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RESEARCH PAPER SERIES

Interpreting Conjoint Analysis Data

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Conjoint analysis provides a number of outputs for analysis including: part worth utilities (or counts), importances, shares of preference and purchase likelihood simulations. This article discusses these measures and gives guidelines for interpreting results and presenting findings to management.

Before focusing on conjoint data, we'll review some fundamentals for interpreting quantitative data. The definitions below are adapted from *Statistics for Modern Business Decisions*, Fourth Edition, by Lawrence L. Lapin.

The Nature of Quantitative Data:

There are four general types of quantitative data:

1) **Nominal data** are those wherein the numbers represent categories, such as 1=Male, 2=Female; or 20=Italy, 21=Canada, 22=Mexico. It is not appropriate to perform mathematical operations such as addition or subtraction with nominal data, or to interpret the relative size of the numbers.

2) **Ordinal data** commonly occur in market research in the form of rankings. If a respondent ranks five brands from best "1" to worst "5," we know that a 1 is preferred to a 2. An example of an ordinal scale is the classification of the strength of tornados. A category 3 tornado is stronger and more damaging than a category 2 tornado. It is generally not appropriate to apply arithmetic operations to ordinal data. The difference in strength between a category 1 and 2 tornado is not necessarily equal to the difference in strength between a category 2 and a 3. Nor can we say that a category 2 is twice as strong as a category 1 tornado.

3) **Interval data** permit the simple operations of addition and subtraction. The rating scales so common to market research provide interval data. The Celsius scale also is interval scaled. Each degree of temperature represents an equal heat increment. It takes the same amount of heat to raise the temperature of a cup of water from 10 to 20 degrees as from 20 to 30 degrees. The zero point is arbitrarily tied to the freezing point of distilled water. Sixty degrees is not twice as hot as 30 degrees, and the ratio 60/30 has no meaning.

4) **Ratio data** permit all basic arithmetic operations, including division and multiplication. Examples of ratio data include weight, height, time increments, revenue and profit. The zero point is meaningful in ratio scales. The difference between 20 and 30 kilograms is the same as the difference between 30 and 40 kilograms, and 40 kilograms is twice as heavy as 20 kilograms.

Conjoint Utilities (Part Worths):

Conjoint part worths are scaled to an arbitrary additive constant within each attribute and are **interval data**. The arbitrary origin on the scaling within each attribute results from dummy coding in the design matrix. When using a specific kind of dummy coding called "effects coding," utilities are scaled to sum to 0 within each attribute. A plausible set of part worth utilities for miles per gallon might look like:

30 MPG	-1.0
40 MPG	0.0
50 MPG	1.0

Just because 30 MPG received a negative utility value does not mean that this level was unattractive. In fact, 30 MPG may have been very acceptable to all respondents. But (all else being equal) 40 MPG and 50 MPG are better. The utilities are scaled to sum to 0 within each attribute, so 30 MPG must receive a negative utility value. Other kinds of dummy coding arbitrarily set the part worth of one level within each attribute to zero and estimate the remaining levels as contrasts with respect to zero. Again, the same cautions regarding interpretation apply.

Whether we multiply all the part worth utilities by a positive constant or add a constant to each level within a study, the interpretation is the same. Suppose we have two attributes with the following utilities:

Blue	30	Brand A	20
Red	20	Brand B	40
Green	10	Brand C	10

The increase in preference from Green to Blue (20 points) is equal to the increase in preference between Brand A and Brand B (also 20 points). However, due to the arbitrary origin within each attribute, we cannot directly compare values between attributes to say that Red (20 utiles) is preferred equally to Brand A (20 utiles). And even though we are comparing utilities within the same attribute, we cannot say that Blue is three times as preferred as Green (30/10). Interval data do not support ratio operations.

Counts:

When using Choice-Based Conjoint (CBC), the researcher can analyze the data by counting the number of times an attribute level was chosen relative to the number of times it was available for choice. In the absence of prohibitions (orthogonal plans), counts proportions are closely related to conjoint utilities. If prohibitions were used, counts are biased. Counts are **ratio data** when compared within the *same* attribute. Consider the following counts proportions:

Blue	0.50	Brand A	0.40
Red	0.30	Brand B	0.50
Green	0.20	Brand C	0.10

We can say that Brand A was chosen 4 times as often as Brand C (.40/.10). As with conjoint utilities, we cannot report that Brand A is preferred to Red.

Conjoint Importances:

Sometimes we want to characterize the relative importance of each attribute. We do this by considering how much difference each attribute could make in the total utility of a product. That difference is the range in the attribute's utility values. We percentage those ranges, obtaining a set of attribute importance values that add to 100, as follows:

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                              Range   Percent Importance
Brand (B - C)        60 - 20 = 40         26.7
Color (Red - Pink)   20 -  0 = 20         13.3
Price ($50 - $100)   90 -  0 = 90         60.0
                               ----        ----
                               150        100.0
```

For this respondent, the importance of Brand is 26.7%, the importance of Color is 13.3%, and the importance of Price is 60%. Importances depend on the particular attribute levels chosen for the study. For example, with a narrower range of prices, Price would have been less important.

When summarizing attribute importances for groups, it is best to compute importances for respondents individually and then average them, rather than computing importances from average utilities. For example, suppose we were studying two brands, Coke and Pepsi. If half of the respondents preferred each brand, the average utilities for Coke and Pepsi would be tied, and the importance of Brand would appear to be zero!

When calculating importances from CBC data, we suggest using utilities resulting from Latent Class (with multiple segments) or HB estimation, if there are attributes on which respondents disagree about preference order.

Importances are **ratio data**. An attribute with an importance of 20 (20%) is twice as important as an attribute with an importance of 10.

Shares of Preference:

Conjoint part worths and importances are often very difficult for non-researchers to understand. Many presentations to management have gone awry when the focus of the conversation turned to explaining how part worths were estimated and, given the scaling resulting from dummy coding, how one can or cannot interpret them.

We suggest using market simulators to make the most of your data and for communicating the results of the conjoint analysis project to non-researchers. When two or more products are specified in the market simulator, we can estimate what percent of the respondents would prefer each product. Shares of preference are ratio data. Even so, we recognize that noise inherent in the data, the exponent (scaling multiplier if using logit simulations) and the simulation model used can dramatically affect the scaling of shares of preference. A product that captures twice as much share as another in a first choice simulation (or using a large exponent) may capture considerably less than twice the share using the share of preference (probabilistic) model.

Purchase Likelihoods:

During some conjoint interviews such as ACA or traditional full-profile ratings-based conjoint (CVA), respondents may be asked to rate individual products on a 0 to 100 point purchase likelihood scale. This is very helpful to gauge respondent interest in the product, and for scaling the data for use in purchase likelihood simulations. Once we have scaled conjoint data to reflect purchase likelihoods, we can predict how respondents would have rated any combination of attributes included in the study in terms of purchase likelihood.

Purchase likelihoods should not be considered as strictly **ratio data**. A respondent may not *truly* be twice as likely to purchase a product he rated a 50 versus another he rated a 25. Even so, it is quite common to state that a product with a purchase likelihood of 55 represents a 10% relative increase in purchase likelihood over a product that received a 50.