# *4. PERCEIVED VALUE ANALYSIS*

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Ultimately value is in the mind of the customer. With explicit value analysis, market and economic value of features can be evaluated. But the bottom line remains what is the customer want and what is he willing to pay for. In this section, we explore the methods to measure feature value from the perspective of the customer. There are three basic methods that are used and many variations of them. The basic result of all the methods is a set of market simulators that forecast the impact of changes in features.

## 4.1. MEASURING PERCEIVED FEATURE VALUES

Features from a perceived value perspective, focuses on feature-levels. That is we wish to know the impact of changing the performance or characteristics of a feature. Pricing studies deal with the collective product that includes specific levels of features. In those techniques, it is assumed that the product and its competitors are fully specified. With perceived value measurements, the product is yet to be defined. We seek to know what kind of product to invent by measuring the values of its components.

### 4.1.1. NO UNIVERSALLY "BEST" METHOD

The various methods have different characteristics. Each is a balance in difficulty and underlying assumptions. There is no universally best method. Each has its own limitations and its advantages. Each is best suited for specific conditions. A summary of the characteristics of the major methods is given in Appendix A at the end of this chapter.

### 4.1.2. GOALS

There are several things that we want the perceived value measurement to give us.

#### 4.1.2.1. Evaluating the Importance of Feature Levels

The purpose of perceived value studies is to explore the impact of changes in feature levels. The impact is on overall value and on market share.

#### 4.1.2.2. Estimating Market Behavior

The procedures should be robust enough to permit the exploration of possibilities beyond those measured. The results of the studies should allow us to estimate market behavior for product concepts that do not exist and for which the respondents have not been exposed.

#### 4.1.2.3. Simulating the Buying Process

The bottom line in this form of marketing research is to forecast what customers should be willing to purchase. That process takes place within a specific structure. For measurement of perceived value to be meaningful it should relate to the buying process. The closer our measurement exercises are to the buying process the more reliable the results should be.

#### 4.1.2.4. Controlling Procedural Errors

No method is without sources of error. It is a natural characteristic of all primary research. The goal, should never be the elimination of all error, but the control of those sources of error that may have a material impact on the reliability of the results. The basis of choosing among methods should be the reduction of meaningful error.

### 4.1.3. BLACK-BOX METHODS

No area of marketing research is more prone to the propagation of secret "black-box" proprietary methods than the measurement of perceived value. Unfortunately, all methods have problems and most rely on "heroic" assumptions. "Heroic" assumptions are those that can not be tested. They are fundamental to the method being used. They are not, by definition, bad, except if you do not know them. It is critical that all assumptions and procedures be known. As such, we do not recommend the use of any "Black-Box" method no matter how strongly it is supported.

### 4.1.4. GENERAL CHARACTERISTICS

There is some controversy on characteristics of perceived value methods based on multiple definitions. For clarity the following characteristics are defined. These characteristics differentiate between methods:

#### 4.1.4.1. Self-Explicated versus Derived Measures

When a respondent give a specific value for an attribute, this is referred to as self-explicated. The respondent may give a rating or dollar value. The value is given in isolation and not as a comparison. On the other hand, the respondent may be asked to distribute points or rank or to choose between items. In this case, the values are derived from the responses. Typically, self-explicated values including ratings are viewed as significantly less reliable than derived measures. Values from many of the perceived value methods discussed below are, by this definition, consider derived and not self-explicated.

#### 4.1.4.2. Compositional versus Decompositional Methods

Compositional versus decompositional methods refers to the chore that the respondent has to deal with. If the respondent evaluates feature-levels directly the model is "composed" of those evaluations. On the other hand, the respondent may be presented a number of objects and the value of the features decomposed from them. *Full Profile Conjoint Methods* are decompositional while many others are compositional.

Below is a chart showing examples of each of the four types of methods. However, it should be noted that there is a range of on both measures and methods that can give rise to any number of variations. Each of these measures and methods has inherent sources of error. Choice of the type of methods and measures that are appropriate rest on the potential impact of these sources of error on the overall uncertainty of the final results.

| | Compositional Methods | Decompositional Methods |
|---|---|---|
| **Derived Measures** | **Compositional Conjoint** | **Full Profile Conjoint** |
| **Self Explicated Measures** | **Profiling (Simalto, Build-Your-Own)** | **“Idea Wizard”** |

#### 4.1.4.3. Feature Interaction

Feature interaction takes place when the value of one feature can affect the value of other features. Most of the perceived value methods (excluding *Profiling*) require independence of features. No interaction is included.

### 4.1.5. Selecting the Method

Previously, we’ve noted that there are no universally best methods for measuring the perceived value of features. This is correct; however, some methods are preferred to others depending on the situation and conditions required. It is both an issue of the nature of the problem and the requirements for execution.

#### 4.1.5.1. Nature of the Features

Not all methods lend themselves to the consideration of all types of product features. We should first deal with the general nature of the features. Are they alternatives/choices or are they inherent characteristics of the product? When dealing with alternatives we will almost inevitably be directed towards using some type of profiling allowing the respondent to choose what they like. On the other hand if the features are inherent to the product or are characteristics of the product then we may need to use a more traditional approach of either compositional or full profile conjoint.

Also the way the features need to be described can influence the methods that we can choose. When the whole product has to be described we may be forced to use a full profile structure. On the other hand if these are incremental features we may wish to use a compositional form. We also have constraints dealing with how the features are to be shown. Most methods assume that a semantic description can be used. However, if it has to be visual then we are greatly limited by the methods that we can use. For example, Choice-Based-Conjoint, a popular method, must be used strictly with semantic descriptions.

#### 4.1.5.2. Applications and Functionality

There are multiple applications using perceived value measurement. These include, product bundle evaluation, product "take" modeling, segmentation, and price sensitivity. Various methods are not equally effective for all these applications. Some methods are designed for measurement on an individual basis while others are only applicable to the market. Using a market specific technique, such as Choice-Based-Conjoint produces inaccurate or at least questionable individual response measurements. This greatly limits the use of these sources of data to cases where only market average information is being sought.

#### 4.1.5.3. Accuracy

Accuracy measures the ability of the method to capture the respondents' belief as data. However here again we expand to include the ability of the method to capture reliable data, usable in applications. Some methods tend to be more inherently accurate than others

##### *4.1.5.3.1. Data Accuracy*

Data accuracy is usually determined by the complexity and difficulty of the method to be executed. The more straightforward the method the greater the potential accuracy. The more convoluted hypothetical and tedious the task the more likely there will be error in the data. This is really a question of the potential accuracy rather than the measured accuracy.

##### *4.1.5.3.2. Measure Accuracy*

However, there is a counter in that the simplest methods also produce less accurate descriptions of the underlying phenomena. While simple methods will produce consistently reliable result; they also produce overly simplistic metrics. Some methods use multiple iterative procedures in order to approximate the actual beliefs of the respondents. Unfortunately this may also produce less accurate primary data. It is a balance between the two purposes, error in the data and increased accuracy the metrics.

##### *4.1.5.3.3. Simulating the Buying Process*

Another source of inaccuracy may be the inability to simulate the buying process. The value of features are meaningful in the context of the decision-making process that is involved. We've come to believe that the more accurate measurements are done within a process that simulates the actual decision-making activity. Once again different methods will simulate different buying processes. For example, full profile conjoint and its derivatives tend to simulate a consumer package purchase. A profiling exercise, on the other hand, tends to simulate a negotiation process.

#### 4.1.5.4. Validity

While accuracy indicates the ability of data to capture the respondents' beliefs, validity reflects the ability to test the results against some standard. However, we use the term here in a more general context to be a measure of ability of the results to be believed. Validity therefore takes on three characteristics: the validity of the data itself which goes beyond accuracy, the validity of the applications derived from the data, and the ability of the data to be believed.

#### *4.1.5.4.1. Consistency*

Respondents may not fill out the perceived value exercise correctly. Consistency is a way of testing that the responses are “appropriate”. These are either tests within the actions or statistical tests of results designed to indicate logical consistency. They are built into the exercise or its analysis. Consistency is always tested on an individual respondent basis. In compositional methods consistency is usually tested in terms of the relative value of features. With decompositional methods it is usually tested statistically using in some form $R^2$.

#### *4.1.5.4.2. Test (Choice) Validity*

Exercises can have built-in validity tests. These are choices or decisions executed in the questionnaire that would be predictable on an individual or collective basis with the results of the perceived value exercise. This is also referred to as holdout exercises; and consist of set of options which are not used in the estimation of the perceived value but then can be used to test the results.

#### *4.1.5.4.3. Application Validity*

Application validity is a broader test of the resulting simulations or models. These are rarely done directly and when done usually consists of conditions outside of the survey. They represent the ultimate test of models and simulations. An alternative is the ability to directly link applications with responses. This ability is usually only available when data is collected on a respondent, complete, basis. The flipside of not having application validity is the potential that the results may be fraudulent. That is that the results may not reflect the underlying beliefs of the respondents.

#### *4.1.5.4.4. Face Validity*

Face validity reflects the believability of the results; that is that the individual results are believable based on the direct connection between the responses and the results. For example, you can have a face valid exercise, if you can go to a specific question as a measure of a specific perceived value. Face validity is usually only obtainable for compositional methods where there is a one-to-one correspondence between the questions asked and the perceived values.

### 4.1.5.5. Efficiency

Efficiency focuses on the difficulty of executing the methodology. This includes both the difficulty in execution of the questionnaire and the development of the necessary models and simulators to interpret the results.

#### *4.1.5.5.1. Execution Efficiency*

The more complex the exercise with large numbers of components the less efficient it is in terms of questionnaire length and the time and effort for the respondents to complete. Shorter and simpler exercises are more efficient than longer and more involved ones. Execution efficiency is particularly important when dealing with multiple purpose studies where several different and sometimes complex methodologies are used.

#### *4.1.5.5.2. Analytical Efficiency*

Analytical efficiency focuses on the difficulty or simplicity of analyzing the results from the survey. This efficiency both reflects time and effort required, However, to even a greater effect it reflects the flexibility of the methodology to look at multiple issues and multiple subpopulations. The more complex the methodology the more difficult it is to fully analyze the situation.

## 4.2. FULL PROFILE CONJOINT[1]

### 4.2.1. INTRODUCTION

*Full Profile Conjoint* estimation has become the classic perceived value measurement method. It is an experimental procedure where respondents are asked to perform an evaluation or decision task on a set of hypothetical offerings. It is a decompositional evaluation method, in that, the partial values of the features levels are derived or decomposed from the reaction of the respondents to objects that contain various levels of the features. [2] The set of objects or hypothetical offerings is so designed to allow this type of reduction.

#### 4.2.1.1. Market Analysis

This procedure can be seen as a designed version of market price analysis referred to by economists *as "Hedonic Pricing*." In this approach, the actual sales prices for classes of products are analyzed based on their characteristics. Part-worths of the attribute levels are then computed using some form of regression analysis based on a value model. The attribute levels of the products are set by what has been offered and purchased. Unfortunately, due to the nature of the market, the attribute levels not independent and the computed values are unreliable. Alternatively, a sample of respondents can be given a hypothetical set of products to evaluate whose attribute levels have been designed to be independent. This would result in regression values that are reliable. This is the *Full Profile Conjoint* process.

#### 4.2.1.2. Reducing the Number of Possibilities

How many objects should be exposed to the respondent? Considering all possible combinations of attribute levels usually results in a huge number of objects; some of which are unrealistic. Exposing respondents to hundreds of these objects and asking them to rank or even just rate them would produce an extremely tedious task. Through *Statistical Experimental Design* a sub-set of objects can be selected that makes the task more reasonable.

#### 4.2.1.3. Measurement and Forecasting Models

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[1]Sources of information on *Conjoint Analysis* can be found at:

- An Introduction to Conjoint Analysis ( *http://www.mrainc.com/intro.html*)
- A Technical Tutorial on Conjoint (*http://www.lucameyer.com/kul/)*
- Conjoint Analysis Bibliography (*http://mijuno.larc.nasa.gov/dfc/ppt/cjab.html*)
- The Conjoint Literature Database (*http://www.uni-mainz.de/~bohlp/cld2.html*)

[2] Nice detail application of *Full Profile Conjoint* in the hospitality industry is located at: (*http://borg.lib.vt.edu/ejournals/JIAHR/issue2.html*)

In order to obtain part worth of the attribute levels from any data, value models have to be used. Furthermore, value models are also used to create the market simulators. These forecasting simulators are designed to predict the impact of new offering formulations and are the key output of perceived value research. In *Full Profile Conjoint* the same model is used for the measurement and is used in the forecasting simulator. In other methods, such as *Compositional Conjoint* and *Profiling*, different models and methods are used in the two processes. This is a great advantage for *Full Profile Conjoint* in that the measures of fit to the experimental data also give a measure of reliability of the resulting simulator. No other method provides this assurance.

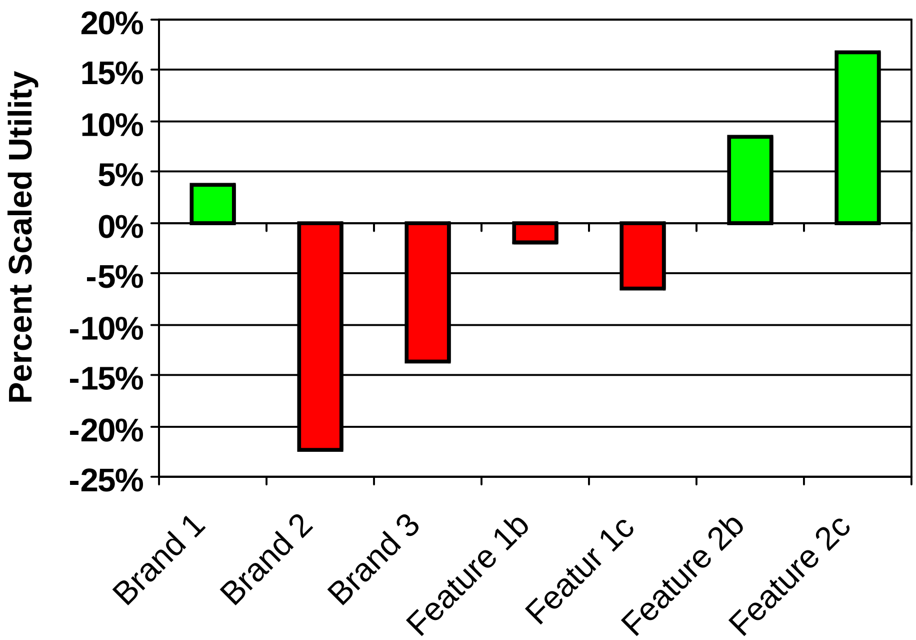
#### 4.2.1.4. Simulating the Buying Process

In *Full Profile Conjoint*, the respondents are presented with completely designed offerings. It simulates conditions where the respondents do not have control over the product attributes. The products are offered for the respondents to select. As such, *Full Profile Conjoint* does a fairly good job in the analysis of:

- Marketing of Package Goods
- Making Organizational Decisions
- Evaluating Single Buy Offer
- Selling of Collective Product Packages
- Evaluating Advertising Materials

#### 4.2.1.5. Positive and Negative Valued Features

A unique advantage of *Full Profile Conjoint* is its ability to handle negative and positive valued features. Further, the positive or negative value nature of the features does not have to be understood during the design or the analysis. As such it is a powerful tool to examining reseller and value chain issues where the ultimate value may negatively impact intermediates in the supply chain. It should be noted that both *Compositional Conjoint* and *Profiling* both require either all positive valued features or at least knowledge of which features could have negative values.




### 4.2.2. VALUE MODELING

The key to all perceived value methods is the value model that is imposed on the decision process. These models relate the "partial" importance or utility of an improvement in a feature to the total value of the resulting offering. As previously noted, these models are used both for measurement and for the construction of forecasting simulators.

#### 4.2.2.1. Feature Levels

The perceived value models are all based on levels of features. These are specific performance levels of each feature. In some cases, this may be just the inclusion or exclusion of a feature or may cover a range of possibilities from how the product is used to the color of the package and price.

In traditional *Full Profile Conjoint*, these levels are considered to be discrete. Finally, the feature levels are usually assumed to be independent of each other. In this regard, it is useful to reformulate the problem in terms of customer benefits rather than features. However, that often conflicts with the interests of the client who wishes to manipulate the offering's characteristics rather than addressing benefits that are difficult to get to.

#### 4.2.2.2. Objects and Parameters

The partial attribute values are obtained from regression analysis of the responses to the hypothetical products or objects. These values are parameters in the value expressions. For any estimation procedure, one needs at least as many objects as parameters. In order to obtain a measure of "goodness of fit," more objects are needed than parameters. The difference between the number of objects and parameters in a design is referred to as the "Degrees of Freedom." This is a measure of the redundancy of data. While statisticians may wish a minimum of a factor of four between the objects and parameters, *with Full Profile Conjoint* we usually settle for less than two.

#### 4.2.2.3. Primary Effects Model

The simplest value model is based on an additive combination of the partial worths of the appropriate feature levels. This is the simple, linear model and assumes that there are no interaction or non-linear effects. It is referred to as the "Primary Effects Model" since only the linear partial worths for each feature level is included.

This model contains the minimum number of parameters and is the basic tool for all *Full Profile Conjoint* measurements. Note that there is a constant in the model. Typically only changes in feature levels are included. The value of the minimum levels of each feature or basis, is assumed to be zero. In some cases, feature levels may be viewed as detrimental and give a negative partial worth. The constant is able to assure that the total values, however, are positive.

$$\mathbf{Value_k} = \sum_{I=1}^{N} \left(\mathbf{Utility_{ik}} \times \mathbf{X_{ik}}\right) + \mathbf{Constant}$$

Where, $\mathbf{Utility_{ik}}$ is the partial worth of feature level $\mathbf{i}$ for the respondent $\mathbf{k}$ and $\mathbf{X_{ik}}$ is the appearance of the feature level $\mathbf{i}$ for the $k^{th}$ respondent. The number of parameters in the Primary Effects Model is equal to the improvements in feature levels plus the constant. If we have three features on four levels in the design, this results in three features, each with three improvements, plus the constant or 10 parameters.

$$\mathbf{Parameters} = \sum_{i=1}^{N} \left(\mathbf{Level_i - 1}\right) + \mathbf{1}$$

#### 4.2.2.4. Interactive Model

The Primary Effects Model excludes all interactions among feature levels. This is a traditional problem with this type of measurement. Often features go together. If we wish to model the interactions we add the effect as a series of additional parameters as shown below. The number of interactions increases quadratically with the numbers of levels and features. Because of the great increase in parameters, interactive models are rarely used[3].

$$\mathbf{Value_k} = \sum_{i=1}^{N} \left(\mathbf{Utility_{ik}} \times \mathbf{X_{ik}}\right) + \sum_{j=1}^{N} \left\{ \sum_{i=1}^{N} \left(\mathbf{Interaction_{jik}} \times \mathbf{X_{jk} X_{ik}}\right) \right\} + \mathbf{Constant}$$

#### 4.2.2.5. General Linear Model

[3] Models that include only a few interactions are difficult to design. They are almost always confounded with other interactions.

Theoretically, the process can be expanded to include all possible grouped interactions. These would include interactions with as many features as were being tested. The value model takes the following form.

$$\textbf{Value}_k = \sum (A_{1ik} \cdot X_{ik}) + \sum\sum (B_{ijk} \cdot X_{jk} X_{ik}) + \sum\sum\sum (C_{ijlk} \cdot X_{jk} X_{ik} X_{ik}) + \cdots + A_{ok}$$

It can be shown that the number of parameters from this model equals the maximum combinations of feature levels. In this way, if we evaluated the value of all possible objects, we could estimate all potential interactions. Unfortunately, this produces extremely large design sets and is almost never undertaken[4].

#### 4.2.2.6. Continuous and Discrete Levels

As previously noted, the features are typically considered to be at discrete levels. This is allows for a broad range of types of features to be examined. However, discrete levels increase the number of parameters. If the feature values are continuous such as operating temperature or price, a continuous linear variable can be used. The Primary Effects Model using both discrete and continuous variables is shown below:

$$\textbf{Value}_k = \sum_{i=1}^{N} (\text{Utility}_{ik} \cdot X_{ik}) + \sum_{j=1}^{M} (\text{Unit Utility}_{jk} \cdot Z_{jk}) + \text{Constant}$$

Where, **Unit Utility**$_{jk}$ and $Z_{jk}$ representing the partial utility (part-worth) for a unit improvement and the corresponding improvement in the $j^{th}$ continuous feature by the $k^{th}$ respondent respectively. This approach can greatly reduce the number of required parameters. However, it also forces a constant value for each improvement in the continuous features. Often it is more useful to consider all features to be discrete and estimate the shape of the value function for the continuous features.

#### 4.2.2.7. Non-Linear Value Models

In some cases, it is reasonable to assume a non-linear relationship between value and feature levels, particularly for continuous features. The benefits of many features can be view as going with the logarithm of the levels rather than the linear. This is particularly the case regarding the perceived rather than the economic benefits. Research has indicated that, for example, that value tends to go with proportional changes in price. This is equivalent to using the logarithm of price. The Primary Effects Model for this is shown below.

$$\textbf{Value}_k = \sum_{i=1}^{N} (\text{Utility}_{ik} \cdot X_{ik}) + (\text{Utility}_{pk} \cdot \text{Log[Price]}) + \text{Constant}$$

[4] The use of a complete design set, however, can be implemented using extended *Choice Based Conjoint* using a highly split sample.

### 4.2.2.8. Monetary Scaling

Utilities may need to be scaled the monetary values. This is not always the case, for example, with pharmaceuticals, monetary values of each attribute may not be meaningful. This is due to the inability of healthcare professionals to attribute monetary value to services and outcomes. However, in most cases is useful if not necessary to scale utilities to a dollar or monetary value. This can be very nonlinear with expanded scales on the upper end and collapse scales on the low-end. Monetary scaling may be done explicitly based on some distributed value or implicitly based on embedded values. In the case of full- profile conjoined the embedded values are associated with each of the objects. That is each potential product choice contains a price which is then used to scale the utilities.

### 4.2.2.9. Dynamic Mapping the Utilities

In many cases future actions are solicited from the respondents for each of the scenarios in the full profile conjoint exercises. For example, with physicians, distributions of therapeutic modalities among expected patients may be requested for each scenario representing outcomes of product tests. Research with frequently purchased packaged goods, the distributions of future purchases can be used. Changes in these distributions are then used directly in the regression models to estimate the impact of the underlying parameters and features. However, in the traditional *Full Profile Conjoint* methods rankings of the scenarios are used. Usually, the utilities are assumed to be a linear function of these rankings used to evaluate the scenarios. This is convenient from an analytical viewpoint but may no theoretical justification.

#### *4.2.2.9.1. Imposed Distributions*

It can be assumed that an S-Shaped curve or a rank order distribution would be a more reasonable fit of the data than a straight line. Several functions can be used including normal, lognormal and logistic as well as several rank order distributions[5].

#### *4.2.2.9.2. Monotonic Regression*

Monotonic or Hierarchical Regression is a set of procedures designed to fit general ranking data is statistical models. This “non-metric” approach fits the spacing between the ranks in such a way as to maximize the regression modeling process[6]. However, Monotonic regression is problematic in that it assumes that all error is due to the non-equal spacing of the rankings.

#### *4.2.2.9.3. Testing Utility Functions*

There are, at least, two means of testing the appropriateness of the utility function: (1) using an external measure and (2) based on regression goodness-of-fit. Objective measures of value such as price are often included with the features. These measures should be proportional to an appropriate measure of utility. This expected relationship can be used to test of the appropriate form of the utility function.

[5] The “Broken Stick Rule” rank order distribution has been used effectively for both full profile and compositional conjoint. This distribution representing the limit (ergotic) share of a random linear process where the ranking of participants is maintained.

[6] Unfortunately, some of the classic methods, such as *Monanova*, can produce multiple solutions.

### 4.2.2.10. Lexicographic Decision Making

Underlying the *Full Profile Conjoint* process is that the feature-levels are traded-off by the respondent. That is, the respondent is willing to sacrifice the levels of some features for gains in others. This is a comparison between levels of various features. Unfortunately, respondents, on occasion, indicate preferences by feature alone. The lowest improvement of one feature is higher than the highest level of any other feature. This produces a hierarchy of features. This is referred to *as Lexicographic* decision making. Trade-off measurement such as *Full Profile Conjoint* will capture the effect but the partial utility measures will not reflect the full value of the feature levels.

## 4.2.3. DESIGN

*Full Profile Conjoint Analysis* is performed as experiments. The respondent is given stimuli and asked to respond to it. As with all experimental procedures the design can affect the results.

### 4.2.3.1. Offering Design

The key to *Full Profile Conjoint* is the design of the offerings or objects. These are hypothetical products that the respondent will see and evaluate.

#### *4.2.3.1.1. Feature-Level Elements*

The objects are made up of features that appear in levels. We differentiate the term features from attributes to emphasize the need to take the respondents' point of view. Attributes refer to the characteristics of products as viewed from the manufacturer and seller. Features, on the other hand, come from the customer viewpoint. The features provide benefits, which in turn become customer values.

**Attributes ➢-Features ➢ Benefits ➢ Values**

While measuring the value of benefits might be a more effective use of *Full Profile Conjoint*, it is rarely the interest of the clients. Typically, in these studies, the clients wish to test changes in the products that can be produced by varying features and their performance.

As previously noted, perceived value measurement focuses on the value of improved features. We measure the importance of changes in feature-level. Selection of the feature levels and the number of such is a key design issue. Typically, we wish to test the present situation and a number of potential improvements.

**Features ➢ Feature-Levels**

#### *4.2.3.1.2. Explicit Features (Cards)*

The objects are usually presented as a number of hypothetical products to be compared. The traditional manner is to use descriptions of the products on cards. Typically, the features are presented as characteristics with their performance levels clearly indicated. This is an explicit feature design and has become the standard approach.

#### *4.2.3.1.3. Integrated Features*

More sophisticated designs can be used where the products are presented either in physical form or as advertising copy where the features may be subtlety included as well as explicitly stated. This approach is particularly useful with visual or tactile features such as color or texture.

However, the approach has problems. The subtlety of the presentation may influence the perceived value in which we are measuring both the feature-levels and the presentation. If the features are embedded into collective features then it is unclear what the respondents are reacting to. This can greatly confound the design and produce unreliable results.

### 4.2.3.2. Experimental Design

The hypothetical products, objects, are selected in such a way to produce a "partial factorial" design. That is, not all-possible combinations of objects are used, only a subset. Statistical Experimental Design[7] methods are able to produce these designs. However, most *Full Profile Conjoint* studies are fairly complex and the designs are compromises between the number of objects and quality. The quality of the design is reflect by being orthogonal and balanced."

#### *4.2.3.2.1. Orthogonally*

The key property that should be established is that the feature-level elements on the objects are independent. This is the original problem that limited the uses of market offerings to evaluate feature value. When the object set is independent or orthogonal than the correlation between feature-levels is always zero. In practice, however, some designs do show some small intercorrelation[8]. When there is high correlation between feature-level elements the design is referred to as being confounded in that it is not feasible to differentiate the values of the elements by using statistical regression.

#### *4.2.3.2.2. Balance*

It is desirable to expose each level of each feature to each level of the other features. This is referred to as balance. A completely balanced design would give show each feature-level the same number of times and would assure the equal comparisons. Unfortunately, with complex conjoint studies, many designs are not full balanced. However, it is desirable to make them as balanced as possible.

#### *4.2.3.2.3. Binary Variables*

Binary variables which are either present or absent provide an additional problem in that the number of apparent features may vary among the scenarios. Even if the design is orthogonal and balanced, it will

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[7]There are several general sources of designs available including those in SYSTAT (SPSS, Inc.). However, there are a number of programs specifically design to produce and *analysis Full Profile Conjoint* exercises; these include:

- CVA by Sawtooth Software (http://sawtoothsoftware.com/CVA.htm)
- SPSS Conjoint by SPSS (http://www.spss.com/software/spss/base/con1.htm)
- SAS Categorical by SAS Institute; (http://www.sas.com/rnd/app/da/market/stat.html)
- Bretton-Clark ((973) 993-3135).

[8] For practical purposes, this is not a problem unless it exceeds 0.1.

appear inconsistent unless the number of features in each scenario is maintained. With a moderate number of variables, such as eight taken four at a time, there are usually sufficient possibilities to select an appropriate design.

However, in very small variable sets this can become a problem. For example, the maximum number of scenarios for four binary variables is six when they appear two at a time. This would leave only one degree of freedom and with high intercorrelation. In this case, as in other, we introduce two hypothetical scenarios: (1) with none of the variables and (2) with all the variables. Neither of these is shown to the respondents but is assumed to be the extreme values of the scenario set. While this trick allows for only six scenarios to be used, it is appropriate only if none of the features have "negative" value.

#### 4.2.3.3. Experimental Issues

There are some fundamental experimental issues that need to be address in the design of the procedure.

##### *4.2.3.3.1. Overly Complex Objects*

While there is no theoretical limit to the number features that can be used, complex objects result in confusing the respondents. For standard *Full Profile Conjoint* tests, six or seven features are usually considered the maximum. However, it is desirable to use even fewer if many levels will be considered.

##### *4.2.3.3.2. Unrealistic Objects*

A fundamental problem with *Full Profile Conjoint* designs is the appearance of unrealistic hypothetical products. This is often a mismatch in features or characteristics that do not logically go together[9].

##### *4.2.3.3.3. Number of Stimuli*

It is generally assumed that respondents can not evaluate effectively large numbers of objects. In the typical exercise the respondent is being asked to rank a set of cards. It is typically found that respondents seem to be able to handle up to twenty- seven cards. However, more than sixteen seem to produce negative reactions[10].

##### *4.2.3.3.4. Resulting Effects*

The effect of these experimental issues is a decrease in the reliability of the results. These effects include.

###### *4.2.3.3.4.1. Respondent Fatigue*

Large complex tasks will result in respondent fatigue in which later evaluations are not as well

[9] Sometimes these objects are on the lowest feature levels. Under this condition, the object is assumed to be at the bottom of rankings or ratings and is deleted from the exercise.

[10] *Conjoint* procedures to handle larger numbers of objects and thereby larger numbers of feature-level elements are discussed later. In some of these methods, respondents are asked to rate up to 120 objects.

considered as earlier ones. This is a decrease in quality and introduces an order effect. This is particularly noticeable if ratings are being used.

###### *4.2.3.3.4.2. Artificial Tasks*

The ultimate desire is to simulate the buying process. As the complexity of the task increases it tends to be increasing artificial and no longer represents the actual buying process. This effect has been particularly noticed when unrealistic objects are included.

#### 4.2.3.4. Modifications

There are several modifications of the traditional *Full Profile Conjoint* approach that allows larger sets of feature-level elements to be included.

##### *4.2.3.4.1. Bridging*

It is possible to split the conjoint exercise into two or more smaller exercises. One or more "bridging" features are included in these experiments and are used to scale the results. While it is an effective way to increase the number of features, it can produce unrealistic objects and does not provide trade-off between all features and levels.

##### *4.2.3.4.2. Hybrid Methods*

Hybrid Conjoint combines both Full Profile and *Compositional Conjoint* methods to allow a larger number of features to be included. This is discussed in more detail later in the section on "Large Attribute Set Conjoint Methods".

#### 4.2.3.5. Evaluation Procedures

There are several ways in which the objects can be evaluated. Each has its own advantages and disadvantages. In many cases, two or more procedures are used.

##### *4.2.3.5.1. Ranking and Paired Comparisons*

The traditional method of evaluation is by ranking the objects. This assures a comparison between all objects. An alternative that gives similar results is paired comparisons[11]. The final result is a ranking of the objects based on interest of the respondent. In some exercises, the respondent may be asked to do the ranking a number of times to reflect alternative uses or conditions. The major difficulty in ranking is that it can not be easily executed using a phone survey. Furthermore, the ranking itself does not provide insight into the intention to purchase.

##### *4.2.3.5.2. Discrete Choice*

Discrete choice is an extension of pair comparisons. In this procedure, the respondent is asked to choose between a number of objects. The results are analyzed using a Logit regression to produce a

[11] If complete paired comparisons are done, it is equivalent to a rank ordering. However, there are procedures that reduce the exercise by assuming logical consistency that does require all objects to be compared.

utility that corresponds to the partial likelihood of choice. It greatest advantage is it similarity to the buying process. The difficulty is in the increased number of exercises required.

##### *4.2.3.5.3. Partial Ranking*

As a means to simplify the ranking process, partial completion ranking has been used though not recommended. In this process, the respondent is asked to first classify the objects into four or more groups and then to rank only the top and bottom groups. The objects in the two middle groups are each considered to have uniform rankings. This Tops and Bottoms ranking allow the use of larger sets but with the loss of precision. It is similar to using an S-Shaped utility function.

##### *4.2.3.5.4. Rating and Evaluation Scales*[12]

Rating can be used as an alternative to ranking. It is the easiest procedure to execute using phone surveys. It is notorious for giving imprecise results and is very sensitive to respondent fatigue. However, it can be used with ranking to provide a secondary, intention to purchase, value measure.

#### 4.2.3.6. Sampling

For industrial (business to business) research we normally desire to capture individual decision models. This involves presenting to the respondent the complete set of objects for evaluations. However, for consumer products or those that resembles consumer products we may only wish to analyze the data for the total market or predetermined market segments. Under this condition, we can split the task among respondents.

##### *4.2.3.6.1. Split Population*

Due to the size of the exercise, it is often useful to split the evaluation task into subsets. Two, four or even sixteen sub-groups are used for large consumer research *Full Profile Conjoint* studies. The results are then merged to form an average for the market and/or segments. The underlying assumption in this type of analysis is the existence of a common market decision model that is being measured. Differences among respondents are considered to be only noise that will be averaged out.

##### *4.2.3.6.2. Monadic*

In some cases, it is expected that the buyer will see only one offering in the purchase process. This is usually a “take it or leave it” situation. In order to properly simulate this process, *the Full Profile Conjoint* exercise is conducted in a similar way with only one object being exposed to each respondent. This is referred to as a monadic procedure. Its disadvantage is the large increased sample size needed for a given level of precision.

#### 4.2.3.7. Fielding Methods

Most of the fielding methods require the presentation of the objects to the respondent. This limits how the exercise can be conducted. There are three common methods of conducting *Full Profile Conjoint*

[12] A discussion on the use of rating scales in conjoint ( *http://www.mrainc.com/rating.html*)

studies:

#### *4.2.3.7.1. Interviews and Workshops*

The traditional method is by interviews and workshops. For consumer products these are often "mall intercepts" where respondents are conveniently sampled from a mall or shopping area to participate in the study. For industrial products, trade shows and recently airport intercepts have been used. However, both of these methods have inherent sampling problems. Workshops are also used where randomly selected respondents are invited to come to an interviewing facility. Recently with the advent of computerized conjoint procedures and inexpensive laptop computers, on-site interviews are feasible. The major disadvantages for these methods are cost and potential non-uniformity of interviewing.

#### *4.2.3.7.2. Phone-Mail (Fax, E-mail)-Phone*

Phone-Mail-Phone is another major method for conducting these studies. This involves recruiting respondents by phone, mailing or faxing the supporting materials. The conjoint data is finally collected in a second phone interview. This has become a major method in North America but is used less in the rest of the world. Its major advantage has been cost compared to personal interviews and consistency in execution.

#### *4.2.3.7.3. The Web (Internet)*

Recently, it has become popular to conduct marketing research studies on the Internet (World Wide Web). This is particularly attractive for *Full Profile Conjoint* since this mode allows for pictorial descriptions of products. Unfortunately, unless the objects are printed, the respondent will not have the ability to physically sort them. The other potential advantage of this method is cost. However, there is one major disadvantage that will depend on the nature of the market that is biased sampling. Not everyone is on the Internet yet. But that is quickly changing.

## 4.2.4. ANALYSES

In this section the key analysis issues are reviewed. It should be noted that most of these are also design issues.

### 4.2.4.1. Aggregation

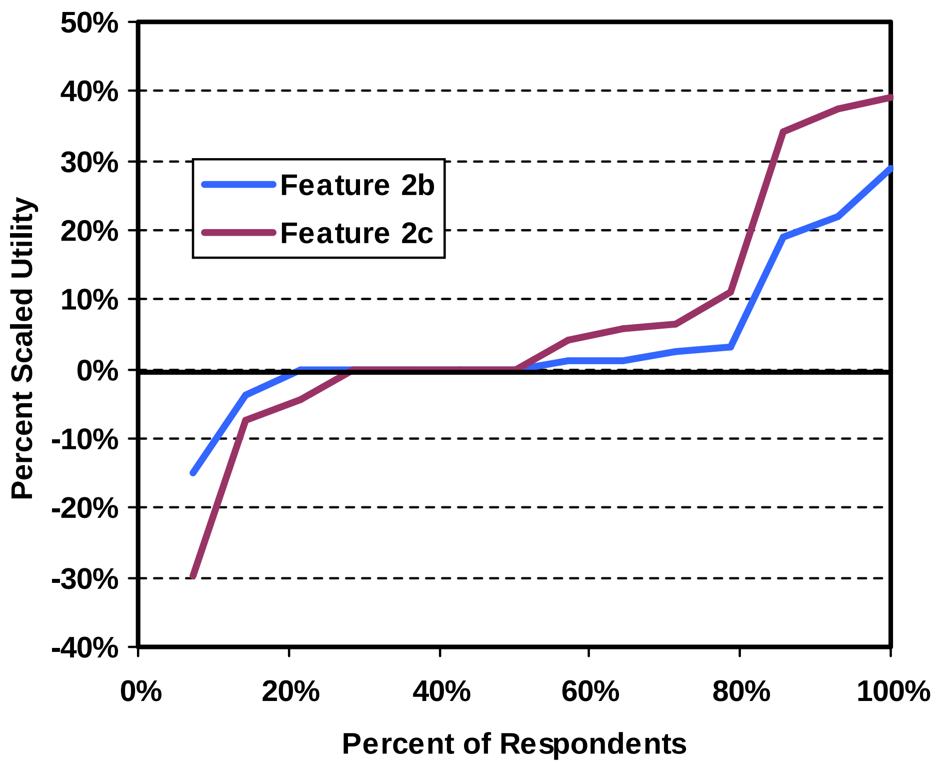
Utility estimation is done either on an individual or group basis.

#### *4.2.4.1.1. Individual Decision Models*

It is desirable to capture individual decision models from an analytical point of view. This allows for distribution analysis as well as overall market simulation. In addition, benefit market segments can be identified as well as customers positioned for potential new product offerings. This is particularly critical with industrial product studies where there is significant market concentration. In this case, a few customers may represent a major portion of the total market. The advantage of individual decision model analysis is the difficult. Separate models need to be computed for each respondent.

#### *4.2.4.1.2. Distribution Analysis*

Distribution analysis shows the relative importance of the features across the sample. The key is to show the relationships between the values of feature levels. In the figure below, we see the distribution of two feature levels compared to a third level that is the base case. Notice that a significant portion of the respondents had negative values of both levels of the feature compared to the base. These values, however, are consistent. Feature level B is better than C for negative values and the reverse for positive ones. This is often the case with features that could be detrimental to some of the respondents but not all, such as in the case of resellers.




#### *4.2.4.1.3. Market and Segment*

The data can be aggregated to form the effective or averaged results by market or predetermined (a priori) market segments. It should be noted, that this aggregation can be done either with split sample[13] or with complete individual data. In many cases initial analysis is done with aggregated data for the total market in order to obtain an overview of the situation.

### 4.2.4.2. Curve Fitting

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13 Aggregation of data for segments can and is often done independently from the sample stratification scheme. With split sample data, this means that the number of respondents for each of the subsets is not necessary each. This makes the estimation of statistical precision problematic. Usually we choose to use the smallest or the average number of respondents. However, neither is statistically correct.

The part-worths or utilities are estimated by some type of statistical regression procedure.

##### *4.2.4.2.1. Linear Dummy Variable Regression*

The standard regression form for traditional *Full Profile Conjoint* is "Linear Dummy Variable Regression." This substitutes a zero-one variable for each feature level element other than a "base-case" level. For example, four levels for a particular feature, produces three dummy variables. Multi-linear regression is then used to estimate the part-worths based on the regression coefficients[14]. Typically the regression is done either against an overall utility taken from the ranking or from the ratings. Based on rankings, the utility is taken as the maximum number of ranks plus one minus the ranking. So that, the highest ranked object has the utility equal to the number of objects in the exercise.

##### *4.2.4.2.2. Monotonic Regression*

The potential non-equal spacing of ranks may be a major source of noise. If we assume that, it is the dominant sources we can use monotonic regression procedures to estimate partial worths given an "optimum" spacing between object ranks[15]. An alternative method that is sometimes included in the procedures is to use a forced distribution. This introduces additional parameters in the regression.

##### *4.2.4.2.3. Logit Regression*

If discrete choice is used in the *Full Profile Conjoint* process then some type of stochastic regression such as Logit might be appropriate. These non-linear regression procedures are designed to handle conditions where the dependent regression variable is bounded by zero and one[16].

#### 4.2.4.3. Price Scaling

Though partial worth or utility values are usually presented as part of the standard *Full Profile Conjoint* analysis, it is often desirable to convert partial worth estimates into monetary (dollar) values. This is typical done by scaling against a price feature in the exercise. Average dollar per unit utility is computed and used to scale the other partial worths. It should be noted, however, that the precision of these estimates is significantly poorer than the underlying estimates of utility. This is particularly the case, if level prices do not span the range of utilities[17].

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[14] It should be noted that the dummy variable structure does generate intercorrelation among dummy variables even if the original design is orthogonal. This can become particular troublesome with even prior intercorrelation. Since that correlation can be magnified by dummy variables.

[15] Monotonic regression procedures are basically 'non-linear" in that the forms of the equations are not straight lines. The procedures introduce a number of new parameters which reduces the degrees of freedom making the measures of goodness-of-fit problematic. It is inappropriate, therefore, to compare the R-Square measures of multi-linear estimates with those using monotonic regression.

[16] Logit is particularly useful if analysis is being done on an individual basis. However, this results in a fairly large error estimates. Alternatively, if analysis is done on the aggregate, the dependent variable, the likelihood of purchase, can be scale or transformed directly and standard dummy variable multilinear regression used.

[17] This is the major reason why *Full Profile Conjoint* is notorious for imprecise collective price/value estimates..

#### 4.2.4.4. Calibration

It is also useful to calibrate the model with estimates of willingness-to-purchase. Typically, respondents are asked their willingness-to-purchase hypothetical and real products based on the same features used in the conjoint test. The utilities or net dollar value of these products is then computed based on the individual or market models. A function of the willingness-to-purchase for the utilities is then computed and used in a similar fashion as price is used to scale the results.

### 4.2.5. VALIDATION AND ERROR

Because of the complexity and expense of using this procedure, it is important to review the sources of error and the problems of evaluating its validity. It should be noted, however, that our interest is not in the theoretical issue of error but in the practical issue of trusting the results.

#### 4.2.5.1. Precision

Precision refers to the sample size problem. Averages from small representative samples will most likely not be equal to that of the total population. This is a simple statistical "truth." How precise do we have to be is the key question. An advantage of using individual decision models is that we can compute the expected error and precision. Because of expense, most *Full Profile Conjoint* studies involve effectively small samples of less than 400 respondents[18]. At this sample size, precision could become a problem particularly when the client is interested in a small sub-population as a target market[19]. Usually, we find with modest sample sizes exceeding 150 respondents, that other sources of potential error exceed imprecision.

Estimates of precision follow standard statistical procedures based on confidence intervals computed around mean values[20]. The confidence interval around a percentage of respondents with feature-level values above some monetary point can also be used[21].

#### 4.2.5.2. Reliability

Reliability is the ability to obtain similar result repeatedly. If we go back to the respondents will they give the same results? Because of the expense of *Full Profile Conjoint* and the limited sample sizes, reliability is rarely tested. Only when clients wish to check if the decision rules have changed over time is repeated studies conducted. Unfortunately, when changes are detected, it is uncertain if it is due

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[18] Note that if split samples are used, the appropriate sample size is that of the smallest split, not the total of all respondents interviewed.

[19] There are several approaches to expand the effective data set using "synthetic data." These allow estimation of extreme values based on assuming that the variation is the population is continuous and that it has the same statistical characteristics as the existing sample. It is an extension of the classical EM algorithm for handling missing data.

[20] We usually assume that the distribution of values are Gaussian (normally) distributed and are able to use standard tests such as the "Student T test" or the "$X^2$" test for tests of inference.

[21] The percentages are usually assumed to be Binomial distributed and confidence interval computed using the Beta distribution.

to a change in the market or the unreliability of the procedure. In general, reliability is usually assumed not to be a major problem.

### 4.2.5.3. Accuracy

Accuracy refers to the whole family of experimental and measurement problems. However, in the context of this discussion, accuracy refers to the ability of *Full Profile Conjoint* to capture the decision process. It is the possible discrepancy between what has been measured and what we think it means. We can get some measure of overall accuracy by comparing results with actual behavior. Alternatively, we can obtain some insight by questioning the respondents about the similarity of the exercise with the buying process. Unfortunately, *Full Profile Conjoint* may do well in that comparison.

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### 4.2.5.5. Experimental Error

Accuracy deals with the total issue of measurement. However, there are a number of specific errors and biases associated with field execution specifically. These issues should be examined during the pre-test of any *Full Profile Conjoint* exercise. However, with care, we have found these not to be major problems.

#### *4.2.5.5.1. Number of Feature Bias*

As previously mentioned, the number of features can greatly affect the “doability” of the exercise. The old rule of thumb is that individual can handle 7 ± 2 ideas at a time holds here. In fact, we have found that it is optimistic it is closer to 5 ± 2.

#### *4.2.5.5.2. Order Bias*

Order bias may or may not be a key problem. Usually with card sorts, the cards are randomized before each exercise to eliminate the problem. However, if letters or numbers are used to designate the objects, could be used as a clue to the respondent.

#### *4.2.5.5.3. Situational (Interviewer) Influence*

The impact of the interviewer or circumstances and surroundings of the interview can influence the results. This can be a problem, even with professionally executed studies, if a tight script is not used by the interviewer. The major problem, however, takes place with “involved” interviewers. These are often the sales and development personnel who give strong "hints" of what "should be" valued.[22]

### 4.2.5.6. Internal Consistency

The fit of the data to the value model reflects its validity and consistency of the respondents' decisions.

#### *4.2.5.6.1. Goodness-of-Fit*

The traditional goodness-of-fit measure for linear regression is the percentage of the variance explained by the model (R-Square). This is used both on an individual level and collectively to estimate the internal consistency. Poorly fitting cases, which are assumed to indicate inconsistent execution of the task, are often dropped from further analysis[23].

#### *4.2.5.6.2. Logical Values*

There is no logical constraint on the values of the feature levels that are feasible using *Full Profile Conjoint*. However, it is logical that we expect that better performance would have higher value than poorer performance. We therefore, expect that the values of features whose levels are clearly ordinal should also be in the same order. Instances where this is not are suspect and are often removed. However, it should be noted, that only where the inconsistency is significant (fairly large) is a problem. Low valued features can show inconsistencies due to random error.

#### *4.2.5.6.3. Internal Predictive Validity (Hold-out Conditions)*

The goodness-of-fit reflects the consistency within the regression modeling procedures. The regression process acts to maximize the R-Square measures. However, does the model reflect data not included in the analysis? To test this additional data is needed that was not used to fit model. These are referred to as "Hold-out" samples or *for Full Profile Conjoint* "Hold-out" cards. Agreement between the computed utilities and the rankings of the evaluation of these cases indicated a more general consistency and is a check on the R-Square measures[24].

This type of comparison is used to construct internal validity tests of the procedures. In that case, the ability of a method to capture the "held out" conditions is used to validate the quality of the procedure. Unfortunately, there are few examples of this type of comparative internal validation[25].

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[22] It is interesting, that *Full Profile Conjoint* can be used to detect differences in respondents stated attitude and what they indicate when used with qualitative research.

[23] In these cases, a criteria of greater than 0.5 R-Square can be used. Unfortunately this can for complex exercise in the removal of over 30% of the respondents.

[24] If hold-out cards are used within the object ranking exercise, the hold-out items have to be removed and the ranks readjusted. Because hold-out objects increases the complexity of the tasks without added additional capabilities to the modeling process, they are rarely introduced unless they are a "natural or real" product offering which is not included in the design.

[25] White Paper: Braden J. L. "*Predictive Accuracy of 1-9 Scaling, Conjoint Analysis and Simalto*" 1981 S1C Pickup Study (for General Motors Corporation). Marketing & Research Services, Study indicated strong internal predictive validity for Compositional (1-9 Scaling) and Simalto (Profiling) perceived value methods. Full Profile Conjoint did comparatively poorly.

### 4.2.5.7. Sources of Model Error

There are two general sources of internal inconsistency:

1. An inability of the respondents to use the features-level in their decision process. This may be due to the artificial nature of the exercise or non-inclusion of key features.

2. An inability of the value model to capture the process.

#### *4.2.5.7.1. Interactions*

Usually we consider only the Primary Effects value model for analysis. Any major interaction among the feature-levels will adversely effect the apparent internal consistency.

#### *4.2.5.7.2. Level Specific Choices*

In extreme cases, the interaction may dominate the decision process. For example, if the respondent would consider the use of a high price product differently than a lower price item it will effect the importance of other features and thereby result in an inconsistent model.

#### *4.2.5.7.3. Non-linear Utilities*

Less problematic are non-linear utilities, with different spacing between levels. While this will reduce the apparent internal consistency, it should not overwhelm the model.

### 4.2.5.8. Aggregation Error

Averaging across different groups can introduce error. While this may show up as internal inconsistency, it may not. This is can be a critical a problem when the sampling does not reflect the importance of segments with vastly different decision processes. This is particularly important with qualitative studies where participants are selected from known customers. Furthermore, there is often a reluctance and difficulty with industrial studies to get key customers and "market movers" to participate.

### 4.2.5.9. Predictability (Predictive Validity)

The ultimate test of validation is if the model predicts actual market behavior. All other tests of error are only a surrogate for predictive validity. This involves testing the model against independent data on the market behavior. This is difficult and problematic since there is a time lag between the construction of the predictive model and the collection of data. Testing the model against current behavior is also problematic since the exercise is usually based on projected behavior in the future rather than what you have already done. This "acid test" of models is unfortunately is rarely done.

### 4.2.5.10. Face Validity

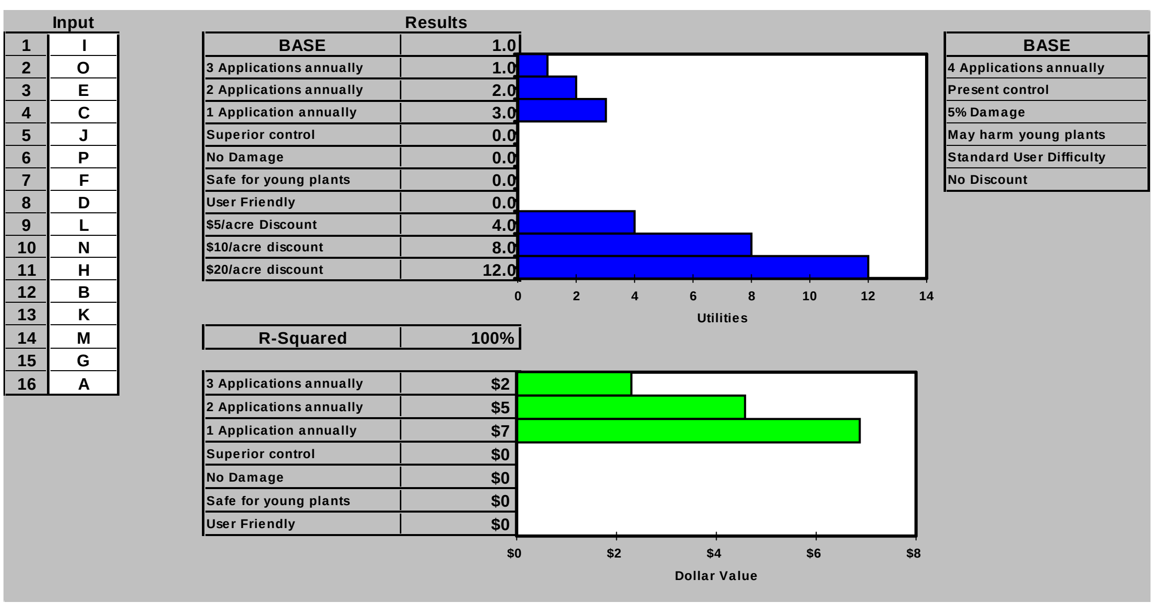
Face validity refers to the apparent trust and acceptance of the procedure by clients. *Full Profile Conjoint* has become the "gold plate" standard for perceived value measurement where it is appropriate. This leads to high face validity. Clients have indicated that the procedure is considered to be sufficiently complex to avoid "cheating" by respondents. Furthermore, it has developed a patina around a "black-box" that conveys the image of the "best practice."

### 4.2.6. DECISION MODELING AND MARKET ANALYSIS

As previously noted, typical analysis is done on the respondent basis. The results are then used for subsequent standard univariate and multivariate statistical analyses similar to analysis of attribute rating scaled data.

#### 4.2.6.1. On-Site (Live) Analysis

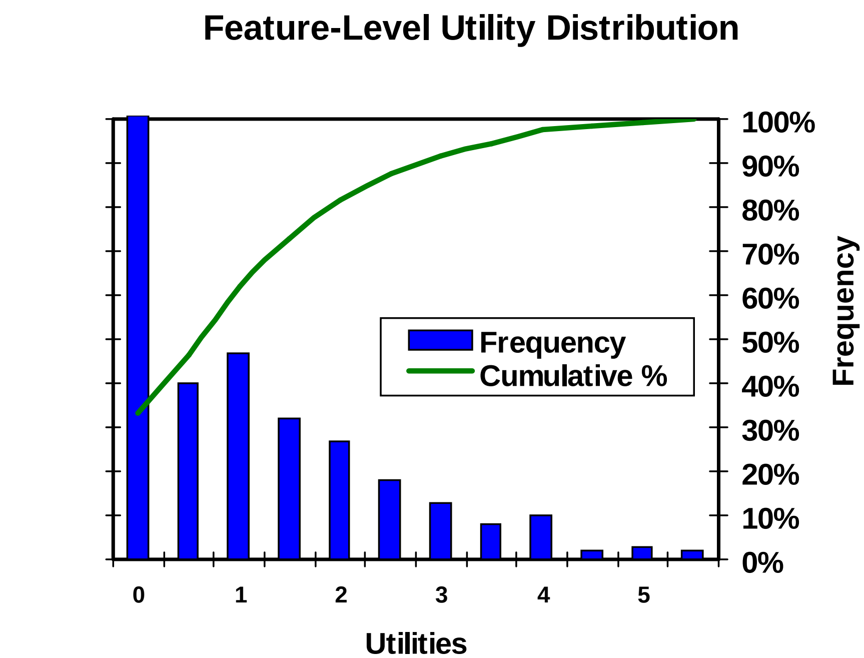
If the *Full Profile Conjoint* exercise is being conducted by personal interview, it is often useful to provide on-site analysis. This allows the respondent to comment on his own decision models. In many cases, the results can be surprising to the respondent. While usually the respondents agree with the results, sometimes there is a conflict. This may result from a misunderstanding of the task or some additional insight into the decision process. Below is a sample of the on-site analysis screen. The input consists of the rank order of the cards.



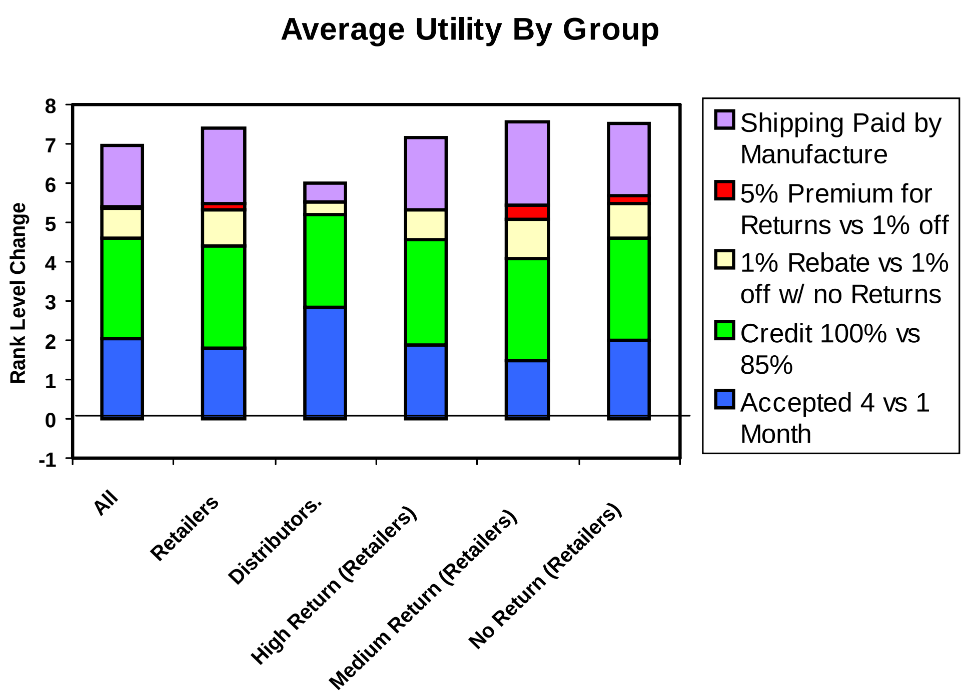

The top graph shows the distribution of linear utilities while the bottom one shows the dollar values.

#### 4.2.6.2. Utilities Distributions

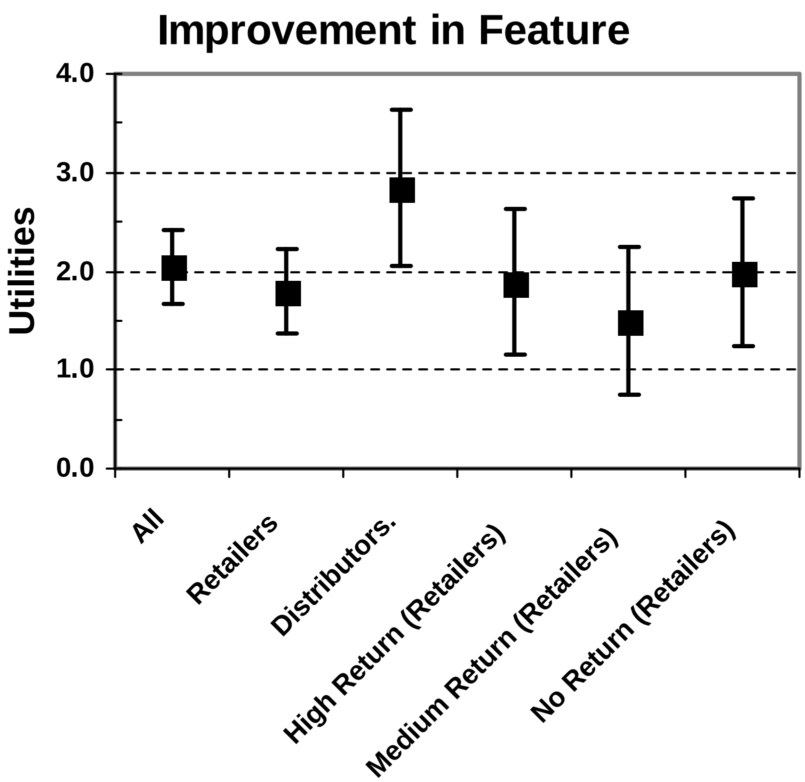
The utilities and the dollar values of each feature are distributed among the respondents as illustrated below. This is insightful to understand the fraction of the respondents who have a high value for a particular improvement of a feature.




Usually, the perceived value data is presented in terms of prior segments or groups of respondents. In the example below we consider five key segments in this value chain study: all retailers, distributors, and three subgroups of Retailers based on their product return rates.




Finally it is useful to examine the range of values by segment. This is shown in the following chart.




#### 4.2.6.3. Benefit Segmentation and Positioning

While a prior segmentation is extremely useful, it is often insightful to examine how respondents group together based on common perceived feature values. This is referred to as benefit segmentation and is ready done using statistical cluster analysis[26]. Similarly, position maps can be constructed based on these data.

### 4.2.7. MARKET SIMULATION

Market simulators are based on comparing total utilities or dollar values of alternative offerings. It is assumed that the respondents will select the offering that has either the highest utility or net dollar value[27].

The figure below shows a typical "multi-policy" simulator. In this case, we are considering two products from the same supplier. The two alternative policies are set by choosing options on the right. The simulator then computes percentages that would be dissatisfied based on scaling of utilities.

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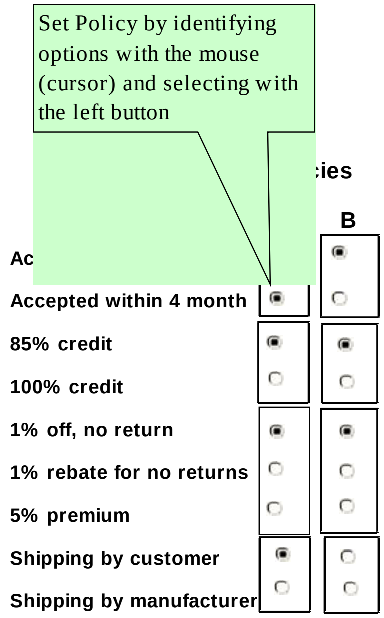
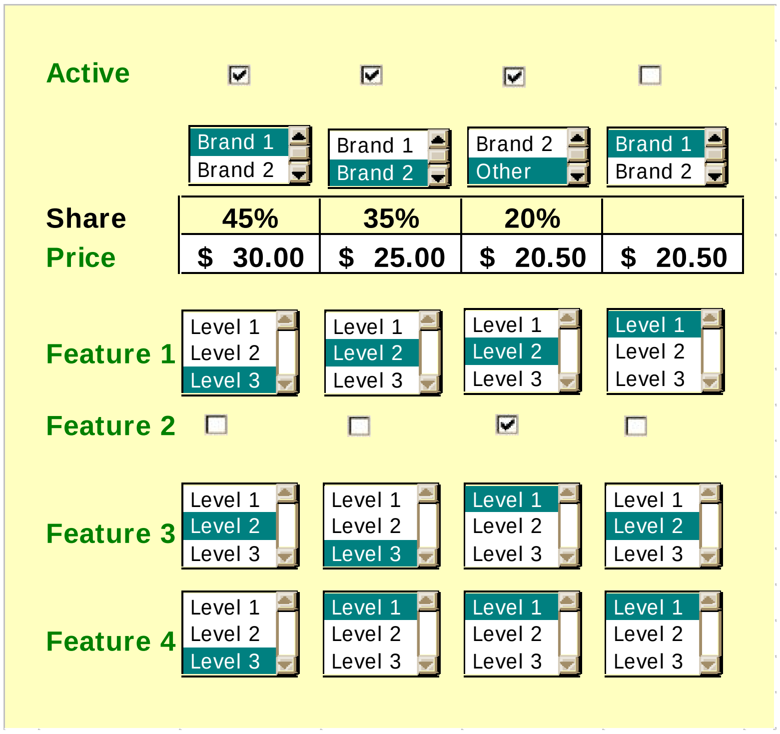
[26] As with other clustering analyses, it is important to either normalize or standardize the perceived values before clustering. This forces, us to examine the relative importance of feature changes rather than the actual levels. Clustering based on the actual dollar values will group respondents solely based on the average values across features and levels rather than difference in importance rates.

[27] This is a "Winner Takes All" policy. There are no points for coming in second.




| | | | | | icy B | |
|---|---|---|---|---|---|---|
| Group | Returns | Percent Preferred | Percent Satisfied | Average Utilities | Percent Satisfied | Average Utilities |
| All | All | 67.7% | 62.2% | 5.19 | 49.0% | 3.12 |
| Retailers | All | 65.2% | 59.8% | 4.76 | 49.1% | 2.93 |
| Dist. | All | 75.7% | 70.0% | 6.56 | 48.6% | 3.70 |
| Retailers | High | 62.7% | 62.7% | 4.93 | 60.0% | 3.00 |
| Retailers | Medium | 66.2% | 55.4% | 4.44 | 39.2% | 2.93 |
| Retailers | Low | 66.7% | 61.3% | 4.92 | 48.0% | 2.87 |
| All | High | 69.3% | 66.3% | 5.57 | 59.4% | 3.20 |
| All | Medium | 68.8% | 60.4% | 4.97 | 38.5% | 3.07 |
| All | Low | 64.9% | 59.8% | 5.02 | 48.5% | 3.07 |
| Dist. | High | 88.5% | 76.9% | 7.41 | 57.7% | 3.79 |
| Dist. | Medium | 77.3% | 77.3% | 6.76 | 36.4% | 3.55 |
| Dist. | Low | 59.1% | 54.5% | 5.37 | 50.0% | 3.75 |

Another type of simulator forecasts the shares from a number of competing products. This is shown below. The analyst or manager (hopefully the client) can choose the competitive situation. In this case, up four competitors can be considered with four features plus brand name and price. Active products are indicated by the check box on the top row. It should be noted that this model was based on net dollar value. If none of the products have a positive net dollar value, then it is assumed that the customer would purchase none of these.




### 4.2.8. Optimization

Optimization of prices and features can be a very long a complex process. Typically this is done off-line by an analyst and involves examining all possible combinations. Generally, we consider two of optimization exercises: (1) price optimization given sets of feature-levels and (2) feature-level optimization given reasonable price points.

#### 4.2.8.1. Optimizing Price

Optimizing price for a single product with given feature-level is similar to that used with *Concept Testing* and *Choice Modeling* using a linear demand model. Generally, the earnings and share are plotted against price and the optimum price is identified at the maximum earnings. Multiple product concept optimizations are more complicated and utilize a search routine with the market simulator[28]. The major problem in doing these types of optimization is the need for good estimates of marginal or variable costs for the proposed products including the costs for the new features. Detail costs are often not fully available. For more detail on price optimization see the Pricing Research chapter.

#### 4.2.8.2. Optimizing Feature-Levels

Optimizing feature levels can be an extremely complex process. Typically, this is a "brute force" process of examining every possible combination of feature-levels with the simulator[29]. The problem

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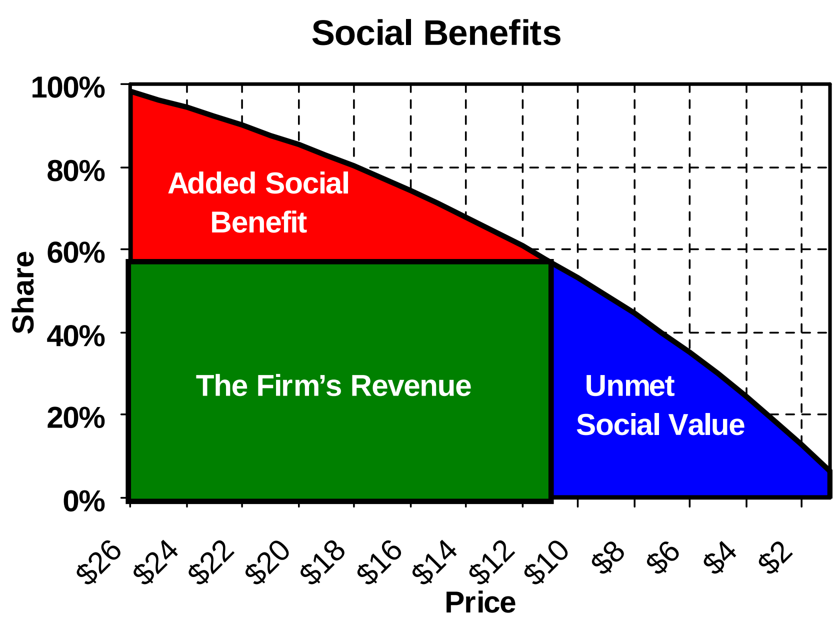
[28] These are done on *Microsoft EXCEL* spreadsheet market simulators using the *SOLVER* facility.

[29] This is one of the cases where spreadsheet simulators are less effective than those developed using procedural languages such as *BASIC* or *VisualBASIC*. This simulators can be used as subprograms for optimization. This is much more difficult with spreadsheets.

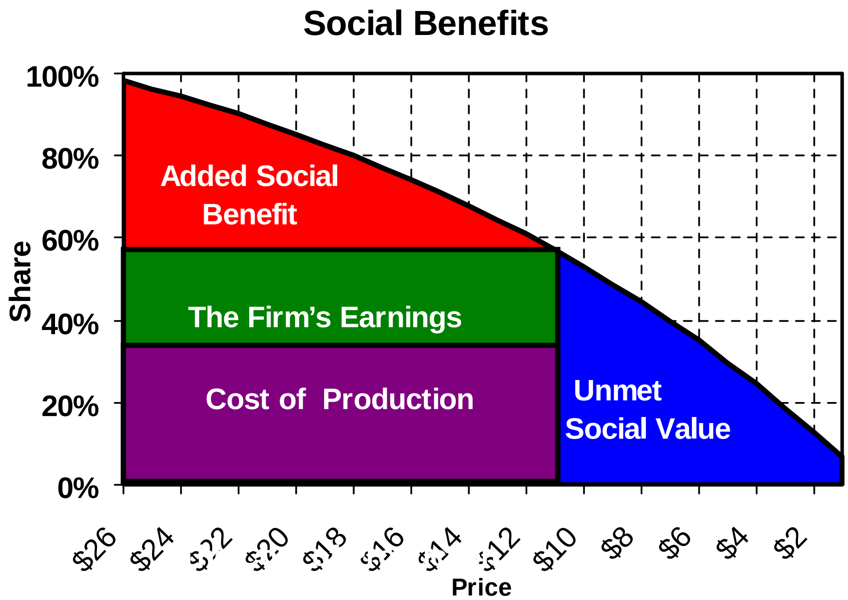
becomes much more complex if we need to deal with multiple offerings where it is necessary to optimize more than one product together. For example, with 6 features at three levels there are slightly over 700 combinations; however, with two such products, there are over half a million.

#### 4.2.9. PUBLIC POLICY MODELING

So far we have discussed simulation modeling from the perspective of the firm selling products in a competitive market. Under this condition, the value to the firm is derived from the revenues that it can obtain. For society as a whole, there is additional value obtained for providing products at prices below those that some customers are willing to pay. This is referred to as social benefit and is illustrated in the chart below.




Government and political agencies focus on the additional social benefit. Solution based on optimizing social benefits may be used to justify pricing below that suggested by the free market model. The total social benefit can be defined as the both the firm's earnings and the added social benefit as shown below. However, it should be noted that since most of the cost of production goes into wages, sometimes these costs are also included.




The social benefit are computed within the market simulation as the totals of the individual values up to the targeted price.

## 4.3. "SELF EXPLICATED (CONJOINT) METHODS

The goal of all perceived value, conjoint, procedures are to obtain the utility or dollar value of features. Compositional conjoint is a perceived value procedure based on the evaluation of features and benefits explicitly. Other methods such as full profile conjoint and profiling, deduce the value of the features by the analysis of respondents' reaction to possible product offerings. These are often referred to as "decomposition" methods[30]. Compositional conjoint focuses on the evaluation of the features themselves.

### 4.3.1. THE BUYING PROCESS

It is useful to think of the measurement process in terms of idealized buying experiences. Compositional conjoint is similar to planning a negotiated purchase. One is planning out what the various aspects of the product are worth. This is similar to most industrial and organizational decisions. Full profile conjoint on the other hand simulates a packaged goods purchase. It's a series of take it or leave it conditions.

### 4.3.2. THE PROCEDURE

While there are a large number of variations on the theme, the traditional compositional conjoint procedures result in a ranking or ratings of a number of features in their order of their importance in purchasing an item or taking an action. Embedded in the features are price references which are then used to scale the results and produce dollar values.

The items consist of changes in the levels or conditions of a set of features. Below is an example of this type of exercise using a ranking procedure. In this example, there are 9 features including the price reference (discounts) and thirteen items. Most of the features have only two levels: there is two with four levels. The base case consists of the worst levels of all features.

[30] This also sometime referred to as "self-explicated" methods. However, that general implies a direct statement of value similar to a Van Westendorp approach to pricing. In these cases, however, the value may be obtained through any number of comparative approaches.

## Base

| |
|---|
| **4 Applications annually** |
| **Controls comparable to existing product** |
| **5% Chemical Damage** |
| **Safe for most trees** |
| **Limited Bareground Control** |
| **Standard non-concentrated Product** |
| **Leaching potential equal to Major Existing Product** |
| **Potential for injury to young trees** |
| **No Discounts** |

**Rank Order the Following Items in their importance to you with 1 being the most important and 13 being the least.**

| | |
|---|---|
| **3 Applications annually ......** | ____ |
| **Superior Control .................** | ____ |
| **$20/acre discount ...............** | ____ |
| **Bareground Effectiveness** | ____ |
| **2 Applications annually ......** | ____ |
| **$10/acre discount ................** | ____ |
| **Minimum leaching ...............** | ____ |
| **No Chemical Damage ..........** | ____ |
| **Safe to trees .........................** | ____ |
| **$5/acre Discount ..................** | ____ |
| **Safe for young plants ..........** | ____ |
| **1 Application annually .........** | ____ |
| **Highly concentrated .............** | ____ |

### 4.3.3. CONDITIONS

Not all features or benefits are amendable to use in compositional conjoint. The features need to be very explicit in that the respondent needs to fully understand the feature and be able to evaluate them independently. To do so, there are three conditions that are necessary:

#### 4.3.3.1. Tangible (Cognitive) Features

The features and benefits have to be "tangible" in that they need to be understood. An alternative view is that the features and benefits need to be understood in such a way that value can be attributed to them. This is referred to as being cognitive. While the fundamental concepts of tangible and cognition are not necessarily synonymous, for this purpose they are nested conditions.

#### 4.3.3.2. Positive Valued Features

Not only must the features be able to be valued, those values must be positively. The analysis procedure assumes that the monetary values are positive. No provision is made for negative values. This property is not required by all other conjoint methods and is a significant limitation to the use of this compositional perceived value method.

#### 4.3.3.3. Not Contextual

Because the feature levels are evaluated in direct comparison, they must be viewed as if they are independent. That is there are no contextual effects; there is no interaction. While this is a standard assumption in most of the conjoint techniques, it is particular strong here.

### 4.3.4. METHODS OF MEASUREMENT

The trick is to find a way to get measurements of the feature level utility compared to other features and levels. Ultimately we would may want to then scale these utilities to obtain a monetary value by feature level. The problem has been that the simplest methods are also explicit and can be difficult for the respondents to execute. Note that the perceptual value of feature levels can be thought as a "mapping" of the respondent's utility. It is a measure of the respondent's reaction to the feature level value. Respondents may or may not actually realize these utilities. Their psychological value processes may not be explicit or "rational". The measurement may in fact be the process of realization for the respondent. It is not simply the capturing of decisions. This is true for all forms of the perceived value measurements using full profile conjoint, compositional methods, or profiling.

#### 4.3.4.1. Ranking (Compositional Conjoint)

The ranking approach as illustrated above is a straight forward exercise and is equivalent to a compared comparison of all feature levels against all other feature levels. The ranking approach is the standard procedure used in the *Compositional Conjoint* process. It is "complete" comparison data. Scaling is usually done with embedded price references. Note that since each ranking exercise is scaled separately, multiple ranking exercises can be used without additional linking items. This reduces the need for long lists of rankings. The task of ranking can be simplified using sorting procedures (such as *Q-Sorts*) but usually are not employed.

**Advantages and Disadvantages**

- This is probably the most efficient method of obtaining perceived value measurement in terms of both questionnaire length and execution time.
- Rank ordering is a difficult task and may lead to missing data or inappropriately executions.
- Inconsistencies in the ranking of references and ordinal feature level values can take place. In some automated questionnaire designs this consistency can be forced, and therefore is not a problem.
- The utility values should be considered only ordinal however and need to be scaled either explicitly using a distribution function, or implicitly using embedded values.

### 4.3.4.2. Rating Approaches

Ratings are may be among the simplest of the compositional forms. They usually involve having the respondents compare features and feature levels and put values against them. Multiple comparisons are used to "correct" values. This is usually an iterative process with a sequential improvement in the value estimates[31]. These estimates are handled either as utilities or actually as price values. Scaling of the utilities is usually handled as part of the rating process.

**Advantages and Disadvantages**

- These are the oldest and most established methods of perceived value with strong face validity.
- The comparative iterative process can be fairly involved with large numbers of features and levels since it is desired to compare each feature and level with each other.
- These exercises can be tedious and the validity of the explicit approach has been questioned.
- Typically to keep the exercise simple, all possible comparisons are not used.

### 4.3.4.3. MaxDiff and Feature Comparisons (ASEMAP™)

As noted above, ranking can be a difficult task. As alternatives, one could use a series of comparisons (either by pairs or by groups) to construct the rankings. One method to implement this would be to identify the most and least favored feature level of sets of options. With adequate minimum and maximum selections, one could then develop the ranking series. This is the basis for the *MaxDiff* approach. It is similar to using a set of limited "*Q-Sort*" procedures. Also logical constraints greatly limit the required comparisons to make the construction.

*Sawtooth Software, Inc*. provides a software package that implements this approach. The only difficulty is that the number of required comparison can exceed that which would be expected of a single respondent. As such, the *Sawtooth Software* implementation can construct the fragmented sample design. This results in the need to construct market rather than respondent level utility functions.

Feature comparisons can be used to perfect the utility measurements. This is done either as a predictor corrector process or by using some form of regression[32]. In this way a non-monetary utility function can be developed which can capture the decision process.

**Advantages and Disadvantages**

- The individual tasks required are probably the simplest and most efficient of all of the compositional conjoint methods.
- Though more efficient than *Full Profile Conjoint* methods, it can still be fairly inefficient. It

[31] Some studies have indicated that this process appears to converge in as few as three steps. That is two corrective steps.

[32] ASEMAP™ uses a log-linear regression of pair comparison data to estimate the utility values from ranked attributes

probably requires the longest time of execution due to the number of exercises required.

- When a fragmented sample is required, only market estimates of the feature level values are explicitly determined. Individual respondent level estimates can be obtained through heroic (Hierarchical Bayesian) estimates, but reliability is questionable.

### 4.3.5. COMPARISON WITH OTHER METHODS

Like all procedures, compositional conjoint has both advantages and disadvantages over alternative methods. There is no single best method for all situations.

#### 4.3.5.1. Adaptive Conjoint

*Adaptive Choice-Based-Conjoint*, *(ACBC*) is a form of compositional conjoint using a computer program to present alternatives for pairwise evaluation and refers to the computer program available from *Sawtooth Software*. This program allows for the exclusion of lower importance attributes and there by makes the process more efficient. However, Adaptive Conjoint is still only a more complex computerized form of compositional conjoint.

#### 4.3.5.2. Full Profile Conjoint

Full profile conjoint is the classical means of measuring perceived value. It is a decomposition procedure where the respondents evaluate hypothetical product concepts. The value of features is determined by regression analysis based on the respondents' choices. Compared to compositional conjoint, full profile conjoint is a complex process. Full profile conjoint is very limited in the number of features and levels that it did handle and tends to be expensive to execute.

#### 4.3.5.3. Hybrid Conjoint

Hybrid conjoint is a modification of full profile conjoint designed to handle larger numbers of features and levels. It consists of using compositional conjoint to handle either the less critical features or those considered to be a screener for the decision process. It is a merged process using both methods.

#### 4.3.5.4. Profiling

Profiling is a collection of techniques with the respondent indicating his preferences based on features and levels. Among the techniques used is compositional conjoint. In this regard, compositional conjoint can be considered to be a natural part of the profiling procedure. However, it should be noted that profiling is not intended to give a feature perceived value. It is designed exclusively for market simulation.

#### 4.3.5.5. Advantages and Disadvantages

Some of the key specific advantages and disadvantages of compositional conjoint are listed below:

##### *4.3.5.5.1. Simplicity*

Compositional conjoint is probably the simplest perceived value technique available. It is simple enough to be used as an add-on to other studies. The other procedures are usually executed as the sole dominate reason for the marketing research project.

##### *4.3.5.5.2. Fault Tolerance*

Fault tolerance is the ability of a procedure to be executed even by "idiots." Perceived value techniques usually are fairly complex with many things that can go wrong, which often do. Compositional conjoint is probably the most fault tolerant of these procedures. However, it should still be noted, that compositional conjoint techniques must be executed carefully.

##### *4.3.5.5.3. Feature Perceived Value*

Compositional conjoint produces a number of measures of perceived value. This is similar to the other conjoint procedures, but not like profiling. It should be noted, however, that the analysis model is not the same as that used for simulation. This can produce an exaggeration in the estimate of overall value.

##### *4.3.5.5.4. Large Number of Elements*

Compositional conjoint can handle a fairly large number of features and elements, significantly more than traditional full profile conjoint. However, profiling (SIMALTO) is able to handle even more types.

##### *4.3.5.5.5. Face Validity*

An apparent limitation with the use of compositional conjoint appears to be its inability to emulate the buying process. These results in a lack of apparent face validity in this procedure compared to full profile conjoint or profiling. These procedures appear to be sophisticated and tend to provide confidence in the reliability of the results.

##### *4.3.5.5.6. Intent to Purchase*

Compositional conjoint provides a number of measures of utility. In addition to price value, compositional conjoint can use intent-to-purchase and simple rank order for measures of utility.

##### *4.3.5.5.7. Over Estimation*

Since a scaling of ranked data is used to estimate the individual monetary values of features, there is a tendency toward over estimation. This is particularly the case for low valued items. Since the ranking is forcing position on some items that may be zero valued, values are imposed. However, this tendency is probably mitigated by the averaging process. Note again that this error is isolated to the lowest valued items which generally are not considered important.

### 4.3.6. Preferred Uses and Examples

Compositional conjoint is probably the most flexible and useful of the perceived value procedures. We have found the procedure applicable to a broad range of applications. The following are some examples:

#### 4.3.6.1. New Product Development

New product development often requires an understanding of the value of potential new features that are often poorly defined. Because the ease of use, compositional conjoint is a preferred method for testing customer value. The capability of compositional conjoint to handle large numbers of items is critical for its use in new product development.

#### 4.3.6.2. Financial Terms Packaging

Financial terms, discounts and other financial benefits are difficult to evaluate and often needs to be customized for market segments. Compositional conjoint has been found to be very effective in measuring customize sales preferences. This is due to its ease of modification and simplicity.

#### 4.3.6.3. Customer/Employee Satisfaction

Traditional customer and employee satisfaction studies tend to lacked the understanding of the actual value for changing performance. Rating the performance and importance of attributes does not substitute for understanding the trade off value achieving performance improvements. Due to the ease of execution, compositional conjoint can be added to satisfaction studies, providing this a further level of understanding.

#### 4.3.6.4. Benefits Portfolio Offering

Obtaining value measures of benefits for employees, customers and the public for service providing organizations has become critical. Compositional conjoint offers a method of obtaining insight into those values efficiently. This is particularly the case when there is a large number of possible items and issues that must be considered.

#### 4.3.6.5. Cable Channel Bundling

A particular portfolio problem exists with the cable television industry. This industry must consider offering packages of cable channels. Out of the hundreds of possible channels, they need to select groups to be bundled together. Compositional conjoint is particularly well suited for this application.

#### 4.3.6.6. Customer/Personnel Evaluation Characteristics

Estimating the importance of customer and personnel characteristics is always a difficult task. Several organizations have made use of surveying procedures to obtain an organizational perspective. When there are a limited number of characteristics, full profile conjoint can be used. However, when there is a large number of features being considered compositional conjoint is a natural choice.

### 4.3.7. DESIGN CONSIDERATIONS

The compositional conjoint exercise consists of having respondents indicate the importance of changes in the performance or characteristics of a product compared to some reference set of properties. Selecting the items and determining how there are presented constitutes the design issues of the exercise. While there is broad latitude in that selection, it is governed by the need to have the exercise and its results to be meaningful and indicative of future behavior.

### 4.3.7.1. Feature/Benefit Items

The selection of feature and benefit items is not straightforward and while we have used mixes of different types of features it is not recommended.

#### *4.3.7.1.1. Tangible verse Intangible Benefits*

A product or offering may give tangible and intangible benefits. Tangible benefits are those that we can physically experience. These include performance and appearance. Intangible benefits consist of the fundamental values and feelings that can be associated with a product. While compositional conjoint can be used for both, it is far more suited for tangible features and benefits.

#### *4.3.7.1.2. Focusing on Features and Benefits*

In order to consider the items for evaluation we need to understand that there is a hierarchy or direction whereby product attributes are perceived as producing customer value. We generally think of a chain where: (1) product attributes as perceived by the selling organization become (2) product and offering features recognizable by the customer who gets (3) identified benefits that provide (4) tangible and intangible value.

**Product Attributes ➢ Features ➢ Benefits ➢ Values**

Compositional conjoint is best-designed around benefits primarily and features secondly. Intangible values tend to be too ill defined for use. Even benefits tend to have a problem of definition.

#### *4.3.7.1.3. Consistent*

The items need to be consistent. The list of items should not include both features and benefits. These are not really comparable. A major problem is avoiding the "I was just curious as to how the respondents would react" syndrome. This leads to an inconsistent item list.

#### *4.3.7.1.4. Simple Understandable Statements*

The items have to be expressed in a simple statement. However, they also need to be extremely understandable by all of the respondents and the client. This is not always easy to put together. This generally requires testing.

#### *4.3.7.1.5. Trade-offs*

The items have to represent trade-offs. That is, they should not each represent minimum acceptable conditions. Some of the item levels, however, may represent that minimum condition. It should not prevail over all of the item levels. There should be levels above which the respondents will be minimally satisfied.

#### *4.3.7.1.6. Independence*

The process of conjoint analysis implicitly assumes that the values of the items are independent. The total value of the offering is assumed to be the sum of the partial values of the items included. This need for independence tends to favor the use of benefits rather than features..

##### *4.3.7.1.7. Worst-Case Ordinal Levels*

Because of the nature of the ranking process, there must be a hierarchy in the levels of benefits and features. There must plainly be a set of worst case conditions. However, that condition need not be a linear progression. Different level items may be viewed differently. However, once again the worst level must be recognized.

#### 4.3.7.2. Standard of Comparison

As previously noted, all conjoint analyses are based on a reference or standard state. For compositional conjoint, the standard of comparison **must** be the least desirable total offering. It consists of the worst of all features. It should be noted that this condition does produce a limitation in its use since the least desirable state must be recognizable to all respondents.

#### 4.3.7.3. Modes of Execution

While ranking is the preferred method for respondent's indicating preference, there are other modes of execution. The objective is to assure that the responses represent trade-offs among the items.

##### *4.3.7.3.1. Ranking*

The standard method of indicating preference for compositional conjoint is by ranking. This requires an implicit comparison between each item with all others.

##### *4.3.7.3.2. Constant Sum*

Having the respondents distribute points (100 points) among the items provides a ratio scale measure of importance. This is typically used for measuring stated attribute importance. Like ranking it forces a trade-off among items. However, it is uncertain that the results using constant sum are an improvement over ranking. It should be noted that constant sum is significantly more complex a task than ranking. Typically much smaller item sets have to be used with constant sum.

##### *4.3.7.3.3. Paired Comparisons*

Paired comparisons can be used to obtain a rank ordering of the items and is used extensively with the Adaptive Conjoint variant of compositional conjoint. Using this automated form, the process goes fairly quickly. However, even with careful dynamic selection of the pairs, it involves significantly more sets and work than ranking.

##### *4.3.7.3.4. Rating*

Rating (1-10 scale) is the traditional way of evaluating items. It can be executed by simple telephone survey. However, it usually does not represent a trade-off. All things tend to be valued. It is very unreliable as a measure of feature worth. However, it can be used to construct a true ranking by requiring sub-rankings when features are given common ratings. In this way no two features will have the same rating value, and therefore a ranking can be constructed. This is used to produce a ranking using simple telephone interviews. It should be noted that this is restricted to rather short lists of features.

##### *4.3.7.3.5. Self-Explication*

Self-explication is very similar to ratings in that respondents are asked how much something is worth. This may be a price scale or a point scale. Often items are listed in two ways: (1) positive process (adding items to their list) and (2) negative (removing items). The final value is taken as the average of the two. This is also not a trade-off process and is suspect. Furthermore, it can be a difficult process to execute.

#### 4.3.7.4. Number of Benefits/Features and Levels

The number of allowable items to be used depends on the complexity of the exercise. This will depend on the mode of execution and the familiarity that the respondent has with the features and benefits.

For a single exercise, we have found that 20 items or less is doable[33]. This includes the price references. The fewer the items - the better the execution. Typically, for larger sets multiple exercises are design. But each needs to be limited to 20 or fewer items. However, it is always more reliable in the final analysis to have the items in a common exercise to assure that the respondent has cross-compared all items with each other.

#### 4.3.7.5. Utilities

Utility covers a wide range of measures of value. Normally, it is used to refer to an artificial measure derived from the data analysis. However, we use it more generally to cover both intermediate values and value equivalence such as dollar value.

##### *4.3.7.5.1. Preference Utilities*

Preference utilities are typically based in compositional conjoint analysis either on the ranking themselves or a direct a conversion from the rankings. The choice of which is used depends on the “individual decision model” in the analysis. In either case, they are values that are assumed to be linear functions of the actual additive partial worth (dollar value) of the benefit. Typically, we prefer to use a derived utility rather than preference utility for analysis. However, the derived utilities often require additional assumptions that may be in question. Under that condition results are often given in both derived and preference utility measures.

##### *4.3.7.5.2. Dollar Value*

[33] We have done studies with as many as 83 items and have used Q-Sort procedures to force the rank ordering. However, this is not recommended since the results are highly questionable..

Dollar value of a feature change represents the approximate trade-off between having that change and an increase in price. It is a derived utility in that we use the embedded price references to compute the value.

##### *4.3.7.5.3. Exclusion from Purchase*

We may ask additional questions during the compositional conjoint process including which features would restrict you from purchasing the product. Similarly, intent to purchase can also be explored[34].

#### 4.3.7.6. Price Referencing

As previously noted, price references are embedded in the list of items. These are used to scale the rankings and provide a means to obtain dollar value of the items.

##### *4.3.7.6.1. Number of Price References*

Clearly, one would like to have as many price references as is feasible. However, given the limited size of the exercise, each additional price reference means the loss of one item of interest. As such, it is usually of interest to minimize the number of price references. Typically, for most types of analyses, at least two and preferably three price references are needed in addition to the zero value point.

##### *4.3.7.6.2. The Zero Value*

The zero value point is implied to mean the lowest ranking of the series. This corresponds to the last rank plus one. It should be noted that this increase in rankings carries into the analysis of the data.

##### *4.3.7.6.3. Types of Price References*

The price references must be improvements in the offering, this usually means a decrease in price. This can be shown as a discount. Percent discounts can also be used. However, when percent discounts are used, they are generally converted to dollar values in the analysis.

Surrogate price references are also used such as credit terms or bonuses and prizes. However, the use of surrogates tends to introduce uncertainty in the true perceived dollar value.

#### 4.3.7.7. Item Placement and Rotation

The items and features are typically randomized. However, if an order bias is expected, it is reasonable to rotate or randomize it for each respondent. Usually if this is done, the items are coded and the rankings are recorded based on the codes. Alternatively, cards are used with individual items on them. They can be randomized for each respondent. Once again it is critical that the data is collected in a consistent fashion based on item codes. However, in most cases, a single randomized list is used.

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[34] Including these options make compositional conjoint very similar to *Profiling*. However, in profiling there are a significantly larger number of probes used.

### 4.3.7.8. Action Referencing

As previously noted, it may be useful to recompute utilities in terms of potential actions, in particular, the intent-to-purchase. This involves recalibrating and scaling the standard utilities in terms of other collected data.

#### *4.3.7.8.1. External References*

Typically external references, in the form of hypothetical offerings, consisting of combinations of items being tested are used. Sufficient examples are used to allow the scaling of the utilities on an individual basis. This usually involves three or four cases. It should be noted, that this is process often takes at least as long to do as the rest of the compositional conjoint exercise and is therefore not recommended unless necessary.

#### *4.3.7.8.2. Interaction Modeling*

A major problem with all conjoint measures is the potential of interaction among the items. That is, that the value of an item will depend on the existence or absence of a specific level of another feature. A measure of this problem can be obtained by using the action reference data for the market as a whole. The larger database allows for estimation of interaction terms in the regression. It should be noted that intercorrelation may be produced by the commonality of the hypothetical test offerings. As such, we again do not recommend the procedure unless it is believed to be a critical issue.

## 4.3.8. INDIVIDUAL DECISION MODELS

The compositional conjoint procedure produces a rank order of features and price references. The trick is to convert those rankings to utilities and dollar values. Rankings are ordinal scaled measures. The spacing between ranks cannot be assumed to be constant and uniform. Individual decision models are used to map rankings into utilities, which are assumed to be "ratio" scaled values. These utilities in turn are converted into dollar values. The price references are used to fit these models and measures of goodness-of-fit is used to test validity.

### 4.3.8.1. Straight Line Function (Linear)

The simplest model is a straight line, which is a linear relationship between utilities and rankings, as shown below. The coefficients $\mathbf{A_0}$ and $\mathbf{A_1}$ are computed based on the ranking of the price references where the utility has the same units as the price reference (usually in either as dollars in the form of a discount or as a change in price). Simple linear regression is used to fit the data. The dollar values are then estimated based on their corresponding rankings. Usually there are, at least, two independent price references and a zero value (maximum ranking plus one). Since only two parameters are computed, an R-Square, goodness-of-fit, can also be estimated[35].

$$\mathbf{Utility_i = A_0 + \{A_1 \times Ranking_i\}}$$

where the subscript "**i**" signifies the individual item.

[35] It is usually advisable when using the linear individual decision model to use more than two price references.

### 4.3.8.2. Stepwise Linear Approach

Rather than using a single average relationship ($A_0$ and $A_1$) across the whole range, one could apply straight-line equations over portions of the ranking set between the reference (discount) points. This represents a stepwise linear approach. Since function will equal the reference values at the corresponding values, there is a "perfect fit". There will be as many relationships as there are reference points.

$$\text{Utility}_i = A_{0,k} + \{A_{1,k} \times \text{Ranking}_i\}$$

That is, if we have three reference points, there will be three steps in the function. One step between the zero value and the first reference point, the second step between the first and second reference point, and third which will extend to beyond the third point. Notice, however, that the position of the reference points will change between respondents[36].

### 4.3.8.3. Stochastic (Broken Stick Rule) Distributions

A more complex model involves the mapping of the utilities with a rank order distribution. The rank order distribution relates a share to a ranked position. Dollar values are estimated by scaling these utilities with the price references. The squared value captured is used as the measure of goodness-of-fit and corresponds to the R-Square measure used for the linear model.

$$\text{Utility}_i = \text{Function}\ (\text{Ranking}_i)$$

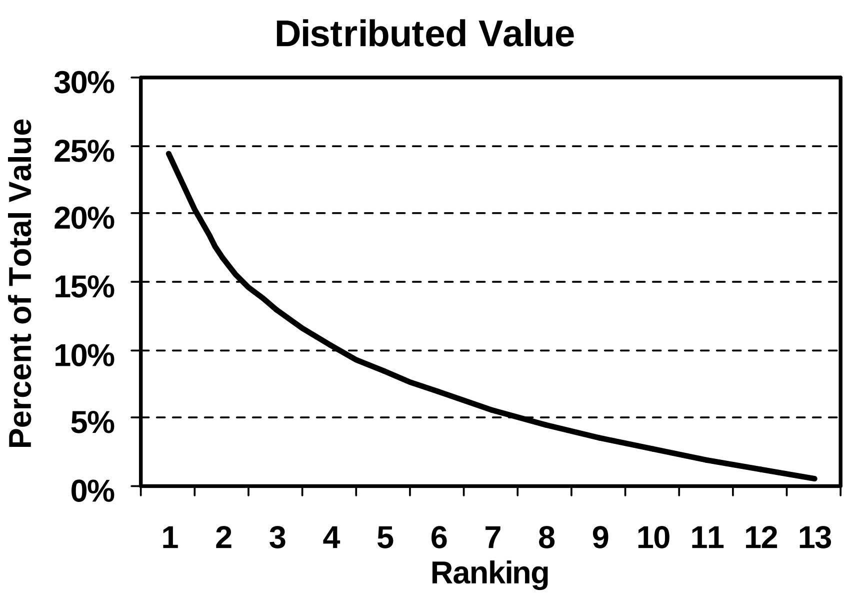
Below are shown the values based on a particular limiting rank order statistical distribution. This is the Broken Stick Rule that tends to track market shares and product values with large sample sizes.

[36] This relatively straight forward in *Microsoft Excel* using a series of IF statements based on the ranking of the item. The slope is taken as the range between the corresponding intermediate reference points and the intercept as the value of the lower level reference point.

**Number of Options**

| Rank | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|
| 1 | 29.29% | 27.45% | 25.86% | 24.46% | 23.23% | 22.12% | 21.13% |
| 2 | 19.29% | 18.36% | 17.53% | 16.77% | 16.08% | 15.45% | 14.88% |
| 3 | 14.29% | 13.82% | 13.36% | 12.92% | 12.51% | 12.12% | 11.75% |
| 4 | 10.96% | 10.79% | 10.58% | 10.36% | 10.13% | 9.90% | 9.67% |
| 5 | 8.46% | 8.51% | 8.50% | 8.44% | 8.34% | 8.23% | 8.11% |
| 6 | 6.46% | 6.70% | 6.83% | 6.90% | 6.92% | 6.90% | 6.86% |
| 7 | 4.79% | 5.18% | 5.44% | 5.62% | 5.73% | 5.79% | 5.82% |
| 8 | 3.36% | 3.88% | 4.25% | 4.52% | 4.71% | 4.84% | 4.92% |
| 9 | 2.11% | 2.75% | 3.21% | 3.56% | 3.81% | 4.00% | 4.14% |
| 10 | 1.00% | 1.74% | 2.29% | 2.70% | 3.02% | 3.26% | 3.45% |
| 11 | | 0.83% | 1.45% | 1.93% | 2.30% | 2.60% | 2.82% |
| 12 | | | 0.69% | 1.23% | 1.65% | 1.99% | 2.26% |
| 13 | | | | 0.59% | 1.06% | 1.43% | 1.73% |
| 14 | | | | | 0.51% | 0.92% | 1.25% |
| 15 | | | | | | 0.44% | 0.81% |
| 16 | | | | | | | 0.39% |

Below is the distribution of values for the case of 13 items. Notice that it is a convex curve with a much higher rate of change for the higher ranked items. This curve tends to provide a good fit with compositional conjoint data.




#### 4.3.8.4. Polynomial (Quadratic)

The general convex, downward bending, curve is typical of what we would expect with these utility ranking relationships. Items high on the list can be expected to carry disproportionately high utility.

Alternatively, we can generalize the linear model using a polynomial series. This is shown below in a general form.

$$\mathbf{Utility_i = A_0 + \sum_{k=1}^{N} \{A_k \cdot Ranking_i^k\}}$$

Fitting this model would take a large number of price reference points. In practice, only the quadratic form is used as shown below. This can be fit with the minimum of two price references and the zero point[37]. However, this leaves no degrees of freedom to test the goodness of fit. Typically, if quadratic models are planned to be used, at least, four price references should be used.

$$\mathbf{Utility_i = A_0 + \{A_1 \cdot Ranking_i\} + \{A_2 \cdot Ranking_i^2\}}$$

A major problem with this analysis is the potential for the price references to be concentrated at the end of the ranking. This can force severely high values of the items using the quadratic or other polynomial forms. As will be discussed later, this is an inherent problem in this methodology.

### 4.3.8.5. Exponential and "Power-Law"

Alternatively other non-linear convex functions can be used. Both the exponential and "power law" models have been used. They have the advantage of having fewer parameters. The exponential model is particularly useful since it will not go infinite for any set of conditions. The exponential form is shown below.

$$\mathbf{Utility_i = A \exp\{B \cdot Ranking_i\}}$$

The power law form, shown below, is a conventional of model for this type of data. However, it has the problem of potentially producing unrealistically high dollar values when the price references are poorly ranked.

$$\mathbf{Utility_i = A \cdot Ranking_i^B}$$

### 4.3.8.6. Inherent Measurement Problems

There is an inherent measurement problem with compositional conjoint. Scaling the ranking is based on the relative position of the items against the reference prices. If respondents are relatively insensitive to the price references, than there will be little information available to scale the items. This problem is particularly severe using the quadratic, exponential and the power-law forms. However, it is also a problem with the linear and stochastic models. In general, the problem is least severe with the linear and stochastic models which are therefore preferred.

### 4.3.8.7. Model Summary

[37] The quadratic form has three parameters which can be estimated with the three price points. This is an algebraic solution.

The following is a summary of these individual decision models and their characteristics.

| Evaluation Model | Logic | End-Point Estimates | Goodness of Fit | Method of Fit | Estimated Parameters |
|---|---|---|---|---|---|
| **Straight Line** | Best Fit | Constrained to Reasonable Limits | R-Square (Weak) | Regression | 2 parameters |
| **Stepwise Linear** | Best Fit | Constrained to Reasonable Limits | Exact | Algebraic Solution | Number of Reference Points |
| **Broken Stick Rule** | Rank Order Statistics | Constrained to Reasonable Limits | R-Square (Strong) | Assignment | None |
| **Quadratic** | Best Fit | Unconstrained, potentially infinite | None | Algebraic Solution | 3 or more parameters |
| **Power Law** | Best Fit | Unconstrained, potentially infinite. | R-Square (Weak) | Regression | Two parameters |

## 4.3.9. Validation and Error

Because of the nature and simplicity of this procedure, measures of error may be problematic. Here again our interest is not in the theoretical issue of error but in the practical issue of trust in the results.

### 4.3.9.1. Precision

Precision refers to the sample size problem. Averages from small representative samples will most likely not be equal to that of the total population. Because of the simplicity of the procedure larger sample sizes are feasible than with other perceived value methods. As such any precision problem would be far smaller here than with methods. Measures of precision follow the same procedures used for *Full Profile Conjoint*.

### 4.3.9.2. Reliability

Reliability is the ability to obtain similar results repeatedly. If we go back to the respondents will they give the same results? Because of the low expense of *Compositional Conjoint*, reliability can be tested but is rarely done.

### 4.3.9.3. Accuracy

Accuracy refers to the whole family of experimental and measurement problems. However, in the context of this discussion, accuracy refers to the ability of *Compositional Conjoint* to capture the decision process. This is a problematic issue. Usually we try to get insight by questioning the respondents about the similarity of the exercise with the buying process. Unfortunately most studies are conducted by remotely and opportunities for discussion are rare. We strongly recommend that pre-testing be used for determining the ability *of Compositional Conjoint* to capture the decision process.

### 4.3.9.4. Experimental Error

Accuracy deals with the total issue of measurement. However, there are a number of specific errors and biases associated with its execution. These issues should also be examined during the pre-test of any *Conjoint* exercise.

#### *4.3.9.4.1. Number of Feature Bias*

Unlike Full Profile Conjoint, Compositional Conjoint can handle a fairly large set of feature-levels. Typical 15 or more can be used for a single exercise. Furthermore it is not unusual to have several exercise connected to cover a hundred or more items. However, it is important to understand the limitations on the size of the exercise. It is inadvisable to use more than 25 items in a sort. More than that makes the task difficult and can result in errors.

#### *4.3.9.4.2. Order Bias*

Order bias can be a major potential problem with Compositional Conjoint. The items need to be, at least, randomized. If on-line execution is being considered, randomizing or rotating the list for each respondent should be considered..

### 4.3.9.5. Internal Consistency

The fit of the pricing data-points to the value model reflects the validity of the model and consistency of the respondents' decisions.

#### *4.3.9.5.1. Goodness-of-Fit*

A Goodness-of-Fit measure is used to test the internal consistency. The quality of the test will depend on the number of price points used. Typically we consider the lowest ranked item being a zero price change. These give an additional point for testing.

#### *4.3.9.5.2. Logical Values*

There is usually no logical constraint on the rankings feature levels that are feasible using *Compositional Conjoint.* However, it is logical that we expect that better performance would have higher value than poorer performance. Instances where this is not the are of course suspect. It should be noted, that sophisticated automated *Compositional Conjoint* systems identify such inconsistencies and bring them to the attention of the respondent during the exercise. In some cases, such inconsistencies are not allowed.

### 4.3.9.6. Predictability (Predictive Validity)

As previously noted, the ultimate test of validation is if the model predicts actual market behavior. This involves testing the model against independent data on the market behavior. As with all other methods this has rarely been done.

#### 4.3.9.7. Face Validity

Face validity refers to the apparent trust and acceptance of the procedure by clients. *Compositional Conjoint* is a less known procedure and therefore does not carry the credibility of *Full Profile Conjoint*. Furthermore, the simplicity of the procedure has lead some client to question it validity. However, we have found that with use client become familiar with it and appreciate its simplicity.

### 4.3.10. MARKET ANALYSIS

It is usually necessary to analyze the data to identify the structure of the market. That structure is critical for the construction of the market simulator and for the clients to get an overall insight into the global issues. There are two key issues that tend to arise: (1) do the values of the exercise reflect the cognitive feelings of the respondents and (2) what is the appropriate market segmentation.

#### 4.3.10.1. On-Line (Live) Analysis

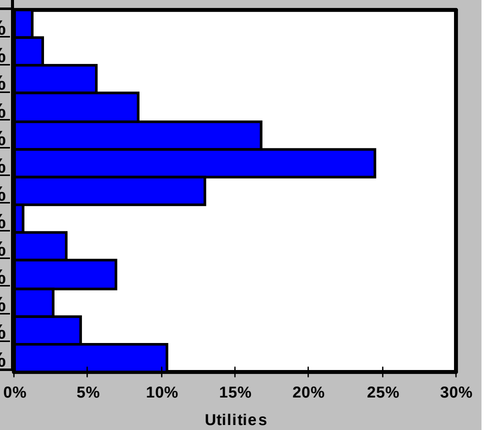
The correspondence between the feelings of the respondents and the exercise results is a measure of the reliability of the data. This is explored using two tools. First, traditional importance measures can be used to test consistency by category. Secondly, if personal interviews are being used, or if the survey is being done on-line, the results of the exercise can be computed and presented to the respondent for comment. Below is the computational screen for this purpose[38].

[38] This is a *Microsoft EXCEL* application which can support any number of alternative approaches and individual decision models.

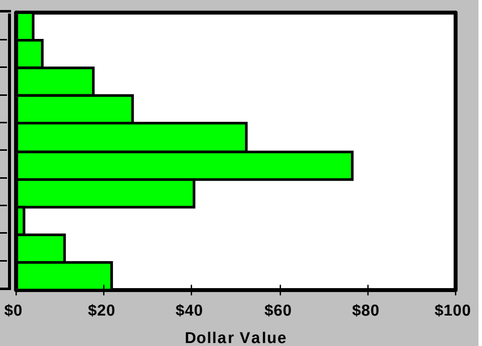
  

| | Input |
|---|---|
| 3 Applications annually | 12 |
| Superior Control | 5 |
| $20/acre discount | 4 |
| No escapes | 3 |
| 2 Applications annually | 11 |
| $10/acre discount | 8 |
| Minimum Leaching | 9 |
| No Damage | 2 |
| Safe to Trees | 6 |
| $5/acre Discount | 10 |
| Safe for young plants | 1 |
| 1 Application annually | 7 |
| User Friendly | 13 |

| | Results |
|---|---|
| 3 Applications annually | 1% |
| 2 Applications annually | 2% |
| 1 Application annually | 6% |
| Superior Control | 8% |
| No Damage | 17% |
| Safe for young plants | 24% |
| No escapes | 13% |
| User Friendly | 1% |
| Minimum Leaching | 4% |
| Safe to Trees | 7% |
| $5/acre Discount | 3% |
| $10/acre discount | 5% |
| $20/acre discount | 10% |




| | |
|---|---|
| 3 Applications annually | $4 |
| 2 Applications annually | $6 |
| 1 Application annually | $18 |
| Superior Control | $26 |
| No Damage | $52 |
| Safe for young plants | $77 |
| No escapes | $40 |
| User Friendly | $2 |
| Minimum Leaching | $11 |
| Safe to Trees | $22 |




#### 4.3.10.2. Benefit Segmentation

The utilities and dollar values can be used to determine benefit segmentation. Typically both hierarchical and K-Means clustering is used for this exercise. The process is similar to that used with rating data. However, these utilities are less prone to the biases of rating data. Furthermore, the segmentation is based on the importance of specific changes in feature levels that is far closer to the decision process than the importance of overall attribute characteristics. Typically, benefit segmentation is done prior to developing the market simulator and is used in its development.

#### 4.3.10.3. Coupled Product Positioning

Utility and dollar value estimates can also be used for product positioning. In this case, the positions of competing products are based on actual performance characteristics rather than perception. The relative positions of segments are placed on the same map using perceived value estimates[39].

### 4.3.11. Decision Support and Simulation

Beyond reviewing tables and maps of average utility and dollar values, it is usually desired to have a “what if” tools to explore potential market offerings. These are the same general type of simulators constructed using full profile conjoint or profiling data. In most cases, the client wishes to explore the

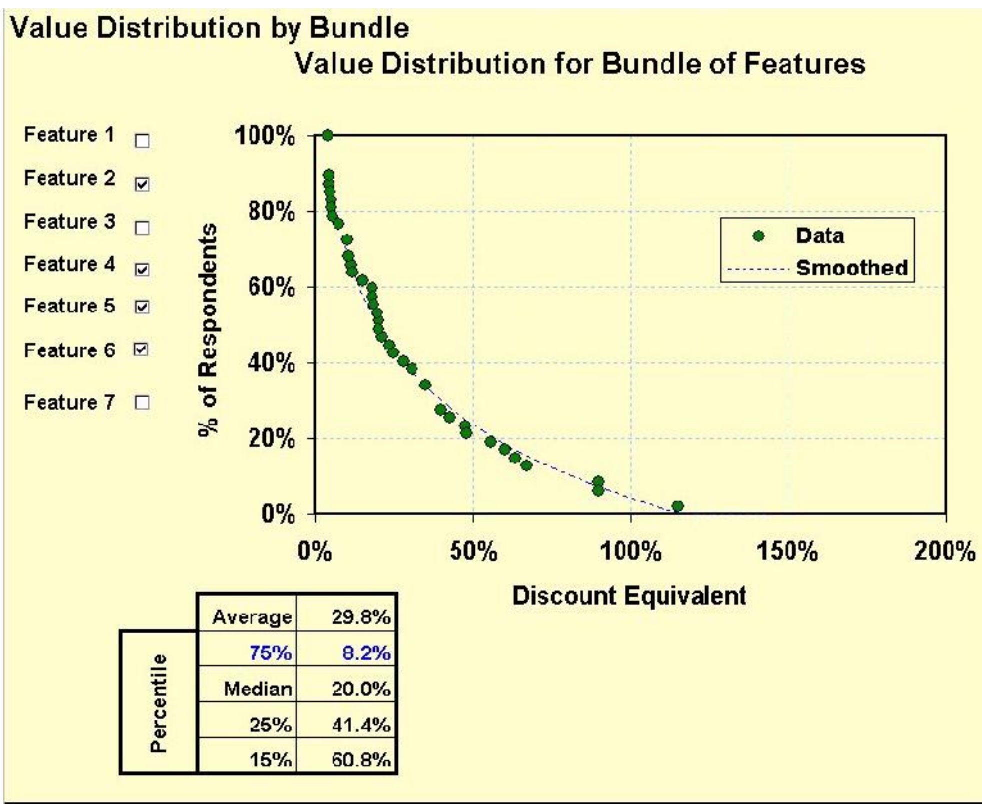
[39] The maps can be constructed using *Multidimensional Scaling* (MDS) with the Unfolding option. The resulting diagram looks like a “correspondence map;” however, the positions are much more reliable and meaningful.

impact of offering a number of potential products defined by their performance levels. The goal would be to obtain a highly satisfactory return.

It should be noted that market simulators are only indicators of potential market behavior. Neither the sample, nor the timing, nor the means of data collection allows for definite prediction of the market behavior. However, market simulators are, in most cases, the best tools that we have available.

### 4.3.11.1. Decision Support Systems

Since the utilities and value of features are available on an individual basis using this technique, there are any number of decision support systems that can be developed. These include both market simulators and displays of the value distributions for bundles of features. The market simulators are constructed to allow estimate the market response to alternative products concepts. For competitive models existing competing products may be included. These models are also useful to test the potential of introducing a number of products into the same market simultaneously. Below is an example of a value-distribution decision support tool. Here the distribution of discount equivalent values is shown for a bundle of features that were checked on the left. Statistics of the data are shown below the chart.




### 4.3.11.2. Market Models

To build the simulator, we need to merge the individual decision data into a market model. To do this we need to determine, for each individual, what they will choose among a set of offerings. There are typically two methods that we use (1) based on price-value differences and (2) calibration by a separate estimate of likelihood-to-purchase.

The simplest and preferred approach is based on assuming the respondents will purchase the offering that has the highest net dollar value. That is the difference between the dollar value and the price. This is a "Winner-Takes-All" type of decision model. Purchases only are allowed if there is a positive net value.

As previously noted, external references using the response to hypothetical offerings can be used to calibrate utility with likelihood-to-purchase. These can be used then to estimate the likelihood-to-purchase a number of alternative offerings. The item with the highest likelihood above a threshold level will be considered the item purchased. Note that the threshold level is arbitrary and involves a significant assumption. This is also a "Winner-Takes-All" model. A potential advantage to this approach is that interaction corrections can be introduced. However, unless there is a major reason to use this method, it is generally not preferred since it is more complex and introduces additional sources of error.

#### 4.3.11.3. Split Populations

While we do not recommend using split populations for compositional conjoint studies, in some cases, they are necessary. These involve testing different sets of items with separate population samples. This can be necessary if the list of items is extremely long and the testing procedure is involved. Unlike, full profile conjoint (and Choice Based Conjoint) data sets can not be combined to produce an overall market model. The simulators are based on individual respondent behavior[40]. There are two ways of handling this split population issue: (1) use separate simulations for each population group and (2) estimating missing data.

##### *4.3.11.3.1. Separate Simulation*

In many cases, the split of items is due to a natural segregation of product offerings. As such, it is reasonable to build separate market simulators for each. Typically, when this is done, a set of items is evaluated in common and the differences among the two populations tested.

##### *4.3.11.3.2. Estimating Missing Data*

An alternative approach is to statistically model the missing data based on the items that the split groups have in common. This can be done using linear. A more sophisticated approach is to use Principal Component Regression to preserve the intercorrelation in the data[41].

---

[40] While this can be a disadvantage for compositional conjoint, it is also a great advantage since the split overall market models always has a element of uncertainty and unreliability about it. Only if we can assume that customers are from the same tight population is merging reasonable.

[41] Some of these procedures are included in missing data processes in major statistical packages (*SAS*, *SPSS* and *SYSTAT*). It should be noted, however, that the classic missing data procedure, *EM algorithm*, is not appropriate here. That tool combines regression substitution with inclusion of controlled noise. the noise is introduced to retain the overall variance in the data. This is unnecessary here and results in artificially poorer estimates.

### 4.3.11.4. Coupling with Choice Modeling

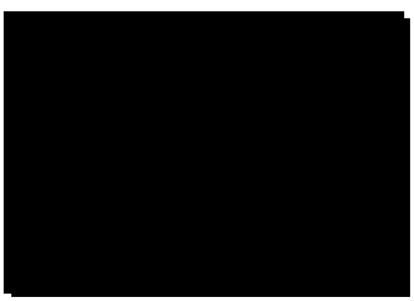
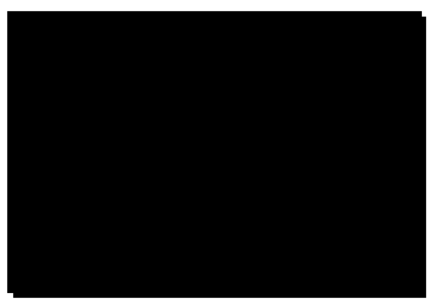
While compositional conjoint can be used to capture the value of brand names and associated price premiums, it will not capture the interaction of brands and prices. As such, it can be useful to do pricing exercises along with compositional conjoint. Since compositional conjoint is a relatively simple task, it is usually feasible to undertake other analytical exercises in the same survey. Compositional conjoint is used to enhance Price Choice Modeling in order to let clients explore the impact of non-pricing features within a competitive market.

The simulator is constructed by allowing the dollar-values to off-set the price of the associated offering. The resulting simulator is shown below. In this case, the non-priced features are associated only with product A. In other simulators, the non-priced features can be associated with any of the competing products. This is used to test potential market reaction for features that can be duplicated.

**Market Pricing and Benefits Simulator**

| Herbicide | New Price | S-Shaped | | Linear | |
|---|---|---|---|---|---|
| | | Estimate | Current '98 | Estimate | Current '98 |
| Product A | $140.00 | 7.0% | 7.0% | 8.1% | 8.1% |
| Competitor B | $50.00 | 25.8% | 25.8% | 26.3% | 26.3% |
| Competitor C | $50.00 | 9.6% | 9.6% | 9.4% | 9.4% |
| Competitor D | $75.00 | 9.2% | 9.2% | 8.8% | 8.8% |
| Competitor E | $100.00 | 27.4% | 27.4% | 27.1% | 27.1% |
| Competitor F | $125.00 | 5.6% | 5.6% | 6.1% | 6.1% |
| Competitor G | $150.00 | 15.4% | 15.4% | 14.2% | 14.2% |

| | Cost | Earnings | |
|---|---|---|---|
| | | S-Shaped | Linear |
| Product A | $48.00 | 6.40 | 7.45 |

### 4.3.11.5. Price/Product Optimization

As discussed in the section on *Full Profile Conjoint*, optimization of product features is significantly more complex than focusing only on price. Any combination of features is possible. Typically product optimization is explored by extensive searching (often by brute force). Fortunately, not all possibilities are of equal value. It is, therefore, useful to use the average dollar values of feature to guide the options to check. The problem becomes significantly more complex if there are multiple products to be considered in the optimization.

## 4.4. PROFILING

*Profiling* represents a group of procedure designed to solicit the desirability of feature levels from respondents. Similar to other perceived value methods, the goal of *Profiling* is to estimate the impact of new product offerings on the market. Profiling represents a broad class of procedures. These are referred to by several names including: **D**esign-**Y**our-**O**wn-**P**roduct (DYOP), **B**uild-**Y**our-**O**wn (BYO) and *Simalto* or "**SI**multaneous **M**ulti-Attribute **L**evel **T**rade-**O**ff."[42] However, the process itself is not narrowly defined and presents a wide range of variations.

### 4.4.1. INTRODUCTION

The method centers around having respondents undertake a number of exercises in the design and evaluation of appropriate products based on a list of feature-levels. Unlike *Full Profile Conjoint*, the respondents are usually not presented with fully defined product concepts until late in the process.

#### 4.4.1.1. The Product Sheets

Typically, *Profiling* is used with a large number of feature-levels. Below is a product sheet for the case of over a hundred feature-levels on 29 features. The product sheet is used consistently throughout all of the *Profiling* exercises. This is a key component of the process. The respondents are asked to work with only a single form. This is intended to reduce any unwarranted confusion in the exercises.

**Example of a 107 Feature-levels Product Decision Sheet**

**Features**

<table>
<tr><td>Gateway</td><td>Few VANs</td><td>All Major</td><td>All Intl</td><td>Ind. Spec.</td></tr>
<tr><td>Messaging</td><td>Files Trans.</td><td>E-Mail</td><td>ECS</td><td>Image Input</td></tr>
<tr><td>Boards</td><td>Not Avail.</td><td>BBs</td><td>Textual</td><td>3rd party</td></tr>
<tr><td>Services</td><td>Not Avail.</td><td>Limited</td><td>In-Country</td><td>Intl</td></tr>
<tr><td>Directory</td><td colspan="4">Lookup | X500 Dir. | LAN E-Mail</td></tr>
<tr><td>EDI</td><td>No</td><td>Interchange</td><td>Document Rptg</td><td>Format Trans.</td></tr>
<tr><td>User I-f</td><td>MS DOS</td><td>GUI</td><td>All 3</td><td>UNIX</td></tr>
<tr><td>Messaging</td><td>X400</td><td>Any system</td><td>Vendor Mess.</td><td>LAN Trans.</td></tr>
<tr><td>Graphics</td><td>Not Avail.</td><td>w/o form</td><td>w/ Id</td><td>Display</td></tr>
<tr><td>Worldwide</td><td>Dom. Only</td><td>Mj Intl Cities</td><td>Mid. Intl Cities</td><td>3rd World</td></tr>
<tr><td>Tracking</td><td>None</td><td>Vendor Ntk</td><td>Vendor Apps</td><td>All Apps</td></tr>
</table>

[42] Simalto (or Simalto Plus®) has been trade marked by John Green as a proprietary procedure. We have, therefore, preferred not to refer to the general profiling procedures as a form of Simalto. But rather refer to Simalto procedures as forms of profiling.

| | | | | |
|---|---|---|---|---|
| **Access** | **Local PDN #s** | **800 #'s** | | |
| **Interface** | **None Created** | **Will Create** | **Provided** | |
| **Software** | **Not Avail.** | **Cosmetic** | **Functional** | |
| **Vendor Asst** | **None** | **Validation** | **Install.** | **Training** |
| **Startup** | **None** | **Tutorial** | **Class** | **On-site** |
| **Response** | **48 hr** | **16 hr** | **8 hr** | **4 hr** |
| **Problems** | **None** | **Note/Fix** | **Note** | **when fixed** |
| **#s down** | **"5-7"** | **"3-4"** | **"1-2"** | **Never** |
| **Time down** | **>3 hr** | **2-3 hr** | **1-2 hr** | **Never** |
| **3rd party** | **not fix** | **sometimes** | **best effort** | |
| **Audit Trail** | **Not Avail.** | **VAN Only** | **All VANS** | |
| **Support** | **900 #** | **Bus. Hrs. 800** | **Help Desk** | |
| **Tel. Rep.** | **No Support** | **<4 hr.** | **<2 hr** | **< 1 hr** |
| **Support Qual.** | **< 60%** | **61-79%** | **>80%** | |
| **Sales** | **Reach** | **Periodic** | **In-person** | **Periodic In-Per.** |
| **Sale People** | **Domestic** | **Mj Int'l Cities** | **Mid Int'l Cities** | **Worldwide** |
| **Tech** | **Reach Rep.** | **Periodic** | **Requested** | **Periodic In-Per** |
| **Tech Reps.** | **Domestic** | **Mj Int'l Cities** | **Mid Int'l Cities** | **Worldwide** |

### 4.4.1.2. The Procedure

The respondent is asked to design products and evaluate features. While *Profiling* processes differ, most contain some of the following types of exercises.

#### *4.4.1.2.1. Last Purchased and Ideal*

The respondent is asked to identify, based on the feature-levels, their last purchases and an ideal. Last purchases may include specific applications as well as most recent or most frequent purchased. The ideal can be particularly useful if the feature-levels are not strictly ordinal in value. That is, if the levels represent alternative conditions rather than just more of something.

#### *4.4.1.2.2. Inclusions and Exclusions*

Respondents are typically asked what feature-levels must be included and what must be excluded for the product to be acceptable. This reflects both expectations and thresholds for purchasing.

#### *4.4.1.2.3. Importance and Value*

The importance of features is also normally included. These measures are often not used in the final market simulation; they are usually used in market analysis and segmentation. Explicit value estimates of feature-levels can also be obtained. However, explicit feature-level values are typically not viewed as reliable[43].

#### *4.4.1.2.4. Priced Features*

Respondents can be asked to design ideal products with alternatively priced features. The prices of the features can be varied to capture the respondents' interest and "willingness to pay". Sequential processes have been developed that allow for refined estimates of the "willingness to pay" feature prices[44]. These procedures are used both as an alternative to measures of feature and feature-level importance or as a direct measure of feature value similar to conjoint measurement.

#### *4.4.1.2.5. Budgeted Products*

The objective of having the respondent design budgeted products is to capture intermediate values of feature-levels. These are done either in terms of priced features or using a fixed number of changes. There are a large number of variations in this task, including: (1) designing a product with feature values equal to a set price, (2) designing a product down from the ideal, (3) designing a product up from the base case.

#### *4.4.1.2.6. Evaluating Product Concepts*

The respondent is usually asked to evaluate a number of specific product concepts. These may be either standard designs or those developed by the respondent. Typically, the respondent will be asked purchase intent or likelihood of purchase. These are generally used to calibrate the final market model.

### 4.4.1.3. The Simulated Buying Process

The *Profiling* exercises simulate the negotiated or product design processes. The respondent is asked to design the product that is desired. As such, the corresponding buying process should also have that characteristic. However, that process might be the ideal not the present reality. It is probably sufficient for the respondents to wish to purchase in the design mode for *Profiling* to capture customer value rather than the need to simulate the present buying process.

## 4.4.2. COMPARISON WITH OTHER METHODS

The major advantages of *Profiling* include its natural ability to handle a large number of feature-levels and to probe desires of the respondent. In addition, *Profiling* does not rely on a "linear" value model. The value of feature-level may depend on other conditions in the profile. Its major disadvantage is its "ad hoc" and the open choice structure. It represents a collection of techniques and measures. There are no strong bases to choose the best methods or procedures[45].

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[43] These explicit measures are "top-of-mind" estimates. Unlike Compositional Conjoint, there are not comparative. If a ranking is used, the results can be similar to Compositional Conjoint, if price values are included.

[44] These procedures have been developed by International Planning & Research Corp. (IPR).

[45] Unlike *Conjoint*, *Profiling* does not have an extensive academic literature, though its history is probably as long.

#### 4.4.2.1. Full Profile Conjoint

It is usually inappropriate to compare *Profiling* with standard *Full Profile Conjoint* since the former technique is designed to handle large numbers of feature-levels. However, its major advantage over all conjoint methods is its ability to capture interaction among feature-levels. This is a property unique to *Profiling* and can be critical in product design.

A more meaningful comparison is between *Profiling* and the large attribute set conjoint methods. As noted in the earlier section on these methods, they all suffer from measurement problems. Many of these other methods require split samples that limit their application compared to *Profiling* that does not. The other methods do not use direct estimation of the impact of lesser-valued features. While still others rely on explicit ratings of objects and products, none of these problems exist with *Profiling*. However, its major limitation is that with *Profiling* accurate measures of the value of feature-levels are typically not obtained.

#### 4.4.2.2. Compositional Conjoint

As previously noted, there are some exercises that can be included in *Profiling* that are similar to *Compositional Conjoint*. If they are included, *Compositional Conjoint* can be viewed as a subset of the *Profiling* exercises. However, normally they are not. Typically *Profiling* is a much more involved and expensive process than *Compositional Conjoint*. While *Compositional Conjoint* can be used to augment other procedures, *Profiling* is usually the focus of the study.

### 4.4.3. PREFERRED USES

While there a broad range of applications that *Profiling* could be applicable for, there are several that appear to be a natural fit.

#### 4.4.3.1. Device and Products

Designing devices and products with large numbers of secondary features is a natural application of *Profiling*. These include:

- Vehicles such as automobiles, trucks, tractors, airplanes, etc.
- Medical devices such as diagnostic and procedural equipment (MIR, CAT, X-Ray equipment).
- Feature filled devices like cameras and computers.
- Industrial and laboratory equipment.

#### 4.4.3.2. Services

Financial, insurance, and governmental services are loaded with sets of features and benefits. These are particularly suited for exploration with *Profiling*, if the final offer will be made in a buffet format.

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Original work has been traced to the automotive industry and Xerox in England.

#### 4.4.3.3. Development Applications

*Profiling* also provides a window into potential design. These are cases where services and products do not yet exist. We seek to understand user benefits to direct the design and invention process. These include:

- Distributor/Reseller Stores - These include the products to be carried as the services rendered as benefits.

- Materials System - In material and chemical systems, it is often desired to understand what customers might want if it was possible to deliver. This is clearly a more speculative application, but one for which *Profiling* is particularly suited.

### 4.4.4. DESIGN CONSIDERATIONS

Profiling provides a means of presenting a long list of features and to consideration a broad range of possibilities.

#### 4.4.4.1. Feature/Benefit Items

Because Profiling is a selection process not strictly a trade-off process the nature of the feature-levels are far more open that using any conjoint technique. A broad range and mix of different types of features can be used.

##### *4.4.4.1.1. Focusing on Features*

As in the case of Conjoint it is useful to return to the hierarchy of value where: (1) product attributes as perceived by the selling organization become (2) product and offering features recognizable by the customer who gets (3) identified benefits that provide (4) tangible and intangible value.

**Product Attributes ➢ Features ➢ Benefits ➢ Values**

For Profile, however, it is usually necessary to use exclusively features and feature-levels. This is important to avoid interaction between benefits and features. The objective is to give the respondent what would appear to be a clear choice of what they want in the product, not what the product does.

##### *4.4.4.1.2. Tangible verse Intangible Features*

While there are always both tangible and intangible features associated with products, the methods of profiling are pretty much restricted to tangible features. Brand names and service conditions can be included in the profiling exercises. These can be used as surrogates for some intangible benefits. However, it should be noted that Profiling, like Compositional Conjoint requires the respondent to recognize and act upon the benefit or feature. Therefore the benefits can not be subtle issues. This can greatly restrict the features and benefits tested.

##### *4.4.4.1.3. Positive Valued Features*

Also like most compositional methods profiling methods requires that features need to be either zero or positive valued. There is one exception here in that we often ask about “Must Not Have” features. This allows for severe negative values to be attributed to the features. Note that “Must Have” and “Must Not Have” conditions are handled as exceptions. However, for the most part, only positive and zero values are handled within standard analyses.

##### *4.4.4.1.4. Simple Understandable Statements*

Because of the potential number of features and levels it is critical that simple understandable statements descriptions are used. Complex descriptions are often separated out for additional explanation. However, that can cause significant bias and should be avoided.

##### *4.4.4.1.5. Trade-offs*

The items do not have to represent trade-offs. These are choice. However, the levels of features must be exclusive. In most cases, the levels tend to be ordinal in that they represent a monotonic increasing value. However, this does not necessarily need to be the case and often produces better results.

#### 4.4.4.2. Number of Benefits/Features and Levels

The number of allowable items to be used depends on the complexity of the exercise. However, Profiling, its nature, is designed to handle relatively large number of features and levels. It is not unusual to have 40 features with as many seven levels. However, typically we tend to deal with less than 80 feature levels.

#### 4.4.4.3. Exercises

The key to Profiling is establishing comparative structures of what the respondents want and do not want. As previously noted, these are indicated on product profile sheets. Often the same sheet is used for several indicated profiles by different marks or more often by different colors. While it is feasible to collect a dozen or more profiles from each respondent, one could expect fatigue to affect the quality of the results on that situation. The following are the types of profile generated.

##### *4.4.4.3.1. Last Purchased*

Indicating what products the respondent last purchased or the last couple of purchases indicates actual behavior. Multiple profiles are used when for frequently purchased items or when one expects a diversity of items purchased by an individual. This is the case with frequently purchased consumer packaged goods.

However, in most cases, the product can be a new concept or a large capital purchase. In both cases, the last purchased item may either never existed or was so long ago that the information is suspect. Under these circumstances last purchase profiles are usually not requested.

##### *4.4.4.3.2. Ideal, Acceptable and Expected Profiles*

Typically the most important and revealing profiles are the products that the respondent wants. Several versions can be used including the ideal product or the acceptable product. The key is the constraints on the ideal. If the feature-levels are clearly ordinal in value, there is a logical ideal as the extreme levels on all features. The issue is then to limit that extension to the range of feature-levels that the respondent truly wants. This can be done often by rephrasing the description of the "ideal" as one that you would expect to be able to purchase within a budget. Another alternative is to start with the extreme ideal and ask for the removal of a number of options.

##### *4.4.4.3.3. Budgeted Choice Profiles*

Budgeted choice profiles involve selecting priced feature-levels in such a way to meet total budget. Alternatively the respondent can profile a product based on a willing to purchase with priced feature-levels. Typically multiple prices are used with the feature-levels that allow estimation of "willingness-to-pay" value estimates.

##### *4.4.4.3.4. Exclusions Feature-Levels*

Identifying what feature-levels are unacceptable is as important as knowing what the respondent want. Typically, respondents' are asked to indicate what feature-levels would force them to consider not purchasing the product. It should be noted that this is often problematic because either most products that are available do not have these levels or that feasible alternatives exist for the respondents. Alternative product availability and the knowledge of their existence will vary among respondents. Therefore, the unacceptable levels may be due to either conviction or knowledge of the alternatives or both.

##### *4.4.4.3.5. Importance of Features*

Many of the decision modeling rules utilize explicit measures of feature importance to scale the results. Typically these are done by a constant-sum scale, a rating, or a ranking. The constant-sum scale is preferred. However, in order to handle the large number of features, they are often broken up into groups and the groups as well as the items in the groups evaluated.

##### *4.4.4.3.6. Explicit Value Feature-Levels*

Finally, it is often useful to get explicit values for features. This is particularly useful if the features are thought of as "extras." This is often done in the same structure as "*Concept Testing*" in which an upper and lower estimate is solicited. However, it should be noted that this can be a very involved process with large sets of feature-levels and therefore not recommended. Typically if it is conducted, it usually is the last exercise in the series, which also raises question of its reliability.

#### 4.4.4.4. Fielding Methods

Profiling requires the presentation of options to the respondent. This leads to either a writing exercise to on-line methods. There are three satisfactory methods of conducting *Profiling* studies.

##### *4.4.4.4.1. Interviews and Workshops*

The traditional method is by interviews and workshops. Though the Profiling has been used for consumer products using "mall intercepts", most applications are for Industrial products where more prepared interviews are used. Representative respondents are invited to come to an interviewing facility where. Recently computerized Profiling has made on-site interviews feasible.

##### *4.4.4.4.2. Phone-Mail (Fax, E-mail)-Phone*

Short Profiling exercises have been executed by Phone-Mail-Phone. This involves recruiting respondents by phone, mailing or faxing the supporting materials and the finally interview is carried out over phone. While it can be an effective way to collect information, the complexity of Profile can make it difficult and error prone.

##### *4.4.4.4.3. The Web (Internet)*

The potential for using the Internet (World Wide Web) for marketing research is huge. It's use for Profiling has been demonstrated and shown to be highly effective. The need to handle large profile sheets for multiple exercises can limit this application. However, for certain uses, particular involving computed budgets this venue appears to work well. The only difficulty with using this approach is the difficulty in programming the complex web forms.

#### 4.4.4.5. Item Placement and Rotation

Because of the large numbers of feature-levels typically considered in the profile sheets, it is necessary to organize them for the respondent. This makes the task easier to accomplish but introduces the potential for order bias. While rotation has been suggested, it produces significant problems in coding as well as the preparation and control of instruments. Typically rotation and randomization is not done with the Profile exercises.

### 4.4.5. "TAKE" OR MARKET MODELING

As previously noted, all evaluation of features, levels and the market structures is derived from estimates of potential actions of the respondents. These estimates are themselves derived from models. "These like all models are built on the quicksand of their assumptions." In the case of *Profiling*, we try to reduce this problem by using a number of models and rely on testing and averaging to reduce the uncertainty.

The models are based on two parts: (1) a model describing how one would expect the respondent to react to a set of alternative offerings and (2) how to merge and aggregate the models to describe markets and segments.

#### 4.4.5.1. Individual Decision Modeling

The key difference between *Profiling* and the conjoint procedures is the lack of focus on utility and monetary perceived value in *Profiling*. Conjoint methods all rely on utility for capturing individual decision and developing an aggregate market model. This is not the case for *Profiling*. The central role is that of a distance measure between what the respondent wants and what is being offered.

##### *4.4.5.1.1. Distance Measures*

The "Cartesian" quadratic measure of distance is generally the basis for all distance measures used.

This is the sum of the squared differences between the values of the preferred profile is the measure of discrepancy. However, there are a large number of variations:

*4.4.5.1.1.1. Root Mean Squared Distance*

For convenience it is often useful to take the square root of the quadratic distance. This is often a cosmetic change unless actual distance measures are used to estimate decision share.

*4.4.5.1.1.2. Absolute Distance*

The quadratic measure tends to over value large differences at the expense of smaller ones. Using the absolute value of each difference rather than squaring the distance reduces this effect.

*4.4.5.1.1.3. Importance Weighed Distance*

Not all features are created equal. Some features are more important than other. As such, importance weighs can be included in the computation of distance.

*4.4.5.1.1.4. Performance Weights*

All features have equally spaced levels. If the features represent performance, their inter-level distances may be adjusted by using either the linear performance difference or the logarithm of that performance to reflect the perception of performance. However, normally, this is not done.

*4.4.5.1.1.5. Exponential Distance*

Though not recommended, there is another approached used to estimate distance on the relative differences. This method scales share[46] using the form:

$$\textbf{Total Distance}_{ki} = \exp[\sim \tilde{o}\ \textbf{Distance}_{ki}]/\exp[\sim \tilde{o}\ (\sum_{j=1}^{N} \textbf{Distance}_{kj})/N]$$

This is the estimate for the total individual distance between the $i^{th}$ product and the $k^{th}$ ideal. It is the ratio of the exponent[47] of the scaled value divided by the exponent of the scaled average value. The scaling factor, ~, is adjusted to the best agreement with the actual market shares given the present utilities[48]. This modified distance measure is not recommended. The model is basically arbitrary. Any form can be used which means that predictions are also somewhat arbitrary.

[46] There is another methods mentioned in the literature to scale this data which is not satisfactory. This alternative approach uses power-law model ($x^a$) to scales distance. Unfortunately the potential interval nature of the distance measure produces inherent problems in comparing results among respondents.

[47] The exponential form allows for the computation of a meaningful ratio scaled value from the interval scaled data. Any number added to the numerator and denominator will cancel out.

[48] The form can be extended to use more scaling factors. As many as 1 minus the number of competitors can be used. This would improve calibration of the model; however, it may not improve its predictability.

#### *4.4.5.1.2. Value (Willingness to Pay) Models*

Value or price modeling is based on estimate of the value or willingness to pay for each feature-level improvement. In *Profiling*, the measure of improvement compared to the ideal and compared the alternatives is viewed as a monetary distance measure. However, it should be noted that this type of value model is similar to that produce by conjoint methods. The basic difference is that typically the estimates of "willingness-to-pay", are considered far less accurate than those using conjoint methods[49].

#### *4.4.5.1.3. Excluding Unacceptable Features*

Typically alternatives that have unacceptable feature-levels can be excluded. The problem here is the believability that the presence of a single detrimental feature-level would exclude the consideration of a product. Furthermore, the situation when all products contain that property. Would the respondent be unwilling to purchase any product under this situation?

#### *4.4.5.1.4. Budgeted Models*

Budgeted models consist of subsets of "ideals" taken at different overall price points. These are important in models when the expectations of feature-levels are strongly linked to overall price. Typically, however, studies are undertaken with a constrained range of price, products and feature-levels to avoid this problem.

### 4.4.5.2. Market Models

The means by which the individual decision models are aggregated to form either market or segment estimates are similar to those used with rating data and individual Conjoint perceived value estimates. They are reviewed here for reference. However, there are significant differences in their application here.

#### *4.4.5.2.1. Winner-Takes-All*

The simplest, and usually the most reliable approach, is to merge respondent predicted behavior is to assign all the sales to the product that is closest to the ideal. This is clearly appropriate in cases with single purchases. However, it is more problematic when the buyer can consider multiple purchases or when the respondent is viewed as representing a group of potential customers. It should be noted that Winner-Takes-All tends to be very good results and is the most common used aggregation rule used. It should be noted, that Winner-Takes-All merely assumes that the product closest to the preferred profile will get the sale. No assumptions regarding the nature of distance are assumed. Distance is only an ordinal type measure in that smaller is better. Though it tends to be the preferred method, the Winner-Takes-All scheme has a few problems.

- It does not take into consideration very close values. This can be a problem with cases where the products are perceived as almost identical.

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[49] In John Hagens' procedure, the estimate of "willingness-to-pay" is the centroid or average of a number of limited estimates.

- Small samples can produce unrealistically large changes in shares with only minor differences in the preferred profile.

- The only adjustable parameters are weighing factors. This makes this type of model difficult to calibrate alone. However, with multiple estimates, weighed averages can be used for calibration.

- Equal product values can be problematic. Usually some rule is imposed to handle the problem.

##### *4.4.5.2.2. Distance Share Rules*

The simplest form type of distance share rule is the linear model. This assumes that the distance measure is a good surrogate for interest. For the linear distance share model we use the inverse distance to a computed measure of interest. The market shares for the alternative products are then equal to the ratio of this measure of interest divided by the total distance. Note that we are assuming that distance is both a linear function of disinterest and that it is metric data[50]. Variations on this model generally focus on the definition of distance rather than in redefining individual share. However, the problems are using a computed distances as a measure of share is problematic. There is no basis that distance is a metric measure of disinterest only that it reflects disinterest.

##### *4.4.5.2.3. Stochastic Distribution*

An alternative approach is to assign a share depending on the rank order of the relative distances. This allows partial assignment of share without assuming that the distances are metric values. Typically those alternatives with unacceptable features are excluded.

The trick is to use a share distribution that reflects expected market behavior. an established rank order statistical distribution (referred to as the broken stick rule) is useful for this purpose. This distribution describes the result of a limiting probabilistic process of collecting the sizes of randomly broken rods. It has been found to describe market share data with large numbers of customers.

**Problems and Issues**

However, there are some key problems in the use of this method.

- Similar to Winner-Takes-All, there is no adjustment on share for close value estimates between products. Near misses are the same as large differences. The underlying assumption is that shares follow position not values level.

- Equal product values also produce problems. As in the case of "Winner-Takes-All," special rules have to be introduced to handle this situation.

#### 4.4.5.3. Multiple Models

Unlike *Conjoint* procedures, *Profiling* provides the development of a fairly large number of market models. Each is based on different assumptions regarding the purchase process and market behavior. This can be viewed as an ensemble of possible market actions. It is, however, desirable to indicate

[50] Metric data are "ratio" scaled in that their is a nature origin as well as additive properties (equal spaced).

only a single prediction for the *Profile* model. Either one of the models is chosen or some weighed average of the models is used.

#### *4.4.5.3.1. Standards of Comparison*

In order to determine the best model or combination of model standards of comparison has to be used. There are two types: (1) those obtained from the respondents and (2) external references.

##### *4.4.5.3.1.1. Choice Data Exercises*

Additional information is often collected from the respondents for use in testing models and for calibration. These are usually a number of predetermined offerings for which the respondent is either asked to indicate purchase choice or comparative value.

##### *4.4.5.3.1.2. External References*

Actual market shares of the existing offerings can be used to test models and for calibration. This is usually preferred since it results in a "ground" or base state that is expected. Unfortunately, this usually involves the exclusion of features that are the focus of the study.

#### *4.4.5.3.2. Single Model Solutions*

From a fundamental perspective, identifying the "correct" or best model is usually preferred. This is can be done by testing the models against external references though choice data has also been used[51].

#### *4.4.5.3.3. Combined Model Solutions*

Alternatively, the key models can be combined to give more "robust or risk adverse" solutions. This is particularly useful if it is suspected that the market is using multiple purchasing strategies. That is, that some respondents are trying to satisfy different purchase goals than others. This situation may be revealed during the qualitative portion of the interviewing process. *Profiling* is often done as part of in-depth interviews. It is during this interviewing process that issues on purchase desires can be explored.

##### *4.4.5.3.3.1. Calibration*

Weighed averaging is a standard procedure for combining estimates. The weights can be estimated using either choice data or external references. However, typically choice data is preferred mainly due to its availability. Sufficient choice data is usually collected for the scaling process[52].

##### *4.4.5.3.3.2. Ad Hoc Scaling Methods*

[51] While each market situation is different, experience has indicated that "Winner-Takes-All" merging of distances from "ideal" models tend to give acceptable if not "best" results.

[52] John Green apparently uses a proprietary version of this type of calibration for his *Simalto Plus*Ē technique. Unfortunately, the procedure is held as a "black-box" and neither the process nor the details are known. Because of this hidden nature of the process, it is not recommended.

Alternatively, less data based methods are used. These often are simple averaging of models or scaling against measure of internal noise or consistency[53]. These are often treated as proprietary procedures based on the experience of the supplier.

### 4.4.6. VALIDATION AND ERROR

Because of the complexity and expense of using this procedure, it is important to review the sources of error and the problems of evaluating validity of the process. Profiling is a pragmatic method. As such there is little developed theoretical basis for error analysis.

#### 4.4.6.1. Precision

Precision refers to the sample size problem. Because of the high cost of this method, sample size tends to be small. *Profiling* uses individual decision models to simulate the total market. As such we can compute the expected error and precision. At sample size of less than 200, precision could become a problem, particularly when the client is interested in a small sub-population as a target market[54]. Usually, we find with modest sample sizes exceeding 150 respondents, that other sources of potential error exceed imprecision. The confidence interval around a percentage of respondents with feature-level values above some monetary point can also be used[55].

#### 4.4.6.2. Reliability

Reliability is the ability to obtain similar result repeatedly. If we go back to the respondents will they give the same results? As in the cases of *Full Profile Conjoint, CBC, Adaptive Conjoint* and extended forms of *Profiling,* because of expense, reliability is rare tested. Only when clients wish to check if the decision rules have changed over time is repeat studies conducted. Unfortunately, when changes are detected, it is uncertain if it is due to a change in the market or the unreliability of the procedure. In general, reliability is usually assumed not to be a major problem.

#### 4.4.6.3. Accuracy

Accuracy refers to the whole family of experimental and measurement problems. However, in the context of this discussion, accuracy refers to the ability of *Profiling* to capture the decision process. Because of the range of exercises, it is often assumed that the desires of the respondents have been captured. The major issue is identifying the drivers of purchase from the exercise results.

#### 4.4.6.4. Experimental Error

[53] Factor analysis can be used to combine the models by identifying latent variables, which can be thought as describing an aggregate model. However, this is still thought of as an ad hoc method since there is no underlying theoretical or pragmatic reason for its use other than consistency.

[54] There are several approaches to expand the effective data set using “synthetic data.” These allow estimation of extreme values based on assuming that the variation is the population is continuous and that it has the same statistical characteristics as the existing sample. It is an extension of the classical EM algorithm for handling missing data.

[55] The percentages are usually assumed to be binomial distributed and confidence interval computed using the Beta distribution.

Accuracy deals with the total issue of measurement. However, there are a number of specific errors and biases associated with its execution specifically.

##### *4.4.6.4.1. Order Bias*

Order bias can be a critical problem in Profiling. Typically the features are presented in a set, “logical” order. However, that order itself can influence the perceived importance. While randomization and rotation can be done, it is usually viewed to be too complex.

##### *4.4.6.4.2. Situational (Interviewer) Influence*

The impact of the interviewer or potential the circumstances of the exercise could influence the results. This is can be a problem, even with professionally executed studies if a tight script is not used by the interview. The major problem, however, takes place with “involved” interviewers.

#### 4.4.6.5. Internal Consistency

Usually, the lack of measures of internal consistency is probably the greatest uncertainty in using Profiling. There is no measure that indicates that the data collected is consistent or that it represents the buying decision. Hold-out profile exercises can be used but rarely are.

#### 4.4.6.6. Aggregation Error

Profiling uses a market simulator model to aggregate respondents. As such aggregation across individual with vastly different decision rules does not compromise the results. This is one of the advantages in this type of market measurement.

#### 4.4.6.7. Predictability (Predictive Validity)

The ultimate test of validation is if how well the model predicts actual behavior. All other tests of error are only a surrogate for predictive validity. This involves testing the model against independent market data. As with any forecasting methodology, testing predictive validity is difficult and problematic since there is a time lag between the construction of the predictive model and the collection of data. Testing the model against current behavior is also problematic since the exercise is usually based on projected behavior in the future rather than what you would have done. Unfortunately, predictive validity is rare tested.

#### 4.4.6.8. Face Validity

Face validity refers to the apparent trust and acceptance of the procedure by clients. *Profiling* is advocated by a number of users who believes it to be the “best practice” for device design. For them it has high face validity. Similar to *Full Profile Conjoint*, clients have indicated that the procedure is considered to be sufficiently complex to avoid “cheating” by respondents.

### 4.4.7. TAKE MARKET SIMULATORS

While *Conjoint* procedures are usually designed to produce estimates of the utility of feature levels, *Profiling* typically is not[56]. Estimating of feature level value with most *Profiling* procedures is based on its impact on share. As such, the market simulator is central to most product and feature evaluations using *Profiling.*

#### 4.4.7.1. Market Simulators

Market simulators based on *Profiling* have the same structure as those developed with *Conjoint* data. Product profiles for a number of competing products are described and the corresponding share generated. Because of the large number of features and their descriptions involved in *Profiling* studies, the layouts of these simulators differ greatly. Typically a hundred or more feature levels distributed among twenty to forty feature categories have to be included. This may be done using a number of profile sheets similar to those used to collect the data or as a coded table.

If several models are being presented, the decision support screen can be fairly complicated as shown below. Here eighteen models are displayed based on distance from an "ideal" and various value models. Other models such as those based on budgeted profiles might also be included. This type of output is normally used internally for model evaluation or with client analysts who wish to be involved in the modeling process.

**Includes Unacceptable Choices**

**Market Share Models**

**Excludes Unacceptable Choices**

| **Competitors:** | **0** | **1** | **2** |
|---|---|---|---|
| **Distance from Idea** | | | |
| **Winner Takes All:** | | **59%** | **41%** |
| **Proportional:** | | **55%** | **45%** |
| **Order Statistics:** | | **55%** | **45%** |
| **Winner Takes All:** | **75%** | **16%** | **9%** |
| **Proportional:** | **75%** | **16%** | **9%** |
| **Order Statistics:** | **75%** | **16%** | **9%** |
| **Last Purchase** | | | |
| **Winner Takes All:** | | **44%** | **56%** |
| **Proportional:** | | **47%** | **53%** |
| **Order Statistics:** | | **47%** | **53%** |

[56] John Hagens' *Simalto* procedure does provide an estimate of "willingness-to-pay", *Adaptive Simalto*Ģ, discussed later. This is a key advantage compared to the more conventional *Profiling* techniques like *Simalto Plus*Ē developed by John Green..

| | | | |
|---|---|---|---|
| Winner Takes All: | 75% | 15% | 10% |
| Proportional: | 75% | 14% | 11% |
| Order Statistics: | 75% | 15% | 10% |
| Explicit Value | | | |
| Winner Takes All: | | 50% | 50% |
| Prop. (Exc. Price): | | 60% | 40% |
| Order Statistics: | | 50% | 50% |
| Winner Takes All: | 75% | 14% | 11% |
| Prop. (Exc. Price): | 75% | 19% | 6% |
| Order Statistics: | 75% | 15% | 10% |

As previously noted, the final simulators resemble those discussed in the *Conjoint* sections with share computed for the market and by segment if desired. Here again, sample size can be critical if segment analysis is desired.

### 4.4.7.2. Segmentation

*Profiling* data can be used to identify market segments. While standard statistical clustering methods can be used, other more custom processes are often desired. The basic problem is that most *Profiling* results are discrete and ordinal in nature. Traditional clustering methods are designed for metric data. Note that Conjoint results in data that can be interpreted as being metric and therefore standard clustering methods are used. There are two basic methods of clustering used with *Profiling*:

#### *4.4.7.2.1. Clustering of Scaled Data*

There are heroic methods to convert discrete and ordinal data to values that are interpreted as metric. Multiple Dimensional Scaling and Correspondence analysis are two of these tools[57]. Importance weights on features and explicit value estimates of feature-levels have also been used[58].

#### *4.4.7.2.2. Hill-Climbing against a Standard*

An alternative approach is to use a Hill-Climbing or cluster averaging process to identify groups of respondents with similar behavior. Most of these processes are based on assignment of respondents to groups based on similarity to base profiles. These are usually ad hoc methods that vary in the

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[57] *Sawtooth Software* segmentation package uses Correspondence Analysis followed by Clustering. Non-metric Multiple Dimensional Scaling can also be used to provide a metric estimate of distance. Correspondence Analysis, Multiple Dimensional Scaling, and Clustering procedures are available in packages such as *SPSS, SYSTAT* and *SAS*.

[58] This is another advantage of using “willingness-to-pay” procedures advocated by John Hagens.

definitions of distances[59].

### 4.4.7.3. Product Optimization

Product optimization with *Profiling* data is problematic. The large number of feature levels as well as the potential for multiple product offerings makes computation of all possibilities extremely difficult[60]. Typically, however, sub-optimum analyses are conducted on specific feature groups or the most important features. Clustering, however, also reveals key differences among respondents and has been used to identify feature groups for seeking optimum product designs.

## 4.4.8. FEATURE PRICE SENSITIVITY

A deficit in the standard profiling methods is the inability to obtain feature level price demand estimates. Typically when standard profiling is used some alternative pricing research procedure is used to determine the overall price sensitivity of the products. However, it is often not designed to obtain the price value of the features themselves. In order to get at feature values coupled procedures have been developed.

### 4.4.8.1. Sequential Profiling

*Sequential Profiling* involves combining a profile exercise with additional tests in order to obtain more detail involved in the feature selection. In the simplest case, it involves identifying which feature levels are required or are "Must Haves" versus those that are repulsive, "Must Not Haves". This is the discrete overlay of the purchase decision. This can be viewed as the extreme price sensitivity reflecting the cases where no price or added value would effect the purchase decision.

Explicit target prices can also be solicited in the form of the Van Westendorp type exercises. That is for each feature level selected, one could ask the expected incremental price, the extreme price that one would pay, the price at which the feature level would be a bargain. Typically a reference price premium or cost is included with the feature level. As such, there would be up to four price points associated by the respondent with acquiring that feature level. In addition to these explicit methods, there are both adaptive pricing testing (*Adaptive BYO*) and Conjoint approaches (*MBC*). These are more complex methods and are discussed below.

**Advantages and Disadvantages**

The simple forms of *Sequential Profiling* have both advantages and difficulties.

- The simple forms of *Sequential Profiling,* like other profiling procedures, simulate the selection or negotiated buying process. This is quite similar to the custom design of computers (with *Dell*) or the purchase of customized industrial equipment. This is opposed to *Full Profile Conjoint*, which simulates packaged good purchases. This makes *Sequential Profiling* like the traditional profiling

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[59] John Green in his *Simalto Plus*Ē package claims to use a proprietary Hill-Climbing clustering algorithm for segmentation. However, once again, it is viewed as a "Black-Box" method and not recommended.

[60] This is one of the cases where *EXCEL* simulators are at a distinct disadvantage over those constructed in procedural languages (not *VisualBasic*). The procedural language programs are far faster and makes optimization by "brute force" (complete enumeration) feasible.

particularly suited for industrial product design.

- The explicit form of the pricing exercises exposes the procedure to manipulation. This is a face validity problem in that the potential for respondents to try to game the survey is apparent.

- These forms of *Sequential Profiling* generate complete data on the respondents as opposed to those needing the use of split samples for even very large sets of features. This allows reliable analysis including segmentation as well as more effective market simulators compared to using heroic methods included with *Choice Based Conjoint*.

- These methods are the most efficient, requiring the least amount of survey time, space and analysis.

#### 4.4.8.2. Adaptive BYOĢ

*Adaptive BYOĢ* [61] is a modification of the profiling procedures designed to capture not only the preferred configurations of products but also the value of the features and levels. The method involves having respondents iteratively configure desired products based on features with changing prices. The prices are selected to incrementally drive toward the maximum price or value for each feature and level that the respondent will accept. The perceived value results are similar to those obtain using sequential pricing and conjoint techniques, with the additional advantage of also capturing preferred profiling information. The procedure is able to handle a fairly large number of features. However, do to the increased complexity of the task; it is usually desirable to keep the number below those that are handled by traditional profiling procedures.

As in the case of *Adaptive Conjoint*, *Adaptive BYO* relies heavily on computerized systems. Presently both are implemented on the Internet (World Wide Web) allowing fairly easy execution. The automation of the process is required due to the customization of the process[62].

**Advantages and Disadvantages**

Like all procedures *Adaptive BYO* carries with it both advantages and difficulties.

- *Adaptive BYO* like other profiling procedures also simulates a selection or negotiated buying process.

- However, due to the explicit nature of the profiling process, *Adaptive BYO* requires cognitive features that respondents can associate with a price. This is similar to most of the other explicit methods such as *Compositional Conjoint*, which also requires more cognitive features. Many of the other conjoint methods, however, are not so limited.

- *Adaptive BYO* generates complete data on the respondents as opposed to those needing the use split samples for even very large sets of features. This allows reliable analysis including segmentation

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[61] This method was developed by John Hagens and is available through *International Planning and Research, Inc.* (IPR) as a proprietary procedure.

[62] Unlike *Adaptive Choice Based Conjoint*, which is available with a full range of software tools, *Adaptive BYO* as well as the other methods are presently a proprietary process requiring individual project development.

as well as more effective market simulators compared to more heroic methods such as *Choice Based Conjoint*.

#### 4.4.8.3. Menu-Based-Conjoint MBC

*Menu-Based-Conjoint, MBC*[63] is a type of sequential profiling. In this case, however, the profiling is followed by a *Choice-Based-Conjoint* procedure to capture the price sensitivity as well as secondary measures of feature utilities. In a sense, it is an alternative application of the *Adaptive Choice-Based-Conjoint* process. While *ACBC* uses the profiling exercise to hone-down the feature list, *MBC* uses the conjoint procedure to determine the price value of the features. While S*equential Profiling* and most applications of *Adaptive BYO* produces complete respondent models, *MBC* only generates market estimates. This is due to the use of *Choice-Base-Conjoint*[64].

As in the case of *ACBC*, *MBC* relies heavily on computerized systems. Presently both are implemented on the Internet (World Wide Web) allowing fairly easy execution. The automation of the process is required due to the customization of the sampling process of the *CBC* portion of the exercise.

**Advantages and Disadvantages**

Like all procedures, *Menu-Based-Conjoint* carries with it both advantages and difficulties.

- *Menu-Based-Conjoint* unlike the other sequential profiling procedures simulates both a feature selection or negotiated buying process and the packaged goods purchase, choice process. This may or may not provide a more robust view of the purchasing process.

- Note that the explicit nature of the profiling process as with the other profiling procedures requires cognitive features that respondents can associate with a price. This is similar to most of the other explicit methods. This imposes restriction of the otherwise more flexible capabilities of the Conjoint procedures that are included.

- *Choice-Based-Conjoint* which is an integral part of the *MBC* procedure requires the use of a fragmented design and produces only market estimates. The form of the resulting demand curves are inherently assumed (usually a form of a continuous linear Multi-Gaussian Distribution). While this not necessarily a problem, it can hide structural issues that can be important for segmentation and market simulations.

- Also a consequence of using the fragmented sampling design is either an increase in the required sample size or the corresponding reduction in statistical precision. This results in a significantly high expected research cost of these estimates.

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[63] In its present form, it is being developed by Byan Orme of *Sawtooth Software, Inc.* with supporting design and analysis software as a commercial package.

[64] Individual respondent estimates can be obtained with *MBC* data using Hierarchical Bayesian procedures; but these all rely on heroic assumptions about the nature of the market demand functions.

## 4.5. LARGE ATTRIBUTE SET AND HYBRID METHODS

There are a number of procedures that have been developed specifically to handle very large sets of feature level elements. Most of these procedures are proprietary in that they are conducted by specific marketing research firms using fairly standardized procedures. While in almost all cases, the promoters of the methods claim that they are useful in a broad set of conditions, we believe that as with all procedure they each have their own limits and are best used under conditions that reduce their disadvantages.

It is almost always better to reduce the feature-level sets than to employ methods that try to circumvent the inherent problems produced by the extended set.

### 4.5.1. IDEA WIZARD Ē

#### 4.5.1.1. Description:

This is a proprietary method by *Moskowitz Jacobs Inc.* It involves the rating of a set Full Profile Conjoint card. The rating usually reflects the intention or likelihood to purchase.

#### 4.5.1.2. Objectives:

Idea Wizard is design to provide the capability to do exploit the advantages of Full Profile Conjoint for a large number of attribute levels and a consistently straight forward execution methodology.

#### 4.5.1.3. Design Issues:

Designs with up 80 elements (total of attribute/feature levels). Up to 120 cards are used in the design. However, fewer cards are probably preferable. As with all Full Profile Conjoint procedures, a statistical experimental design is used to try to produce a orthogonal, balanced, partial factorial design. However, with such a large set, the design may not be fully orthogonal (may have some intercorrelation) and may not be fully balanced. However this is probably not a major problem.

#### 4.5.1.4. Execution:

These are computerized tools with the software available on a disk. It is usually executed in a laboratory setting. However, mailing the disk to respondents is feasible and has been used. At this point, I am unaware of a web-based system. It should be noted, however, that Idea Wizard is not a adaptive process. The choice of variables and the conjoint design is determined prior to the execution and is not altered or customized for the individual respondents.

#### 4.5.1.5. Analysis and Results:

The analysis is basically by regression and is similar to conventional Full Profile Conjoint. Simulators and standard analysis are also similar to that produced by standard Full Profile Conjoint Procedures.

#### 4.5.1.6. Advantages and Disadvantages

As previously noted, any effort to expand the limits of a Full Profile Conjoint produces other limitations and difficulties. For Idea Wizard these limitations include:

- The use of a rating system does not allow for tradeoffs between alternative scenarios (cards). This can result in inconsistency of evaluation this is particularly due to the fatigue involved in large numbers of cards.
- Ratings are notorious for "regression to the mean", that is respondents tend to give a large number of scenarios the same or similar evaluations.
- Common to all Full Profile Conjoint methods, some sets of cards may have unrealistic combinations of feature levels.
- The large size of the exercise is likely to lead to fatigue and will provide a somewhat unrealistic buying environment.
- Most of these difficulties are associated with the size of the attribute level set being considered and would be similar to any other variations of Full Profile Conjoint intended for this purpose. A number of attributes (particularly greater than six) makes the task difficult and may lead to questionable results.
- Model consistency or goodness-of-fit are not particularly good in some cases. It is not unusually to have R-Square values as low as .7 (70% of the variance explained).

There are several advantages to the method including:

- It is able to handle the large number of possibilities, which simplifies the design task.
- Being an automated process, it provides a consistent experimental procedure. This is particularly useful in international and cross-cultural studies.
- The analysis is standardized which allows easy explanation to management.
- The procedure is basically an implementation of a modified established and well-studied measurement procedure.
- It is reported to have a high "face validity" where clients appear to be confident of the procedures and results.
- It should be noted that none of the conjoint methods, by themselves, are recommended for ultimate pricing research.

### 4.5.2. Choice-Based Conjoint (CBC) [65]

*Choice Based Conjoint* is an extension of *Full Profile Conjoint* to allow for the use of a larger set of features and the use of a choice exercise. Traditional *Full Profile Conjoint* tasks usually centers around either the evaluation of each concept or rank ordering of a product set. These tasks are often viewed as too theoretical and unrealistic compared to the actual buying process. Using a choice approach can be use instead of the ranking. However, that introduces a large increase in the number of individual exercises that are required for even traditional *Full Profile Conjoint* problems. In order to

[65] Software packages to do *Choice-Based Conjoint* (*CBC*) are available from *Sawtooth Software (http://www.sawtooth.com.*

accommodate the increase number of tasks, *Choice-Based Conjoint* procedures rely on using a highly split sample[66]. With the use of such split samples, a larger number of features and levels can also be introduced.

### 4.5.2.1. Description:

*Sawtooth Software* has developed and promotes packages that designs and executes *Choice Based Conjoint* designs which allows for vastly expanded feature-level sets. In this approach a complete card set design is produced and set up as a series of choice exercises. This set may involve hundreds (and sometimes thousands) of exercise possibilities. The specific choice exercise scenario usually involves the respondent choosing among three or four option or products include the option to select none. Each respondent is given a number (12 to 30) of these scenarios out of the hundreds of possibilities. The choice of the scenarios, however, is not random since it is desired to provide each respondent with a "balanced" design where he sees all of the possible features and levels.

Due to the large number of products that are required in the method only semantic descriptions are used. Pictures or samples that can be used for traditional *Full Profile Conjoint* are typically too expensive for this procedure.

### 4.5.2.2. Execution:

*CBC* is typically executed by mail, interview or using special software within Internet surveys. *Sawtooth Software* provides packages to design, implement over the Internet, and analyze the resulting data.

### 4.5.2.3. Analysis:

#### *4.5.2.3.1. Feature Value and Market Models*

Primary analysis is done using Logit regression on the individual choices. This results in overall market values of features and levels. This is the appropriate use of the method. Since the products are presented as a "whole" both cognitive and descriptive features can be used. With feature values market models are readily developed allow for the relative value of hypothetical products (bundles) to be evaluated.

#### *4.5.2.3.2. Pricing*

Similar to other forms of conjoint, price values are typically computed. This allows for estimates of price sensitivity. Unfortunately, like all of forms of conjoint, price sensitivity for the collective products is unreliable as a competitive market estimate. These estimates are generally far higher than would be obtainable in the marketplace. However, they do represent some concept of relative total value and cam be appropriately used in the design of products.

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[66] The use of split samples is not new to conjoint designs. With even modest numbers of features and levels, the number of needed product concepts becomes excessive for a single task. Paul Green, in his early work on *Full Profile* and *Hybrid Conjoint* designs, used split samples to cover the range of features necessary. However, *CBC* using an extremely split sample which makes estimating the effective sample size problematic.

#### *4.5.2.3.3. Segmentation*

Because aggregate analysis is required for this procedure, it is important that any subgroups are identified and analyzed separately. Typically care is taken prior to execution to segregate the sample into known segments. However, that is not always possible. *Sawtooth Software* claims to be able to estimate appropriate segment structure directly from the *CBC* data using *Latent Class Clustering* methods. These methods are discussed in the section on Attribute Analysis. It is one of the few methods available that are designed to handle large amounts of missing data. However, the methods are "heroic" and do not produce unique solutions. At best, the resulting clusters using this method should be viewed as indications of groups rather than clear well-structured segments[67]. As such, *CBC* should not be used primarily for segmentation studies.

#### *4.5.2.3.4. Individual Models*

As previously noted, *CBC* relies heavily on highly split data. In some designs no two respondents get the same set of stimuli. As such, there is insufficient data on the individual to produce an explicit preference model. However, *Sawtooth Software* claims to be able to produce estimates of individual decision models with *Choice-Based Conjoint* data. The procedure uses hierarchical Bayesian methods in ways similar to that used *in Idea Map*. However, in this case, the missing data is estimated from the total market (segment) Logit models[68]. This may result in underestimates of the diversity in the individual models.

### 4.5.2.4. Advantages and Disadvantages:

There a number of fundamental disadvantages with this procedure including:

- There is no distinction between individual variation in the linear decision model and the variation of decisions in the market.
- There is no check on poor data. All data is considered useable and none suspect. This can be a problem when 20% or more of *Full Profile Conjoint* data are often deemed unacceptable.
- The conditions of most objects are unrealistic.
- The methods of segmentation and individual model estimation are “heroic” in that they are based on extreme and untestable critical assumptions.

However, there are several very appealing advantages:

- It is based on a choice approach, which is closer to the purchase process than other conjoint procedures.
- It can handle a large range of feature-levels.

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[67] Their method likely relies on an extension of the traditional procedures for use with *Logit Regression*. It should be noted that regression segmentation has not be found to be reliable in identifying subtle difference in groups, and may also falsely identify non-existing groups..

[68] Bayesian procedures rely on a "prior" distribution or results, which is merged with data to estimate the updated or posterior results. In this case, the average models are used to supplement the missing data on the individuals.

- It is robust in regards to design. You can use a full statistical design rather than only a partial design. This makes the basic design process simpler.
- Sub-designs can be used to extract partial market models.

### 4.5.3. Hybrid Conjoint

#### 4.5.3.1. Description:

*Hybrid Conjoint* merges forms of explicit methods of evaluation such as *Compositional Conjoint* with *Full Profile Conjoint*. In a way, it is similar to the process of bridging *Full Profile Conjoint* studies, except those different methodologies are used for each sub-study. This method was developed by Paul Green[69] at the University of Pennsylvania to handling a larger number of variables and levels than usually allowed by *Full Profile Conjoint*. There is a broad range of possible forms based on variation in both the *Full Profile* and the *Compositional Conjoint* parts. Typically, these are ad hoc procedures, designed to handle different situations.

#### 4.5.3.2. Number of Variables:

*Hybrid Conjoint* offers a significant larger number of feature-level elements than traditional *Full Profile Conjoint*. It is still fairly limited. Its capability is similar to that of Compositional Conjoint. Its advantage, however, is the ability to use *Full Profile Conjoint* measures

#### 4.5.3.3. Execution:

Traditionally, it has been executed with interviews often as workshops and intercepts. However, phone-mail-phone and Internet surveys are feasible.,

#### 4.5.3.4. Advantages and Disadvantages

Most of the disadvantages in *Hybrid Conjoint* are the same as those of its parts *Compositional* and *Full Profile Conjoint*. These include:

- Limitation in the number of the Feature-Level elements.
- Lack of Customization
- Complexity of Execution
- Complexity of Design

However, there are a number of unique advantages:

- The procedure can provide multiple measures of common attributes. This can be used a test of reliability and consistency.
- While maintaining the structure of the *Full Profile Conjoint* trade-off test needed for subtle attributes, it allows a greater number of characteristics to be tested.

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[69] In the original application by Paul Green (Marriott Countyard Project) a profiling technique was used *with Full Profile Conjoint* for the *Hybrid* exercise. Profiling is discussed in a separate section but is considered an explicit method.

- It can capture the two phase buying decision involving selection of the consideration set (*Compositional Conjoint*) followed by a trade-off of attributes for the final vendor selection (*Full Profile Conjoint*)

### 4.5.4. IDEA MAPĐ

#### 4.5.4.1. Description:

*Idea Map* is a proprietary hybrid conjoint extension of Idea Wizard to accommodate even more feature-level items. This method promoted by *Moskowitz Jacob Inc*[70] separates variables into key trade-off items that are handled by the modified *Full Profile Conjoint* procedure and another set of feature-levels handled separately. In total Jacob Moskowitz claims to be able to handle up to 300 feature-level elements in this manner with 80 or so being handled using the Idea Wizard procedure and the rest separately.

#### 4.5.4.2. Methodology:

As previously noted the trade-off analysis follows the Idea Wizard method and is automated in a similar fashion. The unique characteristics are how the "common" lower valued feature-level elements are handled. This is done with a small sample of respondents using a positioning exercise. The procedure is based on collecting both similarity and importance information. A map is generated from this data using *Multiple Dimensional Scaling* that relates the importance of feature-levels which can be used to estimate values of unmeasured feature-level elements[71].

It should be noted that the choice of which feature-level elements will appear in the trade-off exercise and which will be estimated based on position is not on an individual basis. A single choice of elements is made based on the results of the positioning exercise.

#### 4.5.4.3. Advantages and Disadvantages

The same disadvantages with *Idea Wizard* hold true for Idea Image plus these:

- The separation of "important" feature-levels is desired based on a very small sample of respondents.
- The basic procedure produces market estimates rather than individual measures.
- Major differences in the importance of non-trade-off feature-level elements among segments are ignored.
- While individual estimates are obtained, they are only approximate and may be very misleading. There is no theoretical or experimental basis for this procedure of estimation of missing data, though the assumption of common deviation from collective behavior is reasonable.

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[70] *http://www.mindspring.com/~mji/*

[71] The exercise can be thought as a type of Bayesian missing data procedure where the common relationship among variables is used with respondent data to estimate missing points.

However, there are key advantages in this procedure:

- There are few other procedures, *Simalto* and *Simalto Plus*Ē that claim to be able to handle the range of feature-level elements as *Idea Map*.
- Unlike those other procedure, *Idea Map* does generate monetary perceived value estimates.
- Similar to, *Idea Wizard*, it is reported to have a high "face validity" where clients appear to be confident of the procedures and results

### 4.5.5. ADAPTIVE HYBRID CONJOINT [72]

#### 4.5.5.1. Description:

In traditional *Hybrid Conjoint* as well as in *Idea Map* the two sets of features, whose values are being measured by the two processes, are determine for the total set of respondents and therefore the market. In *Adaptive Hybrid Conjoint*, that selection is done on an individual basis. This is done on-line using a special purpose software package that allows individual design of the *Full Profile Conjoint* tests and their analyses[73].

It should be noted that this is not a widely used tool and no standardized software exists.

#### 4.5.5.2. Advantages and Disadvantages

Most of the disadvantages in this procedure are the same as with traditional Hybrid Conjoint with an additional major one:

- It is very complex and very fault intolerant.

Its advantages include:

- Customization
- Segmentation based on the decision process

### 4.5.6. ACA "ADAPTIVE" CONJOINT [74]

#### 4.5.6.1. Description:

*Adaptive Conjoint Analysis* "*ACA*" is a proprietary procedure by *Sawtooth Software* to combine the advantages of heuristic testing of perceived value without the difficult with *Adaptive Hybrid Conjoint*. This procedure uses a version of *Compositional Conjoint* with paired comparisons and selected full profile evaluation for calibration. The adaptive component allows for the selection of a subset of

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[72] An abstract of a paper title "Validity of Adaptive Hybrid Conjoint Analysis" *(http://www.wiwi.uni-jena.de/Papers/wp-a9908.html* )

[73] In practice, I would expect that the feature-level structure that is allowed is relatively simple such as have three levels for each attribute. This would allow for a common design to be used no matter what the selection of attributes.

[74] Software packages to do Adaptive Conjoint Analysis (*ACA*) are available from *Sawtooth Software (http://www.sawtooth.com)*.

“important” characteristics for evaluation. The values of non-important feature-level elements are assumed to be zero on the individual basis. The market model is generated by aggregating individual results.

#### 4.5.6.2. Number of Variables:

The procedure can handle to at least 30 variables. However, smaller sets are available on demonstration systems.

#### 4.5.6.3. Execution:

This is a computer driven system. Traditionally this is done by using either a workshop environment or mailing the software disk to the respondent who returns the disk after completion. Using the mailing of the disk is problematic. When it has been done, it is difficult to support. The more acceptable means is by workshop.

#### 4.5.6.4. Advantages and Disadvantages

The disadvantages of the method include most of those associated with *Compositional Conjoint* and those common to other large attribute set methods. The disadvantages include:

- Potentially the procedure can be a long task though shorter than with Idea Wizard.
- Like other *Compositional Conjoint* procedures it relies on the ability of the respondent to evaluate and compare the value levels of features.
- Unlike Idea Map, which uses a measure of the population value for unevaluated characteristics, *ACA* negates them.
- It has not been found to give good predictions of final products value based on eventual price/market acceptance.

However the procedure has some advantages and a large number of supporters.

- It is an impressive procedure.
- It can handle a large number of variables.
- It appears to have favorable face validity.

### 4.5.7. ADAPTIVE CHOICE BASED CONJOINT (ACBC)

#### 4.5.7.1. Description:

*Adaptive Choice Based Conjoint (ACBC)* is a set of procedures developed by *Sawtooth Software* to reduce some of the inherent problems found in their Choice Based Conjoint procedures. In particular, this procedure is a “front end” to reduce the number of variables being considered. In a way it is a merger of the principles of *CBC* with their Adaptive Conjoint techniques. The process involves three stages: (1) an initial screening using a preferred profiling technique referred to as a “Design Your Own”, (2) a testing of the results of the profiling (type of full profile selection) and (3) finally the exclusion of the CBC exercise. The profiling approaches are discussed in the next section of these notes in detail.

#### 4.5.7.2. Number of Variables:

The goal of adaptive portion of the process is to reduce the number variables to be considered. The screening procedure is based on profiling which can handle 30 or more attributes and over 100 total variations, even though the final *CBC* design should only have 7 or fewer attributes with no more than 18 total variations. This requires a major reduction of the number of variations during the initial phases of the procedure.

#### 4.5.7.3. Execution:

Because of the complexity and interaction required, this procedure can only be on-line using special purpose software.

#### 4.5.7.4. Advantages and Disadvantages

Most of the disadvantages in *ACBC* are the same as *CBC*[75]. The use of profiling is only to reduce the attribute set. The other advantages and disadvantages remain with the additional disadvantage coming from increase complexity and execution length. These remaining items include:

- There is no distinction between individual variation in the linear decision model and the variation of decisions in the market.
- There is no check on poor data. All data is considered useable and none suspect. This can be a problem when 20% or more of *Full Profile Conjoint* data are often deemed unacceptable.
- The conditions of many objects may be unrealistic (the adaptive procedures should reduce this but will not eliminate the problem).
- The methods of segmentation and individual model estimation are “heroic” in that they are based on extreme and untestable critical assumptions.

However, there are several very appealing advantages:

- It is based on a choice approach, which is closer to the purchase process than other conjoint procedures.
- It can handle a large range of feature-levels.
- It is robust in regards to design. You can use a full statistical design rather than only a partial design. This makes the basic design process simpler.

# 4.6. APPENDICES

## 4.6.1. Appendix A - Summary of Methods

| | Full Profile Conjoint | Compositional Conjoint | Profiling | Rating |
|---|---|---|---|---|
| **Principal Objective** | Value of changes in attribute levels | Value of changes in attribute levels | Optimum product design | Market sensitivity to offering attributes |
| **Task** | Rank ordering of a set of product descriptions - usually personal interview | Rank a set of attribute levels including price in order of importance | A series of exercises of selecting, ranking and identifying attribute levels | A series of attribute ratings of competitive products and concepts and an importance scale (preferably a constant-sum). |
| **Definition of Levels** | Discrete well defined attribute levels | Discrete well defined attribute levels | Discrete well defined attribute levels | Relative continuous attribute levels (1 to 10 scales) |
| **Execution Method** | Mall Intercept or phone-mail –phone | Often by mail, phone-mail or interview. | Usually personal interview (mall intercept) | Usually mail or telephone interviews |
| **Size Limits** | In practice should not handle more than seven attributes or more than 27 cards which, limits levels. Only single situation can be tested. | While as many as 83 attribute levels have been used, we suggest less than 20. Multiple situations can be tested and linked.. | Large number of attributes and attribute levels (> 100). Multiple situations can be tested. | Only a few attributes can be considered with a few competitors, typically < 16 attributes and < 6 competitors. |
| **Types of Features** | Relatively unrestricted. Can handled non-cognitive but describable feature levels. | Restricted to cognitive (semi-tangible) feature levels that are positive valued. | Restricted to cognitive (tangible) features that are positive valued. | Restricted to cognitive (tangible) features that may be negatively valued. |
| **Contextual Features** | A contextual method of analyzed as a "primary" driver model. However, if collected on a respondent level (complete) correlation can be determined. | In execution, context is not meaningful since all features are considered independent. However, correlation can be determined. | Context is inherent and correlation is normally determined. | All features are considered independent and correlation determined as part of standard analysis. |
| **Non- Textual Features** | Classical full profile can handle graphical (visual) presentation of hypothetical product. Some variants (CBC) | Restricted to textual feature level descriptions. | Some advanced methods of "design-your-own-product" allows for graphic descriptions. This is very difficult and an | Restricted to textual feature level descriptions. |

| | | | | |
|---|---|---|---|---|
| | can not. | | unusual application. | |
| | **Full Profile Conjoint** | **Compositional Conjoint** | **Profiling** | **Rating** |
| **Simulated Decision** | Selection from a broad range of products based on attribute trade-offs | A negotiation purchase, based on a trade-off of attribute levels. | Negotiation or a design decision | Satisfying as minimum price |
| **Underlying Assumptions** | Consistent trade-off respondent behavior based on primary effects. It is assumed that respondent can better select complete offerings than attribute levels[76]. | Respondent is able to trade-off attribute levels. There is some explicit value of attributes. | Ability of respondent to describe past and future purchases in regards to attribute levels and values. | Ratings and importance of attributes are comparable. Ratings and importance are ratio scale values along with minimum performance levels. |
| **Results** | Attribute level value & market simulation | Attribute level value & market simulation | Market simulation and attribute values | Product, attribute position, market simu-lation. |
| **Aggregation, Split Populations** | Either on a respondent basis or aggregated. | Often done on a respondent basis but with pair comparisons aggregated. | Done on a respondent basis | Either on a respondent bases or aggregated. |
| **Analysis** | Regression on the respondent and averages. Monotonic Regression is sometimes used. Rankings are usually scaled to dollars. | Rankings of attribute levels scaled to dollars and segment clusters usually also done. | Represented as tabular data and through market simulation. | Position maps (Factor Maps and MDS) for dis-tance, segment clustering, value modeling, ratings and importance presented as tabulations. |
| **Market Model[77]** | Market simulations based on value, share based on either winner takes all or proportional. | Market simulations based on value. | Multiple simulation models, based on: value, ideal case, last purchase and satisfaction. | Model based on Fisher model: $\Sigma$ (Ratings x importance) |
| **Model Consistency** | Both the analysis and models are linear. | Analysis is nonlinear: model is linear. | Analysis is not linear, model is not linear | No Derivation value |

[76] Some non-trade off decision models can be capture with full-profile conjoint. However, a partial or two phased decision with a preliminary screen can not be modeled. Care must be taken to assure that the attribute levels under consideration are trade-off items.

[77] Usually we consider these to be "brand equity models" rather than market models since they capture of the share that would be expected with all other things kept equal. Rarely, are all other things kept equal!

| | Full Profile Conjoint | Compositional Conjoint | Profiling | Rating |
|---|---|---|---|---|
| **Fault Tolerance** | Fault intolerant, errors in design plague results | Somewhat fault tolerant, | Fault tolerant | Fault tolerant |
| **Price/Value Estimates** | Often gives over estimates of price value. Values may dependent on design, | Can give poor price value of attributes. Depends on specific approach used. | Does not give a price value of attributes. Price is handled as an attribute | Does not give a price value of attributes. Price is handled as an attribute |
| **Competitive Data** | Competitive brands can be included as an attribute | Competitive brands must be included but usually not. | Competitive brands can be included as an attribute | Full competitive data can be usually obtained, |
| **Feature Value** | Perceived Value | Perceived Value | Value of Exchange/ Unmeasured | Value of Exchange/ Unmeasured |
| **Problems** | Prone to decision model problems as well as design problems. Major problems are interaction and unrealistic cases. Task size is another problem. | Inability of the respondent to rate prices against other attributes. Alterna-tively, there is a problem of selecting appropriate price levels. | Complexity and cost are the major fielding difficulties in this method. Selection of an appropriate market model is also a major problem. | Usually not accurate. No evaluation of attribute level - No direct recommendations for action. |
| **Advantage** | Simulates a selection process without an explicit buyer model. It has industry credibility. | Low costs, ability to provide multiple situations and easy integration with other surveys. | Flexibility and in-depth analysis. | Simple and widely undertaken as customer satisfaction. |
| **Relative Costs** | Fairly high costs if personal interview is used, otherwise medium cost range. | Usually very inexpen-sive and can be coupled to existing survey. | Usually very expen-sive due to the need for personal interviews. | Usually inexpensive and coupled to existing survey. |
| **Successful Cases** | Organizational and group decision making, packaged goods, big ticket consumer products, pharmaceuticals, etc. | Agricultural chemicals, industrial and medical products, services. | Industrial and medical products, consumer soft-goods, and big ticket consumer purchases. | Consumer, industrial and service products. |
| **Rules** | Min. # of cards = 1.5 x (Σ attribute levels -1)+1 | Maximum number of attribute level per test < 25 | | |

### 4.6.2. APPENDIX B - FULL PROFILE ORTHOGONAL CONJOINT DESIGNS

The following are statistical designs for Full Profile Conjoint Studies. Analysis of this data is usually done using dummy variable multilinear regression. As such, intercorrelation among dummy variables is expected, however, intercorrelation between a dummy variable and other variables, between other variables and between dummy variables and other sets of dummy variables should be zero. These have all been checked on the following designs. It should be noted that these designs have many variables with a corresponding low or no degrees of freedom left. In these cases, some of the variables should be dropped in the final design[78].

The variables covered by these designs are indicated in the title with an descriptor such as **nXm,** where **n** indicates for the number of variables and **m** is the number of levels. The number of scenarios or cards is indicated in the title as **L#** where **#** represents the number of scenarios. For example **L16(8X2,2X3)** is a 16 scenario design with 8 variables on 2 levels and 2 variables on 3 levels.

| | **L8(7X2)** | | | | | | |
|---|---|---|---|---|---|---|---|
| Card | a2 | b2 | c2 | d2 | e2 | f2 | g2 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 1 | 2 | 2 | 2 | 2 |
| 3 | 1 | 2 | 2 | 1 | 1 | 2 | 2 |
| 4 | 1 | 2 | 2 | 2 | 2 | 1 | 1 |
| 5 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| 6 | 2 | 1 | 2 | 2 | 1 | 2 | 1 |
| 7 | 2 | 2 | 1 | 1 | 2 | 2 | 1 |
| 8 | 2 | 2 | 1 | 2 | 1 | 1 | 2 |

| | **L9(4X3)** | | | |
|---|---|---|---|---|
| Card | a3 | b3 | c3 | d3 |
| 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 2 | 2 | 2 |
| 3 | 1 | 3 | 3 | 3 |
| 4 | 2 | 1 | 2 | 3 |
| 5 | 2 | 2 | 3 | 1 |
| 6 | 2 | 3 | 1 | 2 |
| 7 | 3 | 1 | 3 | 2 |
| 8 | 3 | 2 | 1 | 3 |
| 9 | 3 | 3 | 2 | 1 |

[78] While for standard regression analysis, it is desirable to have at least twice as many points as variables estimated, that is often not feasible with Full Profile Conjoint Studies. Sometimes it is necessary to be statisfied with as few as 4 or 5 degrees of freedom.

| | **L12(11X2)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Card | a2 | b2 | c2 | d2 | e2 | f2 | g2 | h2 | i2 | j2 | k2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 4 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| 5 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| 6 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 |
| 7 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| 8 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| 9 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| 10 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 |
| 11 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 |
| 12 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |

| | **L16(15X2)** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Card | a2 | b2 | c2 | d2 | e2 | f2 | g2 | h2 | i2 | j2 | k2 | l2 | m2 | n2 | o2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 4 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 5 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |
| 6 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 7 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| 8 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 |
| 9 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| 10 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| 11 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 12 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| 13 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 |
| 14 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 |
| 15 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 |
| 16 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |

| | **L16(5X4)** | | | | |
|---|---|---|---|---|---|
| Card | a4 | b4 | c4 | d4 | e4 |
| 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 |
| 3 | 0 | 2 | 2 | 2 | 2 |
| 4 | 0 | 3 | 3 | 3 | 3 |
| 5 | 1 | 0 | 1 | 2 | 3 |
| 6 | 1 | 1 | 0 | 3 | 2 |
| 7 | 1 | 2 | 3 | 0 | 1 |
| 8 | 1 | 3 | 2 | 1 | 0 |
| 9 | 2 | 0 | 2 | 3 | 1 |
| 10 | 2 | 1 | 3 | 2 | 0 |
| 11 | 2 | 2 | 0 | 1 | 3 |
| 12 | 2 | 3 | 1 | 0 | 2 |
| 13 | 3 | 0 | 3 | 1 | 2 |
| 14 | 3 | 1 | 2 | 0 | 3 |
| 15 | 3 | 2 | 1 | 3 | 0 |
| 16 | 3 | 3 | 0 | 2 | 1 |

| | **L16(3X2,3X4)** | | | | | |
|---|---|---|---|---|---|---|
| Card | a42 | b4 | c4 | d2 | e2 | f2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 | 0 |
| 3 | 0 | 2 | 2 | 0 | 1 | 1 |
| 4 | 0 | 3 | 3 | 1 | 0 | 1 |
| 5 | 1 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 0 | 1 | 0 | 1 |
| 7 | 1 | 2 | 3 | 0 | 0 | 0 |
| 8 | 1 | 3 | 2 | 1 | 1 | 0 |
| 9 | 2 | 0 | 2 | 1 | 0 | 1 |
| 10 | 2 | 1 | 3 | 0 | 1 | 1 |
| 11 | 2 | 2 | 0 | 1 | 1 | 0 |
| 12 | 2 | 3 | 1 | 0 | 0 | 0 |
| 13 | 3 | 0 | 3 | 1 | 1 | 0 |
| 14 | 3 | 1 | 2 | 0 | 0 | 0 |
| 15 | 3 | 2 | 1 | 1 | 0 | 1 |
| 16 | 3 | 3 | 0 | 0 | 1 | 1 |

| | L16(8X2,2X3) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Card | a3 | b3 | c2 | d2 | e2 | f2 | g2 | h2 | i2 | j2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |
| 3 | 0 | 2 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 |
| 4 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 |
| 5 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 |
| 7 | 1 | 2 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 8 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 9 | 2 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 10 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| 11 | 2 | 2 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |
| 12 | 2 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 13 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| 14 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 15 | 1 | 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 16 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |

| | L16(2X3,3X4) | | | | |
|---|---|---|---|---|---|
| Card | a4 | b4 | c4 | d3 | e3 |
| 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 2 | 1 |
| 3 | 0 | 2 | 2 | 1 | 1 |
| 4 | 0 | 3 | 3 | 1 | 2 |
| 5 | 1 | 0 | 1 | 1 | 1 |
| 6 | 1 | 1 | 0 | 1 | 2 |
| 7 | 1 | 2 | 3 | 2 | 0 |
| 8 | 1 | 3 | 2 | 0 | 1 |
| 9 | 2 | 0 | 2 | 2 | 2 |
| 10 | 2 | 1 | 3 | 0 | 1 |
| 11 | 2 | 2 | 0 | 1 | 1 |
| 12 | 2 | 3 | 1 | 1 | 0 |
| 13 | 3 | 0 | 3 | 1 | 1 |
| 14 | 3 | 1 | 2 | 1 | 0 |
| 15 | 3 | 2 | 1 | 0 | 2 |
| 16 | 3 | 3 | 0 | 2 | 1 |

| | L16(6X2,2X3) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Card | a3 | b3 | c3 | d2 | e2 | f2 | g2 | h2 | i2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |
| 3 | 0 | 2 | 2 | 1 | 1 | 0 | 0 | 1 | 1 |
| 4 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 |
| 5 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 |
| 7 | 1 | 2 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| 8 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 1 | 0 |
| 9 | 2 | 0 | 2 | 1 | 0 | 1 | 1 | 0 | 1 |
| 10 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 |
| 11 | 2 | 2 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |
| 12 | 2 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 13 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 |
| 14 | 1 | 1 | 2 | 0 | 1 | 1 | 0 | 0 | 0 |
| 15 | 1 | 2 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 16 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |

| | L16(8X2,1X3) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Card | a3 | b2 | c2 | d2 | e2 | f2 | g2 | h2 | i2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |
| 3 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 |
| 4 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 |
| 5 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 6 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 |
| 7 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 8 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 9 | 2 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 10 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| 11 | 2 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |
| 12 | 2 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 13 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| 14 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 15 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 16 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |

| | L16(4X2,1X3,1X4) | | | | | |
|---|---|---|---|---|---|---|
| Card | a4 | b3 | c2 | d2 | e2 | f2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 | 0 |
| 3 | 0 | 2 | 0 | 0 | 1 | 1 |
| 4 | 0 | 1 | 1 | 1 | 0 | 1 |
| 5 | 1 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 0 | 1 | 0 | 1 |
| 7 | 1 | 2 | 1 | 0 | 0 | 0 |
| 8 | 1 | 1 | 0 | 1 | 1 | 0 |
| 9 | 2 | 0 | 1 | 1 | 0 | 1 |
| 10 | 2 | 1 | 0 | 0 | 1 | 1 |
| 11 | 2 | 2 | 1 | 1 | 1 | 0 |
| 12 | 2 | 1 | 0 | 0 | 0 | 0 |
| 13 | 3 | 0 | 0 | 1 | 1 | 0 |
| 14 | 3 | 1 | 1 | 0 | 0 | 0 |
| 15 | 3 | 2 | 0 | 1 | 0 | 1 |
| 16 | 3 | 1 | 1 | 0 | 1 | 1 |

| | L16(1X3,4X4) | | | | |
|---|---|---|---|---|---|
| Card | a4 | b4 | c4 | d4 | e3 |
| 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 2 | 1 |
| 3 | 0 | 2 | 2 | 3 | 1 |
| 4 | 0 | 3 | 3 | 1 | 2 |
| 5 | 1 | 0 | 1 | 1 | 1 |
| 6 | 1 | 1 | 0 | 3 | 2 |
| 7 | 1 | 2 | 3 | 2 | 0 |
| 8 | 1 | 3 | 2 | 0 | 1 |
| 9 | 2 | 0 | 2 | 2 | 2 |
| 10 | 2 | 1 | 3 | 0 | 1 |
| 11 | 2 | 2 | 0 | 1 | 1 |
| 12 | 2 | 3 | 1 | 3 | 0 |
| 13 | 3 | 0 | 3 | 3 | 1 |
| 14 | 3 | 1 | 2 | 1 | 0 |
| 15 | 3 | 2 | 1 | 0 | 2 |
| 16 | 3 | 3 | 0 | 2 | 1 |

| | L18(1X2,7X3) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Card | a2 | b3 | c3 | d3 | e3 | f3 | g3 | h3 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 0 | 0 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4 | 0 | 1 | 0 | 0 | 1 | 1 | 2 | 2 |
| 5 | 0 | 1 | 1 | 1 | 2 | 2 | 0 | 0 |
| 6 | 0 | 1 | 2 | 2 | 0 | 0 | 1 | 1 |
| 7 | 0 | 2 | 0 | 1 | 0 | 2 | 1 | 2 |
| 8 | 0 | 2 | 1 | 2 | 1 | 0 | 2 | 0 |
| 9 | 0 | 2 | 2 | 0 | 2 | 1 | 0 | 1 |
| 10 | 1 | 0 | 0 | 2 | 2 | 1 | 1 | 0 |
| 11 | 1 | 0 | 1 | 0 | 0 | 2 | 2 | 1 |
| 12 | 1 | 0 | 2 | 1 | 1 | 0 | 0 | 2 |
| 13 | 1 | 1 | 0 | 1 | 2 | 0 | 2 | 1 |
| 14 | 1 | 1 | 1 | 2 | 0 | 1 | 0 | 2 |
| 15 | 1 | 1 | 2 | 0 | 1 | 2 | 1 | 0 |
| 16 | 1 | 2 | 0 | 2 | 1 | 2 | 0 | 1 |
| 17 | 1 | 2 | 1 | 0 | 2 | 0 | 1 | 2 |
| 18 | 1 | 2 | 2 | 1 | 0 | 1 | 2 | 0 |

| | L18(2X2,6X3) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Card | a2 | b2 | c3 | d3 | e3 | f3 | g3 | h3 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 1 | 1 | 2 | 1 | 1 | 1 |
| 3 | 0 | 0 | 2 | 2 | 1 | 2 | 2 | 2 |
| 4 | 0 | 1 | 0 | 1 | 1 | 1 | 2 | 0 |
| 5 | 0 | 1 | 1 | 2 | 0 | 2 | 0 | 1 |
| 6 | 0 | 1 | 2 | 0 | 2 | 0 | 1 | 2 |
| 7 | 0 | 1 | 0 | 2 | 2 | 1 | 0 | 2 |
| 8 | 0 | 1 | 1 | 0 | 1 | 2 | 1 | 0 |
| 9 | 0 | 1 | 2 | 1 | 0 | 0 | 2 | 1 |
| 10 | 1 | 0 | 0 | 2 | 1 | 0 | 1 | 1 |
| 11 | 1 | 0 | 1 | 0 | 0 | 1 | 2 | 2 |
| 12 | 1 | 0 | 2 | 1 | 2 | 2 | 0 | 0 |
| 13 | 1 | 1 | 0 | 0 | 2 | 2 | 2 | 1 |
| 14 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 2 |
| 15 | 1 | 1 | 2 | 2 | 0 | 1 | 1 | 0 |
| 16 | 1 | 1 | 0 | 1 | 0 | 2 | 1 | 2 |
| 17 | 1 | 1 | 1 | 2 | 2 | 0 | 2 | 0 |
| 18 | 1 | 1 | 2 | 0 | 1 | 1 | 0 | 1 |

| | **L25(4X3,2X4)** | | | | | |
|---|---|---|---|---|---|---|
| Card | a4 | b4 | c4 | d4 | e3 | f3 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 2 | 2 | 0 |
| 3 | 0 | 2 | 2 | 0 | 1 | 2 |
| 4 | 0 | 3 | 2 | 1 | 0 | 2 |
| 5 | 0 | 0 | 0 | 2 | 2 | 1 |
| 6 | 1 | 0 | 1 | 1 | 1 | 1 |
| 7 | 1 | 1 | 2 | 2 | 0 | 0 |
| 8 | 1 | 2 | 2 | 0 | 2 | 0 |
| 9 | 1 | 3 | 0 | 2 | 0 | 2 |
| 10 | 1 | 0 | 0 | 0 | 2 | 2 |
| 11 | 2 | 0 | 2 | 2 | 2 | 2 |
| 12 | 2 | 1 | 2 | 0 | 0 | 1 |
| 13 | 2 | 2 | 0 | 1 | 2 | 0 |
| 14 | 2 | 3 | 0 | 2 | 1 | 0 |
| 15 | 2 | 0 | 1 | 0 | 0 | 2 |
| 16 | 3 | 0 | 2 | 2 | 2 | 2 |
| 17 | 3 | 1 | 0 | 0 | 1 | 2 |
| 18 | 3 | 2 | 0 | 2 | 0 | 1 |
| 19 | 3 | 3 | 1 | 0 | 2 | 0 |
| 20 | 3 | 0 | 2 | 1 | 0 | 0 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 1 | 0 | 1 | 2 | 2 |
| 23 | 0 | 2 | 1 | 2 | 0 | 2 |
| 24 | 0 | 3 | 2 | 0 | 2 | 1 |
| 25 | 0 | 0 | 2 | 2 | 1 | 0 |

| | **L25(6X5)** | | | | | |
|---|---|---|---|---|---|---|
| Card | a5 | b5 | c5 | d5 | e5 | f5 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 | 1 |
| 3 | 0 | 2 | 2 | 2 | 2 | 2 |
| 4 | 0 | 3 | 3 | 3 | 3 | 3 |
| 5 | 0 | 4 | 4 | 4 | 4 | 4 |
| 6 | 1 | 0 | 1 | 2 | 3 | 4 |
| 7 | 1 | 1 | 2 | 3 | 4 | 0 |
| 8 | 1 | 2 | 3 | 4 | 0 | 1 |
| 9 | 1 | 3 | 4 | 0 | 1 | 2 |
| 10 | 1 | 4 | 0 | 1 | 2 | 3 |
| 11 | 2 | 0 | 2 | 4 | 1 | 3 |
| 12 | 2 | 1 | 3 | 0 | 2 | 4 |
| 13 | 2 | 2 | 4 | 1 | 3 | 0 |
| 14 | 2 | 3 | 0 | 2 | 4 | 1 |
| 15 | 2 | 4 | 1 | 3 | 0 | 2 |
| 16 | 3 | 0 | 3 | 1 | 4 | 2 |
| 17 | 3 | 1 | 4 | 2 | 0 | 3 |
| 18 | 3 | 2 | 0 | 3 | 1 | 4 |
| 19 | 3 | 3 | 1 | 4 | 2 | 0 |
| 20 | 3 | 4 | 2 | 0 | 3 | 1 |
| 21 | 4 | 0 | 4 | 3 | 2 | 1 |
| 22 | 4 | 1 | 0 | 4 | 3 | 2 |
| 23 | 4 | 2 | 1 | 0 | 4 | 3 |
| 24 | 4 | 3 | 2 | 1 | 0 | 4 |
| 25 | 4 | 4 | 3 | 2 | 1 | 0 |

| | **L27(6X2,4X3)** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Card | a3 | b3 | c3 | d3 | e2 | f2 | g2 | h2 | i2 | j2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 2 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 3 | 0 | 1 | 2 | 2 | 0 | 0 | 0 | 0 | 1 | 1 |
| 4 | 0 | 0 | 1 | 2 | 1 | 0 | 0 | 1 | 1 | 0 |
| 5 | 0 | 2 | 2 | 0 | 1 | 1 | 1 | 0 | 0 | 1 |
| 6 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| 8 | 0 | 2 | 0 | 2 | 0 | 1 | 1 | 0 | 1 | 0 |
| 9 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 10 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 |
| 11 | 1 | 0 | 1 | 2 | 0 | 1 | 0 | 0 | 0 | 0 |
| 12 | 1 | 2 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 14 | 1 | 0 | 2 | 1 | 1 | 1 | 0 | 0 | 1 | 0 |
| 15 | 1 | 2 | 0 | 2 | 1 | 0 | 0 | 1 | 0 | 1 |
| 16 | 1 | 1 | 2 | 2 | 0 | 0 | 1 | 0 | 0 | 0 |
| 17 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 |
| 18 | 1 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 19 | 2 | 2 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 2 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 |
| 21 | 2 | 0 | 2 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 22 | 2 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| 23 | 2 | 1 | 2 | 2 | 1 | 1 | 0 | 1 | 0 | 0 |
| 24 | 2 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| 25 | 2 | 2 | 2 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| 26 | 2 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 27 | 2 | 0 | 1 | 2 | 0 | 0 | 1 | 0 | 0 | 1 |

| | **L27(13X3)** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Card | a3 | b3 | c3 | d3 | e3 | f3 | g3 | h3 | i3 | j3 | k3 | l3 | m3 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 0 | 0 | 0 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 2 | 2 | 2 |
| 5 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 0 | 0 | 0 |
| 6 | 0 | 1 | 1 | 1 | 2 | 2 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 7 | 0 | 2 | 2 | 2 | 0 | 0 | 0 | 2 | 2 | 2 | 1 | 1 | 1 |
| 8 | 0 | 2 | 2 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 2 | 2 | 2 |
| 9 | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 0 | 0 | 0 |
| 10 | 1 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 2 |
| 11 | 1 | 0 | 1 | 2 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 2 | 0 |
| 12 | 1 | 0 | 1 | 2 | 2 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 1 |
| 13 | 1 | 1 | 2 | 0 | 0 | 1 | 2 | 1 | 2 | 0 | 2 | 0 | 1 |
| 14 | 1 | 1 | 2 | 0 | 1 | 2 | 0 | 2 | 0 | 1 | 0 | 1 | 2 |
| 15 | 1 | 1 | 2 | 0 | 2 | 0 | 1 | 0 | 1 | 2 | 1 | 2 | 0 |
| 16 | 1 | 2 | 0 | 1 | 0 | 1 | 2 | 2 | 0 | 1 | 1 | 2 | 0 |
| 17 | 1 | 2 | 0 | 1 | 1 | 2 | 0 | 0 | 1 | 2 | 2 | 0 | 1 |
| 18 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 1 | 2 | 0 | 0 | 1 | 2 |
| 19 | 2 | 0 | 2 | 1 | 0 | 2 | 1 | 0 | 2 | 1 | 0 | 2 | 1 |
| 20 | 2 | 0 | 2 | 1 | 1 | 0 | 2 | 1 | 0 | 2 | 1 | 0 | 2 |
| 21 | 2 | 0 | 2 | 1 | 2 | 1 | 0 | 2 | 1 | 0 | 2 | 1 | 0 |
| 22 | 2 | 1 | 0 | 2 | 0 | 2 | 1 | 1 | 0 | 2 | 2 | 1 | 0 |
| 23 | 2 | 1 | 0 | 2 | 1 | 0 | 2 | 2 | 1 | 0 | 0 | 2 | 1 |
| 24 | 2 | 1 | 0 | 2 | 2 | 1 | 0 | 0 | 2 | 1 | 1 | 0 | 2 |
| 25 | 2 | 2 | 1 | 0 | 0 | 2 | 1 | 2 | 1 | 0 | 1 | 0 | 2 |
| 26 | 2 | 2 | 1 | 0 | 1 | 0 | 2 | 0 | 2 | 1 | 2 | 1 | 0 |
| 27 | 2 | 2 | 1 | 0 | 2 | 1 | 0 | 1 | 0 | 2 | 0 | 2 | 1 |

| | L27(1X6,9X3) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Card | a6 | b3 | c3 | d3 | e3 | f3 | g3 | h3 | i3 | j3 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 2 | 1 | 1 | 2 | 2 | 1 | 2 |
| 3 | 0 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 1 |
| 4 | 1 | 0 | 2 | 0 | 0 | 1 | 1 | 2 | 1 | 1 |
| 5 | 1 | 1 | 0 | 2 | 1 | 2 | 0 | 1 | 2 | 0 |
| 6 | 1 | 2 | 1 | 1 | 2 | 0 | 2 | 0 | 0 | 2 |
| 7 | 2 | 0 | 1 | 0 | 0 | 2 | 2 | 1 | 2 | 2 |
| 8 | 2 | 1 | 2 | 2 | 1 | 0 | 1 | 0 | 0 | 1 |
| 9 | 2 | 2 | 0 | 1 | 2 | 1 | 0 | 2 | 1 | 0 |
| 10 | 3 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 11 | 3 | 2 | 2 | 0 | 1 | 2 | 0 | 0 | 1 | 2 |
| 12 | 3 | 0 | 0 | 2 | 2 | 0 | 2 | 2 | 2 | 1 |
| 13 | 4 | 1 | 0 | 1 | 0 | 2 | 2 | 0 | 1 | 1 |
| 14 | 4 | 2 | 1 | 0 | 1 | 0 | 1 | 2 | 2 | 0 |
| 15 | 4 | 0 | 2 | 2 | 2 | 1 | 0 | 1 | 0 | 2 |
| 16 | 4 | 1 | 2 | 1 | 0 | 0 | 0 | 2 | 2 | 2 |
| 17 | 4 | 2 | 0 | 0 | 1 | 1 | 2 | 1 | 0 | 1 |
| 18 | 4 | 0 | 1 | 2 | 2 | 2 | 1 | 0 | 1 | 0 |
| 19 | 5 | 2 | 2 | 2 | 0 | 2 | 2 | 2 | 0 | 0 |
| 20 | 5 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 2 |
| 21 | 5 | 1 | 1 | 0 | 2 | 1 | 0 | 0 | 2 | 1 |
| 22 | 5 | 2 | 1 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 23 | 5 | 0 | 2 | 1 | 1 | 1 | 2 | 0 | 2 | 0 |
| 24 | 5 | 1 | 0 | 0 | 2 | 2 | 1 | 2 | 0 | 2 |
| 25 | 0 | 2 | 0 | 2 | 0 | 1 | 1 | 0 | 2 | 2 |
| 26 | 0 | 0 | 1 | 1 | 1 | 2 | 0 | 2 | 0 | 1 |
| 27 | 0 | 1 | 2 | 0 | 2 | 0 | 2 | 1 | 1 | 0 |

| | L27 (1X6,2X3,3X2) | | | | | |
|---|---|---|---|---|---|---|
| Card | a6 | b3 | c3 | d2 | e2 | f2 |
| **1** | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 0 | 1 | 2 | 0 | 1 | 1 |
| **3** | 0 | 2 | 1 | 1 | 0 | 0 |
| **4** | 1 | 2 | 1 | 0 | 0 | 1 |
| **5** | 1 | 0 | 0 | 0 | 1 | 0 |
| **6** | 1 | 1 | 2 | 1 | 0 | 0 |
| **7** | 2 | 1 | 2 | 0 | 0 | 0 |
| **8** | 2 | 2 | 1 | 0 | 1 | 0 |
| **9** | 2 | 0 | 0 | 1 | 0 | 1 |
| **10** | 3 | 1 | 1 | 1 | 1 | 1 |
| **11** | 3 | 2 | 0 | 0 | 0 | 0 |
| **12** | 3 | 0 | 2 | 0 | 0 | 0 |
| **13** | 4 | 0 | 2 | 1 | 1 | 0 |
| **14** | 4 | 1 | 1 | 0 | 0 | 0 |
| **15** | 4 | 2 | 0 | 0 | 0 | 1 |
| **16** | 4 | 2 | 0 | 1 | 1 | 0 |
| **17** | 4 | 0 | 2 | 0 | 0 | 1 |
| **18** | 4 | 1 | 1 | 0 | 0 | 0 |
| **19** | 5 | 2 | 2 | 0 | 0 | 0 |
| **20** | 5 | 0 | 1 | 1 | 0 | 0 |
| **21** | 5 | 1 | 0 | 0 | 1 | 1 |
| **22** | 5 | 1 | 0 | 0 | 0 | 0 |
| **23** | 5 | 2 | 2 | 1 | 0 | 1 |
| **24** | 5 | 0 | 1 | 0 | 1 | 0 |
| **25** | 0 | 0 | 1 | 0 | 0 | 1 |
| **26** | 0 | 1 | 0 | 1 | 0 | 0 |
| **27** | 0 | 2 | 2 | 0 | 1 | 0 |

| | L25 (4X5) | | | |
|---|---|---|---|---|
| Card | a5 | b5 | c5 | d5 |
| **1** | 0 | 0 | 0 | 0 |
| **2** | 1 | 1 | 3 | 4 |
| **3** | 2 | 2 | 1 | 3 |
| **4** | 3 | 3 | 4 | 2 |
| **5** | 4 | 4 | 2 | 1 |
| **6** | 1 | 0 | 1 | 1 |
| **7** | 2 | 1 | 4 | 0 |
| **8** | 3 | 2 | 2 | 4 |
| **9** | 4 | 3 | 0 | 3 |
| **10** | 0 | 4 | 3 | 2 |
| **11** | 2 | 0 | 2 | 2 |
| **12** | 3 | 1 | 0 | 1 |
| **13** | 4 | 2 | 3 | 0 |
| **14** | 0 | 3 | 1 | 4 |
| **15** | 1 | 4 | 4 | 3 |
| **16** | 3 | 0 | 3 | 3 |
| **17** | 4 | 1 | 1 | 2 |
| **18** | 0 | 2 | 4 | 1 |
| **19** | 1 | 3 | 2 | 0 |
| **20** | 2 | 4 | 0 | 4 |
| **21** | 4 | 0 | 4 | 4 |
| **22** | 0 | 1 | 2 | 3 |
| **23** | 1 | 2 | 0 | 2 |
| **24** | 2 | 3 | 3 | 1 |
| **25** | 3 | 4 | 1 | 0 |

| | L25 (1X5,4X4) | | | | |
|---|---|---|---|---|---|
| Card | a5 | b4 | c4 | d4 | e4 |
| 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 2 | 3 | 0 | 1 | 1 |
| 3 | 4 | 1 | 0 | 2 | 2 |
| 4 | 1 | 0 | 0 | 3 | 3 |
| 5 | 3 | 2 | 0 | 0 | 0 |
| 6 | 1 | 1 | 1 | 1 | 0 |
| 7 | 3 | 0 | 1 | 2 | 1 |
| 8 | 0 | 2 | 1 | 3 | 2 |
| 9 | 2 | 0 | 1 | 0 | 3 |
| 10 | 4 | 3 | 1 | 0 | 0 |
| 11 | 2 | 2 | 2 | 2 | 0 |
| 12 | 4 | 0 | 2 | 3 | 1 |
| 13 | 1 | 3 | 2 | 0 | 2 |
| 14 | 3 | 1 | 2 | 0 | 3 |
| 15 | 0 | 0 | 2 | 1 | 0 |
| 16 | 3 | 3 | 3 | 3 | 0 |
| 17 | 0 | 1 | 3 | 0 | 1 |
| 18 | 2 | 0 | 3 | 0 | 2 |
| 19 | 4 | 2 | 3 | 1 | 3 |
| 20 | 1 | 0 | 3 | 2 | 0 |
| 21 | 4 | 0 | 0 | 0 | 0 |
| 22 | 1 | 2 | 0 | 0 | 1 |
| 23 | 3 | 0 | 0 | 1 | 2 |
| 24 | 0 | 3 | 0 | 2 | 3 |
| 25 | 2 | 1 | 0 | 3 | 0 |

| | L25 (1X5, 5X3) | | | | | |
|---|---|---|---|---|---|---|
| Card | a5 | b3 | c3 | d3 | e3 | f3 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 4 | 1 | 2 | 2 | 0 | 1 |
| 3 | 3 | 2 | 1 | 0 | 0 | 2 |
| 4 | 2 | 2 | 0 | 1 | 0 | 2 |
| 5 | 1 | 0 | 2 | 2 | 0 | 0 |
| 6 | 1 | 0 | 1 | 1 | 1 | 1 |
| 7 | 0 | 1 | 0 | 2 | 1 | 2 |
| 8 | 4 | 2 | 2 | 0 | 1 | 2 |
| 9 | 3 | 2 | 0 | 2 | 1 | 0 |
| 10 | 2 | 0 | 2 | 0 | 1 | 0 |
| 11 | 2 | 0 | 2 | 2 | 2 | 2 |
| 12 | 1 | 1 | 0 | 0 | 2 | 2 |
| 13 | 0 | 2 | 2 | 1 | 2 | 0 |
| 14 | 4 | 2 | 1 | 2 | 2 | 0 |
| 15 | 3 | 0 | 0 | 0 | 2 | 1 |
| 16 | 3 | 0 | 2 | 2 | 2 | 2 |
| 17 | 2 | 1 | 1 | 0 | 2 | 0 |
| 18 | 1 | 2 | 0 | 2 | 2 | 0 |
| 19 | 0 | 2 | 2 | 0 | 2 | 1 |
| 20 | 4 | 0 | 0 | 1 | 2 | 2 |
| 21 | 4 | 0 | 0 | 0 | 0 | 0 |
| 22 | 3 | 1 | 2 | 1 | 0 | 0 |
| 23 | 2 | 2 | 0 | 2 | 0 | 1 |
| 24 | 1 | 2 | 2 | 0 | 0 | 2 |
| 25 | 0 | 0 | 1 | 2 | 0 | 2 |

| | L25 (1X5,2X3,3X2) | | | | | |
|---|---|---|---|---|---|---|
| Card | a5 | b3 | c3 | d2 | e2 | f2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 2 | 1 | 0 | 0 | 1 | 1 |
| 3 | 4 | 2 | 0 | 1 | 1 | 1 |
| 4 | 1 | 2 | 0 | 1 | 1 | 0 |
| 5 | 3 | 0 | 0 | 1 | 0 | 1 |
| 6 | 1 | 0 | 1 | 1 | 1 | 1 |
| 7 | 3 | 1 | 1 | 0 | 1 | 0 |
| 8 | 0 | 2 | 1 | 0 | 1 | 1 |
| 9 | 2 | 2 | 1 | 1 | 0 | 0 |
| 10 | 4 | 0 | 1 | 1 | 0 | 1 |
| 11 | 2 | 0 | 2 | 1 | 1 | 1 |
| 12 | 4 | 1 | 2 | 1 | 1 | 0 |
| 13 | 1 | 2 | 2 | 0 | 0 | 1 |
| 14 | 3 | 2 | 2 | 0 | 0 | 1 |
| 15 | 0 | 0 | 2 | 1 | 1 | 0 |
| 16 | 3 | 0 | 2 | 1 | 1 | 1 |
| 17 | 0 | 1 | 2 | 1 | 0 | 1 |
| 18 | 2 | 2 | 2 | 1 | 0 | 0 |
| 19 | 4 | 2 | 2 | 0 | 1 | 1 |
| 20 | 1 | 0 | 2 | 0 | 1 | 0 |
| 21 | 4 | 0 | 0 | 0 | 0 | 0 |
| 22 | 1 | 1 | 0 | 1 | 0 | 1 |
| 23 | 3 | 2 | 0 | 1 | 1 | 0 |
| 24 | 0 | 2 | 0 | 1 | 1 | 1 |
| 25 | 2 | 0 | 0 | 0 | 1 | 1 |

| | L25 (1X5,1X4,1X3,1X2) | | | |
|---|---|---|---|---|
| Card | a5 | b2 | c4 | d3 |
| 1 | 0 | 0 | 0 | 0 |
| 2 | 3 | 1 | 0 | 0 |
| 3 | 1 | 0 | 0 | 2 |
| 4 | 4 | 1 | 0 | 2 |
| 5 | 2 | 1 | 0 | 1 |
| 6 | 1 | 1 | 1 | 1 |
| 7 | 4 | 1 | 1 | 0 |
| 8 | 2 | 0 | 1 | 0 |
| 9 | 0 | 1 | 1 | 2 |
| 10 | 3 | 0 | 1 | 2 |
| 11 | 2 | 1 | 2 | 2 |
| 12 | 0 | 0 | 2 | 1 |
| 13 | 3 | 1 | 2 | 0 |
| 14 | 1 | 1 | 2 | 0 |
| 15 | 4 | 0 | 2 | 2 |
| 16 | 3 | 1 | 3 | 2 |
| 17 | 1 | 0 | 3 | 2 |
| 18 | 4 | 1 | 3 | 1 |
| 19 | 2 | 0 | 3 | 0 |
| 20 | 0 | 1 | 3 | 0 |
| 21 | 4 | 0 | 0 | 0 |
| 22 | 2 | 1 | 0 | 2 |
| 23 | 0 | 1 | 0 | 2 |
| 24 | 3 | 0 | 0 | 1 |
| 25 | 1 | 1 | 0 | 0 |

| | L16 (1X6,8X2) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Card | a6 | b2 | c2 | d2 | e2 | f2 | g2 | h2 | i2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 |
| 4 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 |
| 5 | 2 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| 6 | 2 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 7 | 3 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| 8 | 3 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 |
| 9 | 4 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |
| 10 | 4 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| 11 | 5 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| 12 | 5 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| 13 | 2 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| 14 | 2 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| 15 | 3 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |
| 16 | 3 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |

| | L16 (1X5,8X2) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Card | a5 | b2 | c2 | d2 | e2 | f2 | g2 | h2 | i2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| 4 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 |
| 5 | 2 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 6 | 2 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 7 | 3 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| 8 | 3 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |
| 9 | 4 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 |
| 10 | 4 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 |
| 11 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| 12 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 13 | 2 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| 14 | 2 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 |
| 15 | 3 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 |
| 16 | 3 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 |

| | L16 (1X4,4X3) | | | | |
|---|---|---|---|---|---|
| Card | a4 | b3 | c3 | d3 | e3 |
| 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 1 | 1 | 0 | 2 | 1 |
| 3 | 2 | 2 | 0 | 1 | 1 |
| 4 | 3 | 1 | 0 | 1 | 2 |
| 5 | 0 | 1 | 1 | 1 | 1 |
| 6 | 1 | 0 | 1 | 1 | 2 |
| 7 | 2 | 1 | 1 | 2 | 0 |
| 8 | 3 | 2 | 1 | 0 | 1 |
| 9 | 0 | 2 | 2 | 2 | 2 |
| 10 | 1 | 1 | 2 | 0 | 1 |
| 11 | 2 | 0 | 2 | 1 | 1 |
| 12 | 3 | 1 | 2 | 1 | 0 |
| 13 | 0 | 1 | 1 | 1 | 1 |
| 14 | 1 | 2 | 1 | 1 | 0 |
| 15 | 2 | 1 | 1 | 0 | 2 |
| 16 | 3 | 0 | 1 | 2 | 1 |

| | **L16 (1X4,2X3,3X2)** | | | | | |
|---|---|---|---|---|---|---|
| Card | a4 | b3 | c3 | d2 | e2 | f2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 1 | 2 | 1 | 0 | 0 | 1 |
| 3 | 2 | 1 | 2 | 0 | 0 | 1 |
| 4 | 3 | 1 | 1 | 0 | 0 | 0 |
| 5 | 0 | 1 | 1 | 1 | 1 | 1 |
| 6 | 1 | 1 | 0 | 1 | 1 | 0 |
| 7 | 2 | 2 | 1 | 1 | 1 | 0 |
| 8 | 3 | 0 | 2 | 1 | 1 | 1 |
| 9 | 0 | 2 | 2 | 1 | 0 | 0 |
| 10 | 1 | 0 | 1 | 1 | 0 | 1 |
| 11 | 2 | 1 | 0 | 1 | 0 | 1 |
| 12 | 3 | 1 | 1 | 1 | 0 | 0 |
| 13 | 0 | 1 | 1 | 0 | 1 | 1 |
| 14 | 1 | 1 | 2 | 0 | 1 | 0 |
| 15 | 2 | 0 | 1 | 0 | 1 | 0 |
| 16 | 3 | 2 | 0 | 0 | 1 | 1 |

| | **L16 (3X3,3X2)** | | | | | |
|---|---|---|---|---|---|---|
| Card | a3 | b3 | c3 | d2 | e2 | f2 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 1 | 0 | 0 |
| 3 | 0 | 2 | 1 | 0 | 1 | 1 |
| 4 | 0 | 1 | 2 | 1 | 1 | 1 |
| 5 | 1 | 0 | 1 | 1 | 1 | 0 |
| 6 | 1 | 1 | 2 | 0 | 1 | 0 |
| 7 | 1 | 2 | 0 | 1 | 0 | 1 |
| 8 | 1 | 1 | 1 | 0 | 0 | 1 |
| 9 | 2 | 0 | 2 | 0 | 0 | 1 |
| 10 | 2 | 1 | 1 | 1 | 0 | 1 |
| 11 | 2 | 2 | 1 | 0 | 1 | 0 |
| 12 | 2 | 1 | 0 | 1 | 1 | 0 |
| 13 | 1 | 0 | 1 | 1 | 1 | 1 |
| 14 | 1 | 1 | 0 | 0 | 1 | 1 |
| 15 | 1 | 2 | 2 | 1 | 0 | 0 |
| 16 | 1 | 1 | 1 | 0 | 0 | 0 |

| | **L9 (2X3,2X2)** | | | |
|---|---|---|---|---|
| Card | a3 | b3 | c2 | d2 |
| 1 | 0 | 0 | 0 | 0 |
| 2 | 1 | 1 | 0 | 0 |
| 3 | 2 | 2 | 0 | 1 |
| 4 | 0 | 1 | 1 | 1 |
| 5 | 1 | 2 | 1 | 0 |
| 6 | 2 | 0 | 1 | 0 |
| 7 | 0 | 2 | 0 | 0 |
| 8 | 1 | 0 | 0 | 1 |
| 9 | 2 | 1 | 0 | 0 |

### 4.6.3. Appendix C - Developing Experimental Designs

The development of high speed computers and powerful optimization routines have allowed for more general approaches to experimental design. Traditionally, since the data from experiments is intended to be analyzed by regression, the focus has been on maintaining orthogonality in the exclusion of other features and constraints. The designs presented in the preceding appendix are of this type. These are the standard forms that have been used for full profile conjoint. These designs, while technically correct, may be less than desirable in other respects. For example, with full profile conjoint designs, unrealistic cases are often included. Furthermore, information regarding likely selections are not integrated and the resulting designs may be viewed as “inefficient”.

In general, experimental designs can be obtained numerically by allowing the selection of assignments obeying specified constraints and optimizing a given objective function. It should be noted that this would involve the selection of hundreds of assigned values obeying hundreds of constraints. And the optimum may not be very good.

#### 4.6.3.1. Conditions, Criteria, and Constraints

Conditions are the specification of the design. They are typically the number of scenarios, features and levels that are to be tested. These are usually considered to be “givens” in seeking the design. However, in reality they are constraints that may or may not be realized. For example, there may not be a reasonable design for the number of desired scenarios.

While theoretically, criteria and constraints can be considered interchangeable[79], it is useful to think of the separately. Similar to conditions discussed above criteria are also handled as approximations. They are not usually fully met.

#### 4.6.3.2. Constraints

Constraints can be considered to be of two types (1) Distribution of Feature Levels and (2) Specific Sets or Scenarios

##### *4.6.3.2.1. The Distribution of Feature Levels*

There are usually several desired characteristics, of the ensemble of scenarios, intended to avoid bias. For example, for discrete variables, it is usually desirable for the design to be “balanced” where each option is tested against all other options the same number of times. For continuous variables, we tend to wish that the samplings are both centered, in that the mean values tested agrees with the middle of the range, and balanced in that the number of levels tested above the middle is the same as that below.

Even more complex constraints can be applied involving types of forced distributions. For example, with claims testing it is necessary that the same number of claims appear in each scenario. This greatly constrains the structure of the design.

[79] From Mathematical Programming it well established that one could change the coordinate system (orthogonal coordinates) to restate any problem where the constraints become part of a compound objective and the objective is split into constraints. This is the classic reformulation of the dual problem.

#### *4.6.3.2.2. Specific Sets or Scenarios*

As previously noted, there are often situations of unrealistic cases generated using traditional orthogonal designs. This is a classic problem with conjoint design. This would require either imposing interactive constraints or the exclusion of certain combinations.

### 4.6.3.3. Criteria for Portfolio Selection

The prospect of using alternative criteria for statistical design is still relatively new. As such, there are only a few options being suggested.

#### *4.6.3.3.1. Importance Orthogonal Designs*

Generally, we have assumed that the only desirable statistical property is orthogonality. That is we always wish to reduce the intercorrelation between the variables. However, recently the importance of intercorrelation on regression analysis has been brought into question. Analysis has indicated that a fairly large amount of intercorrelation (up to 0.5) seems not to significantly effect the estimation of regression coefficients. However, that still leaves open the problem of validity of the value assignments. That is if two variables are intercorrelated, at least one of the values will be uncertain.

There are also other uncomfortable artifacts that occur with intercorrelated variables. Occasionally, with moderate or high intercorrelation, the sign of the correlation coefficient is not the same as that of the regression coefficient. This is difficult to rectify[80]. In any event, it is usually advisable to reduce the intercorrelation among variables as much as feasible, though probably not to the degree that has been traditionally done.

##### *4.6.3.3.1.1. Minimizing Maximum Correlation*

The traditional objective for reducing intercorrelation is to minimize the maximum correlation among variables. This is a fairly straight-forward computation on ***Excel*** and can be readily done with the standard ***Solver*** to obtain continuous variable designs. The designs in the pricing chapter were developed using this approach.

##### *4.6.3.3.1.2. Efficiency (Maximizing the Precision)*

A recent suggested criteria is to weigh the design by the more frequently selected feature levels or conditions. The expected or prior frequency is captured by the previously computed utility in a conjoint or choice modeling exercise. The objective then is to balance the utility into the design to improve the precision of the sample. Think of it as focusing on the more frequently chosen items. This should allow for an improved precision in the estimation of the utilities from the design[81]. This is said to thereby improve the "efficiency" of the design. The major difficulty with this procedure referred to as "Utility Balancing," is, the assumption that the frequency of selection in the forthcoming exercise

[80] Ridge regression can be used to handle this problem, but it is a heroic method which involves a heuristic process.

[81] This is the same general logic as used in the development of Gaussian Quadrature where increase precision is obtained by selecting specifically weighed points.

with be the same as used for the design[82]. In most cases, such foresight is unavailable or worse it may lead to a biased design.

#### 4.6.3.4. Discrete versus Continuous Variables

In this chapter, we have dealt almost exclusively with discrete feature levels design. This is particularly traditional with conjoint methods where features are generally considered to be at fixed levels. However, there are some features that can and should be considered continuous such as horsepower in vehicles or prices. In the next chapter, we deal with pricing research. Both discrete and continuous models are used there. It is generally preferred to use continuous or at least point-wise continuous descriptions of demand and therefore, use continuous experimental design models. Optimizing design using both discrete and continuous variables is referred to as the "Mix-Integer" problem and produces some difficulty in computation. However, new tools such as ***Premium Solver*** for ***Excel*** allows for large problems of this type[83].

[82] The criteria design to capture the impact of the utility is based on the covariance matrix of the feature levels with the utilities. The objective is then to create designs that minimize either the trace or determinate of this matrix which represents a overall scalar value of the covariance. Note that this is not likely to generate an orthogonal design. This is based on a 1996 SAS paper: **A General Method for Constructing Efficient Choice Designs**, by Klas Zwerina, Joel Huber and Warren F. Kuhfeld , (September 1996) (TS-650A) available at http://www.sas.com/service/techsup/tnote/tnote_stat.html

[83] Available from Frontline Systems, Inc. (http://www.solver.com)