Conjoint Analysis: Explaining Full Profile and Self Explicated Approaches

Conjoint analysis answers the question of which attributes are important to consumers and how important they really are. Taken in combination, individual product attributes can be used to describe an entire product. Conjoint analysis determines the combination of product attributes that consumers most prefer. Conjoint analysis, when applied to product, service, and communications projects identifies which product and service attributes, or which communications messages are most preferred and are best combined to produce maximum effect.

Conjoint Analysis originated out of the mathematical psychology research of conjoint measurement[1] . Green and Wind[2] state that conjoint measurement is "concerned with measuring the joint effect of two or more independent variables on the ordering of a dependent variable.

The output of conjoint measurement consists of the simultaneous measurement of the joint effect and separate independent variable contributions to that joint effect, all at the level (asymptotically) of interval scales with common unit." " From the standpoint of multi-attribute choice making, conjoint measurement can sometimes be used to decompose overall evaluation into implicit utilities for components of the multicomponent alternatives"

In layman's terms, conjoint analysis (1) identifies the attributes important in a choice decision, (2) identifies the way the attributes are combined to make the decision, and (3) determines the utility value to each of the levels of each of the attributes considered in the decision.

Green and Wind further point out that the method of conjoint analysis used represent the different theories of how people choose between multi-attribute alternatives. Conjoint analysis attempts to jointly identify the composition model for decision choices and at the same time estimate the utility value of the attributes that are important in the choice decision. As the choices are analyzed, the researcher may predict choice share for different product configurations that may be introduced into the competitive marketplace.

EXHIBIT 1: CONJOINT ANALYSIS IN A NUTSHELL

> Conjoint analysis is a methodology for the measurement of psychological judgments, such as consumer prefer ences. Stimuli (product configurations, advertisements, movie endings, etc.) are presented to the respondent for evaluation.
>
> For example, a respondent may be presented with a set of alternative product descriptions (automobiles). The automobiles are described by their stimulus attributes (level of gas mileage, size of engine, type of transmis sion, etc.). The respondent reviews presented alternatives and choice or preference evaluations are made.
>
> From these evaluations or choices, the researcher determines the respondent's utility for each attribute level (i.e., what is the relative value of an automatic versus a five-speed manual transmission). Once the utilities for all attribute and all levels are determined for all respondents, the analysis of the utility data can begin.

[1] November 1, 2011 Version, from PC-MDS documentation of MDPREF.

Preference curves are identified for each attribute so as to show how the market of consumers values each of the different attribute levels. This analysis may be conducted for all respondents or for selected market seg ments.

Simulations are then run to determine the relative choice share (and thereby estimate market share) of compet ing sets of new or existing products.

CONJOINT METHODOLOGY

Conducting a conjoint analysis is at best a non-trivial endeavor for a researcher. A full understanding of conjoint requires years of experience in mathematical statistics, computer programming, and spreadsheets. Full understanding is however, not required to conduct and correctly interpret conjoint analysis. None the less, a healthy overview of the conjoint "land-scape" will provide an appreciation of some of the approaches and options for modeling human choice behavior.

Conjoint analysis allows the researcher to predict choice share for evaluated stimuli such as competitive brands. When using conjoint analysis, the researcher is concerned with the identification of utilities—values used by people making tradeoffs and choosing among objects having many attributes and/or characteristics.

The typical sequence that one goes through to implement a conjoint study involves seven steps. These steps are very general and allow for differences between the different conjoint methodologies that can be deployed (Exhibit 2).

EXHIBIT 2: RESEARCH STAGES IN A CONJOINT ANALYSIS STUDY

1. Identification of the problem, along with dimensions of the product to be studied. How many attributes are considered and what are the levels of each attribute.

2. Develop the study protocol including all contact, sampling and follow-up protocols. Also develop the survey and associated visual aids, products, graphics, etc. that are to be used.

3. Develop the questionnaire... and then pretest the survey and data collection activity. Evaluate the process and revise until you are satisfied with the approach, instrument and the methodology.

4. Using one of a variety of data collection procedures described below, collect the data.

5. Process the data to derive at the individual respondent level estimates of the part-worths of each person's utility function.

6. Segmentation Analysis: The matrix of respondent by attribute-level part-worths may then be related to other subject background data in an effort to identify possible market segments based on similarities in part-worth functions.

7. Build and Run the Choice Simulator using a set of product configurations that represent feasible competitive offerings. These product profiles are entered into a consumer choice simulator, along with the earlier com puted individual utility functions. Choice simulators differ, in the simplest case each respondent's individual part-worth function is used to compute the utility for each of the competing profiles.

The stages in designing a conjoint analysis study involve a series of decisions that must be made reflecting how people choose between multi-attribute alternatives within complex decisions. Each of these choice options must be presented for evaluation, measured by the collected data, analyzed to estimate the utility value of the attribute levels, and analyzed in a simulation to estimate choice share to project market share. These activities are now described as outlined in Table 1.

TABLE 1: Alternative Conjoint Analysis Methodologies

Stimulus Construction	Two Factor at a Time; Full Factorial Design; Fractional Factorial Design; Self Explicated; Adaptive Choice; Choice Based; Max-Diff
Data Collection	Two Factor at a Time Tradeoff Analysis; Full Profile Concept Evaluation; Self Explicated; Adaptive Choice; Choice Based; Max-Diff
Model Estimation Method	Compensatory and Non-Compensatory Models; Part Worth Function; Vector Model; Mixed Model; Ideal Point Model;
Measurement and Scaling Tasks	Paired Comparisons; Constant Sum Scales; Rank Order; Rating Scales
Estimation Procedures	Metric and Non-Metric Methods including: MONANOVA; PREFMAP; LINMAP; Non-metric Tradeoff; Multiple Regression; LOGIT; PROBIT; TOBIT; Hierarchical Bayes;
Simulation Analysis Models	Maximum Utility; Average Utility (Bradley-Terry-Luce); LOGIT; PROBIT

Constructing the stimuli is the first step in conjoint analysis and involves specifying an appropriate conjoint methodology and constructing the stimuli to be evaluated by the respondents under that methodology. For example, does the actual consumer decision process best reflect a decision where attributes are considered two at a time; as a full profile of attributes in a product description; as an independent set of attributes evaluated one level at a time; or as a series of profile choices that are compared as a whole, evaluating one full product profile description over another full product profile description? The stimulus construction methodologies have received more emphasis in that they are now commonly associated with specific types of conjoint analysis computer programs available commercially.

CURRENT APPROACHES TO CONSTRUCTING THE STIMULI

There are many methodologies for conducting conjoint analysis, including two-factor at a time tradeoff, full profile, adaptive conjoint analysis (ACA), choice-based conjoint, self explicated conjoint, hybrid conjoint, and Hierarchical Bayes (HB). In this brief overview, each methodology will be given and in depth examples will be given of two of the most popular methodologies: the full-profile and self-explicated models.

Two Attribute Tradeoff Analysis: One early conjoint data collection method presented a series of attribute-by-attribute (two attributes at a time) tradeoff tables where respondents ranked their preferences of the different combinations of the attribute levels. For example, if each attribute had three levels, the tradeoff table would have nine cells and the respondents would rank their preferences from 1 to 9. The two-factor-at-a-time approach makes few cognitive demands of the respondent and is simple to follow . . . but it is both time-consuming and tedious. Moreover, respondents often lose their place in the table or develop some stylized pattern just to get the job done. Most importantly, however, the task is unrealistic in that real world choice alternatives are not presented for evaluation two attributes at a time.

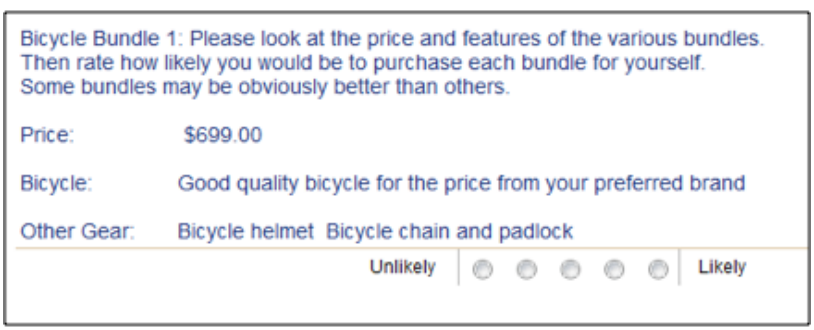
TABLE 1: Sample 3 x 3 Tradeoff Data from an Apartment Preference Study

Now let's consider a new apartment based on safety of the location and the walking time from the apartment to school. Please enter your preference by ranking each cell of this matrix from 1 to 9, where 1 is your most preferred choice.

Safety of Apt. Location ------- Walking time to Class	Very Safe	Average Safety	Very Unsafe
10 Minutes	1	2	7
20 Minutes	3	4	8
30 Minutes	5	6	9

Full-profile conjoint analysis is the most fundamental approach for measuring attribute utilities. In the full-profile conjoint task, different product descriptions (or even different actual products) are developed and presented to the respondent for acceptability or preference evaluations. Each product profile is designed as part of a full factorial, or fractional factorial experimental design that evenly matches the occurrence of each attribute with all other attributes. By controlling the attribute pairings in a fractional factorial design, the researcher can estimate the respondent's utility for each level of each attribute tested using a reduced set of profiles. An example of this type of conjoint analysis will be shown in detail in the next section.

FIGURE 1: Full Profile Conjoint Analysis Example


Bicycle Bundle 1: Please look at the price and features of the various bundles. Then rate how likely you would be to purchase each bundle for yourself. Some bundles may be obviously better than others.

Price: $699.00

Bicycle: Good quality bicycle for the price from your preferred brand

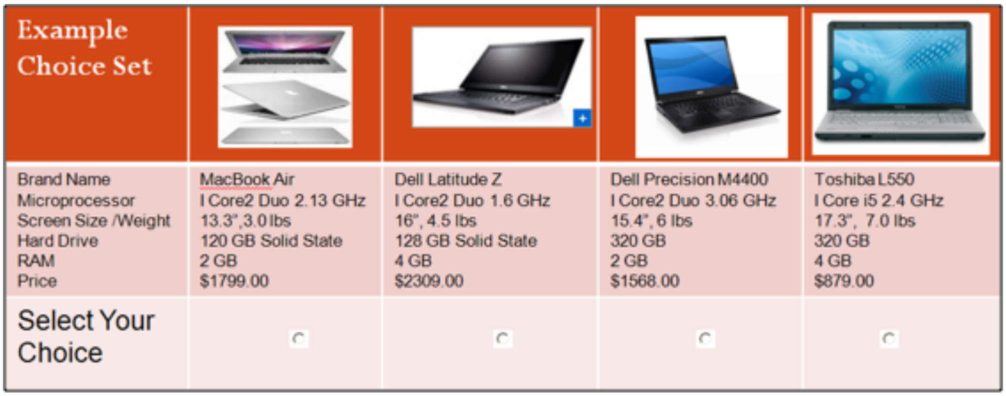
Other Gear: Bicycle helmet Bicycle chain and padlock

Unlikely ○ ○ ○ ○ ○ Likely

Adaptive Conjoint Analysis was developed to handle larger problems that required more descriptive attributes and levels. The unique contribution of ACA was to adapt each respondent's interview to the evaluations provided by each respondent. Early in the interview, the respondent is asked to eliminate attributes and levels that would not be considered in an acceptable product under any conditions. The remaining attributes are then presented for evaluation. The attributes of lesser importance receive less detailed questioning. Sets of full profiles are then presented two at a time, for evaluation. The choice pairs are presented in an order that increasingly focuses on determining the utility associated with each attribute.

Choice-based conjoint requires the respondent to make a choice of their preferred full-profile concept. This choice is made repeatedly from sets of 3–5 full profile concepts. This choice activity resembles an actual buying situation, and results are thought to accurately estimate actual shopping behavior.

FIGURE 2: Choice Based Conjoint Example



Example Choice Set				
Brand Name Microprocessor Screen Size /Weight Hard Drive RAM Price	MacBook Air I Core2 Duo 2.13 GHz 13.3",3.0 lbs 120 GB Solid State 2 GB $1799.00	Dell Latitude Z I Core2 Duo 1.6 GHz 16", 4.5 lbs 128 GB Solid State 4 GB $2309.00	Dell Precision M4400 I Core2 Duo 3.06 GHz 15.4", 6 lbs 320 GB 2 GB $1568.00	Toshiba L550 I Core i5 2.4 GHz 17.3", 7.0 lbs 320 GB 4 GB $879.00
Select Your Choice				

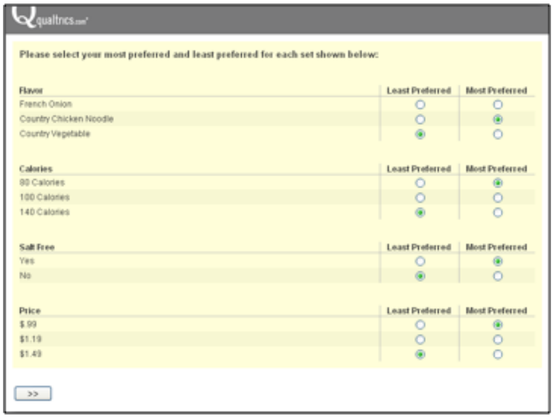
Self-explicated conjoint analysis offers a simple but surprisingly robust approach that is very simple to implement and does not require the development of full-profile concepts. First, factors and levels are presented to respondents for elimination if they are not acceptable in products under any condition.

The attribute levels retained in the analysis are then evaluated for desirability. Finally, the relative importance of attributes is measured using a constant sum scale to allocate 100 points between the most desirable levels of each attribute.

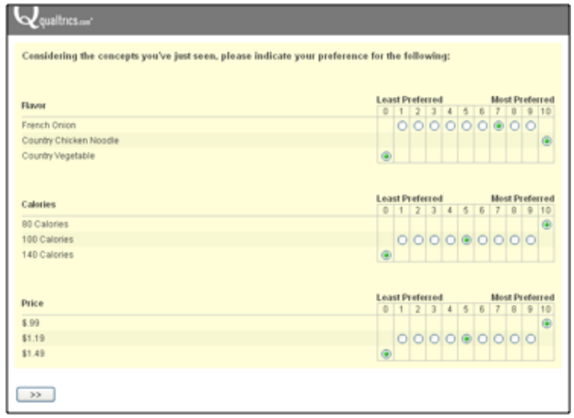
The attribute level preference is then weighted by the attribute importance to provide utility values for each attribute level. This approach does not require regression analysis or aggregated solution required in many other conjoint approaches. This approach has been shown to provide results equal or superior to full-profile approaches, and places fewer demands on the respondent. This technique will also be discussed in detail in the last section of this paper.

FIGURE 3: Self Explicated (Three Different Tasks)

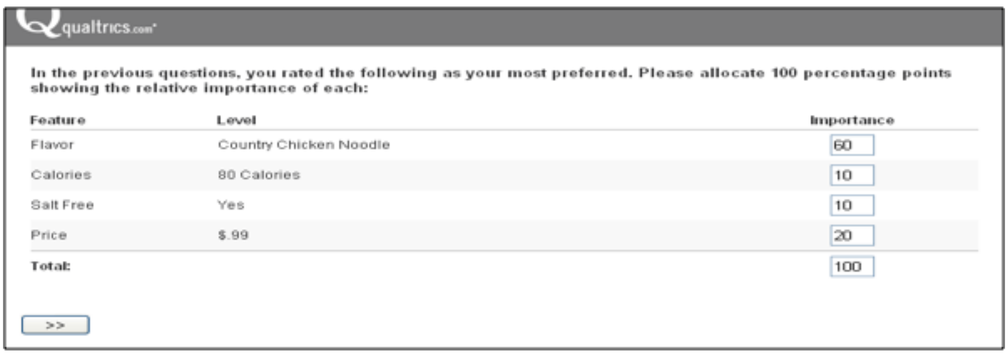
Task 1: Identify Most and Least Preferred Attribute Levels



Task 2: Rate Remainder of Attribute Levels



Task 3: Point Allocation for Attribute Importance



Hierarchical Bayes Conjoint Analysis (HB) is similarly used to estimate attribute level utilities from choice data. HB is particularly useful in situations where the data collection task is so large that the respondent cannot reasonably provide preference evaluations for all attribute levels. The HB approach uses averages (information about the distribution of utilities from all respondents) as part of the procedure to estimate attribute level utilities for each individual. This approach again allows more attributes and levels to be estimated with smaller amounts of data collected from each individual respondent.

Conjoint analysis models are constrained by the amount of data required in the data collection task. Managers demand models that define products with increasingly more stimulus attributes and levels within each attribute. Because more detail increases the size, complexity, and time of the evaluation task, new data collection methodologies and analysis models such as Hierarchical Bayes and Self Explicated conjoint are continually being developed. Online data collection of conjoint data has greatly eased this researcher burden.

The data collection task reflects and differs with each conjoint method. The data collection tasks vary from a rank order or scaled evaluation task in two factor at a time and full factorial design conjoint… to scaled evaluation in self-explicated models… to evaluation and pick your most preferred profile: A or B in choice based designs.

Model estimation method refers to the type of utility function assumed to exist for the attribute. Some attributes are totally nominal in nature and are unrelated from level to level of the attribute (for example, city location). Other attributes, like price tend to be more linear or curvilinear in nature. Yet others, like sweetness are more bell shaped, having an "ideal point" at the top of the curve. Models can also be compensatory, meaning that shortfalls or underperformance on one attribute can be compensated for by excellent performance in other attributes (i.e., the Olympic decathlon). Non-compensatory models operate on the premise that a fixed level of performance on certain attributes is required and substandard performance on those attributes cannot be cannot be compensated for by other attributes (a place kicker in the NFL must be able to kick with a certain range and accuracy, and blocking, catching or passing ability does not matter).

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 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 may vary 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 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.

Y_{jp} = the 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's treatment of the attribute levels as a series of dummy variables, the vector model defines the attribute variable as a single linear variable where the values are the measured values or levels associated with the attribute.

The ideal point model 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.

Y_{jp} = 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 Yjp 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.

Measurement and scaling tasks refer to the type of activity the respondent will engage in during the preference measurement task. Conjoint analysis can be conducted using a variety of tasks ranging from ranking of attribute levels presented in an attribute by attribute tradeoff matrix, to ranking full profile product descriptions, to picking a most preferred product profile from a set of 2 to five full profile product descriptions, to rating full profile product descriptions, to rating individual attribute levels.

Estimation procedures refer to the method of deriving utility scores from the data that has been collected. Estimation procedures range from non-metric heuristic algorithms to different forms of regression analysis, to hybrid approaches that combine data averaging with estimation techniques.

Simulation analysis models are used to estimate choice share (a surrogate for market share) based on respondent preferences for different "simulated products" each of which is defined by specifying a select set of attribute levels. Simulation models employ different assumptions that reflect market conditions.

The following sections describe two types of conjoint analysis and show in detail the analysis procedures. These are called the "full profile" approach popularized by Paul E. Green of the Wharton School at the University of Pennsylvania, and the self-explicated conjoint approach researched by Green, but later refined and shown to provide estimates of equal or superior quality to other methods by V. Srinivasan of Stanford University.

FULL PROFILE CONJOINT

The following conjoint example focuses on the evaluation of advertising appeal for allergy medication. The medication is described by 4 attributes that describe part of the message to be presented in an advertisement: Efficacy Claim, Endorsement Source, Superiority Claim, and Relief Claim. Each attribute has 4 levels .

TABLE 2: Conjoint Example 4^4 Design

Advertising Appeal Study for Allergy Medication *44 Fractional Factorial Design: (4 levels $^{4\ Factors}$)*	
0,0,0,0 1,0,1,2 2,0,2,3 3,0,3,1 0,1,1,1 1,1,0,3 2,1,3,2 3,1,2,0 0,2,2,2 1,2,3,0 2,2,0,1 3,2,1,3 0,3,3,3 1,3,2,1 2,3,1,0 3,3,0,2 **Legend:** Profile 1 has levels 0,0,0,0: No Medication is More Effective Most Recommended by Allergists Less Sedating than Benadryl Won't Quit on You	**Column 1, Efficacy,** has 4 Levels: No med more effective No med works faster Relief all day Right Formula **Column 2, Endorsements**, has 4 Levels: Most recom. by allergists Most recom. by pharmacist Nat. Gardening Assoc. Prof. Gardeners (Hortic.) **Column 3, Superiority**, has 4 Levels: Less sedating than Bened Rec. 2:1 over Benedryl Relief 2x longer than Ben Leading long acting OTC **Column 4, Gardening**, has 4 Levels: Won't quit on you Enjoy relief while garden Brand used by millions Relieves allergy symptoms

In this example there are 4x4x4x4=256 different advertisements that could be assembled using the different combinations of the four attributes. The left column of Table 2 shows the fractional factorial design that design makes it possible to estimate the utilities of each of the levels of each of the four attributes using only 16 ad profiles. These profiles are constructed and evaluated by representative consumers (See Table 3). The numbers in each row of the design represent the levels of each of the four attributes. The first profile: 0, 0, 0, 0 represents an advertisement that claims:

Attribute 1 – Level 0:	No medicine is more effective
Attribute 2 – Level 0:	Most recommended by allergists
Attribute 3 – Level 0:	Less sedating than Benadryl
Attribute 4 – Level 0:	Won't quit on you.

Each of the 16 profiles would be identified and printed on cards as shown in Table 3, or otherwise made available for the respondent to evaluate. The evaluation task is most often a rank order from 1 to 16 of cards to show preference or a rating evaluation using a 1 – 10 scale to indicate preference for each card.

TABLE 3: Cards for the 4x4x4x4 Allergy Advertising Design

Efficacy **Endorsements** **Superiority** **Gardening**	**Card 1** No med more effective Most recom. by allergists Less sedating than Bened Won't quit on you	**Card 2** No med works faster Most recom. by allergists Rec. 2:1 over Benedryl Brand used by millions	**Card 3** Relief all day Most recom. by allergists Relief 2x longer than Ben Relieves allergy symptoms	**Card 4** Right Formula Most recom. by allergists Leading long acting OTC Enjoy relief while garden
Efficacy **Endorsements** **Superiority** **Gardenin**	**Card 5** No med more effective Most recom. by pharmacist Rec. 2:1 over Benedryl Enjoy relief while garden	**Card 6** No med works faster Most recom. by pharmacist Less sedating than Bened Relieves allergy symptoms	**Card 7** Relief all day Most recom. by pharmacist Leading long acting OTC Brand used by millions	**Card 8** Right Formula Most recom. by pharmacist Relief 2x longer than Ben Won't quit on you
Efficacy **Endorsements** **Superiority** **Gardening**	**Card 9** No med more effective Nat. Gardening Assoc. Relief 2x longer than Ben Brand used by millions	**Card 10** No med works faster Nat. Gardening Assoc. Leading long acting OTC Won't quit on you	**Card 11** Relief all day Nat. Gardening Assoc. Less sedating than Bened Enjoy relief while garden	**Card 12** Right Formula Nat. Gardening Assoc. Rec. 2:1 over Benedryl Relieves allergy symptoms
Efficacy **Endorsements** **Superiority** **Gardening**	**Card 13** No med more effective Prof. Gardeners (Hortic.) Leading long acting OTC Relieves allergy symptoms	**Card 14** No med works faster Prof. Gardeners (Hortic.) Relief 2x longer than Ben Enjoy relief while garden	**Card 15** Relief all day Prof. Gardeners (Hortic.) Rec. 2:1 over Benedryl Won't quit on you	**Card 16** Right Formula Prof. Gardeners (Hortic.) Less sedating than Bened Brand used by millions

Table 4 shows utility values for each of the attribute levels derived for one respondent. These values can be obtained from an ordinary multiple regression analysis using the rank data as the dependent variable and the profile designs (using dummy-variable coding) as the independent variables.

TABLE 4: Summary of Full Profile Conjoint Analysis Procedures

DESIGN MATRIX	MATRIX OF DUMMY VARIABLES	CARD RANK MATRIX
Describes the profiles ranked	The design matrix is converted into a binary matrix of dummy variables: (0 = 0 0; 1 = 1 0; 2 = 0 1)	The dependent variable is the rank order preference score of each card viewed.
0, 0, 0, 0 1, 0, 1, 2 2, 0, 2, 3 3, 0, 3, 1 0, 1, 1, 1 1, 1, 0, 3 2, 1, 3, 2 3, 1, 2, 0 0, 2, 2, 2 1, 2, 3, 0 2, 2, 0, 1 3, 2, 1, 3 0, 3, 3, 3 1, 3, 2, 1 2, 3, 1, 0 3, 3, 0, 2	1 0 0 0 0 0 0 0 0 0 0 0 0 2 1 0 0 0 0 0 1 0 0 0 1 0 3 0 1 0 0 0 0 0 1 0 0 0 1 4 0 0 1 0 0 0 0 0 1 1 0 0 5 0 0 0 1 0 0 1 0 0 1 0 0 6 1 0 0 1 0 0 0 0 0 0 0 1 7 0 1 0 1 0 0 0 0 1 0 1 0 8 0 0 1 1 0 0 0 1 0 0 0 0 9 0 0 0 0 1 0 0 1 0 0 1 0 10 1 0 0 0 1 0 0 0 1 0 0 0 11 0 1 0 0 1 0 0 0 0 1 0 0 12 0 0 1 0 1 0 1 0 0 0 0 1 13 0 0 0 0 0 1 0 0 1 0 0 1 14 1 0 0 0 0 1 0 1 0 1 0 0 15 0 1 0 0 0 1 1 0 0 0 0 0 16 0 0 1 0 0 1 0 0 0 0 1 0	Ranks are shown for 3 respondents. Ranks appear as two digit numbers one after another. Respondent 1 5 16 9 4 2 3 13 14 8 6 1 7 11 10 15 12 Respondent 2 3 8 7 11 4 1 12 9 13 5 10 14 16 2 15 6 Respondent 3 13 14 15 6 11 4 5 1 10 2 7 9 12 8 3 16

The conjoint analysis conducts a regression analysis using the matrix of dummy variables and the data matrix of card ranks for the respondent. The regression is repeated for each respondent's data using the same matrix of dummy variables. The respondent's regression analysis beta weights are the "utility values" for each factor and level for each factor:

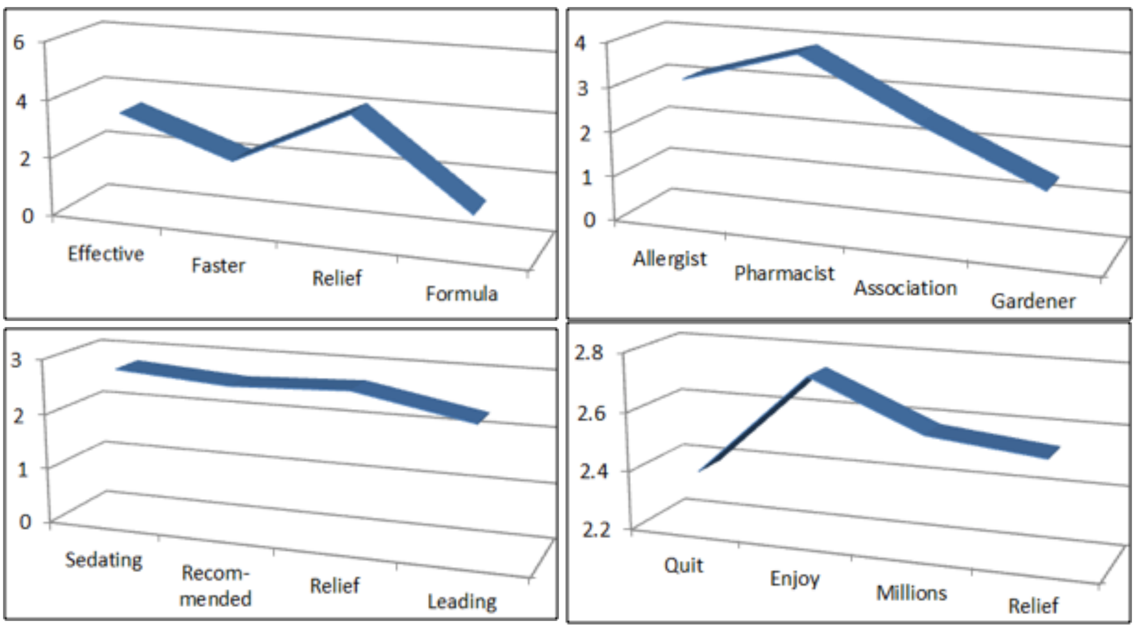
```
 R1   .00  2.25  3.00  2.75  3.00  2.50   .00  6.50   .00  4.75  5.00  3.25  5.75   .00  8.00  3.25
 R2  5.00   .00  7.00  6.00   .75   .00  4.00  3.25   .00  5.25  2.75  6.00  1.25   .00  3.00  2.75
 R3  4.50   .00   .50  1.00  6.75   .00  1.75  4.50  3.75  3.00  2.25   .00  1.25  4.50  7.75  6.50

For respondent 1 above,
 Attribute 1: Levels 1 - 4      .00  2.25  3.00  2.75
 Attribute 2: Levels 1 - 4     3.00  2.50   .00  6.50
 Attribute 3: Levels 1 - 4      .00  4.75  5.00  3.25

 Attribute 4: Levels 1 - 4     5.75   .00  8.00  3.25
```

The data analysis, once completed can be averaged over all respondents to show the average utility level for each level of each attribute, and graphed to show trends over the levels (trends only apply if the levels are in some order from low to high. Categorical levels simply show the average utility of the individual levels).

TABLE 5: Average Utility Scores

Efficacy	No med	No med	Relief	Right F
IMPORT.%:14.63	3.48	2.17	4.10	1.18
Endorsements	Most re	Most re	Nat. Ga	Prof. G
IMPORT.%:54.24	3.13	3.88	2.57	1.41
Superiority	Less se	Rec. 2:	Relief	Leading
IMPORT.%:17.76	2.78	2.63	2.71	2.31
Gardening	Won	Enjoy r	Brand u	Relieve
IMPORT.%:13.37	2.39	2.74	2.58	2.54

FIGURE 4: Graphing of Average Utility Scores



The final stage in this full profile conjoint analysis is the preparation of estimates of choice share using a market simulator. For a given concept profile that is defined by a level for each of the four attributes, the respondent's four utility scores (for the respective levels) are added together. For example, to obtain the respondent's estimated evaluation of profile 1, one sums the part-worth values:

TABLE 6: Sum of Part Worth Values for one Respondent

Value for:	Efficacy "No med more effective"	=	0.00
Value for:	Endorsements "Most recommended By allergists"	=	3.00
Value for:	Superiority "Less sedating than Benedryl"	=	0.00
Value for:	Gardening "Won't quit on you"	=	6.00
	Total	=	9.00

A simulator computes utility values for the "new product profiles" being included in the simulator and determines that the respondent's choice is the new product having the highest utility value. The votes are tabulated across all respondents to estimate relative choice share. Different decision rules can be employed in the simulator to reflect market conditions. For example, the maximum utility model (also known as the first choice model) adds the utilities associated with the attribute levels defined as making up the new product. After the total utility is computed by summing the attribute levels for each of the simulated products, the product with the highest utility is selected. Operationally, the selected product receives a value of 1 and all others receive a value of 0. In the case of ties, the tied products receive a .5 value (if two are tied). After the process is repeated for each respondent's utility set, the cumulative "votes" for each product are tabulated based on the proportion of votes for each product in the universe. Below, we observe that simulated product 2 is found to have 38.1% of the first choice votes.

TABLE 7: Maximum Utility Model

Row Totals, Average Ranks, Frequency Of Rankings And Percentages By Product

			RANK OF CHOICE			
ROW	TOTAL	AVGRANK	1	2	3	4
PRODUCT 1			78.0	165.5	172.0	84.5
	300.00	2.53	15.60	33.10	34.40	16.90
PRODUCT 2			190.5	57.5	40.0	212.0
	300.00	2.55	38.10	11.50	8.00	42.40
PRODUCT 3			78.0	165.5	172.0	84.5
	300.00	2.53	15.60	33.10	34.40	16.90
PRODUCT 4			135.5	129.5	134.0	101.0
	300.00	2.40	27.10	25.90	26.80	20.20

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

```
BRADLEY-TERRY-LUCE MODEL:
AVG. PROB. FOR EACH SIMULATED PRODUCT

    n     1     2     3     4
  --------------------------
  300   .25   .25   .25   .25
```

EXAMPLE 2: FULL PROFILE EXAMPLE FOR STUDENT APARTMENT CHOICE (WITH COMPUTATIONS)

In this example, we go into more depth in the calculation of the regression analysis to derive the conjoint "utility scores" for each respondent.

The problem: Students select an apartment based on six attributes – each with three levels.

TABLE 8: Student Apartment Decision Attributes and Levels*

Walking Time to Class	1. 30 Minutes 2. 20 Minutes 3. 10 Minutes
Noise Level of Apartments	1. Extremely Noisy 2. Average Noise Level 3. Very Quiet
Safety of Apartment Location	1. Very Unsafe Location 2. Average Safety 3. Very Safe Location
Condition of Apartment	1. Poor Condition 2. Renovated Kitchen Only 3. Newly Renovated Throughout
Size of Living/Dining Area	1. 9 by 12 feet 2. 15 by 20 feet 3. 24 by 30 feet
Monthly Rent	1. $540 2. $360 3. $225
* 6 attributes with 3 levels each: Example is from a study by Paul Green and Catherine Schaffer	

Six attributes, each with three levels each produce 3^6 = 3x3x3x3x3x3 = 729 different combinations of possible apartments that could be evaluated. Of course, we can't ask a research respondent to consider that many, so we use a fractional factorial design consisting of 18 profiles. These 18 produce an orthogonal and balanced design that allows us to estimate all levels of each of the 6 attributes.

To view the size of this problem, consider the following table that shows 1/27th of the total number of apartment configurations. Note that this is not a fractional factorial because each of the attributes is not balanced (we have only one level of quietness, living/dining room size and renovation.

TABLE 9: Full Factorial Experimental Design: Apartment Data

Full Factorial Experimental Design: Apartment Data One of 27 Segments of the Full Factorial Matrix 3x3x3x3x3x3 = 729 different combinations, 27 of which are shown below. The Cell Values show the possible rankings of the options by one respondent.									
	Very Quiet								
	24 x 30 Living/Dining								
	Newly Renovated Throughout								
	10 Minute Walk			20 Minute Walk			30 Minute Walk		
Very Safe	1	2	5	15	17	22	7	8	11
Average	4	3	6	16	18	23	9	10	12
Very Unsafe	25	26	27	20	21	24	13	14	19

The 1/27th fractional factorial design that we produce using the "Conjoint Designer" software program appears below. Note how attribute levels are rotated to make the design "balanced" such that each attribute level appears with each other level (as nearly as possible):

TABLE 9: Full Factorial Experimental Design: Apartment Data

Card	Rent	Walking Time	Level of Noise	Renovation	Living/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	15 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

The design is then used to develop cards that are presented to the respondent for rating or ranking.

TABLE 1: Sample Full Profile Cards

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

EXHIBIT 3: A NOTE ABOUT FRACTIONAL FACTORIAL DESIGN MATRICES

Fractional factorials are subsets of all possible combinations that enable each level of each factor to be estimated in an uncorrelated manner. This "main effects" model does not permit the estimation of interaction effects (joint effects of different combinations of two or more variables at a time… such as taste and color, where a combination may be much greater than expected by simply taking the additive combination of the attributes).

According to the Engineering Statistics Handbook, "we pick a fraction such as ½, ¼, etc. of the runs called for by the full factorial. We use various strategies that ensure an appropriate choice of runs. The following sections will show you how to choose an appropriate fraction of a full factorial design to suit your purpose at hand. Properly chosen fractional factorial designs for 2-level experiments have the desirable properties of being both balanced and orthogonal:

Balanced Design: An experimental design where all cells (i.e. treatment combinations) have the same number of observations."

Orthogonality: Orthogonality means the variables are un-correlated. "An experimental design is orthogonal if the effects of any factor balance out (sum to zero) across the effects of the other factors." (Source: Engineering Statistics Handbook, http://www.itl.nist.gov)

TABLE 12: Fractional Factorial Design Matrix for the Apartment Data

```
2 , 2 , 2 , 2 , 2 , 0        ROW 1 OF DESIGN USES LEVELS 2,2,2,2,2,0
1 , 1 , 0 , 1 , 1 , 1        ROW 2 OF DESIGN USES LEVELS 1,1,0,1,1,1
0 , 0 , 1 , 0 , 0 , 2         .
2 , 1 , 1 , 1 , 0 , 0         .
1 , 0 , 2 , 0 , 2 , 1        ETC.
0 , 2 , 0 , 2 , 1 , 2
2 , 0 , 0 , 1 , 2 , 2        THESE ROWS DEFINE THE LEVELS THAT APPEAR ON EACH
1 , 2 , 1 , 0 , 1 , 0        OF THE CARDS USED TO COLLECT THE FULL PROFILE
0 , 1 , 2 , 2 , 0 , 1        CONJOINT DATA.
2 , 0 , 1 , 2 , 1 , 1
1 , 2 , 2 , 1 , 0 , 2
0 , 1 , 0 , 0 , 2 , 0
2 , 2 , 0 , 0 , 0 , 1
1 , 1 , 1 , 2 , 2 , 2
0 , 0 , 2 , 1 , 1 , 0
2 , 1 , 2 , 0 , 1 , 2
1 , 0 , 0 , 2 , 0 , 0
0 , 2 , 1 , 1 , 2 , 1
```

We will not use this design matrix to actually compute the utilities (regression coefficients) using a matrix algebra approach and Excel. The following table shows the design matrix after it is converted to dummy 0-1 coding.

TABLE 13: X Matrix Generated with 18 Profiles and 12 Dummy Variables

Row	Column	Dummy Variables	Ratings of One Respondent
1	12	0 1 0 1 0 1 0 1 0 1 0 0	50
2	12	1 0 1 0 0 0 1 0 1 0 1 0	30
3	12	0 0 0 0 1 0 0 0 0 0 0 1	40
4	12	0 1 1 0 1 0 1 0 0 0 0 0	10
5	12	1 0 0 0 0 1 0 0 0 1 1 0	60
6	12	0 0 0 1 0 0 0 1 1 0 0 1	50
7	12	0 1 0 0 0 0 1 0 0 1 0 1	50
8	12	1 0 0 1 1 0 0 0 1 0 0 0	10
9	12	0 0 1 0 0 1 0 1 0 0 1 0	40
10	12	0 1 0 0 1 0 0 1 1 0 1 0	60
11	12	1 0 0 1 0 1 1 0 0 0 0 1	70
12	12	0 0 1 0 0 0 0 0 0 1 0 0	00
13	12	0 1 0 1 0 0 0 0 0 0 1 0	30
14	12	1 0 1 0 1 0 0 1 0 1 0 1	90
15	12	0 0 0 0 0 1 1 0 1 0 0 0	10
16	12	0 1 1 0 0 1 0 0 1 0 0 1	90
17	12	1 0 0 0 0 0 0 1 0 0 0 0	00
18	12	0 0 0 1 1 0 1 0 0 1 1 0	90

This matrix corresponds to the 6 factor design matrix. Each value of the design matrix (0,1,2) corresponds to two columns in this matrix that are coded in binary format (0 0, 1 0, 0 1). The final column is the rating of one respondent for the profile represented

By using dummy variables we move from 6 to 12 variables to estimate the 18 levels. With regression analysis the intercept value of 0 is used as the third level for each of the attributes- thus we have 18 regression coefficients that are derived for the 18 attribute levels.

We next begin completing the regression analysis. Recall that regression coefficients, b, may be computed using matrix algebra as $[\, b \,] = [\, x'x \,]^{-1} * [\, x'y \,]$ which defines the matrices used in the computations. We will now follow this formulation to estimate our own utilities.

The basic starting matrices for analysis of one respondent's data involves first computing a matrix of deviation scores for the dummy variable matrix such that the matrix contains the values x = (Deviation scores – Mean deviation score). We also show the deviation scores for the ratings scores of the respondent.

TABLE 14: Dummy Regression Analysis Matrices

Matrix [b] = [x’x]$^{-1}$ * [x’y]
Matrix Size 12 x 1 12 x 12 12 x 1

x MATRIX of deviation scores x = (X - Mean)												Y Matrix
-0.33	0.66	-0.33	0.66	-0.33	0.66	-0.33	0.66	-0.33	0.66	-0.33	-0.33	6.66
0.66	-0.33	0.66	-0.33	-0.33	-0.33	0.66	-0.33	0.66	-0.33	0.66	-0.33	-13.33
-0.33	-0.33	-0.33	-0.33	0.66	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	0.66	-3.33
-0.33	0.66	0.66	-0.33	0.66	-0.33	0.66	-0.33	-0.33	-0.33	-0.33	-0.33	-33.33
0.66	-0.33	-0.33	-0.33	-0.33	0.66	-0.33	-0.33	-0.33	0.66	0.66	-0.33	16.66
-0.33	-0.33	-0.33	0.66	-0.33	-0.33	-0.33	0.66	0.66	-0.33	-0.33	0.66	6.66
-0.33	0.66	-0.33	-0.33	-0.33	-0.33	0.66	-0.33	-0.33	0.66	-0.33	0.66	6.66
0.66	-0.33	-0.33	0.66	0.66	-0.33	-0.33	-0.33	0.66	-0.33	-0.33	-0.33	-33.33
-0.33	-0.33	0.66	-0.33	-0.33	0.66	-0.33	0.66	-0.33	-0.33	0.66	-0.33	-3.33
-0.33	0.66	-0.33	-0.33	0.66	-0.33	-0.33	0.66	0.66	-0.33	0.66	-0.33	16.66
0.66	-0.33	-0.33	0.66	-0.33	0.66	0.66	-0.33	-0.33	-0.33	-0.33	0.66	26.66
-0.33	-0.33	0.66	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	0.66	-0.33	-0.33	-43.33
-0.33	0.66	-0.33	0.66	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	0.66	-0.33	-13.33
0.66	-0.33	0.66	-0.33	0.66	-0.33	-0.33	0.66	-0.33	0.66	-0.33	0.66	46.66
-0.33	-0.33	-0.33	-0.33	-0.33	0.66	0.66	-0.33	0.66	-0.33	-0.33	-0.33	-33.33
-0.33	0.66	0.66	-0.33	-0.33	0.66	-0.33	-0.33	0.66	-0.33	-0.33	0.66	46.66
0.66	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	0.66	-0.33	-0.33	-0.33	-0.33	-43.33
-0.33	-0.33	-0.33	0.66	0.66	-0.33	0.66	-0.33	-0.33	0.66	0.66	-0.33	46.66

Next, the x matrix is multiplied by itself to produce [x’x] the matrix of sum of squares and cross products.

Matrix of Sum of Squares and Cross Products [x’x]

4.00	-2.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.00	0.00
-2.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	4.00	-2.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00
0.00	0.00	-2.00	4.00	-0.00	0.00	-0.00	0.00	0.00	0.00	-0.00	0.00
0.00	0.00	0.00	-0.00	4.00	-2.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00
0.00	0.00	0.00	0.00	-2.00	4.00	0.00	0.00	-0.00	0.00	0.00	0.00
0.00	0.00	0.00	-0.00	-0.00	0.00	4.00	-2.00	0.00	-0.00	-0.00	0.00
-0.00	0.00	0.00	0.00	0.00	0.00	-2.00	4.00	0.00	0.00	-0.00	0.00
0.00	0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	4.00	-2.00	0.00	0.00
0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-2.00	4.00	0.00	0.00
0.00	0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	4.00	-2.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-2.00	4.00

It is then inverted using the Excel inversion function to produce [x’x]-1, and the x matrix is multiplied by the y matrix to produce [x’y]. When the two resulting matrices are multiplied together the matrix of regression coefficients, b, is produced showing the regression coefficients (without the intercept value.

TABLE 15: The Regression Computation of Utilities for Respondent 1

b =	$[x'x]^{-1}$												$[x'y]$
5	0.33	0.17	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	0
10	0.17	0.33	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	30
6.67	-0.00	-0.00	0.33	0.17	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0
13.33	-0.00	-0.00	0.17	0.33	0.00	-0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	40
23.33	-0.00	-0.00	-0.00	0.00	0.33	0.17	0.00	0.00	0.00	0.00	0.00	-0.00	40
26.67	-0.00	-0.00	-0.00	-0.00	0.17	0.33	-0.00	-0.00	0.00	0.00	-0.00	-0.00	60
5	0.00	0.00	-0.00	0.00	0.00	-0.00	0.33	0.17	-0.00	-0.00	0.00	0.00	0
10	0.00	0.00	-0.00	0.00	0.00	-0.00	0.17	0.33	-0.00	-0.00	0.00	0.00	30
10	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	0.33	0.17	-0.00	-0.00	-10
25	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	0.17	0.33	-0.00	-0.00	80
38.33	-0.00	-0.00	0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	0.33	0.17	50
51.67	-0.00	-0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	0.17	0.33	130

The utilities (regression coefficients or beta weights from regression analysis come from a regression analysis of the profile codes on the consumer ratings of each level for each profile. The analysis is shown below in a matrix algebra computation of b = $[(x'x]^{-1}\ [x'y]$. Note that there are only 12 utility values for the 18 profiles that were tested. This is because the first level of each attribute is the intercept and is set to b0 - = 0.00. Thus for this respondent, the three levels of attribute one has utility values of: 0.00 5.00 10.00, as shown below.

TABLE 16: REspondent One's Utility Values

	Levels		
Attributes	**1**	**2**	**3**
Walking Time to Class	0.00	5.00	10.00
Noise Level of Apartment	0.00	6.67	13.33
Safety of Apartment Location	0.00	23.33	26.67
Condition of Apartment	0.00	5.00	10.00
Size of Living/Dining Area	0.00	10.00	25.00
Monthly Rent	0.00	38.33	51.67
RSQ = 0.92208			

For those who are more mathematically sophisticated, the design matrix can be modified such that instead of a "part worth" model that estimates each level separately, vector model (straight line regression) or ideal point (curvilinear regression) can be estimated (Table 17).

TABLE 17: Design with Modified Variables

```
X MATRIX GENERATED WITH 18 PROFILES AND 8 PARAMETERS
==============================================================
ROW COLUMN      DUMMY VARIABLES        MODEL
==============================================================
    1    8      3 3 3 9 3 3 1 1    ATTRIBUTE 1: VECTOR MODEL (Metric)
    2    8      2 2 1 1 2 2 2 4    ATTRIBUTE 2: VECTOR MODEL (Metric)
    3    8      1 1 2 4 1 1 3 9    ATTRIBUTE 3: IDEAL POINT  (Squared)
    4    8      3 2 2 4 2 1 1 1    ATTRIBUTE 4: VECTOR MODEL (Metric)
    5    8      2 1 3 9 1 3 2 4    ATTRIBUTE 5: VECTOR MODEL (Metric)
    6    8      1 3 1 1 3 2 3 9    ATTRIBUTE 6: IDEAL POINT  (Squared)
    7    8      3 1 1 1 2 3 3 9
    8    8      2 3 2 4 1 2 1 1
    9    8      1 2 3 9 3 1 2 4
   10    8      3 1 2 4 3 2 2 4
   11    8      2 3 3 9 2 1 3 9
   12    8      1 2 1 1 1 3 1 1
   13    8      3 3 1 1 1 1 2 4
   14    8      2 2 2 4 3 3 3 9
   15    8      1 1 3 9 2 2 1 1
   16    8      3 2 3 9 1 2 3 9
   17    8      2 1 1 1 3 1 1 1
   18    8      1 3 2 4 2 3 2 4
```

SELF-EXPLICATED CONJOINT ANALYSIS

The self-explicated conjoint model provides a simple alternative to factorial design based conjoint that produces utility score estimates equal to or superior to that of full-profile and other popular approaches such as Adaptive Conjoint Analysis. The self-explicated model is theoretically well founded, being based on the multi-attribute attitude models that combine attribute importance with attribute desirability to estimate overall preference.

Initially, all attribute levels are presented to respondents for evaluation to eliminate any levels that would not be acceptable in a product under any conditions. Next, attribute levels are presented and each level is evaluated for desirability. Finally, based on these evaluations, the most desirable levels of all attributes are evaluated relative importance. As with the full-profile model, these scores can be summed and simulations run to obtain a score for any profile of interest. This simple self-reporting approach is easier for the respondent to complete and straight forward in terms of determining the importance or desirability of attributes and attribute levels (See Srinivasan, V. 1997. Surprising robustness of the self-explicated approach to customer preference structure measurement. Journal of Marketing Research, 34, May, 286-291.

The self-explicated model is based theoretically on the multi-attribute attitude models that combine attribute importance with attribute desirability to estimate overall preference. This model is expressed as: $E_o = \sum_{j=1}^{m} \sum_{k=1}^{n} I_j D_{jk}$ where Ij is the importance of attribute j and Djk is the desirability of level k of attribute j. In this model, Eo, the evaluation of product or service o, is formed by summing the importance weighted desirabilities of the attributes and attribute levels that make up the profile.

THE SELF-EXPLICATED DATA COLLECTION TASK

Step 1: All attribute levels are presented to respondents for evaluation to eliminate any levels that would not be acceptable in a product under any conditions. Caution must be exercised here to make sure the respondent understands that this option should be selected only if, for example no car would ever be acceptable if it were in “color x” (they would rather walk than drive this color car).

Step 2: All attribute levels are presented to the respondent and each level is evaluated for desirability (0 to 10 scales). Most and least desirable attribute levels are identified, and then the remaining levels for each attribute are rated on 1 to 9 scales.

Step 3: Overall importance of each attribute is determined. This may be done in either of two ways: first, the most desirable and least desirable levels of each attribute are presented as an “upgrade” option. The most desirable “upgrade” is selected and then all other “upgrades” are evaluated on 0 to 9 scales.   The second approach is to evaluate the most desirable level of every attribute (as reported by the respondent) using a constant sum question. The respondent allocates 100 points across all “most preferred levels” to assign relative importance to the attributes. Experimental research has shown that the constant sum approach gives a broader spread to the resulting utilities and is generally preferred.

Using this self-reported information, the attribute importance scores are used to weight the standardized attribute level scores. This process produces what are called “self-explicated utility values” for each attribute level. Utility values are computed for each respondent. The self-explicated conjoint analysis does not require a fractional factorial design or regression analysis.

FIGURE 5: Selection of Least and Most Preferred Attribute Levels

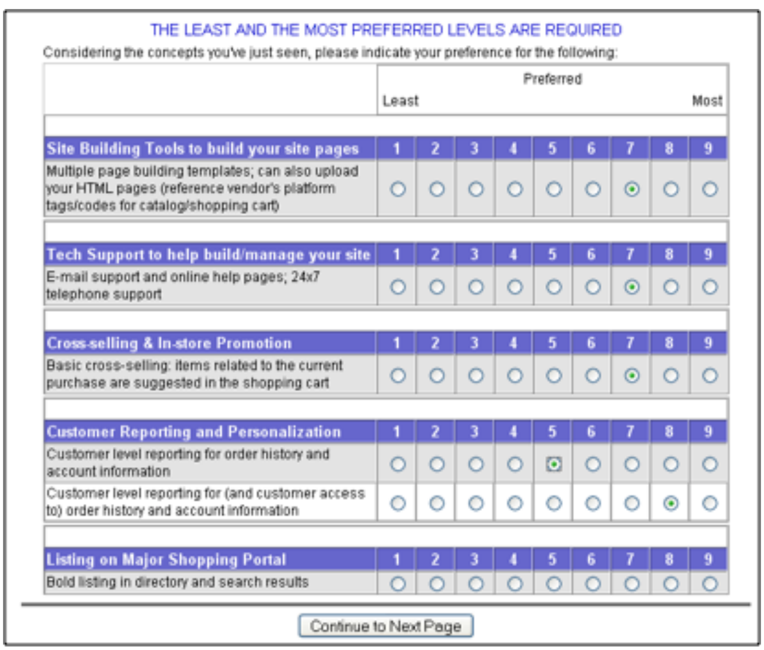


FIGURE 6: Rating of Remaining Attribute Levels

21. We're now going to ask some questions about what features and services would be most important to you when using an online store vendor to help design, manage and promote your online store.

Please select your **most preferred** and **least preferred** for each set shown below::

	Preferred Least	Preferred Most
Site Building Tools to build your site pages		
2 basic page templates for your store and checkout	○	○
Multiple page building templates; can also upload your HTML pages (reference vendor's platform tags/codes for catalog/shopping cart)	○	○
Multiple page building templates; can also upload your HTML pages (reference vendor's platform tags/codes for catalog/shopping cart); advanced scripting (PHP, ASP, etc.)	○	○
Tech Support to help build/manage your site		
E-mail support and online help pages	○	○
E-mail support and online help pages; 24x7 telephone support	○	○
E-mail support and online help pages; 24x7 telephone support; designated Account Manager for all support needs	○	○
Integration of order data with your offline systems		
User initiated download of order data into Excel™ and QuickBooks™	○	○
User initiated download of order data into Excel™ and QuickBooks™ plus automatic interaction between the store and your other systems/data (e.g., catalog, check out, accounting, order processing, unique shipping rules, etc.)	○	○
Cross-selling & In-store Promotion		
No cross-selling	○	○
Basic cross-selling: items related to the current purchase are suggested in the shopping cart	○	○
Basic cross-selling plus dynamic pricing based on rules you define (e.g. link used to reach the site, customer purchase history, customer attributes, etc.)	○	○
Customer Reporting and Personalization		
No customer level reporting	○	○
Customer level reporting for order history and account information	○	○
Customer level reporting for (and customer access to) order history and account information	○	○
Customer level reporting for (and customer access to) order history and account information; can personalize site content for each customer based on log-in	○	○
Listing on Major Shopping Portal		
Standard listing in directory and search results	○	○
Bold listing in directory and search results	○	○
Bold and preferential listing in directory and search results	○	○

Continue to Next Page

FIGURE 7: Importance Measure Upgrade from Lowest to Highest Level for Each Attribute

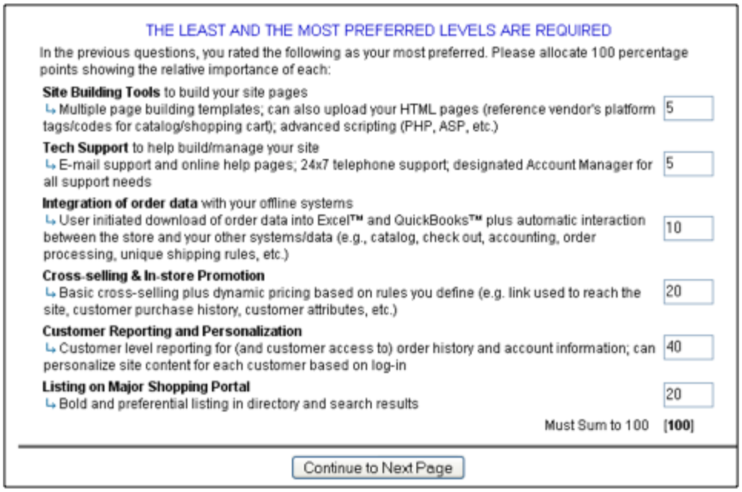
THE LEAST AND THE MOST PREFERRED LEVELS ARE REQUIRED

Assume you are **upgrading**.. Please select the one change that would be the most valuable for you to receive.

		Most Valuable Upgrade
Site Building Tools to build your site pages		
From :	2 basic page templates for your store and checkout	○
To :	Multiple page building templates; can also upload your HTML pages (reference vendor's platform tags/codes for catalog/shopping cart); advanced scripting (PHP, ASP, etc.)	
Tech Support to help build/manage your site		
From :	E-mail support and online help pages	○
To :	E-mail support and online help pages; 24x7 telephone support; designated Account Manager for all support needs	
Integration of order data with your offline systems		
From :	User initiated download of order data into Excel™ and QuickBooks™	○
To :	User initiated download of order data into Excel™ and QuickBooks™ plus automatic interaction between the store and your other systems/data (e.g., catalog, check out, accounting, order processing, unique shipping rules, etc.)	
Cross-selling & In-store Promotion		
From :	No cross-selling	○
To :	Basic cross-selling plus dynamic pricing based on rules you define (e.g. link used to reach the site, customer purchase history, customer attributes, etc.)	
Customer Reporting and Personalization		
From :	No customer level reporting	◉
To :	Customer level reporting for (and customer access to) order history and account information; can personalize site content for each customer based on log-in	
Listing on Major Shopping Portal		
From :	Standard listing in directory and search results	○
To :	Bold and preferential listing in directory and search results	

Continue to Next Page

FIGURE 8: Importance Upgrade of Items Not Selected



THE LEAST AND THE MOST PREFERRED LEVELS ARE REQUIRED

In the previous questions, you rated the following as your most preferred. Please allocate 100 percentage points showing the relative importance of each:

Site Building Tools to build your site pages ↳ Multiple page building templates; can also upload your HTML pages (reference vendor's platform tags/codes for catalog/shopping cart); advanced scripting (PHP, ASP, etc.)	5
Tech Support to help build/manage your site ↳ E-mail support and online help pages; 24x7 telephone support; designated Account Manager for all support needs	5
Integration of order data with your offline systems ↳ User initiated download of order data into Excel™ and QuickBooks™ plus automatic interaction between the store and your other systems/data (e.g., catalog, check out, accounting, order processing, unique shipping rules, etc.)	10
Cross-selling & In-store Promotion ↳ Basic cross-selling plus dynamic pricing based on rules you define (e.g. link used to reach the site, customer purchase history, customer attributes, etc.)	20
Customer Reporting and Personalization ↳ Customer level reporting for (and customer access to) order history and account information; can personalize site content for each customer based on log-in	40
Listing on Major Shopping Portal ↳ Bold and preferential listing in directory and search results	20
Must Sum to 100	**[100]**

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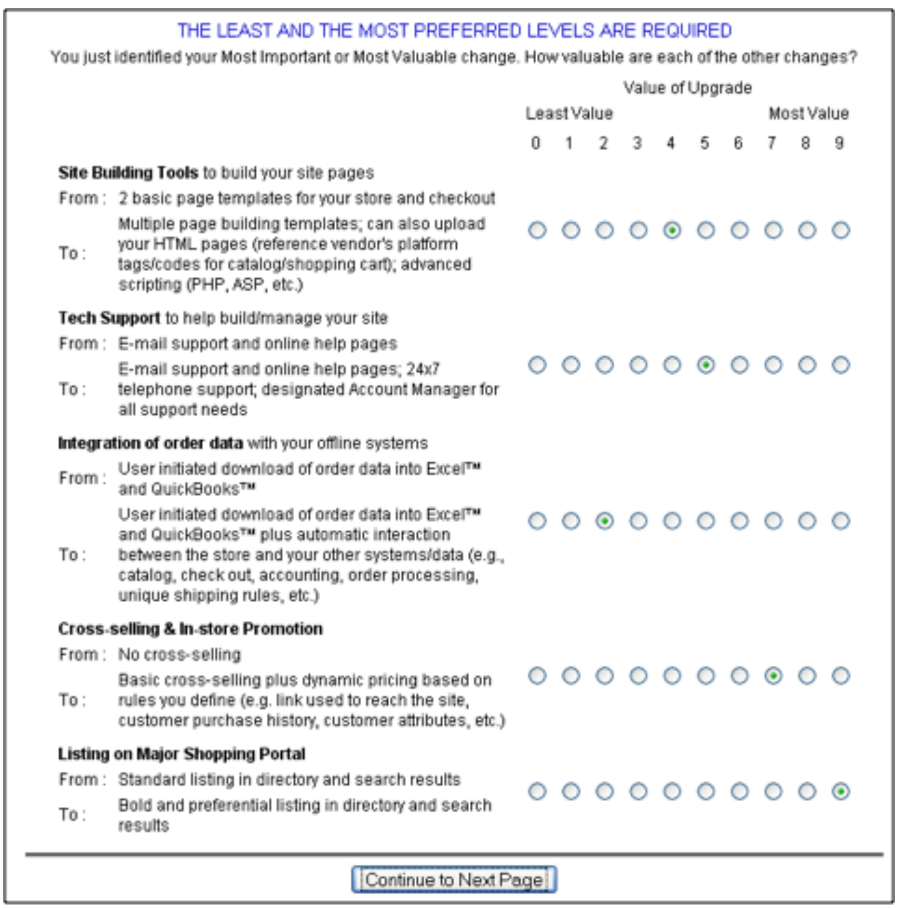
FIGURE 9: Importance Measure Using Constant Sum Evaluation



THE LEAST AND THE MOST PREFERRED LEVELS ARE REQUIRED

You just identified your Most Important or Most Valuable change. How valuable are each of the other changes?

Value of Upgrade (Least Value 0 – Most Value 9)

	0	1	2	3	4	5	6	7	8	9
Site Building Tools to build your site pages From: 2 basic page templates for your store and checkout To: Multiple page building templates; can also upload your HTML pages (reference vendor's platform tags/codes for catalog/shopping cart); advanced scripting (PHP, ASP, etc.)	○	○	○	○	◉	○	○	○	○	○
Tech Support to help build/manage your site From: E-mail support and online help pages To: E-mail support and online help pages; 24x7 telephone support; designated Account Manager for all support needs	○	○	○	○	○	◉	○	○	○	○
Integration of order data with your offline systems From: User initiated download of order data into Excel™ and QuickBooks™ To: User initiated download of order data into Excel™ and QuickBooks™ plus automatic interaction between the store and your other systems/data (e.g., catalog, check out, accounting, order processing, unique shipping rules, etc.)	○	○	◉	○	○	○	○	○	○	○
Cross-selling & In-store Promotion From: No cross-selling To: Basic cross-selling plus dynamic pricing based on rules you define (e.g. link used to reach the site, customer purchase history, customer attributes, etc.)	○	○	○	○	○	○	○	◉	○	○
Listing on Major Shopping Portal From: Standard listing in directory and search results To: Bold and preferential listing in directory and search results	○	○	○	○	○	○	○	○	○	◉

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As with all conjoint models, individual attribute level utility values can be weighted by the individual attribute importance value, and then summed to report total average utility values. At this point, the individual utility values can be input into simulations to obtain a score for any hypothetical product profile of interest.

This simple self-reporting approach is easier for the respondent to complete and is straightforward in terms of determining the importance or desirability of attributes and attribute levels (Srinivasan, 1997).

An easy to use online implementation of the self-explicated model is part of the Qualtrics online survey software. For this implementation, the conjoint analysis is automatically developed after the attribute level descriptors are entered into the question builder.

Table 18 shows how the collected data appears, followed by an importance weighting using the constant sum data.

TABLE 18: Raw Data for Respondent Attribute Evaluations and Importance Weights

Raw Data for Respondents 1 through 3																		
	Raw Data for Respondents 1 through 3																	
	Attribute 1			Attribute 2			Attribute 3		Attribute 4			Attribute 5				Attribute 6		
Respondent 1	0	5	10	0	6	10	0	10	0	10	5	-1	0	6	10	7	0	10
Respondent 2	10	3	0	2	10	0	10	0	1	10	0	3	10	-1	0	10	1	0
Respondent 3	0	5	10	10	5	0	10	0	3	10	0	0	6	7	10	5	10	0
	Constant Sum Attribute Weights																	
	Attribute 1			Attribute 2			Attribute 3		Attribute 4			Attribute 5				Attribute 6		
Weights Respondent 1	0.30			0.05			0.05		0.10			0.10				0.40		
Weights Respondent 2	0.10			0.10			0.10		0.30			0.20				0.20		
Weights Respondent 3	0.15			0.15			0.20		0.15			0.20				0.15		
	Weighted Data for Respondents 1 through 3																	
	Attribute 1			Attribute 2			Attribute 3		Attribute 4			Attribute 5				Attribute 6		
Weighted Data Respondent 1	0.00	1.50	3.00	0.00	0.30	0.50	0.00	0.50	0.00	1.00	0.50	-0.10	0.00	0.60	1.00	2.80	0.00	4.00
Weighted Data Respondent 2	1.00	0.30	0.00	0.20	1.00	0.00	1.00	0.00	0.30	3.00	0.00	0.60	2.00	-0.20	0.00	2.00	0.20	0.00
Weighted Data Respondent 3	0.00	0.75	1.50	1.50	0.75	0.00	2.00	0.00	0.45	1.50	0.00	0.00	1.20	1.40	2.00	0.75	1.50	0.00

When the weighted data for all respondents is summed and averaged, the following table can be produced, showing the average utility scores for each feature level.

TABLE 19: Average Utility Values Summed Over All Respondents

Average Utility Scores for Feature Levels		Summary Analysis All Respondents			
		None	+HTML	+PHP	
Programming Language	Avg Utility	0.98	3.72	4.67	
		e-mail	+ Phone	+Acct.Mgr	
Technical Support	Avg Utility	1.15	3.39	2.68	
		Download	+Database		
Data Access	Avg Utility	0.91	3.18		
		None	+Cart	+Database	
Commerce	Avg Utility	0.49	2.49	3.36	
		None	+CustInfo	+CustAcc	Personalized
Design	Avg Utility	0.34	2.44	2.66	4.55
		Std.	+Bold	+Preferred	
Credit Card Logo	Avg Utility	1.01	2.70	4.79	

CONJOINT SIMULATORS

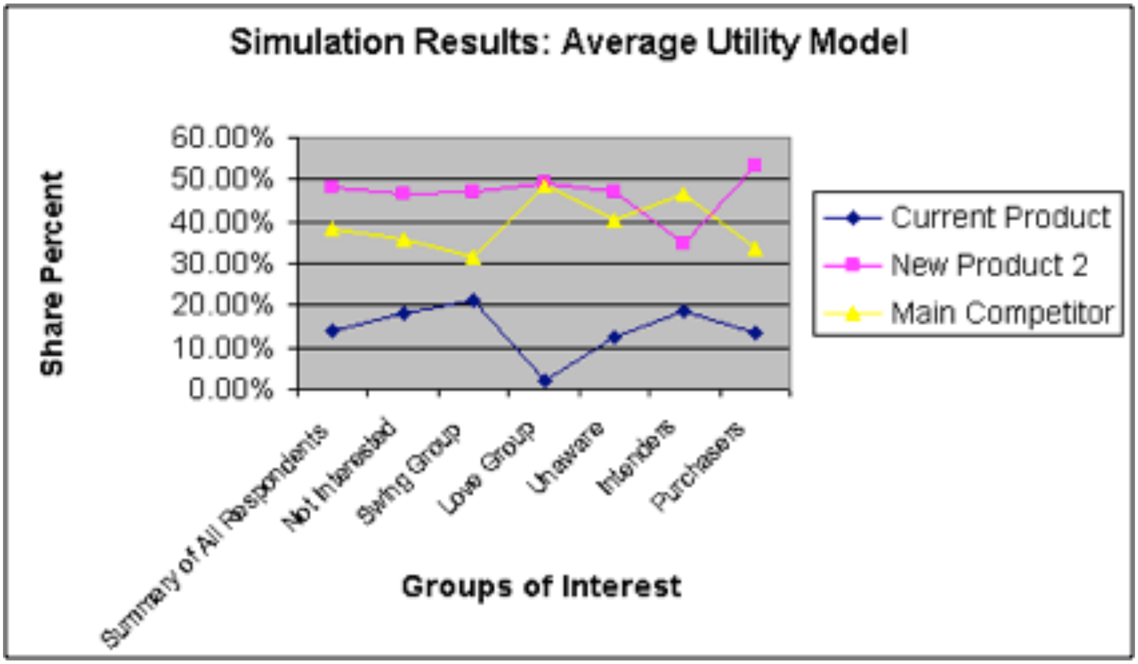
At this point in the conjoint analysis, the "conjoint" portion is completed. The simulation analysis to test the preference for new attributes may begin. As explained above, simulators simply use a rule for tabulating votes for the product concepts being tested in the simulator. The objective of the simulator is to create a "market environment" that tests preferences between options being tested. One would obviously create a simulation of the current market and then adjust the simulator so that it produces results that mirror the current market share conditions. Next, a new product or changes to the current product would be entered into the simulator to test the impact of such changes.

The simulation procedure involves specifying a decision rule as to how respondents decide which product to purchase (maximum utility or average utility model); creating a market simulation that represents today's market; "dialing in" the simulation so the choice shares replicate today's market share; introducing a set of product changes, new products, or competitive reactions into the simulator to estimate the new choice (market) shares. After these analysis steps have been completed, simulations can be completed for specific market segments.

TABLE 20: Example Conjoint Simulator Analysis

				Weighting Factor	Pricing Information:			Actual Revenue
			Revenue	0.7	Inexpensive	Moderate	Expensive	18.69
			Preference	0.3	$32.00	$51.00	$79.00	145.41
Conjoint Profile Number	Listing Fee %	Commission Fee %	Fixt Cost $/mo	Weighted Sum of Preference and Revenue Higher=Better	Preference Order	**Rank Order Lowest=Best** Revenue Order	Total Rank Order	Actual Monthly Revenue for Profile
1	1	3.5	49	2.41	1	27	27	109.87
2	1.5	3.5	49	3.46	3	22	18	128.89
3	2	3.5	49	4.51	7	13	9	147.91
4	1	3.5	59	2.62	4	25	25	119.87
5	1.5	3.5	59	3.67	9	17	16	138.89
6	2	3.5	59	4.72	15	8	7	157.91
7	1	3.5	69	2.83	12	21	22	129.87
8	1.5	3.5	69	3.88	18	12	13	148.89
9	2	3.5	69	4.92	23	4	4	167.91

FIGURE 10: Simulation Analysis for Market Segments



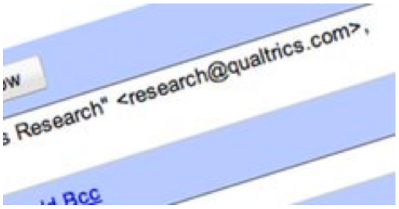
Online conjoint analysis is especially appealing because graphic images, video and audio clips can be presented to add realism and authenticity to the choice decision. Furthermore, blocks of questions and individual attribute levels can be randomized to control for presentation order bias. This added realism and control increases the accuracy of the choice share estimates.

Conjoint analysis is a powerful tool that determines what actually drives customers' decision to purchase and where their preferences lie. Proper experimental designs combined with the precise estimates of utilities derived from Hierarchical Bayes Analysis yields an enlightened view at how the various possible configurations of your product are viewed.

Conjoint analysis can be a complex process intensive in mathematical and statistical theory.

The good news is that the Qualtrics team of mathematicians and statisticians specialize in conjoint analysis. Yes, we have a deep understanding of the concepts that conjoint analysis is founded on. But we pride ourselves on our ability to explain the process and output so a manager can develop and execute a plan. The team is experienced in all types of conjoint analysis and has the expertise to use Qualtrics to run your conjoint projects. We will lead you through the process… from defining the features and levels of the conjoint to the interpretation and implementation of the results.

The Qualtrics Conjoint Team Can Help You!



All types of conjoint analysis

- Conjoint survey builds
- What-If simulators
- Conjoint analysis findings
- Executive reports

The Qualtrics conjoint team is dedicated to making you a rock star within your company and will go above and beyond in every aspect of your conjoint project.