# THE CONCEPT OF CONJOINT ANALYSIS

Scott M. Smith, Ph.D.

Marketing managers are faced with numerous difficult tasks directed at assessing future profitability, sales, and market share for new product entries or modifications of existing products or marketing strategies. These specific tasks include:

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| 1. Predicting the profitability and/or market share for proposed new product concepts given the current offering of competitors. |
| 2. Predicting the impact of new competitor products on profits or market share if we make no change in our competitive position. |
| 3. Predicting customer switch rates either from our current products to new products we offer (cannibalism), or from our competitors' products to our new products (draw). |
| 4. Predicting the differential response of items 1-3 by key market segments purchasing our product. |
| 5. Predicting competitive reaction to our strategies of introducing a new product. Specifically, should a new product be introduced, and if so, what is the optimal design configuration for this new product? Further, should pricing or other attributes of our current products be modified in response to the competition). |
| 6. Predicting the impact of situational variables on customer preference. |
| 7. Predicting the differential response to alternative advertising strategies and/or advertising themes. |
| 8. Predicting the customer response to alternative pricing strategies, specific price levels, and proposed price changes. |
| 9. Predicting competitive response to distribution strategies studying such diverse problems as determining the optimal channel of distribution, number or type of outlets, vendor selection, or sale person quotas. |

Each of the identified management problems may be addressed and solved using the conjoint analysis methodology. In addition, a conjoint based competitive strategy may be implemented by modifying the marketing mix, i.e., new product/concept identification, pricing, advertising and distribution. This competitive strategy may focus on new segments or product re-positioning.

In addition to product and corporate strategy, conjoint research has been applied to family decision making; Tourism, tax analysis; time management; direct foreign; and medicine.

## How does Conjoint Analysis Work?

Conjoint analysis involves the measurement of psychological judgments (such as consumer preferences, or acceptance) or perceived similarities or differences between choice alternatives.

The name "Conjoint analysis" implies the study of the joint effects. In marketing applications, we study the joint effects of multiple product attributes on product choice.

**Alternative Conjoint Analysis Methodologies**

**Stimulus Construction**: Two Factor at a Time; Full Factorial design, Fractional Factorial Design, Self Explicated, Adaptive Conjoint Analysis, Hierarchical Bayes Estimation.

**Data Collection**: Two Factor at a Time Tradeoff Analysis; Full Profile Concept Evaluation; Feature and Level Evaluation; Combinatorial Approaches.

**Model Type**: Compensatory and Non-Compensatory Models; Part Worth Function; Vector Model; Mixed Model; Ideal Point Model;

**Measurement Scale**: Rating Scale; Paired Comparisons; Constant Sum; Rank Order

**Estimation Procedure**: Metric and Non-Metric Regression; MONANOVA; PREFMAP; LINMAP; Non-metric Tradeoff; Multiple Regression; LOGIT; PROBIT; Hybrid; TOBIT; Discrete Choice Self Explicated Additive Models

**Simulation Analysis**: Maximum Utility; Average Utility (Bradley-Terry-Luce); LOGIT; PROBIT

**CONJOINT MEASUREMENT**

As consumers or decision makers we often think in terms of concepts, objects or solutions, rather than relative numerical values.

Conjoint measurement (as distinguished from conjoint analysis) permits the use of rank or rating data, when evaluating pairs of attributes or attribute profiles (rather than single attributes). Based on this rank or rating input, the conjoint measurement procedures are applied to identify a mathematical function of the m brand attributes, which (1) is interval scaled (produces a set of interval scaled output), (2) best corresponds to the set of subjective evaluations (ordinal judgments) of the brand alternatives made by the respondent, and (3) is either a categorical or polynomial function in the attributes for the rank order data.

The conjoint measurement model assumes that (1) the set of objects being evaluated is at least weakly ordered (may contain ties), (2) each object evaluated may be represented by an additive combination of separate utilities existing for the individual attribute levels, and (3) the derived evaluation model is interval scaled and comes as close as possible to recovering the original rank order [non- metric] or rating [metric] input data.

The power of conjoint measurement to convert rank or scaled evaluations into interval scaled output has resulted in much methodological advancement, including multidimensional scaling and conjoint analysis.

Several different implementations of conjoint measurement are evidenced in conjoint analysis algorithms and computer programs. These implementations reflect both algorithmic differences and alternative approaches to data collection and measurement. The most noticeable are categorical conjoint measurement, monotone ANOVA models, OLS regression methods and linear programming methods. For purposes of this tutorial, only OLS regression methods are discussed.

The Ordinary Least Squares regression approach to conjoint analysis offers a simple, yet robust method of deriving alternative forms of respondent utilities (part-worth, vector, or ideal point models). The attractiveness of the OLS model is in part a result of the ability to scale respondent choices using rating scales, rather than rankings. The ability to implement designs having larger numbers of attributes and levels (through fractional factorial designs) has made this methodology the de facto standard for conjoint analysis.

The objective of OLS conjoint analysis is to produce a set of additive part-worth utilities (vector or ideal point utilities may also be estimated) that identify each respondent's preference for each level of a set of product attributes. In application, the OLS model solves for utilities using a dummy matrix of independent variables. Each independent variable indicates the presence or absence of a particular attribute level. The dependent variable is the respondent's evaluation of one of the profiles described by the independent variables. This model is expressed:

$$zi = f(y_{i1\ i2\ \ldots\ im}) = B_{1i1}(x_{1i1}) + B_{2i2}(x_{2i2}) + ,\ldots, + B_{mim}(x_{mim})$$

where:
B = the beta weights estimated in the regression
X = the matrix of dummy values identifying the levels of the factorial design, and
y = the ranking or rating evaluations of the respondent.

The first step in the analysis is to develop either a full or fractional factorial design. A full profile approach is demonstrated in Figure 1-2 for our six-attribute example. The use of fractional factorial designs permits the estimation of a parameter for the main effect of each attribute included in the analysis. This design, when analyzed, would produce estimates of individual respondent utilities for each of the 18 attribute levels. The utilities are additive.

**The Measurement of Preference**

The measurement of preference is an established part of consumer research that is based in expectancy value models of attitude theory and measurement. In conjoint analysis, we examine the preference for a set of brands or other choice alternatives that are described by an inventory of attributes.

The domain of preference research in conjoint analysis is both broad and multi-faceted. It extends to such diverse issues as how many attributes should be measured; the influence of the number of attribute levels; the appropriateness of measuring choice behavior rather than rating or ranking choice alternatives; the advantages of constructing individualized rather than generic attribute sets. A second line of preference research has focused on the appropriateness of alternate scaling methodologies for the measuring of preferences.

Modeling the decision process itself is a third major area of research, and includes the appropriateness of alternative decision models (compensatory, conjunctive, disjunctive, Elimination by Aspect, etc.) that may be used either singularly or in combination to predict preference; the form of the utility preference model estimated for a given attribute (part worth, linear, or ideal point); and the type of simulation models used to estimate choice preferences.

While we are tempted to engage in an extended discussion of each of these topics, we are constrained by the introductory nature of this discussion. We will limit this section to a basic discussion of modeling the form of the utility model.

### Preference Models

Utility preference models are the mathematical formulations that define the utility levels for each of the attributes. In practice, the attributes are modeled as either a piecewise linear (part-worth), linear, or curvilinear function.

### The Part-Worth Model

The part-worth model is the simplest of the utility estimation models. This model represents attribute utilities by a piecewise linear curve. This curve is formed by a set of straight lines that connect the point estimates of the utilities for the attribute levels (Figure 2-1).

The part-worth function is defined as:

$$s_j = \sum_{p=1}^{t} f_p Y_{jp}$$

where:
$s_j$ = Preference for the stimulus object at level j,
$f_p$ = the function representing the part worth of each of the
j different levels of the stimulus object, $Y_{jp}$ for the pth attribute.
$Y_{jp}$ = the level of the pth attribute for the jth stimulus object.

The part worth model reflects a utility function that defines a different utility (part worth) value for each of the j levels of a given attribute. Because of design considerations, most conjoint studies constrain the number of levels to be less than 5, though in actuality, the number of levels varies from 2 to 9 or more.

The implications of specifying a given preference model (part-worth, linear, or ideal point) extend beyond the actual shape of the preference curve being modeled. Each preference model requires that a different number of parameters be estimated. The part worth model requires that a distinct dummy variable column within the design matrix define each level of an attribute. As would be expected, a total of j-1 dummy variables are required to estimate j levels.

### The Vector Model

The Vector model is represented by a single linear function that assumes preference will increase as the quantity of attribute p increases (preference decreases if the function is negative). Preference for the jth attribute is defined as:

$$s_j = \sum_{p=1}^{t} W_p Y_{jp}$$

where:
$W_p$ = the individual's weights assigned to each of the p attributes. One weight is derived for each attribute.
Yjp = Level of the pth attribute for the jth Stimulus

The vector model for the attribute with four levels would appear as a straight line, with the levels on the line. The vector model requires that a single parameter be estimated for each variable treated as a vector. In contrast to the part-worth model, the vector model defines the attribute variable not as a series of dummy variables, but as a single linear variable where the values are the measured values or levels associated with the attribute.

### The Ideal Point Model

The ideal point function is implemented as a curvilinear function that defines an optimum or ideal amount of an attribute. The ideal point model is appropriate for many qualitative attributes, such as those associated with taste or smell. Too much sweetness may be less than optimal, while just the right amount is highly preferred.

The ideal point model establishes an inverse relationship between preferences and the weighted distance (dj2) between the location of the jth stimulus and the individual's ideal point, Xp. The ideal point model is expressed as:

$$d_j^2 = \sum_{p=1}^{t} W_p(Y_{jp} - X_p)2$$

Where:

$Y_{jp}$ = Level of the jth Stimulus with respect to the individual's ideal point, $X_p$.

$X_p$ = The Individual's ideal point, p, and

$W_p$ = the individual's weights assigned to each of the p attributes. One weight is derived for each attribute.

Yjp = Level of the pth attribute for the jth Stimulus

The ideal-point model for the attribute with three levels would appear as a curve with the center of the curve higher than either end, with the highest point being the ideal quantity of the attribute.

Mathematically, the implications of specifying each of the models ultimately extend to the number of parameters that must be estimated. The vector model treats the variable $Y_{jp}$ as a continuous (interval scaled) variable, such that only t parameters (j=1,...,t) must be estimated.

For the ideal point model, 2t parameters must be estimated ($W_p$ and $X_p$), and for the part worth model, (q-1)t parameters must be estimated, where q is specified to the number of levels for each of the t attributes.

### Stimulus Construction: The Basis for Conjoint Analysis

Stimulus construction in conjoint analysis focuses on the related problems of determining which attributes to present to the respondent, and how (in terms of what kinds of conjoint model) the attributes are presented. Because these problems are not independent of the conjoint model employed, we will consider the tradeoff and full profile conjoint methodologies and their associated models.

The sample case, provided by Paul Green and Catherine Schaeffer, identifies 30 students recruited from an MBA level Marketing Research class to answer questions about student apartments. The questionnaire and associated materials are found in Appendix B. The apartments considered were described by six attributes or factors, each with 3 "levels":

(1) **Walking Time to Classes**: (10, 20, 30 minutes)
(2) **Noise Level of Apartment House**: (Very Quiet, Average, Extremely Noisy)

(3) **Safety of Apartment Location**: (Very Safe, Average, Very Unsafe)
(4) **Condition of Apt**: (Newly Renovated Throughout, Renovated Kitchen, Poor Condition)
(5) **Size of Living/Dining Area**: (24 x 30, 15 x 20, 9 x 12)
(6) **Monthly Rent Including Utilities**: ($225, $360, $540)

**The Full Profile and Fractional Factorial Models**

Full profile descriptions are an attempt to represent real world decision alternatives in a realistic manner. Like real world alternatives, full profile descriptors present an integrated multi-attribute concept (Green, 1974).

The first full profile designs took the form of non-metric additive models and were initially applied to complete block-full factorial designs. Because the full factorial designs expand the number of profiles in exponential fashion, the number of factors and levels considered in these early studies were small. The sample data illustrates this problem, where a 36 design results in 729 possible unique profiles can be produced from the set of 6 factors that we are investigating. The full profile approach is illustrated by the following two sample profiles:

| | CARD #1 | CARD #2 |
|---|---|---|
| Walking Time To Class | 10 MINUTES | 20 MINUTES |
| Noise Level of Apartment | VERY QUIET | AVERAGE NOISE LEVEL |
| Safety of Apartment Location | VERY SAFE | VERY UNSAFE |
| Condition of Apartment | RENOVATED | KITCHEN RENOVATED |
| Size of Living/Dining Area | 24 BY 30 FEET | 15 BY 20 FEET |
| Monthly Rent With Utilities | $540 | $360 |

For the respondent to evaluate 729 profiles is an unmanageable task. It is fortunate that fractional factorial statistical designs may be invoked to greatly reduce the data collection task. In the example case of six factors each with 3 levels, the use of a fractional factorial design reduces the 36 = 729 possible profiles to only 18 profiles (Figure 1-3).

It is from this reduced set of profiles that we estimate the set of choice utilities associated with each of the individual factors and their associated levels. It is noteworthy that while the 18 trial design is sufficient to estimate main effects, interaction effects between factors can not be estimated with this small number of profiles. The estimation of interaction between specific variables requires that additional variables be added to the design matrix.

Figure 1-3: Stimulus Combinations

| Card | Rent | Time | Noise | Renovation | Dining | Safety |
|---|---|---|---|---|---|---|
| 1 | $540 | 10 Min. | V. Quiet | All | 24 x 30 | V. Safe |
| 2 | $360 | 20 Min. | Average | Kitchen | 15 x 20 | V. Unsafe |
| 3 | $225 | 30 Min. | E. Noisy | None | 9 x 12 | Average |
| 4 | $540 | 10 Min. | Average | Kitchen | 9 x 12 | Average |
| 5 | $360 | 20 Min. | E. Noisy | None | 24 x 30 | V. Safe |
| 6 | $225 | 30 Min. | V. Quiet | All | 15 x 20 | V. Unsafe |
| 7 | $225 | 10 Min. | E. Noisy | Kitchen | 24 x 30 | V. Unsafe |
| 8 | $540 | 20 Min. | V. Quiet | None | 5 x 20 | Average |
| 9 | $360 | 30 Min. | Average | All | 9 x 12 | V. Safe |
| 10 | $360 | 10 Min. | E. Noisy | All | 15 x 20 | Average |
| 11 | $225 | 20 Min. | V. Quiet | Kitchen | 9 x 12 | V. Safe |

| | | | | | | |
|---|---|---|---|---|---|---|
| 12 | $540 | 30 Min. | Average | None | 24 x 30 | V. Unsafe |
| 13 | $360 | 10 Min. | V. Quiet | None | 9 x 12 | V. Unsafe |
| 14 | $225 | 20 Min. | Average | All | 24 x 30 | Average |
| 15 | $540 | 30 Min. | E. Noisy | Kitchen | 15 x 20 | V. Safe |
| 16 | $225 | 10 Min. | Average | None | 15 x 20 | V. Safe |
| 17 | $540 | 20 Min. | E. Noisy | All | 9 x 12 | V. Unsafe |
| 18 | $360 | 30 Min. | V. Quiet | Kitchen | 24 x 30 | Average |

Again, the objective is to find a set of part-worths for the separate factor levels so that when these are appropriately added, one can find a total utility for each combination.

**Conjoint Analysis Steps**

The steps of the full profile analysis follow:

1. The respondent is given a set of stimulus profiles (constructed along factorial design principles in the full profile case). In the two-factor approach, pairs of factors are presented, each appearing approximately an equal number of times.

2. The respondents rank or rate the stimuli according to some overall criterion, such as preference, acceptability, or likelihood of purchase.

3. In the analysis of the data, part-worths are identified for the factor levels such that each specific combination of part-worths equals the total utility of any given profile. A set of part-worths is derived for each respondent.

4. The goodness-of-fit criterion relates the derived ranking or rating of stimulus profiles to the original ranking or rating data.

5. A set of objects are defined for the choice simulator. Based on previously determined part-worths for each respondent, each simulator computes an utility value for each of the objects defined as part of the simulation.

6. Choice simulator models are invoked which rely on decision rules (first choice model, average probability model or logit model) to estimate the respondent's object of choice. Overall choice shares are computed for the sample.

**Results of Conjoint Analysis**

The OLS conjoint analysis results for one respondent in the example of Table 1-3 would appear as:

0.00 5.00 10.00 0.00 6.67 13.33 0.00 23.33 26.67 0.00 5.00 10.00
0.00 10.00 25.00 0.00 38.33 51.67

This set of derived utility values can be used to obtain a total utility for each of the 18 combinations in Figure 1-3. For example, to find the utility of the first combination in Figure 1-3, we simply add the part worths of the respective levels identified by combination 1:

| Dimension | Value | Respondent Utility |
|---|---|---|
| Walking Time to Class | 10 Min. | 10.00 |
| Noise Level of Apartment | Very Quiet | 13.33 |
| Safety of Apartment Location | Very Safe | 26.67 |
| Renovations | All Renovated | 10.00 |
| Size of Living Room and Dining Room | 24x30 | 25.00 |
| Monthly Rent | $540 | 0.00 |
| Total | | 85.00 |

The total part worths sum to 85.00. The utility of the combination with the highest value is described as an apartment that rents for $250, is 10 minutes from campus, is very quiet, is all renovated, has a dining/living room that is 24 x 30, and is in a neighborhood judged to be very safe. It is possible to construct total utility values for each of the 729 possible combinations of the six attributes.

Computing Factor Importance

The estimation of utilities for each of the factors permits the estimation of average factor importance in addition to the estimation of average utility levels for each of the factors.

The importance of each of the i factors is estimated as a function of the range of the average observed utilities for the levels of each the factors. Importance is computed as:

$$I_i = \Sigma \frac{(\text{Maxu } i - \text{Minu } i)}{(\text{Maxu } i - \text{Minu } i)}$$

For the six factors graphed in Figure 1-6, the utilities with their associated importance are:

| | Lowest - Utility | | Highest Utility | Relative Importance |
|---|---|---|---|---|
| Time to Class | 1.72 | 4.65 | 2.93 | 11.27 |
| Neighborhood Noise | 1.61 | 4.54 | 2.93 | 11.27 |
| Neighborhood Safety | 1.42 | 8.70 | 7.28 | 28.00 |
| Condition of Apt. | .54 | 6.27 | 5.73 | 22.04 |
| Dining/Living Size | 2.21 | 3.21 | 1.00 | 3.85 |

| | | | | |
|---|---|---|---|---|
| Rental Amount | 1.49 | 7.62 | 6.13 | 23.58 |
| Sum of Importance: | | | 26.00 | 100.00 |

**Choice Simulators**

The final stage of the conjoint analysis is the choice simulator. The purpose of the choice simulator is to estimate percent of respondent choice for specific factor profiles entered into the simulator. Most often, the current competitors in the market are defined by identifying specific levels of the choice attributes. The simulator estimates choice share for the current market. Next, the data set identifying the competitors is supplemented with new products that are being considered for introduction into the market. The simulator responds by assigning choice shares for each of the items. The increase or decrease in brand shares is noted, as is the source of that share increase or decrease.

The most common simulator models include the first choice model, the average choice (Bradley-Terry-Luce) model, and the Logit model. The First choice model identifies the product with the highest utility as the product of choice. This product is selected and receives a value of 1. Ties receive a .5 value. After the process is repeated for each respondent's utility set, the cumulative "votes" for each product are evaluated as a proportion of the votes or respondents in the sample.

The Bradley-Terry-Luce model estimates choice probability in a different fashion. The choice probability for a given product is based on the utility for that product divided by the sum of all products in the simulated market.

The logit model uses an assigned choice probability that is proportional to an increasing monotonic function of the alternative's utility. The choice probabilities are computed by dividing the logit value for one product by the sum for all other products in the simulation. These individual choice probabilities are averaged across respondents. In summary, while the literature shows the maximum utility (first choice model) to provide the best overall validation, choice behavior has a strong probabilistic component. We have not measured this component adequately, but instead attributed lack of validity to "noise", our inability to model information search and overload effects, and measurement error.

**References**

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