Whereas, so far, we have considered only quantitative data, qualitative data can also be mapped using procedures such as correspondence analysis.

CORRESPONDENCE ANALYSIS

correspondence analysis A MDS technique for scaling qualitative data that scales the rows and columns of the input contingency table in corresponding units so that each can be displayed in the same low-dimensional space.

Correspondence analysis is an MDS technique for scaling qualitative data in marketing research. The input data are in the form of a contingency table indicating a qualitative association between the rows and columns. Correspondence analysis scales the rows and columns in corresponding units, so that each can be displayed graphically in the same low-dimensional space. These spatial maps provide insights into (1) similarities and differences within the rows with respect to a given column category; (2) similarities and differences within the column categories with respect to a given row category; and (3) relationship among the rows and columns.[12]

The interpretation of results in correspondence analysis is similar to that in principal components analysis (Chapter 19), given the similarity of the algorithms. Correspondence analysis results in the grouping of categories (activities, brands, or other stimuli) found within the contingency table, just as principal components analysis involves the grouping of the variables. The results are interpreted in terms of proximities among the rows and columns of the contingency table. Categories that are closer together are more similar in underlying structure.

The advantage of correspondence analysis, as compared to other multidimensional scaling techniques, is that it reduces the data-collection demands imposed on the respondents, because only binary or categorical data are obtained. The respondents are merely asked to check which attributes apply to each of several brands. The input data are the number of "yes" responses for each brand on each attribute. The brands and the attributes are then displayed in the same multidimensional space. The disadvantage is that between-set (i.e., between column and row) distances cannot be meaningfully interpreted. Correspondence analysis is an exploratory data analysis technique that is not suitable for hypothesis testing.[13]

MDS, including correspondence analysis, is not the only procedure available for obtaining perceptual maps. Two other techniques that we have discussed before, discriminant analysis (Chapter 18) and factor analysis (Chapter 19), can also be used for this purpose.

RELATIONSHIP AMONG MDS, FACTOR ANALYSIS, AND DISCRIMINANT ANALYSIS

If the attribute-based approaches are used to obtain input data, spatial maps can also be obtained by using factor or discriminant analysis. In this approach, each respondent rates n brands on m attributes. By factor analyzing the data, one could derive for each respondent, n factor scores for each factor, one for each brand. By plotting brand scores on the factors, a spatial map could be obtained for each respondent. If an aggregate map is desired, the factor score for each brand for each factor can be averaged across respondents. The dimensions would be labeled by examining the factor loadings, which are estimates of the correlations between attribute ratings and underlying factors.

The goal of discriminant analysis is to select the linear combinations of attributes that best discriminate between the brands or stimuli. To develop spatial maps by means of discriminant analysis, the dependent variable is the brand rated and the independent or predictor variables are the attribute ratings. A spatial map can be obtained by plotting the discriminant scores for the brands. The discriminant scores are the ratings on the perceptual dimensions, based on the attributes that best distinguish the brands. The dimensions can be labeled by examining the discriminant weights, or the weightings of attributes that make up a discriminant function or dimension.[14]

BASIC CONCEPTS IN CONJOINT ANALYSIS

conjoint analysis A technique that attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the levels of attributes.

Conjoint analysis attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the levels of attributes. This information is derived from consumers' evaluations of brands, or brand profiles composed of these attributes and their levels. The respondents are presented with stimuli that consist of combinations of attribute levels. They are 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 respondents. The underlying assumption is that any set of stimuli, such as products, brands, or stores, is evaluated as a bundle of attributes.[15]

Like multidimensional scaling, conjoint analysis relies on respondents' subjective evaluations. However, in MDS, the stimuli are products or brands. In conjoint analysis, the stimuli are combinations of attribute levels determined by the researcher. The goal in MDS is to develop a spatial map depicting the stimuli in a multidimensional perceptual or preference space. Conjoint analysis, on the other hand, seeks to develop the part-worth or utility functions describing the utility consumers attach to the levels of each attribute. The two techniques are complementary.

Conjoint analysis has been used in marketing for a variety of purposes, including:

- Determining the relative importance of attributes in the consumer choice process. A standard output from conjoint analysis consists of derived relative importance weights for all the attributes used to construct the stimuli used in the evaluation task. The relative importance weights indicate which attributes are important in influencing consumer choice.
- Estimating market share of brands that differ in attribute levels. The utilities derived from conjoint analysis can be used as input into a choice simulator to determine the share of choices, and hence the market share, of different brands.
- Determining the composition of the most preferred brand. The brand features can be varied in terms of attribute levels and the corresponding utilities determined. The brand features that yield the highest utility indicate the composition of the most preferred brand.
- Segmenting the market based on similarity of preferences for attribute levels. The part-worth functions derived for the attributes may be used as a basis for clustering respondents to arrive at homogeneous preference segments.[16]

Applications of conjoint analysis have been made in consumer goods, industrial goods, financial, and other services. Moreover, these applications have spanned all areas of marketing. A survey of conjoint analysis reported applications in the areas of new product/concept identification, competitive analysis, pricing, market segmentation, advertising, and distribution.[17]

STATISTICS AND TERMS ASSOCIATED WITH CONJOINT ANALYSIS

The important statistics and terms associated with conjoint analysis include:

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 respondents evaluate two attributes at a time until all the required pairs of attributes have been evaluated.

Cyclical designs. Cyclical designs are designs employed to reduce the number of paired comparisons.

Fractional factorial designs. Fractional factorial designs are designs employed to reduce the number of stimulus profiles to be evaluated in the full profile approach.

Orthogonal arrays. Orthogonal arrays are a special class of fractional designs that enable the efficient estimation of all main effects.

Internal validity. This involves correlations of the predicted evaluations for the holdout or validation stimuli with those obtained from the respondents.

CONDUCTING CONJOINT ANALYSIS

Figure 21.8 lists the steps in conjoint analysis. Formulating the problem involves identifying the salient attributes and their levels. These attributes and levels are used for constructing the stimuli to be used in a conjoint evaluation task. The respondents rate or rank the stimuli using a suitable scale and the data obtained are analyzed. The results are interpreted and their reliability and validity assessed.

Formulate the Problem

In formulating the conjoint analysis problem, the researcher must identify the attributes and attribute levels to be used in constructing the stimuli. Attribute levels denote the values assumed by the attributes. From a theoretical standpoint, the attributes selected should be salient in influencing consumer preference and choice. For example, in the choice of an automobile brand, price, gas mileage, interior space, and so forth should be included. From a managerial perspective, the attributes and their levels should be actionable. To tell a manager that consumers prefer a sporty car to one that is conservative looking is not helpful, unless sportiness and conservativeness are defined in terms of attributes over which a manager has control. The attributes can be identified through discussions with management and industry experts, analysis of secondary data, qualitative research, and pilot surveys. A typical conjoint analysis study involves six or seven attributes.

Once the salient attributes have been identified, their appropriate levels should be selected. The number of attribute levels determines the number of parameters that will be estimated and also influences the number of stimuli that will be evaluated by the respondents. To minimize the respondent evaluation task, and yet estimate the parameters with reasonable accuracy, it is desirable to restrict the number of attribute levels. The utility or part-worth function for the levels of an attribute may be nonlinear. For example, a consumer may prefer a medium-sized car to either a small or large one. Likewise, the utility for price may be nonlinear. The loss of utility in going from a low to a medium price may be much smaller than the loss in utility in going from a medium to a high price. In these cases, at least three levels should be used. Some attributes, though, may naturally occur in binary form (two levels): a car does or does not have a sunroof.

The attribute levels selected will affect the consumer evaluations. If the price of an automobile brand is varied at \$10,000, \$12,000, and \$14,000, price will be relatively unimportant. On the other hand, if the price is varied at \$10,000, \$20,000, and \$30,000, it will be an important factor. Hence, the researcher should take into account the attribute levels prevalent in the marketplace and the objectives of the study. Using attribute levels that are beyond the range reflected in the marketplace will decrease the believability of the evaluation task, but it will increase the accuracy with which the parameters are estimated. The general guideline is to select attribute levels so that the ranges are somewhat greater

Figure 21.8
Conducting Conjoint Analysis

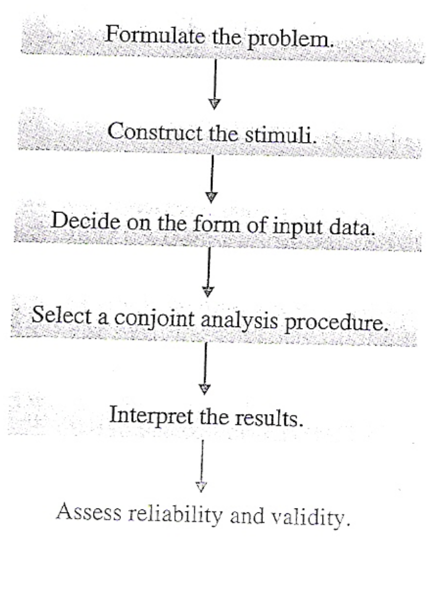


TABLE 21.2

Sneaker Attributes and Levels

ATTRIBUTE	LEVEL NO.	DESCRIPTION
Sole	3	Rubber
	2	Polyurethane
	1	Plastic
Upper	3	Leather
	2	Canvas
	1	Nylon
Price	3	$30.00
	2	$60.00
	1	$90.00

than that prevalent in the marketplace but not so large as to adversely impact the believability of the evaluation task.

We illustrate the conjoint methodology by considering the problem of how students evaluate sneakers. Qualitative research identified three attributes as salient: the sole, the upper, and the price.[18] Each was defined in terms of three levels, as shown in Table 21.2. These attributes and their levels were used for constructing the conjoint analysis stimuli. Note, to keep the illustration simple, we are using only a limited number, i.e., only three attributes. It has been argued that pictorial stimuli should be used when consumers' marketplace choices are strongly guided by the product's styling, such that the choices are heavily based on an inspection of actual products or pictures of products.[19]

Construct the Stimuli

Two broad approaches are available for constructing conjoint analysis stimuli: the pairwise approach and the full-profile procedure. In the pairwise approach, also called *two-factor evaluations,* the respondents evaluate two attributes at a time until all the possible pairs of attributes have been evaluated. This approach is illustrated in the context of the sneaker example in Figure 21.9. For each pair, respondents evaluate all the combinations of levels

Figure 21.9
Pairwise Approach to Collecting Conjoint Data

Upper \ Sole	Rubber	Polyurethane	Plastic
Leather			
Canvas			
Nylon			

Price \ Sole	Rubber	Polyurethane	Plastic
$30.00			
$60.00			
$90.00			

Upper \ Price	$30.00	$60.00	$90.00
Leather			
Canvas			
Nylon			

TABLE 21.3

Full-Profile Approach to Collecting Conjoint Data

EXAMPLE OF A SNEAKER PRODUCT PROFILE	
Sole	Made of rubber
Upper	Made of nylon
Price	$30.00

of both the attributes, which are presented in a matrix. 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. This approach is illustrated in the context of the sneaker example in Table 21.3.

It is not necessary to evaluate all the possible combinations, nor is it feasible in all cases. In the pairwise approach, it is possible to reduce the number of paired comparisons by using cyclical designs. Likewise, in the full-profile approach, the number of stimulus profiles can be greatly reduced by means of fractional factorial designs. A special class of fractional designs, called orthogonal arrays, allows for the efficient estimation of all main effects. Orthogonal arrays permit the measurement of all main effects of interest on an uncorrelated basis. These designs assume that all interactions are negligible.[20] Generally, two sets of data are obtained. One, the *estimation set,* is used to calculate the part-worth functions for the attribute levels. The other, the *holdout set,* is used to assess reliability and validity.

The advantage of the pairwise approach is that it is easier for the respondents to provide these judgments. However, its relative disadvantage is that it requires more evaluations than the full-profile approach. Also, the evaluation task may be unrealistic when only two attributes are being evaluated simultaneously. Studies comparing the two approaches indicate that both methods yield comparable utilities, yet the full-profile approach is more commonly used.

The sneaker example follows the full-profile approach. Given three attributes, defined at three levels each, a total of $3 \times 3 \times 3 = 27$ profiles can be constructed. To reduce the respondent evaluation task, a fractional factorial design was employed and a set of nine profiles was constructed to constitute the estimation stimuli set (see Table 21.4). Another set of nine stimuli was constructed for validation purposes. Input data were obtained for both the estimation and validation stimuli. However, before the data could be obtained, it was necessary to decide on the form of the input data.

Decide on the Form of Input Data

As in the case of MDS, conjoint analysis input data can be either nonmetric or metric. For nonmetric data, the respondents are typically required to provide rank order evaluations. For the pairwise approach, respondents rank all the cells of each matrix in terms of their desirability. For the full-profile approach, they rank all the stimulus profiles. Rankings involve relative evaluations of the attribute levels. Proponents of ranking data believe that such data accurately reflect the behavior of consumers in the marketplace.

In the metric form, the respondents provide ratings, rather than rankings. In this case, the judgments are typically made independently. Advocates of rating data believe that they are more convenient for the respondents and easier to analyze than rankings. In recent years, the use of ratings has become increasingly common.

In conjoint analysis, the dependent variable is usually preference or intention to buy. In other words, respondents provide ratings or rankings in terms of their preference or intentions to buy. However, the conjoint methodology is flexible and can accommodate a range of other dependent variables, including actual purchase or choice.

In evaluating sneaker profiles, respondents were required to provide preference ratings for the sneakers described by the nine profiles in the estimation set. These ratings were obtained using a nine-point Likert scale (1 = not preferred, 9 = greatly preferred). Ratings obtained from one respondent are shown in Table 21.4.

TABLE 21.4
Sneaker Profiles and Their Ratings

	Attribute Levels[a]			
Profile No.	Sole	Upper	Price	Preference Rating
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

[a]The attribute levels correspond to those in Table 23.2

Select a Conjoint Analysis Procedure

conjoint analysis model The mathematical model expressing the fundamental relationship between attributes and utility in conjoint analysis.

The basic ***conjoint analysis model*** may be represented by the following formula:[21]

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

where

$U(X)$ = overall utility of an alternative
α_{ij} = the part-worth contribution or utility associated with the jth level ($j, j = 1, 2, \ldots k_i$) of the ith attribute ($i, i = 1, 2, \ldots m$)
k_i = number of levels of attribute i
m = number of attributes
x_{ij} = 1 if the jth level of the ith attribute is present
= 0 otherwise

Sneaker manufacturers like Nike have made use of conjoint analysis to develop sneakers with appealing features.

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

$$I_i = \{\max(\alpha_{ij}) - \min(\alpha_{ij})\}, \text{ for each } i$$

The attribute's importance is normalized to ascertain its importance relative to other attributes, W_i:

$$W_i = \frac{I_i}{\sum_{i=1}^{m} I_i}$$

so that

$$\sum_{i=1}^{m} W_i = 1$$

Several different procedures are available for estimating the basic model. The simplest, and one which is gaining in popularity, is dummy variable regression (see Chapter 17). In this case, the predictor variables consist of dummy variables for the attribute levels. If an attribute has k_i levels, it is coded in terms of $k_i - 1$ dummy variables (see Chapter 14). If metric data are obtained, the ratings, assumed to be interval scaled, form the dependent variable. If the data are nonmetric, the rankings may be converted to 0 or 1 by making paired comparisons between brands. In this case, the predictor variables represent the differences in the attribute levels of the brands being compared. Other procedures that are appropriate for nonmetric data include LINMAP, MONANOVA, and the LOGIT model.[22]

The researcher must also decide whether the data will be analyzed at the individual-respondent or the aggregate level. At the individual level, the data of each respondent are analyzed separately. If an aggregate-level analysis is to be conducted, some procedure for grouping the respondents must be devised. One common approach is first to estimate individual-level part-worth or utility functions. The respondents are then clustered on the basis of the similarity of their part-worths. Aggregate analysis is then conducted for each cluster. An appropriate model for estimating the parameters should be specified.[23]

The data reported in Table 21.4 were analyzed using ordinary least-squares (OLS) regression with dummy variables. The dependent variable was the preference ratings. The independent variables or predictors were six dummy variables, two for each variable. The transformed data are shown in Table 21.5. Because the data pertain to a single respondent, an individual-level analysis was conducted. The part-worth or utility functions estimated for each attribute, as well the relative importance of the attributes, are given in Table 21.6.[24]

TABLE 21.5

Sneaker Data Coded for Dummy Variable Regression

Preference Ratings	Attributes					
	Sole		Upper		Price	
Y	X_1	X_2	X_3	X_4	X_5	X_6
9	1	0	1	0	1	0
7	1	0	0	1	0	1
5	1	0	0	0	0	0
6	0	1	1	0	0	1
5	0	1	0	1	0	0
6	0	1	0	0	1	0
5	0	0	1	0	0	0
7	0	0	0	1	1	0
6	0	0	0	0	0	1

TABLE 21.6
Results of Conjoint Analysis

Attribute	Level No.	Level Description	Utility	Importance
Sole	3	Rubber	0.778	
	2	Polyurethane	−0.556	
	1	Plastic	−0.222	0.286
Upper	3	Leather	0.445	
	2	Canvas	0.111	
	1	Nylon	−0.556	0.214
Price	3	$30.00	1.111	
	2	$60.00	0.111	
	1	$90.00	−1.222	0.500

The model estimated may be represented as:

$$U = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$$

where

X_1, X_2 = dummy variables representing Sole
X_3, X_4 = dummy variables representing Upper
X_5, X_6 = dummy variables representing Price

For Sole, the attribute levels were coded as follows:

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

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

$$\begin{aligned} b_0 &= 4.222 \\ b_1 &= 1.000 \\ b_2 &= -0.333 \\ b_3 &= 1.000 \\ b_4 &= 0.667 \\ b_5 &= 2.333 \\ b_6 &= 1.333 \end{aligned}$$

Given the dummy variable coding, in which level 3 is the base level, the coefficients may be related to the part-worths. As explained in Chapter 17, each dummy variable coefficient represents the difference in the part-worth for that level minus the part-worth for the base level. For Sole, we have the following:

$$\alpha_{11} - \alpha_{13} = b_1$$
$$\alpha_{12} - \alpha_{13} = b_2$$

To solve for the part-worths, an additional constraint is necessary. The part-worths are estimated on an interval scale, so the origin is arbitrary. Therefore, the additional constraint that is imposed is of the form

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

These equations for the first attribute, Sole, are

$$\begin{aligned} \alpha_{11} - \alpha_{13} &= 1.000 \\ \alpha_{12} - \alpha_{13} &= -0.333 \\ \alpha_{11} + \alpha_{12} + \alpha_{13} &= 0 \end{aligned}$$

Solving these equations, we get

$$\alpha_{11} = 0.778$$
$$\alpha_{12} = -0.556$$
$$\alpha_{13} = -0.222$$

The part-worths for other attributes reported in Table 21.6 can be estimated similarly. For Upper, we have

$$\alpha_{21} - \alpha_{23} = b_3$$
$$\alpha_{22} - \alpha_{23} = b_4$$
$$\alpha_{21} + \alpha_{22} + \alpha_{23} = 0$$

For the third attribute, Price, we have

$$\alpha_{31} - \alpha_{33} = b_5$$
$$\alpha_{32} - \alpha_{33} = b_6$$
$$\alpha_{31} + \alpha_{32} + \alpha_{33} = 0$$

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

$$\begin{aligned}\text{Sum of ranges} &= (0.778 - (-0.556)) + (0.445 - (-0.556)) \\ \text{of part-worths} &\quad + (1.111 - (-1.222)) \\ &= 4.668\end{aligned}$$

$$\text{relative importance of Sole} = \frac{[0.778 - (-0.556)]}{4.668} = \frac{1.334}{4.668} = 0.286$$

$$\text{relative importance of Upper} = \frac{[0.445 - (-0.556)]}{4.668} = \frac{1.001}{4.668} = 0.214$$

$$\text{relative importance of Price} = \frac{[1.111 - (-1.222)]}{4.668} = \frac{2.333}{4.668} = 0.500$$

The estimation of the part-worths and the relative importance weights provides the basis for interpreting the results.

Interpret the Results

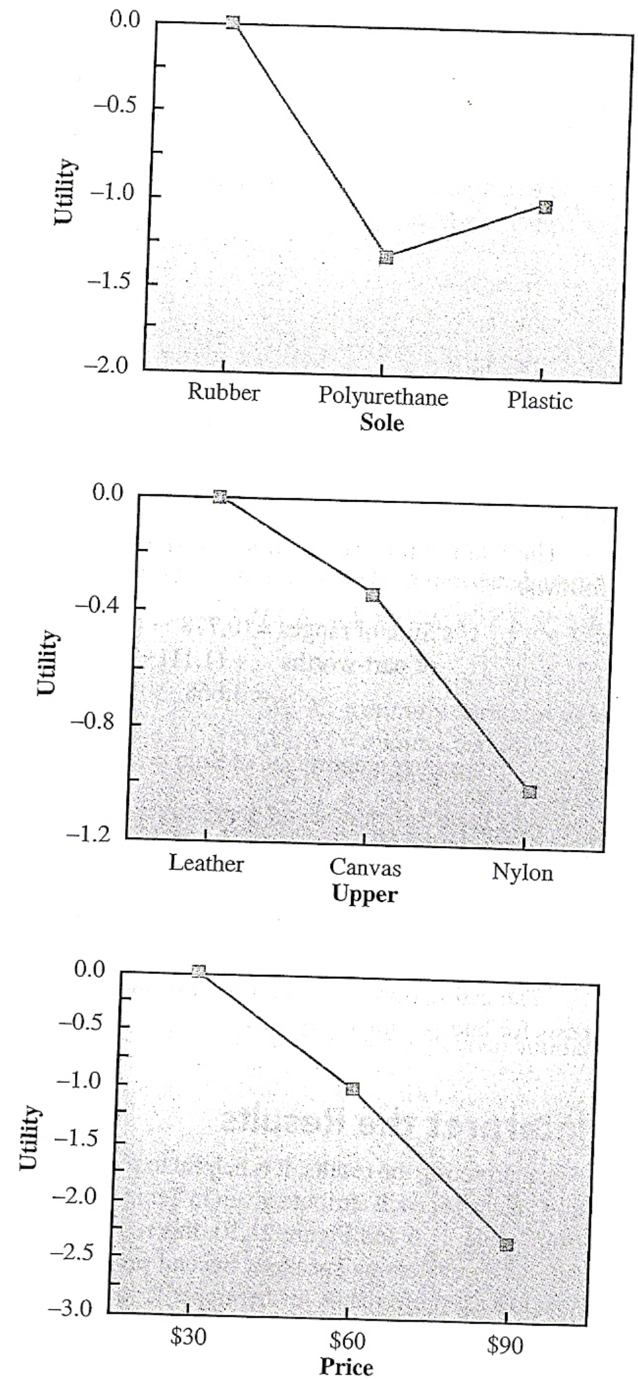
For interpreting the results, it is helpful to plot the part-worth functions. The part-worth function values for each attribute given in Table 21.6 are graphed in Figure 21.10. As can be seen from Table 21.6 and Figure 21.10, this respondent has the greatest preference for a rubber sole when evaluating sneakers. Second preference is for a plastic sole, and a polyurethane sole is least preferred. A leather upper is most preferred, followed by canvas and nylon. As expected, a price of \$30.00 has the highest utility and a price of \$90.00 the lowest. The utility values reported in Table 21.6 have only interval-scale properties, and their origin is arbitrary. In terms of relative importance of the attributes, we see that Price is number one. Second most important is Sole, followed closely by Upper. Because price is by far the most important attribute for this respondent, this person could be labeled as price sensitive.

Assessing Reliability and Validity

Several procedures are available for assessing the reliability and validity of conjoint analysis results.[25]

1. 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. Models with poor fit are suspect.
2. Test-retest reliability can be assessed by obtaining a few replicated judgments later in data collection. In other words, at a later stage in the interview, the respondents are asked to evaluate certain selected stimuli again. The two values of these stimuli are then correlated to assess test-retest reliability.

Figure 21.10
Part-Worth Functions



3. 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 respondents to determine internal validity.
4. 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.

In running a regression analysis on the data of Table 21.5, an R^2 of 0.934 was obtained, indicating a good fit. The preference ratings for the nine validation profiles were predicted from the utilities reported in Table 21.6. These were correlated with the input ratings for these profiles obtained from the respondent. The correlation coefficient was 0.95, indicating good predictive ability. This correlation coefficient is significant at $\alpha = 0.05$.

REAL RESEARCH

Examining Microcomputer Trade-Offs Microscopically

Consumers make trade-offs amongst various attributes when buying microcomputers.

Conjoint analysis was used to determine how consumers make trade-offs between various attributes when selecting microcomputers. Four attributes were chosen as salient. These attributes and their levels are:

Input mode
- Keyboard
- Mouse

Display monitor
- CRT
- LCD (Flat Panel)

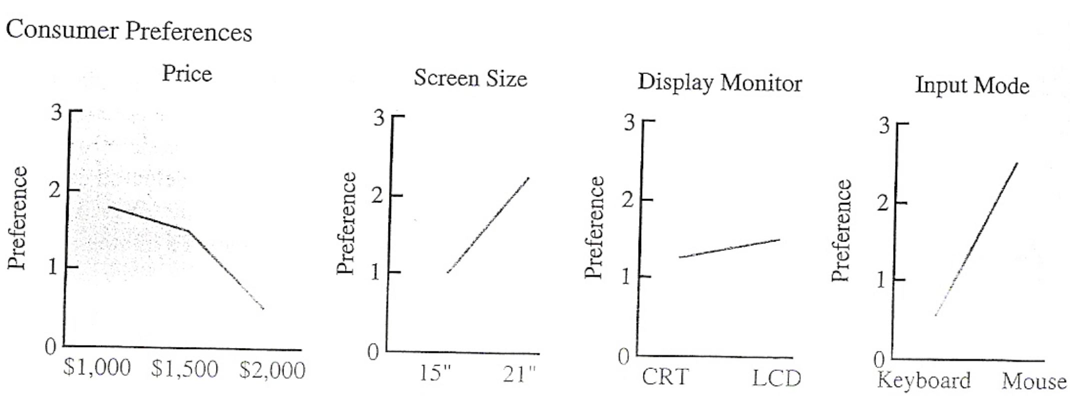
Screen size
- 21 inch
- 15 inch

Price level
- $1,000
- $1,500
- $2,000

All possible combinations of these attribute levels result in 24 (2 × 2 × 2 × 3) profiles of microcomputers. One such profile is as follows:

Input mode:	Mouse
Display monitor:	LCD (Flat Panel)
Screen size:	15″
Price level:	$1,500

Respondents rank-ordered these profiles in terms of preferences. The data for each respondent can be utilized to develop preference functions. The preference functions for one individual are illustrated.



Based on the derived part-worth or preference functions, the relative importance of the various attributes in determining these consumer preferences can be estimated by comparing part-worths as follows:

Relative Importance

Evaluative Criteria	*Importance*
Input mode	35%
Display monitor	15%
Screen size	25%
Price level	25%

For this consumer, input mode is the most important feature and the mouse is the preferred option. Although price and screen size are also important, price becomes a factor only between \$1,500 and \$2,000. As expected, a screen size of 21″ is preferred. Whether the display monitor is CRT or LCD does not matter as much as the other factors. Information provided by the part-worth functions and relative importance weights can be used to cluster respondents to determine benefit segments for microcomputers.

Desktop and notebook computer makers such as Dell (*www.dell.com*) can make use of conjoint analysis as a way to find out whether consumers place more value on features such as speed, screen size, or disk space, or if consumers place more value on cost or weight. Anyway you look at it, conjoint analysis is continually being used by computer manufacturers and many other industries to deliver preferred products to consumers.[26]

ASSUMPTIONS AND LIMITATIONS OF CONJOINT ANALYSIS

Although conjoint analysis is a popular technique, like MDS, it carries a number of assumptions and limitations. Conjoint analysis assumes that the important attributes of a product can be identified. Furthermore, it assumes that consumers evaluate the choice alternatives in terms of these attributes and make trade-offs. However, in situations where image or brand name is important, consumers may not evaluate the brands or alternatives in terms of attributes. Even if consumers consider product attributes, 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 are involved and the model must be estimated at the individual level. This problem has been mitigated to some extent by procedures such as interactive or adaptive conjoint analysis and hybrid conjoint analysis. It should also be noted that the part-worth functions are not unique.

HYBRID CONJOINT ANALYSIS

hybrid conjoint analysis A form of conjoint analysis that can simplify the data-collection task and estimate selected interactions as well as all main effects.

Hybrid conjoint analysis is an attempt to simplify the burdensome data-collection task required in traditional conjoint analysis. Each respondent evaluates a large number of profiles, yet usually only simple part-worths, without any interaction effects, are estimated. In the simple part-worths or main effects model, the value of a combination is simply the sum of the separate main effects (simple part-worths). In actual practice, two attributes may interact, in the sense that the respondent may value the combination more than the average contribution of the separate parts. Hybrid models have been developed to serve two main purposes: (1) simplify the data-collection task by imposing less of a burden on each respondent, and (2) 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 respondents 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 respondents evaluate different sets of profiles, so that over a group of respondents, all the profiles of interest are evaluated. In addition, respondents 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.[27]

MDS and conjoint analysis are complementary techniques and may be used in combination, as the following example shows.

REAL RESEARCH

Weeding Out the Competition

ICI Americas Agricultural Products did not know whether it should lower the price of Fusilade, its herbicide. It knew it had developed a potent herbicide, but it was not sure the weed killer would survive in a price-conscious market. So a survey was designed to assess the relative importance of different attributes in selecting herbicides and measure and map perceptions of major herbicides on the same attributes. Personal interviews were conducted with 601 soybean and cotton farmers who had at least 200 acres dedicated to growing these crops and who had used herbicides during the past growing season. First, conjoint analysis was used to determine the relative importance of attributes farmers use when selecting herbicides. Then multidimensional scaling was used to map farmers' perceptions of herbicides. The study showed that price greatly influenced herbicide selections, and respondents were particularly sensitive when costs were more than $18 an acre. But price was not the only determinant. Farmers also considered how much weed control the herbicide provided. They were willing to pay higher prices to keep the pests off their land. The study showed that herbicides that failed to control even one of the four most common weeds would have to be very inexpensive to attain a reasonable market share. Fusilade promised good weed control. Furthermore, multidimensional scaling indicated that one of Fusilade's competitors was considered to be expensive. Hence, ICI kept its original pricing plan and did not lower the price of Fusilade.

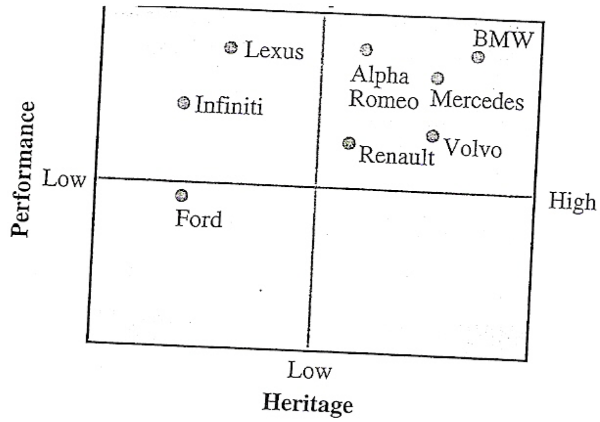
As of 2003, however, the agriculture industry has changed. One factor that has changed the industry is a shift in technology, especially biotechnology. Roundup Ready soybeans had a huge effect on the herbicide market, by making farmers switch from using traditional soybean herbicides to a new combined technology of Roundup and transgenic seed. The new technology cut the cost of per-acre herbicides in half and, as a result, competing chemical companies were forced to meet the price of the new technology. It is very important for companies to research consumer acceptance of technological innovations using techniques such as MDS and conjoint analysis to avoid being left by the wayside.[28]

Both MDS and conjoint analysis are useful in conducting international marketing research as illustrated by the next two examples. The example after that presents an application of MDS in researching ethical perceptions.

REAL RESEARCH

Herit-Age or Merit-Age in Europe?

European car manufacturers are increasingly focusing on an attribute that competitors will not be able to buy or build—it is heritage. For BMW, it is superior engineering. A. B. Volvo of Sweden has a reputation for safe cars. Italian Alfa Romeo rides on the laurels of engines that have won numerous races. The French Renault has savoir-faire. On the other hand, Japanese cars are advanced technologically but they do not have class or heritage. For example, Lexus and Infiniti are high-performance cars, but they lack class. Philip Gamba, VP-marketing at Renault, believes Japanese brands lack the "French touch" of that automaker's design and credibility. These days, Renault is building a car with a focus on comfort. BMW is trying to emphasize not the prestige of owning a luxury automobile but the "inner value" of its cars. To communicate value in cars is of growing importance. BMW has the edge of German heritage.



Because performance and heritage are important attributes or dimensions in automobile preferences of Europeans, the positioning of different European cars on these two dimensions is shown. Note that BMW has attained the best positioning on both these dimensions. Typical of most American and Japanese cars in the 2000s has been the emphasis on quality, reliability, and efficiency. However, to compete in the European market in the 21st century, Americans and Japanese are faced with the challenge of an added dimension—heritage. This calls for new marketing strategies by American and Japanese automakers. Due to the 2002 economic slowdown, it will be necessary for American automakers to employ new marketing strategies. For example, Ford introduced in 2003 a top-to-bottom evaluation of its overall marketing strategy in an effort to make the most of every dollar it spends for every brand and to compete effectively with European and Japanese brands.[29] ■

REAL RESEARCH

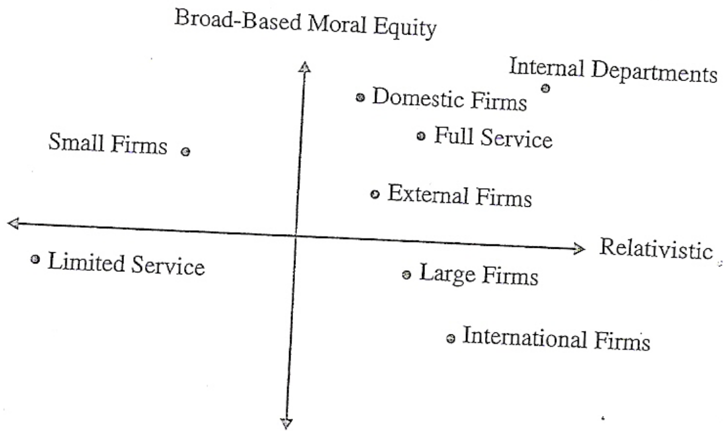
Fabs' Fabulous Foamy Fight

Competition in the detergent market was brewing in Thailand. Superconcentrate detergent is fast becoming the prototype as of 2003. Market potential research in Thailand indicated that superconcentrates would continue to grow at a healthy rate, although the detergent market had slowed. In addition, this category had already dominated other Asian markets such as Taiwan, Hong Kong, and Singapore. Consequently, Colgate entered this new line of competition with Fab Power Plus with the objective of capturing 4 percent market share. The main players in the market were Kao Corp.'s Attack, Lever Brothers' Breeze Ultra and Omo, and Lion Corp.'s Pao Hand Force and Pao M. Wash. Based on qualitative research and secondary data, Colgate assessed the critical factors for the success of superconcentrates. Some of these factors were environmental appeal, hand washing and machine wash convenience, superior cleaning abilities, optimum level of suds for hand wash, and brand name. Market research also revealed that no brand had both hand and machine wash capabilities. Pao Hand Force was formulated as the hand washing brand. Pao M. Wash was the machine wash version. Lever's Breeze Ultra was targeted for machine use. Therefore, a formula that had both hand and machine wash capability was desirable. A conjoint study was designed and these factors varied at either two or three levels. Preference ratings were gathered from respondents and part-worths for the factors estimated both at the individual and the group level. Results showed that the factor on hand-machine capability had a substantial contribution supporting earlier claims. Based on these findings, Fab Power Plus was successfully introduced as a brand with both hand and machine wash capabilities.[30] ■

REAL RESEARCH

Ethical Perceptions of Marketing Research Firms

In a refined scale to measure the degree a certain situation is ethical or unethical, three factors have been found to have acceptable validity and parsimony. Two of these dimensions



are particularly interesting. These are a broad-based moral equity dimension (factor 1), and a relativistic dimension (factor 2). Using multidimensional scaling, one can plot the perceived ethicalness of marketing research firms using these dimensions For example, an MDS plot might look like this.

In this example, internal marketing research departments are perceived to be the most ethical on both dimensions. Large marketing research firms are perceived to be more ethical on the relativistic dimension, whereas small firms are more ethical on the moral equity factor. International marketing research firms are more ethical on relativistic terms, whereas the domestic firms are higher on the moral equity dimension. Finally, full-service firms are perceived to be more ethical on both the dimensions as compared to the limited-service firms.

As of 2003, the marketing research industry was trying hard to portray that it maintained high ethical standards. These findings imply that marketing research firms (external firms) must convince the business world that their ethical standards are as high as those of internal marketing research departments of business firms. Also, if limited-service suppliers are to compete, then they must maintain and project the same ethical standards maintained by the full-service marketing research firms.[31]

INTERNET AND COMPUTER APPLICATIONS

Over the years, several computer programs have been developed for conducting MDS analysis using microcomputers and mainframes. The ALSCAL program, available in the mainframe versions of both SPSS and SAS, incorporates several different MDS models and can be used for conducting individual or aggregate-level analysis. Other MDS programs are easily available and widely used. Most are available in both microcomputer and mainframe versions.

- MDSCAL 5M derives a spatial map of brands in a specified number of dimensions. Similarity data are used. A variety of input data formats and distance measures can be accommodated.
- KYST performs metric and nonmetric scaling and unfolding using similarity data.
- INDSCAL, denoting individual differences scaling, is useful for conducting MDS at the aggregate level. Similarity data are used as input.
- MDPREF performs internal analysis of preference data. The program develops vector directions for preferences and the configuration of brands or stimuli in a common space.
- PREFMAP performs external analysis of preference data. This program uses a known spatial map of brands or stimuli to portray an individual's preference data. PREFMAP2 performs both internal and external analysis.
- PC-MDS contains a variety of multidimensional scaling algorithms, including factor analysis, discriminant analysis, and some other multivariate procedures. It is available for the IBM PC and compatibles.

FOCUS ON BURKE

A major role for Burke is advising clients in research design. Often clients will come to Burke with a request to execute the client's study design. It is our responsibility to advise the client if we see issues of application or interpretation. For example, in a full-profile conjoint for a cellular phone manufacturer, the following design was specified by the client.

Factors: levels

Power: 3 watts or 6 watts

Weight: 10 ounces or 14 ounces

Battery life: 30 minutes talk time; 1 hour talk time; 1.5 hours talk time; or 2 hours talk time

Brand: brand A; brand B

Price: Free with two-year subscription, \$100, \$200, or \$250 (if you buy the phone, you can use any service you desire)

Design Specifications: Full factorial = 2 × 2 × 4 × 2 × 4 = 128 possible combinations

Because having a respondent evaluate 128 possible cellular phones was out of the question, a fractional factorial design (main effects only) using 16 profiles was selected. To see one of our objections to this design, a hypothetical respondent's answers are shown. The 16 profiles are:

	Power	*Weight*	*Talk Time*	*Brand*	*Price*
Profile 1:	3 w	10 oz.	30 min	Brand B	Free
Profile 2:	6 w	10 oz.	30 min	Brand B	\$200
Profile 3:	6 w	14 oz.	30 min	Brand A	\$250
Profile 4:	3 w	14 oz.	30 min	Brand A	\$100
Profile 5:	6 w	10 oz.	1 hour	Brand A	\$100
Profile 6:	3 w	10 oz.	1 hour	Brand A	\$250
Profile 7:	3 w	14 oz.	1 hour	Brand B	\$200
Profile 8:	6 w	14 oz.	1 hour	Brand B	Free
Profile 9:	3 w	14 oz.	1.5 hours	Brand A	\$200
Profile 10:	6 w	14 oz.	1.5 hours	Brand A	Free
Profile 11:	6 w	10 oz.	1.5 hours	Brand B	\$100
Profile 12:	3 w	10 oz.	1.5 hours	Brand B	\$250
Profile 13:	6 w	14 oz.	2 hours	Brand B	\$250
Profile 14:	3 w	14 oz.	2 hours	Brand B	\$100
Profile 15:	3 w	10 oz.	2 hours	Brand A	Free
Profile 16:	6 w	10 oz.	2 hours	Brand A	\$200

- APM (Adaptive Perceptual Mapping) is an adaptive scaling program, available for the microcomputer, which can handle up to 30 brands and 50 attributes. There is no limit on the number of respondents per study or the number of computers that can be used to collect the data.
- MAPWISE by Market Action Research Software, Inc., is perceptual mapping software for conducting correspondence analysis. CORRESPONDENCE ANALYSIS by the Beaumont Organization Ltd. conducts correspondence analysis, what-if simulations, and ideal product analysis. Another program for correspondence analysis is SIMCA by Greenacre.

If OLS regression is used as the estimation procedure in conjoint analysis, these programs are universally available. In particular, the microcomputer and mainframe versions of SAS, SPSS, MINITAB, and EXCEL have several regression programs. These were dis-

One respondent's ratings on a 10-point purchase interest scale:

Profile 1: 2	Profile 9: 1
Profile 2: 5	Profile 10: 4
Profile 3: 1	Profile 11: 10
Profile 4: 1	Profile 12: 5
Profile 5: 5	Profile 13: 6
Profile 6: 1	Profile 14: 8
Profile 7: 3	Profile 15: 3
Profile 8: 6	Profile 16: 5

Subjecting this respondent's data to OLS regression, using the design matrix as predictor variables, the following results emerge.

Attribute	*Utility Value*	*Relative Importance*
Power		
3 Watts	−1.12	
6 Watts	1.12	18.8%
Weight		
10 oz.	0.375	
14 oz.	−0.375	6.0%
Battery Life		
30 min.	−1.875	
1 hour	−0.375	
1.5 hours	0.875	
2.0 hours	1.375	27.1%
Brand		
A	1.5	
B	−1.5	25.0%
Price		
Free w/ 2 yr. sub.	−0.375	
$100	1.875	
$200	−0.625	
$250	−0.875	22.9%

Why would Burke question this design?

First, management wanted to understand the sensitivity to price. This model would assume that either both brands had the same price elasticity or management would gain the needed information from an "average" price elasticity for the two brands. When directly asked about this, the client had not considered that this "price sensitivity" may not actually fit either brand. Burke suggested a design that would examine the interaction between brand and price, as this is a way to examine the price elasticity of a brand (not an average of brands).

cussed in Chapter 17. Several specialized programs are also available for conjoint analysis. MONANOVA (Monotone Analysis of Variance) is a nonmetric procedure that uses full-profile data. For pairwise data, the TRADEOFF procedure can be used. TRADEOFF is also a nonmetric procedure that uses the rank ordering of preferences for attribute-level pairs. Both MONANOVA and TRADEOFF are available for the mainframe and microcomputers. Other popular programs include LINMAP and ACA (Adaptive Conjoint Analysis). ACA focuses on the attributes and levels most relevant for each individual respondent. PC-MDS also contains a program for conjoint analysis. Other useful programs include software by Bretton-Clark, including CONJOINT DESIGNER, CONJOINT ANALYZER, CONJOINT LINMAP, SIMGRAF, and BRIDGER. POSSE (Product Optimization and Selected Segmentation Evaluation) by Robinson Associates, Inc., is a generalized system for optimizing product and service designs using hybrid conjoint analysis and experimental design methods. It uses consumer choice simulators, response surface modeling, and optimization procedures to develop optimal product configurations. Choice-based conjoint (CBC) and multimedia conjoint programs that demonstrate product features rather than just describe them are also available, for example, from Sawtooth Technologies (*www.sawtooth.com*).

SPSS Windows

The multidimensional scaling program allows individual differences as well as aggregate analysis using ALSCAL. The level of measurement can be ordinal, interval, or ratio. Both the direct and the derived approaches can be accommodated. To select multidimensional scaling procedures using SPSS for Windows, click:

Analyze>Scale>Multidimensional Scaling . . .

The conjoint analysis approach can be implemented using regression if the dependent variable is metric (interval or ratio). This procedure can be run by clicking:

Analyze>Regression>Linear . . .

SUMMARY

Multidimensional scaling is used for obtaining spatial representations of respondents' perceptions and preferences. Perceived or psychological relationships among stimuli are represented as geometric relationships among points in a multidimensional space. Formulating the MDS problem requires a specification of the brands or stimuli to be included. The number and nature of brands selected influences the resulting solution. Input data obtained from the respondents can be related to perceptions or preferences. Perception data can be direct or derived. The direct approaches are more common in marketing research.

The selection of an MDS procedure depends on the nature (metric or nonmetric) of the input data and whether perceptions or preferences are being scaled. Another determining factor is whether the analysis will be conducted at the individual or aggregate level. The decision about the number of dimensions in which to obtain a solution should be based on theory, interpretability, elbow criterion, and ease-of-use considerations. Labeling of the dimensions is a difficult task that requires subjective judgment. Several guidelines are available for assessing the reliability and validity of MDS solutions. Preference data can be subjected to either internal or external analysis. If the input data are of a qualitative nature, they can be analyzed via correspondence analysis. If the attribute-based approaches are used to obtain input data, spatial maps can also be obtained by means of factor or discriminant analysis.

Conjoint analysis is based on the notion that the relative importance that consumers attach to salient attributes, and the utilities they attach to the levels of attributes, can be determined when consumers evaluate brand profiles that are constructed using these attributes and their levels. Formulating the problem requires an identification of the salient attributes and their levels. The pairwise and the full-profile approaches are commonly employed for constructing the stimuli. Statistical designs are available for reducing the number of stimuli in the evaluation task. The input data can be either nonmetric (rankings) or metric (ratings). Typically, the dependent variable is preference or intention to buy.

Although other procedures are available for analyzing conjoint analysis data, regression using dummy variables is becoming increasingly important. Interpretation of the results requires an examination of the part-worth functions and relative importance weights. Several procedures are available for assessing the reliability and validity of conjoint analysis results.

KEY TERMS AND CONCEPTS

multidimensional scaling (MDS), *611*
similarity judgments, *612*
preference rankings, *612*
stress, *612*
R-square, *612*
spatial map, *612*
coordinates, *612*
unfolding, *612*
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