Block 19: Conjoint analysis

(Activity solutions can be found at the end of the document.)

Conjoint analysis attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the levels of attributes. The participants are presented with stimuli which consist of combinations of attribute levels and asked to evaluate these stimuli in terms of their desirability. Conjoint procedures attempt to *assign values to the levels of each attribute* so that the resulting values or utilities attached to the stimuli match, as closely as possible, the input evaluations provided by the participants.

Learning Objectives

- Discuss the basic concepts of conjoint analysis and discuss its various applications
- Describe the procedure for conducitng conjoint analysis, including formulating the problem, constructing the stimuli, deciding the form of input data, selecting a conjoint analysis procedure, interpreting results and assessing reliability and validity.

Reading List

Malhotra, N.K., D. Nunan and D.F. Birks. *Marketing Research: An Applied Approach.* (Pearson, 2017) 5th edition [ISBN 9781292103129] Chapter 26 (from page 776).

19.1 Conjoint analysis

For each section of *Conjoint analysis*, use the LSE ELearning resources to test your knowledge with the Key terms and concepts flip cards.

Statistics and terms associated with conjoint analysis

Part-worth functions: The part-worth functions, or utility functions, describe the *utility* consumers attach to the levels of each attribute.

Relative importance weights: The relative importance weights are estimated and indicate which attributes are important in influencing consumer choice.

Attribute levels: The attribute levels denote the values assumed by the attributes.

Full profiles: Full profiles or complete profiles of brands are constructed in terms of all the attributes by using the attribute levels specified by the design.

Pairwise tables: In pairwise tables, the participants evaluate two attributes at a time until all the required pairs of attributes have been evaluated.

The process to conduct conjoint analysis is as follows:

Formulate the problem

⇓⇓

Construct the stimuli

⇓⇓

Decide on the form of input data

⇓⇓

Select a conjoint analysis procedure

⇓⇓

Interpret the results

⇓⇓

Assess the reliability and validity

Conducting conjoint analysis

Conducting conjoint analysis

Identify the attributes and attribute levels to be used in constructing the stimuli. The attributes selected should be salient in influencing consumer preference and choice, and should be *actionable*. A typical conjoint analysis study involves *six or seven attributes*. At least three levels should be used, unless the attribute naturally occurs in binary form (two levels). The researcher should take into account the attribute levels prevalent in the marketplace and the objectives of the study.

In the **pairwise approach**, also called *two-factor evaluations*, the participants evaluate two attributes at a time until all the possible pairs of attributes have been evaluated.

In the **full-profile approach**, also called *multiple-factor evaluations*, full or complete profiles of brands are constructed for all the attributes. Typically, each profile is described on a separate index card.

Table 26.2 of the textbook provides an example of boot attributes and levels. An example of a full-profile approach to collecting conjoint data is shown in Table 26.3 of the textbook. An example of a pairwise approach to collecting conjoint data is shown in Figure 26.9 of the textbook.

For **non-metric data**, the participants are typically required to provide rank-order evaluations.

In **metric form**, the participants provide ratings, rather than rankings. In this case, the judgements are typically made independently. In recent years, the use of ratings has become increasingly common.

The *dependent variable is usually preference or intention to buy*. However, the conjoint methodology is flexible and can accommodate a range of other dependent variables, including actual purchase or choice.

In evaluating boot profiles, participants were required to provide preference. Consider the hypothetical results below for a participant:

Profile number	**Attribute levels**			**Preference rating**
	Upper	**Country**	**Price**	

1	1	1	1	9
2	1	2	2	7
3	1	3	3	5
4	2	1	2	6
5	2	2	3	5
6	2	3	1	6
7	3	1	3	5
8	3	2	1	7
9	3	3	2	6

Activity 19.1

What is involved in formulating a conjoint analysis problem?

Activity 19.2

Describe the full-profile approach to constructing stimuli in conjoint analysis.

Activity 19.3

Describe the pairwise approach to constructing stimuli in conjoint analysis.

The conjoint analysis model

The basic **conjoint analysis model** may be represented by the following formula:

$$U(X) = \sum_{i=1}^{m} \sum_{j=1}^{k_i} a_{ij}\, x_{ij}$$

where:

- U(X) = the overall utility of an alternative
- a_{ij} = the part-worth contribution or utility associated with the *j*th level (j=1, 2, …, k_i) of the *i*th attribute (i=1, 2, …, m)

- x_{ij} = 1 if the *j*th level of the *i*th attribute is present, and 0 otherwise
- k_i = the number of levels of attribute ii
- m = the number of attributes.

The *importance of an attribute*, I_i, is defined in terms of the *range of the part-worths*, a_{ij}, across the levels of that attribute:

Ii=(max(αij)−min(αij))for each *i*.

The attribute's importance is *normalised* to ascertain its importance relative to other attributes, Wi, where:

$W_i = \frac{I_i}{\sum_{i=l}^{m} I_i}$ such that $\sum_{i=l}^{m} W_i = 1$.

The simplest estimation procedure, and one which is gaining in popularity, is **dummy variable regression**. If an attribute has k_i levels, it is coded in terms of k_i−1 dummy variables.

The *estimated model* may be represented as:

$$U = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \hat{\beta}_4 X_4 + \hat{\beta}_5 X_5 + \hat{\beta}_6 X_6$$

where:

- $X_1 X_2$ = dummy variables representing uppers
- $X_3 X_4$ = dummy variables representing country
- $X_5 X_6$ = dummy variables representing price.

For uppers, for example, the attribute levels were coded as follows:

	X_1	X_2
Level 1	**1**	**0**
Level 2	**0**	**1**
Level 3	**0**	**0**

Table 26.5 of the textbook shows the boot data coded for dummy variable regression. The data can be found in the file *Conjoint_analysis_example.sav*.

The levels of the other attributes were coded similarly. The parameters were estimated as follows:

$$\hat{\beta}_0 = 4.22, \hat{\beta}_1 = 1.000, \hat{\beta}_2 = -0.333, \hat{\beta}_3 = 1.000, \hat{\beta}_4 = 0.667, \hat{\beta}_5 = 2.333, \widehat{\beta}_6 = 1.333$$

Given the dummy variable coding, in which level 3 is the base level, the *coefficients may be related to the part-worths*:

$$\alpha_{11} - a_{13} = \hat{\beta}_1 \quad \text{and} \quad a_{12} - a_{13} = \hat{\beta}_2.$$

To solve for the part-worths, an *additional constraint* is necessary:

$$\alpha_{11} + a_{12} + a_{13} = 0$$

These equations for the first attribute, uppers, are:

$\alpha_{11} - a_{13} = 1.000,\ \ a_{12} - a_{13} = -0.333,\ \ a_{11} + a_{12} + a_{13} = 0$

Solving these equations, we get:

$$a_{11} = 0.778, a_{12} = -0.556, \qquad a_{13} = -0.222$$

The part-worths for other attributes can be estimated similarly. For the second attribute, country, we have:

$$a_{21} - a_{23} = \hat{\beta}_3, \quad a_{22} - a_{23} = \hat{\beta}_4, \quad a_{21} + a_{22} + a_{23} = 0$$

For the third attribute, price, we have:

$$a_{31} - a_{33} = \hat{\beta}_5, \quad a_{32} - a_{33} = \hat{\beta}_6, \quad a_{31} + a_{32} + a_{33} = 0$$

The alpha coefficients can be found usign Excel's *Solver*. An example can be found in the file *Conjoint_analysis_Solver_example.xlsx* or can be viewed in the table below.

Estimates of regression model coefficients

beta_0	4.222	alpha_11 - alpha_13 =	1	alpha_11=	0.777667		
beta_1	1	alpha_12 - alpha_13 =	-0.333	alpha_12=	-0.55533		
beta_2	-0.333			alpha_13=	-0.22233	Sum =	0
beta_3	1	alpha_21 - alpha_23 =	1				
beta_4	0.667	alpha_22 - alpha_23 =	0.667	alpha_21=	0.444333		
beta_5	2.333			alpha_22=	0.111333		
beta_6	1.333	alpha_31 - alpha_33 =	2.333	alpha_23=	-0.55567	Sum =	0
		alpha_32 - alpha_33 =	1.333001				
				alpha_31=	1.111		
				alpha_32=	0.111001		
				alpha_33=	-1.222	Sum =	0

The relative importance weights are calculated based on ranges of part-worths as follows:

sum of ranges of part-worths=(0.778−(−0.556))+(0.445−(−0.556))+(1.111−(−1.222))=4.668. Hence:

- Relative importance of uppers =1.334/4.668=0.286
- Relative importance of country =1.001/4.668=0.214=
- Relative importance of price =2.333/4.668=0.500.

For interpreting the results, it is helpful to *plot the part-worth functions*. The utility values have only interval-scale properties and their origin is arbitrary. The relative importance of attributes should be considered. Figure 26.10 of the textbook plots part-worth functions for the boots example.

Activity 19.4
How can regression analysis be used for analysing conjoint data?

Activity 19.5
Graphically, illustrate what is meant by part-worth functions.

The conjoint analysis model
To watch the videos, go to *Block 19 / 3. The Conjoint analysis model*

Dummy variable regression in SPSS (Video)
Solver in Excel (Video)

Assess reliability and validity
The **goodness-of-fit** of the estimated model should be evaluated. For example, if dummy variable regression is used, the value of R^2 will indicate the extent to which the model fits the data.

Test-retest reliability can be assessed by obtaining a few replicated judgements later in data collection.

The evaluations for the holdout or validation stimuli can be predicted by the estimated part-worth functions. The predicted evaluations can then be correlated with those obtained from the participants to determine internal validity.

If an aggregate-level analysis has been conducted, the estimation sample can be split in several ways and conjoint analysis conducted on each subsample. The results can be compared across subsamples to *assess the stability of conjoint analysis solutions*.

Activity 19.6
What procedures are available for assessing the reliability and validity of conjoint analysis results?

Assumptions and limitations of conjoint analysis
Conjoint analysis assumes that the important attributes of a product can be identified. It assumes that consumers evaluate the choice alternatives in terms of these attributes and make trade-offs. The trade-off model may not be a good representation of the choice process.

Another limitation is that data collection may be complex, particularly if a large number of attributes is involved and the model must be estimated at the individual level. The part-worth functions are not unique.

Hybrid conjoint analysis
Hybrid conjoint analysis uses hybrid models which have been developed to serve two main purposes:

- Simplify the data collection task by imposing less of a burden on each participant
- Permit the estimation of selected interactions (at the subgroup level) as well as all main (or simple) effects at the individual level.

In the hybrid approach, the participants evaluate a limited number, generally no more than nine, conjoint stimuli, such as full profiles. These profiles are drawn from a large master design and different participants evaluate different sets of profiles so that, over a group of participants, all the profiles of interest are evaluated.

In addition, participants directly evaluate the relative importance of each attribute and desirability of the levels of each attribute.

By combining the direct evaluations with those derived from the evaluations of the conjoint stimuli, it is possible to estimate a model at the aggregate level and still retain some individual differences.

Discussion forum and activity

To access the solutions to these questions and case study, click here to access the printable Word document or click here to go to LSE's Elearning resources.

Activity 1

Identify two market research problems where conjoint analysis could be applied. Explain how you would use this technique in these situations.

Learning outcomes checklist

Use this to assess your own understanding of the chapter. You can always go back and amend the checklist when it comes to revision!

- Discuss the basic concepts of conjoint analysis and discuss its various applications
- Describe the procedure for conducitng conjoint analysis, including formulating the problem, constructing the stimuli, deciding the form of input data, selecting a conjoint analysis procedure, interpreting results and assessing reliability and validity.

Block 19: Conjoint analysis

Solution to Exercise 19.1

It involves the following two steps.

- Identification of the salient attributes through discussions with management, research or surveys. Generally, six or seven attributes are involved in a problem.
- Identification of the level of the attributes prevalent in the market and conforming to the objectives of the study. Care should be taken to select only those attributes and their levels which are actionable. These attributes and levels are used for constructing the stimuli to be used in the conjoint evaluation task.

Solution to Exercise 19.2

In the full-profile approach, complete profiles of brands are constructed in terms of all the attributes, with each profile being described on a separate index card.

Generally, two sets of data are obtained, the estimation sample and the holdout sample. The former is used for the calculation of the part-worth or utility functions for the attribute levels, whereas the latter is used for assessing reliability and validity.

Solution to Exercise 19.3

In the pairwise approach, the participants evaluate the attribute combinations, two at a time until all possible pairwise comparisons have been made. For each pair, the participants evaluate all the combinations of levels of both the attributes, which are presented in a matrix form.

In this method, it is easier for the participants to provide judgements, as compared to the full-profile approach, but it requires the participant to make more evaluations.

Solution to Exercise 19.4

How can regression analysis be used for analysing conjoint data?

Regression analysis can be used in conjoint analysis by applying dummy variable regression. In this method, the predictor variables consist of dummy variables for the attribute levels. If an attribute has k levels it is coded with $k - 1$ dummy variables. For metric data, the ratings (assumed to be interval-scaled) form the dependent variable. If the data are non-metric in nature, the rankings can be converted to a binary form (0 or 1) after making pairwise comparisons between brands. Here the predictor variables represent the differences in the attribute levels of the brands being compared.

Solution to Exercise 19.5

Part-worth or utility functions describe the utility which consumers attach to the levels of each attribute. Graphically, this may be represented by plotting the different part-worth values against the corresponding levels of a particular attribute.

Figure 26.10 of the textbook plots part-worth functions for the in-chapter boots example. It can be seen from the top figure that while evaluating boots, the participant has the greatest preference for the leather uppers (‘boot upper’ being the attribute and ‘leather’ being the level of this attribute). Similarly, in the bottom figure, the price of 200 euros (a level of the attribute ‘price’) has the lowest utility or part-worth value.

Solution to Exercise 19.6

Several procedures are available for this purpose.

- The value of R^2 provides an indication of the goodness-of-fit of the estimated model (in the case of dummy variable regression).
- If an aggregate level analysis has been conducted, the estimation sample may be split in several ways and a comparison of conjoint analysis results conducted on these subsamples may help assess the stability of the solutions.
- The internal validity can be determined by comparing the responses of the participants and the predicted evaluations (for the holdout stimuli) by the estimated part-worth functions.
- The test-retest reliability can be tested by comparing the evaluations of certain selected stimuli of the participant at two different points of time during an interview.

Commentary on Exercise 1

Some possible examples in which conjoint analysis can be used are the following.

- Determining the relative importance of attributes in the consumer choice process.
- Estimating market shares of brands which differ in terms of attribute levels.
- Determining the composition of the most preferred brand.
- Segmenting the market based on similarity of preferences for attribute levels.