability to predict shares in a holdout sample at the individual level [21], both approaches predict holdout sample choices well, with neither approach dominant and the results mixed in different situations. Ultimately, the decision to use one method over the other is dictated by the objectives and scope of the study, the researcher's familiarity with each method, and the available software to properly analyze the data.

Managerial Applications. Choice-based models estimated at the aggregate level provide the values and statistical significance of all estimates, easily produce realistic market-share predictions for new profiles [44, 108], and offer the added assurances that "choices" among profiles were used to calibrate the model. However, aggregate choice-based conjoint models hinder segmentation of the market. The development of segment-based or even individual-level models was the response to this need [56, 103, 111]. Their ability to represent interaction terms and complex interattribute relationships does provide greater insight into both the actual choice process as well as the expected aggregate relationships seen through choice simulators. Yet, for most basic choice situations, the ratings-based models described earlier are well suited to segmentation studies and the simulation of choice shares. Again, the researcher must decide on the level of realism versus complexity desired in any application of conjoint analysis.

RULES OF THUMB S2-7

Alternative Conjoint Models

- When 10 or more attributes are included in the conjoint variate, two alternative models are available:
  - Adaptive models can easily accommodate up to 30 attributes, but require a computer-based interview
  - Self-explicated models can be done through any form of data collection, but represent a distinct departure from traditional conjoint methods
- Choice-based conjoint models have become the most popular format of all, even though they

generally accommodate no more than six attributes, with popularity based on:

- Use of a realistic choice task of selecting most preferred stimulus from a choice set of stimuli, including a "No Choice" option
- Ability to more easily estimate interaction effects
- Increased availability of software, particularly with Bayesian estimation options

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Availability of Computer Programs. The good news is that several choice-based programs are now available for researchers that assist in all phases of research design, model estimation, and interpretation [42, 88]. Moreover, recent research by academicians and applied researchers is being integrated into these commercially available programs. These improvements and enhanced capabilities, after rigorous validation by the research community, should become a standard part of all choice-based programs.

Overview of the Three Conjoint Methodologies

Conjoint analysis evolved past its origins of what we now know as traditional conjoint analysis to develop two additional methodologies, each of which addresses two substantive issues: dealing with large numbers of attributes and making the choice task more realistic [74]. Each methodology provides distinctive features that help define those situations in which it is most applicable (see our earlier discussion in stage 2). Yet, in many situations two or more methodologies are feasible and the researcher has the option of selecting one or, increasingly, combining the methodologies. Only by being knowledgeable about the strengths and weaknesses of each methodology can the researcher make the more appropriate choice. The advantages of the choice-based approach are making it the most widely used. The adaptive approach also has considerable use given its ability to accommodate large numbers of attributes and levels. Whatever approach is used, they all rely on the basic principles of conjoint design. Researchers interested in conjoint analysis are encouraged to continue to monitor the developments of this widely employed multivariate technique.

AN ILLUSTRATION OF CONJOINT ANALYSIS

In this section we examine the steps in an application of conjoint analysis to a product design problem. The discussion follows the model-building process introduced in Chapter 1 and focuses on (1) design of the profiles, (2) estimation and interpretation of the conjoint part-worths, and (3) application of a conjoint simulator to predict market shares for a new product formulation. The CONJOINT module of SPSS is used in the design, analysis, and choice simulator phases of this example [97]. Comparable results are obtained with other conjoint analysis programs available for commercial and academic use. The dataset of conjoint responses is available on the text's Web sites (accessed through cengagebrain.co.uk or www.mvstats.com).

Stage 1: Objectives of the Conjoint Analysis

Conjoint analysis, as discussed earlier, has been quite effectively applied to product development situations requiring (1) an understanding of consumer preferences for attributes as well as (2) a method for simulating consumer response to various product designs. Through the application of conjoint analysis, researchers can develop either aggregate (e.g., segment-level) estimates of consumer preferences or estimate disaggregate models (i.e., individual-level) from which segments can be derived.

HBAT was seriously considering designing a new industrial cleanser for use in not only its industry, but also in many manufacturing facilities. In developing the product concept, HBAT wanted a more thorough understanding of the needs and preferences of its industrial customers. Thus, in an adjunct study to the one described in Chapter 1, HBAT commissioned a conjoint analysis experiment among 86 industrial customers.

Before the actual conjoint study was performed, internal marketing research teams, in consultation with the product development group, identified five factors as the determinant attributes in the targeted segment of the industrial cleanser market. The five attributes are shown in Table S2-8. Focus group research confirmed that these five attributes represented the primary determinants of value in an industrial cleanser for this segment, thus enabling the design phase to proceed with further specification of the attributes and their levels.

Stage 2: Design of the Conjoint Analysis

The decisions at this phase are (1) selecting the conjoint methodology to be used, (2) designing the profiles to be evaluated, (3) specifying the basic model form, and (4) selecting the method of data collection.

SELECTING A CONJOINT METHODOLOGY The first issue to be resolved is the selection of the conjoint methodology from among the three options: traditional conjoint, adaptive/hybrid conjoint, or choice-based conjoint. The choice of method should be based not only on design considerations (e.g., number of attributes, type of survey administration, etc.), but also on the appropriateness of the choice task to the product decision being studied.

Given the small number of factors (five), all three methodologies would be appropriate. Because the emphasis was on a thorough understanding of the preference structure and the decision was expected to be one of fairly high consumer involvement, the traditional conjoint methodology was chosen as suitable in terms of response burden on the respondent and depth of information portrayed. Choice-based conjoint was also strongly considered, but the absence of proposed interactions and the desire for reducing the task complexity led to the selection of the traditional conjoint method. The adaptive approach was not strongly considered given the small number of attributes and the desire to utilize traditional survey-based approaches such as written surveys.

TABLE S2-8 Attributes and Levels for the HBAT Conjoint Analysis Experiment Involving Product Design of an Industrial Cleanser

Attribute Description		Levels	
Form of the Product	Premixed liquid	Concentrated liquid	Powder
Number of Applications per Container	50	100	200
Addition of Disinfectant to Cleanser	Yes	No	
Biodegradable Formulation	No	Yes	
Price per Typical Application	35 cents	49 cents	79 cents

DESIGNING PROFILES With the traditional full-profile method selected, the next step involves the design of the profiles. Although the attributes have already been selected, the researcher must take great care during this stage in specifying the attribute levels to operationalize the attributes for use in design profiles. Among the considerations to be addressed are the nature of the levels (ensuring they are actionable and communicable), the magnitude and range of the levels for each attribute, and the potential for interattribute correlation.

The first consideration was to ensure that each level was actionable and communicable. Focus group research established specific levels for each attribute (see Table S2-8). The levels were each designed to (1) employ terminology used in the industry and (2) represent aspects of the product routinely specified in buying decisions.

Three attributes of *Product Form, Disinfectant,* and *Biodegradability* only portrayed specific characteristics; two attributes needed further examination for appropriateness of the ranges of levels. First, *Number of Applications* ranged from 50 to 200. Given the product form selected, these levels were chosen to result in the typical types of product packaging found in industrial settings, ranging from small containers for individuals to larger containers normally associated with centralized maintenance operations. Next, the three levels of *Price per Application* were determined from examining existing products. As such they were deemed to be realistic and to represent the most common price points in the current market. It should be noted that the price levels are considered monotonic (i.e., have a rank ordering), but not linear, because the intervals (differences between levels) are not consistent.

The product type did not suggest intangible factors that would contribute to interattribute correlation, and the attributes were specifically defined to minimize interattribute correlation. All of the possible combinations of levels were examined to identify any inappropriate combinations, and none were found. A small-scale pretest and evaluation study was conducted to ensure that the measures were understood and represented reasonable alternatives when formed into profiles. The results indicated no problems with the levels, thus allowing the process to continue.

SPECIFYING THE BASIC MODEL FORM With the levels specified, the researcher must next specify the type of model form to be used. In doing so, two critical issues must be addressed: (1) whether interactions are to be represented among the attributes and (2) the type of relationship among the levels (part-worth, linear, or quadratic) for each attribute.

After careful consideration, HBAT researchers felt confident in assuming that an additive composition rule was appropriate. Although research showed that price often has interactions with other factors, it was assumed that all of the other factors were reasonably orthogonal and that interaction terms were not needed. This assumption allowed for the use of either aggregate or disaggregate models as needed.

Three of the attributes (*Product Form, Applications per Container,* and *Price per Application*) have more than two levels, thus requiring a decision on the type of part-worth relationship to be used. The *Product Form* attribute represented distinct product types, so separate part-worth estimates are appropriate. The *Application per Container* attribute also had three levels, yet they did not have equal intervals. Thus, separate part-worth estimates were used here as well. Finally, price also was specified with separate part-worth estimates because the intervals were not consistent among levels.

Of these three factors, only *Price per Application* was specified as monotonic, because of the implied relationship for price. *Product Form* represented separate levels with no preconceived order. The factor *Applications per Container* was not considered monotonic, even though the levels are defined in numeric terms (e.g., 50 applications per container). In this situation, no prior knowledge led researchers to propose that the part-worths should either increase or decrease consistently across these levels.

SELECTING THE METHOD OF DATA COLLECTION The final step in designing the conjoint analysis revolves around the actual collection of preferences from respondents. In doing so, several issues must be addressed, including selection of the presentation method, actual creation of the profiles and identification of any unacceptable profiles, selecting a preference measure, and finalizing the survey administration procedure.

Selection of Presentation Method. To ensure realism and allow for the use of ratings rather than rankings, HBAT decided to use the full-profile method of obtaining respondent evaluations. An adaptive/hybrid method was not needed due to the relatively small number of factors. A choice-based method would have been equally appropriate given the smaller number of attributes and the realism of the choice task, but the full-profile approach was ultimately selected due to the need for disaggregate additive results with the simplest method of estimation.

Profile Subsets. In choosing the additive rule, researchers were also able to use a fractional factorial design to avoid the evaluation of all 108 possible combinations (3 × 3 × 2 × 2 × 3). The profile design component of the computer program generated a set of 18 full-profile descriptions (see Table 8-9), allowing for the estimation of the orthogonal main effects for each factor. Four additional profiles were generated to serve as the validation profiles. None of the profiles were deemed unacceptable after being reviewed for realism and appropriateness to the research question.

TABLE S2-9 Set of 18 Full-Profiles Used in the HBAT Conjoint Analysis Experiment for Designing an Industrial Cleanser

Profile #	*Levels of Attributes*				
	Product Form	Number of Applications	Disinfectant Quality	Biodegradable Form	Price per Application
Profiles Used in Estimation of Part-Worths					
1	Concentrate	200	Yes	No	35 cents
2	Powder	200	Yes	No	35 cents
3	Premixed	100	Yes	Yes	49 cents
4	Powder	200	Yes	Yes	49 cents
5	Powder	50	Yes	No	79 cents
6	Concentrate	200	No	Yes	79 cents
7	Premixed	100	Yes	No	79 cents
8	Premixed	200	Yes	No	49 cents
9	Powder	100	No	No	49 cents
10	Concentrate	50	Yes	No	49 cents
11	Powder	100	No	No	35 cents
12	Concentrate	100	Yes	No	79 cents
13	Premixed	200	No	No	79 cents
14	Premixed	50	Yes	No	35 cents
15	Concentrate	100	Yes	Yes	35 cents
16	Premixed	50	No	Yes	35 cents
17	Concentrate	50	No	No	49 cents
18	Powder	50	Yes	Yes	79 cents
Holdout Validation Profiles					
19	Concentrate	100	Yes	No	49 cents

20	Powder	100	No	Yes	35 cents
21	Powder	200	Yes	Yes	79 cents
22	Concentrate	50	No	Yes	35 cents

Sample Size. HBAT researchers considered samples sizes ranging from 50 to 200. Obviously, larger samples would provide a more accurate representation of the population of interest, but practical considerations (relatively small population of customers and fairly high cost of personal interviews) called for smaller sample sizes. Given the relative homogeneity of the respondents it was determined that a sample of approximately 100 would be adequate. After the data collection was completed, a total of 86 respondents completed the entire survey. This was deemed adequate to represent the buyer group in question.

Collecting Respondent Preferences. The conjoint analysis experiment was administered during a personal interview. After collecting some preliminary data, the respondents were handed a set of 22 cards, each containing one profile description. A ratings measure of preference was gathered by presenting each respondent with a foldout form that had seven response categories, ranging from "not at all likely to buy" to "certain to buy." Respondents were instructed to place each card in the response category best describing their purchase intentions. After initially placing the cards, they were asked to review their placements and rearrange any cards, if necessary. The validation profiles were rated at the same time as the other profiles but withheld from the analysis at the estimation stage. Upon completion, the interviewer recorded the category for each card and proceeded with the interview. A total of 86 respondents successfully completed the entire conjoint task.

Stage 3: Assumptions in Conjoint Analysis

The relevant assumption in conjoint analysis is the specification of the composition rule and thus the model form used to estimate the conjoint results. This assessment must be based on conceptual terms as well as practical issues.

In this situation, the nature of the product, the tangibility of the attributes, and the lack of intangible or emotional appeals justifies the use of an additive model. HBAT felt confident in using an additive model for this industrial decision-making situation. Moreover, it simplified the design of the profiles and facilitated the data collection efforts.

Stage 4: Estimating the Conjoint Model and Assessing Overall Model Fit

With the conjoint tasks specified and responses collected, the next step is to utilize the appropriate estimation approach for deriving the part-worth estimates and then assess overall goodness-of-fit. In doing so, the researcher must consider not only the responses used in estimation, but also those collected for validation purposes.

MODEL ESTIMATION Given that the preference measure used was a metric rating, either the traditional regression-based approach or the newer Bayesian methodology could be employed. Because the fractional factorial design provided enough profiles for estimation of disaggregate models, the traditional approach was used. It should be noted, however, that Bayesian estimation would have been just as appropriate, particularly because additional interaction effects were desired.

The estimation of part-worths of each attribute was first performed for each respondent separately, and the results were then aggregated to obtain an overall result. Separate part-worth estimates were made for all levels initially, with examination of the individual estimates undertaken to determine the possibility of placing constraints on a factor's relationship form (i.e., employ a linear or quadratic relationship form). Table S2-10 shows the results for the overall sample, as well as for the first five respondents in the data set. Examination of the overall results suggests that perhaps a linear relationship could be estimated for the price variable (i.e., the part-worth values decrease from 1.13 to .08 to −1.21 as the price per application increases from 35 cents to 49 cents to 79 cents). However, review of the individual results shows that only three of the five respondents (107, 123, and 135) had part-worth estimates for the price factors that were of a generally linear pattern. For respondent

129 the pattern was essentially flat, and respondent 110 had a somewhat illogical pattern where the part-worths actually increase when going from 49 cents to 79 cents. Thus, application of a linear form for the price factor would severely distort the relationship among levels, and the estimation of separate part-worth values for the *Price per Application* attribute was retained.

TABLE S2-10 Conjoint Part-Worth Estimates for the Overall Sample and Five Selected Respondents

PART-WORTH ESTIMATES													
Product Form			*Number of Applications*			*Disinfectant*		*Biodegradable*		*Price per Application*			
Premixed	**Concentrate**	**Powder**	**50**	**100**	**200**	**Yes**	**No**	**No**	**Yes**	**$.35**	**$.49**	**$.79**	
Overall Sample													
−.2171	.1667	.0504	−.3450	.0233	.3217	.5102	−.5102	−.1541	.1541	1.1318	.0814	−1.2132	
Selected Respondents (107, 110, 123, 129, and 135, respectively)													
−.0556	.6111	−.5556	.4444	.6111	−1.0556	−.2083	.2083	.5417	−.5417	1.4444	.9444	−2.3889	
.4444	−.5556	.1111	−.0556	−.3889	.4444	.1667	−.1667	−.5833	.5833	.6111	−.8889	.2778	
−.6111	.3889	.2222	−.4444	.2222	.2222	−.4167	.4167	−.5417	. 5417	2.5556	.0556	−2.6111	
−.0556	.1111	−.0556	−.0556	−.0556	.1111	.4167	−.4167	−.0833	.0833	−.0556	−.0556	.1111	
−.2222	−.3889	.6111	−.2222	−.3889	.6111	.1667	−.1667	.1667	−.1667	2.944	−.7222	−2.2222	

ASSESSING GOODNESS-OF-FIT For both disaggregate and aggregate results, three goodness-of-fit measures were provided. Preference was measured using ratings (metric data); therefore, Pearson correlations were calculated for the estimation sample. The ratings values also were converted to rank orders and a Kendall's tau measure calculated. The holdout sample had only four profiles, so goodness-of-fit, for validation purposes, used only the rank-order measure of Kendall's tau.

Unlike many other multivariate techniques, when evaluating disaggregate results no direct statistical significance test evaluates the goodness-of-fit measures just described. However, we can use generally accepted levels of correlation to assess goodness-of-fit for both the estimation and validation phases. In establishing any threshold for evaluating the goodness-of-fit measures, the researcher must look at both the very low and very high values, because each may indicate respondents for whom the choice task was not applicable.

Assessing Low Goodness-of-Fit Values. In evaluating the lower values, the obvious threshold is some minimum value of correlation between the actual preference scores and the predicted utility values. One way to set a minimum value is to examine the distribution of values for the goodness-of-fit measures. Outlying values may indicate respondents for whom the choice task was not applicable when compared to the other respondents. A second approach is to establish a minimum correlation value based on the small number of profiles for each respondent, similar to the adjusted R^2 measure in multivariate regression (see Chapter 4 for more details).

In this example, the estimation process used 18 profiles and five attributes as independent variables. In a regression model of 18 observations and five independent variables, an adjusted R^2 of zero is found when the R^2 is approximately .300. This establishes a minimum correlation of .55 (the square root of .300) so that the adjusted R^2 would always be above zero. The researcher may also wish to set some minimum threshold that corresponds to a level of fit. For example, if the researcher wanted for the estimation process to explain at least 50 percent of the variation, then a correlation of .707 is required.

Using a minimum goodness-of-fit level of .55 and a desired level of .707 for the Pearson correlation (metric-based), only three respondents had values less than .707 and all of these were above the lower threshold of .55 (see Table S2-11). The Kendall's tau values, although generally lower in value given their use of rank order rather than the ratings, demonstrated the same general pattern. For the validation profiles, four respondents (110, 229, 266, and 372) had particularly low Kendall's tau values (all .40 or lower). Although one of these respondents (266) also had low estimation values, the other three had low values only on the validation process.

TABLE S2-11 Goodness-of-Fit Measures for Conjoint Analysis Results

	Estimation Sample		*Validation Sample*		*Estimation Sample*		*Validation Sample*
Respondent	**Pearson**	**Kendall'sTau**	**Kendall'sTau**	**Respondent**	**Pearson**	**Kendall'sTau**	**Kendall'sTau**
107	.929	.784	.707	363	.947	.819	.548
110	.756	.636	.408	364	.863	.760	.707
123	.851	.753	.707	366	.828	.751	.548
129	.945	.718	.816	368	.928	.783	.775
135	.957	.876	.816	370	.783	.690	.913
155	.946	.736	.707	372	.950	.813	.183
161	.947	.841	.913	382	.705	.463	.548
162	.880	.828	.667	396	1.000	1.000	1.000
168	.990	.848	.913	399	.948	.766	.913
170	.808	.635	.667	401	.985	.869	.913

171	.792	.648	.548	416	.947	.762	.816
173	.920	.783	.548	421	.887	.732	.548
174	.967	.785	.913	422	.897	.832	1.000
181	.890	.771	.913	425	.945	.743	.707
187	.963	.858	.913	428	.967	.834	.913
193	.946	.820	.816	433	.864	.754	.548
194	.634	.470	.913	440	.903	.778	.816
197	.869	.731	.548	441	.835	.666	.548
211	.960	.839	.707	453	.926	.815	.913
222	.907	.761	.707	454	.894	.661	.816
225	.990	.931	1.000	467	.878	.798	.913
229	.737	.582	.236	471	.955	.840	.707
235	.771	.639	.775	472	.899	.748	.707
236	.927	.843	.707	475	.960	.875	.667
240	.955	.735	.816	476	.722	.538	.775
260	.939	.738	.775	492	.944	.791	.816
261	.965	.847	.707	502	.946	.832	.707
266	.570	.287	.236	507	.857	.746	.548
271	.811	.654	.707	514	.924	.795	.707
277	.843	.718	.707	516	.936	.850	.548
287	.892	.744	.913	518	.902	.803	1.000
300	.961	.885	.707	520	.888	.812	.913
302	.962	.871	.816	522	.957	.903	.548
303	.898	.821	1.000	528	.917	.797	.816

309	.876	.821	.800	535	.883	.748	.816
318	.896	.713	.816	538	.827	.665	1.000
323	.874	.762	.816	557	.948	.854	.913
336	.878	.780	.667	559	.900	.767	.913
348	.949	.747	.816	578	.905	.726	.707
350	.970	.861	.816	580	.714	.614	.913
354	.795	.516	.707	586	.974	.862	1.000
356	.893	.780	.913	589	.934	.679	.913
357	.915	.730	.913	592	.931	.832	.913
Aggregate	.957	.876	.816				

Assessing Very High Goodness-of-Fit Values. Extremely high goodness-of-fit measures should also be examined; they may indicate that the choice tasks did not capture the decision process, similar to extremely low values. For example, values of 1.0 indicate that the estimated part-worths perfectly captured the choice process, which may occur when the respondent utilizes only a single or small number of attributes. But it may also indicate a respondent who did not follow the spirit of the task, and thus provides unrepresentative results. Although assessing these values requires a degree of researcher judgment, it is important to evaluate the results for every value to ensure that they are truly representative of the choice process.

Three respondents (225, 396, and 586) were identified based on their extremely high goodness-of-fit values for the estimation sample. The goodness-of-fit values for the estimation sample are .990, 1.000, and .974, respectively, and all three have goodness-of-fit values of 1.000 for the validation sample. Thus, all three should be examined to see whether the part-worth estimates represent reasonable preference structures.

When looking at the individual part-worth estimates, quite different preference structures emerge (see Table S2-12). For respondent 225, all of the attributes are valued to some degree with *Price per Application* and *Disinfectant* being the most important. Yet when we examine respondent 396, we see a totally different pattern. Only *Price per Application* has estimated part-worths, indicating that the decision was made solely on this attribute. Respondent 586 placed some importance on *Product Form* and *Number of Applications,* but *Price per Application* still played a dominant role.

As a result, the researcher must determine whether these respondents are retained based on the appropriateness of their preference structures. In this situation, all three respondents will be retained. For respondent 225, the preference structure seems quite reasonable. For the other two respondents, even though their preference structure is highly concentrated in the *Price per Application* attribute, it still represents a reasonable pattern that would reflect the preferences of specific consumers.

Assessing Validation Sample Goodness-of-Fit Levels. In addition, the researcher must also examine the goodness-of-fit levels for the validation sample. Here the focus is on low values of fit, because the relatively few number of profiles makes higher values quite possible along with the reasonable expectation that the estimated model would perfectly fit the validation profiles.

For the validation profiles four respondents (110, 229, 266, and 372) had very low goodness-of-fit values. Thus, in order to maintain the most appropriate characterization of the preference structures of the sample, these four respondents will be candidates for elimination. The final decision will be made after the part-worths are examined for theoretically consistent patterns.

TABLE S2-12 Examining Part-Worth Estimates for Respondents with Extremely High Goodness-of-Fit Values

PART-WORTH ESTIMATES FOR RESPONDENTS 225, 396, AND 586, RESPECTIVELY													
Product Form			*Number of Applications*			*Disinfectant*		*Biodegradable*		*Price per Application*		
Premixed	**Concen-trate**	**Powder**	**50**	**100**	**200**	**Yes**	**No**	**No**	**Yes**	**$.35**	**$.49**	**$.79**
−.4444	.2222	.2222	−.7778	−.4444	1.2222	1.2083	−1.2083	−.0417	.0417	1.0556	.3889	−1.4444
.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	2.6667	.6667	−3.3333
−.1667	.0000	.1667	.1667	.0000	−.1667	.0000	.0000	.0000	.0000	2.1667	.667	−2.8333

Note: The goodness-of-fit values for the estimation sample are .990, 1.000, and .974, respectively. All three respondents have goodness-of-fit values of 1.000 for the validation sample.

Stage 5: Interpreting the Results

The first task is to examine the part-worths and assess whether reversals (violation of monotonic relationships) exist that would cause deletion of any respondents. To assist in this task, the part-worths will be rescaled to provide a measure of comparison. With any reversals identified, the focus shifts to interpreting the part-worth estimates and examining each respondent's importance score for the attributes.

RESCALING Comparing part-worth estimates both across attributes and between respondents can sometimes be difficult given the nature of the estimated coefficients. They are centered on zero, making a direct comparison difficult without any obvious reference point. One approach to simplifying the interpretation process is rescaling the part-worths to a common standard, which typically involves a two-step process. First, within each attribute, the minimum part-worth is set to zero and the other part-worth(s) are expressed as values above zero (easily done by adding the minimum part-worth to all levels within each attribute). Then, the part-worths are totaled and rescaled proportionately to equal 100 times the number of attributes. This type of rescaling does not affect the relative magnitude of any part-worth, but provides a common scale across all part-worth values for comparison across attributes and respondents.

Table S2-13 presents the rescaling process and results for respondent 107 in the HBAT study. The process described is used with rescaling such that the sum of the part-worths across the five attributes equals 500. As shown in Table S2-13, step 1 restates each part-worth within each attribute as the difference from the lowest level in the attribute. Then the part-worths are totaled and rescaled to equal 500 (100×5). When rescaled, the lowest part-worth on each attribute has a value of zero. Other part-worths can now be compared either within or between respondents knowing that they are all on the same scale.

EXAMINING PART-WORTH ESTIMATES Now that the part-worths are rescaled, the researcher may examine the part-worth estimates for each respondent to understand not only the differences between levels within a factor or across factors, but also between respondents. The profiles created for each respondent based on the part-worths enable the researcher to quickly categorize the preference structure of a respondent or even sets of respondents. Although more sophisticated techniques could be used, such as cluster analysis (see Chapter 9 for a more detailed discussion), even a visual inspection will identify patterns. If a monotonic relationship is assumed between the levels of an attribute, then the researcher must also identify any reversals (i.e., theoretically inconsistent part-worth patterns) as discussed in the next section.

TABLE S2-13 Rescaling Part-Worth Estimates for Respondent 107

Product Form			*Number of Applications*			*Disinfectant*		*Biodegradable*		*Price per Application*		
Premixed	**Concentrate**	**Powder**	**50**	**100**	**200**	**Yes**	**No**	**No**	**Yes**	**$.35**	**$.49**	**$.79**
Original Part-Worth Estimates												
−.0556	.6111	−.5556	.4444	.6111	−1.0556	−.2083	.2083	.5417	−.5417	1.4444	.9444	−2.3889
Step 1. Restating Part-Worths in Relationship to Minimum Levels Within Each Attribute:[a]												
.5000	1.1667	0.00	1.500	1.6667	0.00	0.00	.4166	1.0834	0.00	3.8333	3.3333	0.00
Step 2. Rescaling the Part-Worth Estimates:[b]												
18.52	43.21	.00	55.56	61.73	.00	.00	15.43	40.13	.00	141.96	123.46	.00

[a]Minimum part-worth on each attribute added to other part-worths of that attribute [e.g., minimum part-worth of product form is .5556, which when added to premixed value (.5556) equals .5000].

[b]Total of restated part-worths is proportionally rescaled to total 500 [e.g., total of restated part-worths is 13.50; thus, premixed part-worth rescaled to 18.52 (500 ÷ 13.50 × 500)].

Figure S2-5 shows the diversity of part-worth estimates across the five attributes for three selected respondents (107, 123, and 135) as well as the aggregate results compiled for all respondents. The aggregate results might be thought of as the average respondent, against which the researcher can view the preference structures of each respondent separately as portrayed by the part-worths to gain unique insights into each individual.

For example, for the attribute *Product Form* the aggregate results indicate that *Concentrate* (part-worth of 28.8) is the most preferred form, followed closely by *Powder* (20.1) and then *Premixed* (0.0).When viewing the three respondents, we can see that respondent 123 has an almost identical pattern, although with slightly higher part-worths for *Concentrate* and *Powder*. For respondent 107, *Concentrate* (43.2) is also the most preferred, but then *Premixed* (18.5) is second most preferred followed by *Powder* (0.0). Respondent 135 has an almost reversed pattern from the aggregate results, with *Powder* (51.7) valued most highly across the entire set of part-worths shown here and *Premixed* (8.6) and *Concentrate* (0.0) valued quite low.

In retrospect, we can see how the aggregate results portray the group overall, but we must also be aware of the differences between respondents. For just these three respondents, we see that two prefer the *Concentrate* over all other forms, yet it is also the lowest valued form for another respondent who values *Powder* most. We can also say that *Premixed* is generally valued low, although it is not the lowest valued level for all respondents as might be surmised if only the aggregate results are viewed.

REVERSALS A specific form of examining part-worths involves the search for reversals—those patterns of part-worths that are theoretically inconsistent. As noted earlier, some attributes may have implied patterns among the part-worths, typically monotonic relationships that define at least the rank ordering of the levels in terms of preference. For example, in a retail context travel distance should be monotonic, such that stores farther away are preferred less than closer stores. These relationships are defined by the researcher and should be reflected in the estimated part-worths.

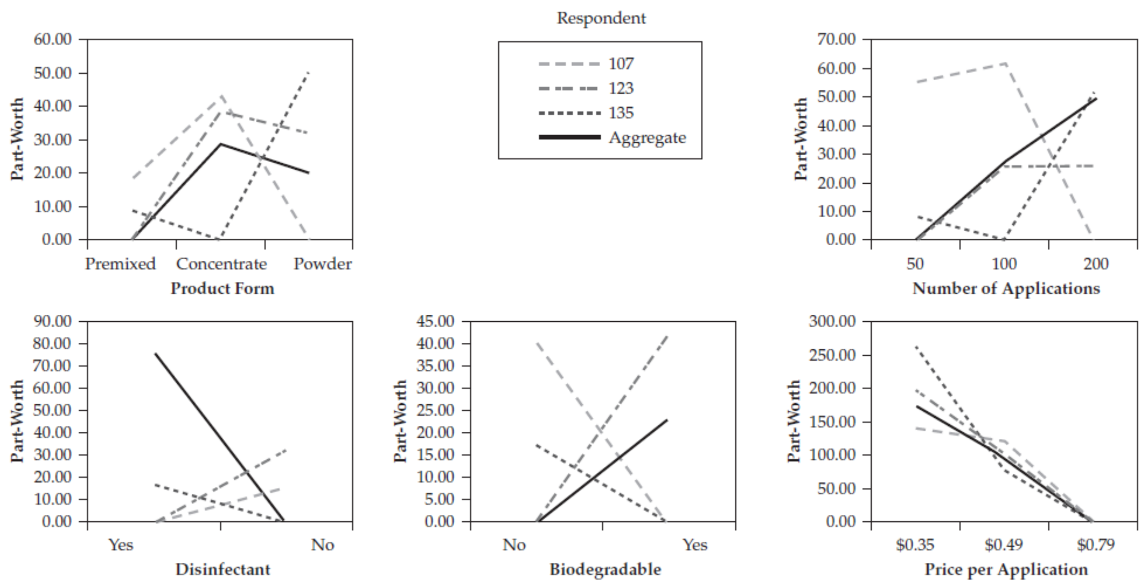

FIGURE S2-5 Part-Worth Estimates for Aggregate Results and Selected Respondents

Identification. The first task is to review all the part-worth patterns and identify any that may reflect reversals. The most direct approach is to examine the differences between adjacent levels that should be monotonically related. For example, if level A is hypothesized to be more preferred than level B, then the difference between the part-worths of level A and level B (i.e., part-worth of level A minus the part-worth of level B) should be positive.

In our example, *Price per Application* was deemed to be monotonic, such that increasing the price per application should decrease preference (and thus estimated part-worths). If we view Figure S2-5 again, we can see that the patterns of part-worths for the aggregate and individual respondents all follow the expected pattern. Although some variability is found at each level, we see the monotonic pattern (35 cents preferred over 49 cents with 79 cents preferred least) is maintained.

When we scan across the entire set of respondents, however, we do find patterns that seem to indicate a reversal of the monotonic relationship. Figure 8-6 illustrates such patterns as well as an example of the part-worth pattern that follows the monotonic relationship. First, respondent 229 has the expected pattern, with 39 cents the most preferred, then 49 cents, and finally 79 cents. Respondent 382 shows an unexpected pattern between the first two levels (39 cents and 49 cents) where the part-worth actually increases for 49 cents when compared to 35 cents. A second example is the reversal between the levels of 49 cents and 79 cents for respondent 110. Here we find a decrease between 35 cents and 49 cents, but then an increase between 49 cents and 79 cents.

As we look across the entire sample, a number of possible reversals can be identified. Table 8-14 contains all of the part-worth pairs that exhibit part-worth patterns contrary to the monotonic relationship (i.e., the part-worth difference is positive rather than negative or zero). Seven respondents had potential reversals when considering the first two levels (35 cents versus 49 cents), whereas five respondents had potential reversals for the last two levels (49 cents versus 79 cents).

A key question must still be answered: How large does the difference have to be to denote a reversal? Any difference greater than zero would theoretically meet the monotonic relationship.

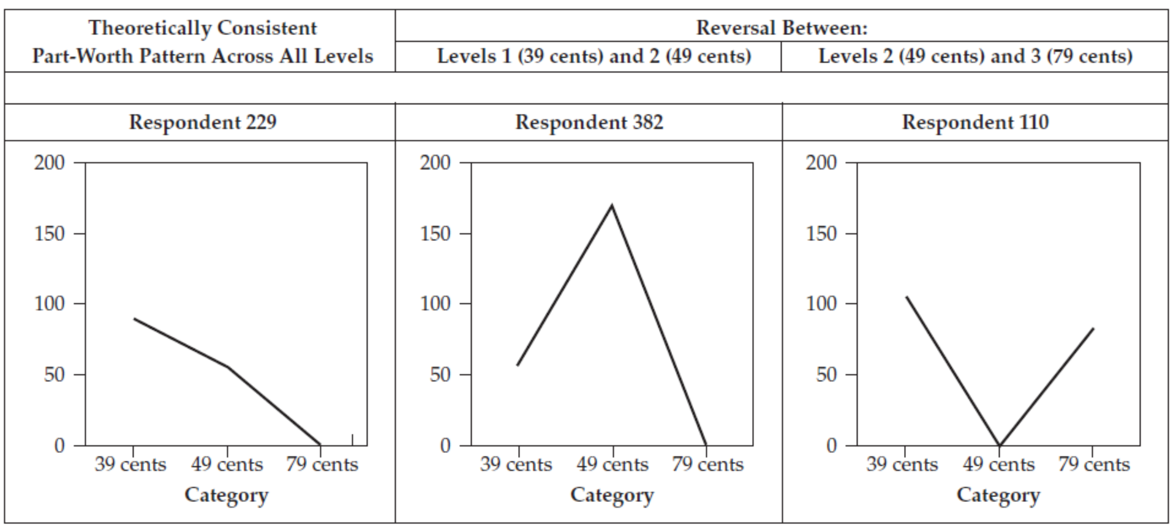

FIGURE S2-6 Identifying Reversals

Subjective and empirical approaches to identifying reversals have been discussed. A researcher should never rely totally on just subjective or empirical approaches, because either approach should act only as a guide to the researcher's judgment in assessing the appropriateness of the part-worths in representing the respondent's preference structure.

TABLE S2-14 Identifying Reversals of the Monotonic Relationship in the Price per Application Attribute

Possible Reversals Between Level 1 (35 cents) and Level 2 (49 cents)		*Possible Reversals Between Level 2 (49 cents) and Level 3 (79 cents)*	
Respondent	**Part-Worth Difference[a]**	**Respondent**	**Part-Worth Difference[a]**
382	112.68	110	83.33
194	15.87	129	55.56
580	12.82	194	15.87
260	12.66	538	12.82
370	11.90	440	8.77
336	11.49		
514	9.80		

[a] The expected part-worth difference is negative (i.e., a decrease in utility as you go from 35 cents to 49 cents or from 49 cents to 79 cents). Positive values indicate a possible violation of the monotonic relationship.

Reviewing the potential reversals in Table S2-14, we can see that in each instance one or more respondents have part-worth differences that are substantially higher than the remainder. For example, in the differences between levels 1 and 2, respondent 382 has a difference of 112.68, whereas the next largest difference is 15.87. Likewise, for the differences between levels 2 and 3, respondents 110 and 129 have values much higher (83.33 and 55.56, respectively) than the other respondents. If using a more qualitative approach to examine the distribution of the differences, these three respondents would seem likely to be categorized as having reversals that justify their removal.

A more quantitative approach is to examine statistically the differences. Although no direct statistical test is available, one approach is to calculate the standard error of the differences between levels 1 and 2 and levels 2 and 3 (7.49 and 5.33, respectively) and use them to specify a confidence interval. Using a 99% confidence level, the confidence intervals would be 19.32 (7.49 × 2.58) for the differences between levels 1 and 2 and 13.75 between levels 2 and 3. Applying these results around a difference of zero, we see that the outlying values identified in our visual examination also fall outside the confidence intervals.

Combining these two approaches leads to the identification of three respondents (382, 110, and 129) with reversals in their part-worth estimates. The researcher is now faced with the task of identifying the approach for dealing with these reversals.

Remedies for Reversals and Poor Levels of Goodness-of-Fit. As discussed earlier, the three basic remedies for reversals are to do nothing if reversals are small enough or disaggregate results are the only focus of the analysis, apply constraints in the estimation process, or eliminate the respondents. The issue of reversals is distinct, and the ultimate choice for the remedy should be coupled with remedies for respondents with poor levels of estimation or validation fit.

Given the emphasis on the preference structure of respondents, HBAT felt that the only appropriate remedy was elimination of respondents with substantial reversals. Moreover, respondents were also to be eliminated if significantly low levels of estimation or validation fit were found. Three respondents had reversals (110, 129, and 382), whereas four respondents had low levels of model fit (110, 229, 266, and 372). *Only one respondent failed on both criteria, but all six respondents were eliminated resulting in a sample size of 80 respondents.* Elimination was made to ensure the most representative set of respondents for depicting the preference structures while also maintaining an adequate sample size. *The reduced sample will be used for additional interpretation or further analyses.*

CALCULATING ATTRIBUTE IMPORTANCE A final approach to examining the preference structure of part-worths is to calculate attribute importance. These values reflect the relative impact each attribute has in the calculation of overall preference (i.e., utility scores). As described earlier, these values are calculated for each respondent and provide another concise basis of comparing between the preference structures of respondents.

Table S2-15 compares the derived importance values of each attribute for both the aggregate results and the disaggregate results of three respondents. Although we see a general consistency in the results, each respondent has unique aspects differing from each other and from the aggregate results. The greatest differences are seen for the attribute of *Price per Application,* although substantial variation is also seen on the attributes of *Biodegradability* and *Number of Applications.* Just these limited results show the wide range of part-worth profiles among the respondents and highlight the need for a complete depiction of the preference structures at the disaggregate level as well as the aggregate level.

One extension of conjoint analysis is to define groups of respondents with similar part-worth estimates or importance values of the factors using cluster analysis. These segments may then be profiled and assessed for their unique preference structures and market potential.

Stage 6: Validation of the Results

The final step is to assess the internal and external validity of the conjoint task. As noted earlier, internal validity involves confirmation of the selected composition rule (i.e., additive versus interactive). One approach is to compare alternative models (additive versus interactive) in a pretest study. The second approach is to make sure the levels of model fit are acceptable for each respondent. External validation involves in general the ability of conjoint analysis to predict actual choices, and in specific terms the issue of sample representativeness. The validation process with the holdout profiles is the most common approach to assess external validity, while ensuring sample representativeness requires analysis outside the conjoint modeling process.

The high levels of predictive accuracy for both the estimation and holdout profiles across respondents confirm the additive composition rule for this set of respondents. In terms of external validity, the holdout validation process identified four respondents with poor levels of model fit and they were excluded from the analysis. The issue of representativeness of the sample must be addressed based on the research design rather than a specific assessment of the conjoint results. In this situation, HBAT would most likely proceed to a larger-scale project with greater coverage of its customer bases to ensure representativeness. Another consideration is the inclusion of noncustomers, especially if the goal is to understand the entire market, not just HBAT customers.

TABLE S2-15 Derived Attribute Importance Values for Overall Sample and Three Selected Respondents

	Derived Attribute Importance[a]				
	Product Form	**Number of Applications**	**Disinfectant**	**Biodegradable**	**Price per Application**
Overall Sample[b]					
	15.1	17.6	18.6	9.6	39.1
Select Respondents					
107	14.3	20.4	5.1	13.3	46.9
123	11.4	7.6	9.5	12.4	59.1
135	12.8	12.8	4.2	4.2	66.0

[a] Attribute importance scores sum to 100 across all five attributes for each respondent.

[b] Based on the 80 respondents remaining after elimination of 6 respondents as the remedy for reversals and poor model fit.

A Managerial Application: Use of a Choice Simulator

In addition to understanding the aggregate and individual preference structures of the respondents, the part-worth estimates provide a useful approach to representing the preference structure of respondents using other multivariate techniques (e.g., the use of part-worths or attribute importance scores in multiple regression or cluster analysis) or applications. One specific application is the choice simulator, which utilizes the part-worth estimates to make predictions of choice between specified sets of profiles. The respondent can construct a set of profiles to represent any competitive position (i.e., current competitive market or new product entry) and then use the choice simulator to simulate the market and derive market share estimates among the profiles.

The process of running a choice simulation involves three steps: (1) specifying the scenarios, (2) simulating choices, and (3) calculating share of preference. Each of these steps will be discussed in terms of our conjoint example of the industrial cleanser.

STEP 1: SPECIFYING THE SCENARIOS HBAT also used the conjoint results to simulate choices among three possible products. The products were formulated to identify whether a new value product line might be viable. As such, the new product plus two existing product configurations were developed to represent the existing products. In our example, products 1 and 2 are existing products, and product 3 is new:

- *Product 1.* A premixed cleanser in a handy-to-use size (50 applications per container) that was environmentally safe (biodegradable) and still met all sanitary standards (disinfectant) at only 79 cents per application.
- *Product 2.* An industrial version of product 1 with the same environmental and sanitary features, but in a concentrate form in large containers (200 applications) at the low price of 49 cents per application.
- *Product 3.* A real cleanser value in powder form in economical sizes (200 applications per con-

tainer) for the lowest feasible price of 35 cents per application.

STEP 2: SIMULATING CHOICES Once the product configurations were specified, they were submitted to the choice simulator using the results from the remaining 80 respondents. In this process, the part-worths for each respondent were used to calculate the expected utility of each product.

For example, for respondent 107 (see Table S2-10), the utility of product 1 is calculated by taking that respondent's part-worth estimates for the levels of premixed (−.0556), 50 applications per container (.4444), biodegradable (−.5417), disinfectant (−.2083), and 79 cents per application (−2.3889), plus the constant (4.111) for a total utility value of 1.361. Utility values for the other two products were calculated in a similar manner. It should be noted that rescaled utilities could also be used just as easily, because the prediction of choice preferences in the next step focuses on the relative size of the utility values.

Thus, the process derives a set of utility values for each product unique to each individual. In this way the preference of each respondent is used to simulate that individual's expected choices when faced with this choice of products. The three products used in the choice simulator are most representative of the differential impact effect among products when similarity among products was minimized.

TABLE S2-16 Choice Simulator Results for the Three Product Formulations

	MARKET SHARE PREDICTIONS		
		Probabilistic Models	
Product Formulation	**Maximum Utility Model (%)**	**BTL (%)**	**Logit (%)**
1	6.88	18.00	7.85
2	21.25	36.58	29.09
3	71.88	45.42	63.06

STEP 3: CALCULATING SHARE OF PREFERENCE The choice simulator then calculated the preference estimates for the products for each respondent. Predictions of the expected market shares were made with two choice models: the maximum utility model and a probabilistic model. The maximum utility model counts the number of times each of the three products had the highest utility across the set of respondents. The probabilistic approach to predicting market shares uses either the BTL or logit model. Both models assess the relative preference of each product and estimate the proportion of times a respondent or the set of respondents will purchase a product.

As seen in Table 8-16, product 1 was preferred (it had the highest predicted preference value) by only 6.88 percent of the respondents. Product 2 was next, preferred by 21.5 percent. The most preferred was product 3, with 71.88 percent. The fractional percentages are due to tied predictions among products 2 and 3.

As an example of the calculations, the aggregate results can be used. The aggregated predicted preference values for the products were 2.5, 4.9, and 5.9 for products 1, 2, and 3, respectively. The predicted market shares of the aggregate model results using the BTL model are then calculated as follows:

$$\text{Market share}_{\text{product 1}} = 2.5/(2.5 + 4.9 + 5.9) = .188\text{, or } 18.8\%$$

$$\text{Market share}_{\text{product 2}} = 4.9/(2.5 + 4.9 + 5.9) = .368, \text{ or } 36.8\%$$

$$\text{Market share}_{\text{product 3}} = 5.9/(2.5 + 4.9 + 5.9) = .444, \text{ or } 44.4\%$$

These results are very close to the results derived from using the individual respondent utilities, as shown in Table S2-16.

Similar results are obtained using the logit probabilistic model and are shown in Table S2-16 as well. Using the model recommended in situations involving repetitive choices (probability models), as is the case with an industrial cleanser, HBAT has market share estimates indicating an ordering of product 3, product 2, and finally product 1.

It should be remembered that these results represent the entire sample, and the market shares may differ within specific segments of the respondents.

Summary

Conjoint analysis places more emphasis on the ability of the researcher or manager to theorize about the behavior of choice than it does on analytical technique. As such, it should be viewed primarily as exploratory, because many of its results are directly attributable to basic assumptions made during the course of the design and the execution of the study. This chapter helps you to do the following:

Explain the managerial uses of conjoint analysis. Conjoint analysis is a multivariate technique developed specifically to understand how respondents develop preferences for objects (products, services, or ideas). The flexibility of conjoint analysis means it can be used in almost any area in which decisions are studied. Conjoint analysis assumes that any set of objects (e.g., brands, companies) or concepts (e.g., positioning, benefits, images) is evaluated as a bundle of attributes. Having determined the contribution of each factor to the consumer's overall evaluation, the researcher can then (1) define the object or concept with the optimum combination of features, (2) show the relative contributions of each attribute and each level to the overall evaluation of the object, (3) use estimates of purchaser or customer judgments to predict preferences among objects with differing sets of features, (4) isolate groups of potential customers that place differing importance on the features to define high and low potential segments, and (5) identify marketing opportunities by exploring the market potential for combinations of features not currently available. Knowledge of the preference structure for each individual enables almost unlimited flexibility to examine both individual and aggregate reactions to a wide range of product- or service-related issues.

Know the guidelines for selecting the variables to be examined by conjoint analysis. Conjoint analysis employs a variate quite similar in form to what we have seen in other multivariate techniques. The conjoint variate is a linear combination of effects of the independent variables (factors) on a dependent variable. The researcher specifies both the independent variables (factors) and their levels, but the respondent only provides information on the dependent measure. The design of the profiles involves specifying the conjoint variate by selecting the factors and levels to be included in the profiles. When operationalizing factors or levels, the researcher should ensure the measures are both communicable and actionable. Having selected the factors and ensured the measures will be communicable and actionable, the researcher still must address three issues specific to defining factors: the number of factors to be included, multicollinearity among the factors, and the unique role of price as a factor.

Formulate the experimental plan for a conjoint analysis. For conjoint analysis to explain a respondent's preference structure based only on overall evaluations of a set of profiles, the researcher must make two key decisions regarding the underlying conjoint model: specify the composition rule to be used and select the type of relationships between part-worth estimates. These decisions affect both the design of the profiles and the analysis of respondent evaluations. The composition rule describes how the researcher postulates that the respondent combines the part-worths of the factors to obtain overall worth or utility. It is a critical decision because it defines the basic nature of the preference structure that will be estimated. The most common composition rule is an additive model.

The composition rule using interaction effects is similar to the additive form in that it assumes the consumer sums the part-worths to get an overall total across the set of attributes. It differs in that it allows for certain combinations of levels to be more or less than just their sum. The choice of a composition rule determines the types and number of treatments or profiles the respondent must evaluate, along with the form of estimation method used. Trade-offs accompany the use of one approach over the other. An additive form requires fewer evaluations from the respondent and makes it easier to obtain estimates for the part-worths. However, the interactive form is a more accurate representation because respondents utilize more complex decision rules in evaluating a product or service.

Understand how to create factorial designs. Having specified the factors and levels, plus the basic model form, the researcher must next make three decisions involving data collection: type of presentation method for the profiles (trade-off, full-profile, or pairwise comparison), type of response variable, and the method of data collection. The overriding objective is to present the attribute combinations (profiles) to respondents in the most realistic and efficient manner possible. In a simple conjoint analysis with a small number of factors and levels, the respondent evaluates all possible profiles in what is known as a factorial design. As the number of factors and levels increases, this design becomes impractical. So with the number of choice tasks specified, what is needed is a method for developing a subset of the total profiles that will still provide the information necessary for making accurate and reliable part-worth estimates. The process of selecting a subset of all possible profiles must be done in a manner to preserve the orthogonality (no correlation among levels of an attribute) and balance (each level in a factor appears the same number of times) of the design. A fractional factorial design is the most common method for defining a subset of profiles for evaluation. The process develops a sample of possible profiles, with the number of profiles depending on the type of composition rule assumed to be used by respondents. If the number of factors becomes too large and adaptive conjoint is not acceptable, a bridging design can be employed in which the factors are divided in subsets of appropriate size, with some attributes overlapping between the sets so that each set has a factor(s) in common with other sets of factors. The profiles are then constructed for each subset so that the respondents never see the original number of factors in a single profile.

Explain the impact of choosing rank choice versus ratings as the measure of preference. The measure of preference—rank ordering versus rating (e.g., a 1–10 scale)—also must be selected. Although the trade-off method employs only ranking data, both the pairwise comparison and full-profile methods can evaluate preferences either by obtaining a rating of preference of one profile over the other or just a binary measure of which is preferred. A rank-order preference measure is likely to be more reliable because ranking is easier than rating with a reasonably small number (20 or fewer) of profiles and it provides more flexibility in estimating different types of composition rules. In contrast, rating scales are easily analyzed and administered, even by mail. Still, respondents can be less discriminating in their judgments than when they are rank ordering. The decision on the type of preference measure to be used must be based on practical as well as conceptual issues. Many researchers favor the rank-order measure because it depicts the underlying choice process inherent in conjoint analysis—choosing among objects. From a practical perspective, however, the effort of ranking large numbers of profiles becomes overwhelming, particularly when the data collection is done in a setting other than personal interview. The ratings measure has the inherent advantage of being easy to administer in any type of data collection context, yet it too has drawbacks. If the respondents are not engaged and involved in the choice task, a ratings measure may provide little differentiation among profiles (e.g., all profiles rated about the same). Moreover, as the choice task becomes more involved with additional profiles, the researcher must be concerned with not only task fatigue, but reliability of the ratings across the profiles.

Assess the relative importance of the predictor variables and each of their levels in affecting consumer judgments. The most common method of interpretation is an examination of the part-worth estimates for each factor in order to determine their magnitude and pattern. Part-worth estimates are typically scaled so the higher the part-worth (either positive or negative) the more impact it has on overall utility. In addition to portraying the impact of each level with the part-worth estimates, conjoint analysis can assess the relative importance of each factor. Because part-worth estimates are typically converted to a common scale, the greatest contribution to overall utility—and hence the most important factor—is the factor with the greatest range (low to high) of part-worths. The importance values of each factor can be converted to percentages summing to 100 percent by dividing each factor's range by the sum of all range values. In evaluating any set of part-worth estimates, the researcher must consider both practical relevance as well as correspondence to any theory-based relationships among levels. In terms of practical relevance, the primary consideration is the degree of differentiation among part-worths within each attribute. Many times an attribute has a theoretically based structure for the relationships between levels. The most common is a monotonic relationship, such that the part-worths of level C should be greater than those of level B, which should in turn be greater than the part-worths of level A. A problem arises when the part-worths do not follow the theorized pattern and violate the assumed monotonic relationship, causing what is referred to as a reversal. Reversals can cause serious distortions in the representation of a preference structure.

Apply a choice simulator to conjoint results for the prediction of consumer judgments of new attribute combinations. Conjoint findings reveal the relative importance of the attributes and the impact of specific levels on preference structures. Another primary objective of conjoint analysis is to conduct what-if analyses to predict the share of preferences a profile (real or hypothetical) is likely to capture in various competitive scenarios of interest to management. Choice simulators enable the researcher to simulate any number of competitive scenarios and then estimate how the respondents would react to each scenario. Their real benefit, however, involves the ability of the researcher to specify conditions or relationships among the profiles to more realistically represent market conditions. For example, will all objects compete equally with all others? Does similarity among the objects create differing patterns of preference? Can the unmeasured characteristics of the market be included in the simulation? When using a choice simulator, at least three basic types of effects should be included: (1) differential impact—the impact of any attribute/level is most important when the respondent values that object among the top two objects, indicating its role in actual choice among these objects; (2) differential substitution—the similarity among objects affects choice, with similar objects sharing overall preference (e.g., when choosing whether to ride the bus or take a car, adding buses of differing colors would not increase the chance of taking a bus, but rather the two objects would split the overall chance of taking a bus); and (3) differential enhancement—two highly similar objects of the same basic type can be distinguished by rather small differences on an attribute that is relatively inconsequential when comparing two objects of different types. The final step in conjoint simulation is to predict preference for each individual and then calculate share of preferences for each profile by aggregating the individual choices.

Compare a main effects model and a model with interaction terms and show how to evaluate the validity of one model versus the other. A key benefit of conjoint analysis is the ability to represent many types of relationships in the conjoint variate. A crucial consideration is the type of effects (main effects plus any desired interaction terms) that are to be included, because they require modifications in the research design. Use of interaction terms adds generalizability to the composition rule. The addition of interaction terms does present certain drawbacks in that each interaction term requires an additional part-worth estimate with at least one additional profile for each respondent to evaluate. Unless the researcher knows exactly which interaction terms to estimate, the number of profiles rises dramatically. Moreover, if respondents do not utilize an interactive model, estimating the additional interaction terms in the conjoint variate reduces the statistical efficiency (more part-worth estimates) of the estimation process and makes the conjoint task more arduous. Even when used by respondents, interactions predict substantially less variance than the additive effects, most often not exceeding a 5- to 10-percent increase in explained variance. Thus, in many instances, the increased predictive power will be minimal. Interaction terms are most likely to be substantial in cases for which attributes are less tangible, particularly when aesthetic or emotional reactions play a large role. The potential for increased explanation from interaction terms must be balanced with the negative consequences from adding interaction terms. The interaction term is most effective when the researcher can hypothesize that unexplained portions of utility are associated with only certain levels of an attribute.

Recognize the limitations of traditional conjoint analysis and select the appropriate alternative methodology (e.g., choice-based or adaptive conjoint) when necessary. The full-profile and trade-off methods are unmanageable with more than 10 attributes, yet many conjoint studies need to incorporate 20, 30, or even more attributes. In these cases, some adapted or reduced form of conjoint analysis is used to simplify the data collection effort and still represent a realistic choice decision. The two options include (1) an adaptive/self-explicated conjoint for dealing with a large number of attributes and (2) a choice-based conjoint for providing more realistic choice tasks. In the self-explicated model, the respondent provides a rating of the desirability of each level of an attribute and then rates the relative importance of the attribute overall. With the adaptive/hybrid model, the self-explicated and part-worth conjoint models are combined. The self-explicated values are used to create a small subset of profiles selected from a fractional factorial design. The profiles are then evaluated in a manner similar to traditional conjoint analysis. The sets of profiles differ among respondents, and although each respondent evaluates only a small number, collectively all profiles are evaluated by a portion of the respondents. To make the conjoint task more realistic, an alternative conjoint methodology, known as choice-based conjoint can be used. It asks the respondent to choose a full profile from a set of alternative profiles known as a choice set. This process is much more representative of the actual process of selecting a product from a set of competing products. Moreover, choice-based conjoint provides an option of not choosing any of the presented profiles by including a "No Choice" option in the choice set. Although traditional conjoint assumes respondents' preferences will always be allocated among the set of profiles, the choice-based approach allows for market contraction if all the alternatives in a choice set are unattractive.

To use conjoint analysis the researcher must assess many facets of the decision-making process. Our focus has been on providing a better understanding of the principles of conjoint analysis and how they represent the consumer's choice process. This understanding should enable researchers to avoid misapplication of this relatively new and powerful technique whenever faced with the need to understand choice judgments and preference structures.

Questions

1. Ask three of your classmates to evaluate choice combinations based on the following variables and levels relative to their preferred textbook style for a class, and specify the compositional rule you think they will use. Collect information with both the trade-off and full-profile methods.

Factor	**Level**
Depth	Goes into great depth on each subject
	Introduces each subject in a general overview
Illustrations	Each chapter includes humorous pictures
	Illustrative topics are presented
	Each chapter includes graphics to illustrate the numeric issues
References	General references are included at the end of the textbook

2. How difficult was it for respondents to handle the wordy and slightly abstract concepts they were asked to evaluate? How would you improve on the descriptions of the factors or levels? Which presentation method was easier for the respondents?

3. Using either the simple numerical procedure discussed earlier or a computer program, analyze the data from the experiment in question 1.

4. Design a conjoint analysis experiment with at least four variables and two levels of each variable that is appropriate to a marketing decision. In doing so, define the compositional rule you will use, the experimental design for creating profiles, and the analysis method. Use at least five respondents to support your logic.

5. What are the practical limits of conjoint analysis in terms of variables or types of values for each variable? What types of choice problems are best suited to analysis with conjoint analysis? Which are least well served by conjoint analysis?

6. How would you advise a market researcher to choose among the three types of conjoint methodologies? What are the most important issues to consider, along with each methodology's strengths and weaknesses?

Suggested Readings

A list of suggested readings illustrating issues and applications of multivariate techniques in general is available on the Web accessed through cengagebrain.co.uk or www.mvstats.com.

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