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CHAPTER 10

Multidimensional Scaling

LEARNING OBJECTIVES

Upon completing this chapter, you should be able to do the following:

- Define multidimensional scaling and describe how it is performed.
- Understand the differences between similarity data and preference data.
- Select between a decompositional or compositional approach.
- Determine the comparability and number of objects.
- Understand how to create a perceptual map.

CHAPTER PREVIEW

Multidimensional scaling (MDS) refers to a series of techniques that help the researcher identify key dimensions underlying respondents' evaluations of objects and then position these objects in this dimensional space. For example, multidimensional scaling is often used in marketing to identify key dimensions underlying customer evaluations of products, services, or companies. Other common applications include the comparison of physical qualities (e.g., food tastes or various smells), perceptions of political candidates or issues, and even the assessment of cultural differences between distinct groups. Multidimensional scaling techniques can infer the underlying dimensions using only a series of similarity or preference judgments about the objects provided by respondents. Once the data are in hand, multidimensional scaling can help determine the number and relative importance of the dimensions respondents use when evaluating objects, as well as how the objects are related perceptually on these dimensions, most often portrayed graphically.

Correspondence analysis (CA) is a related technique with similar objectives. CA infers the underlying dimensions that are evaluated as well as the positioning of objects, yet follows a quite different approach. It differs in that similarities are estimated from a cross-tabulation table, typically associating objects with attributes. This approach to perceptual mapping objects is discussed in Chapter 11.

KEY TERMS

Before starting the chapter, review the key terms to develop an understanding of the concepts and terminology used. Throughout the chapter the key terms appear in **boldface.** Other points of emphasis in the chapter and key term cross-references are *italicized.*

Aggregate analysis Approach to MDS in which a *perceptual map* is generated for a group of respondents' evaluations of *objects*. This composite perceptual map may be created by a computer program or by the researcher to find a few "average" or representative subjects.

Compositional method An approach to perceptual mapping that derives overall *similarity* or *preference* evaluations from evaluations of separate attributes by each respondent. With compositional methods separate attribute evaluations are combined (composed) into an overall evaluation. The most common examples of compositional methods are the techniques of factor analysis and discriminant analysis.

Confusion data Procedure to obtain respondents' perceptions of *similarities data*. Respondents indicate the similarities between pairs of stimuli. The pairing (or confusing) of one stimulus with another is taken to indicate similarity. Also known as *subjective clustering*.

Correspondence analysis (CA) *Compositional approach* to perceptual mapping that is based on categories of a *contingency table*. Most applications involve a set of *objects* and attributes, with the results portraying both objects and attributes in a common *perceptual map*. To derive a multidimensional map, you must have a minimum of three attributes and three objects.

Cross-tabulation table Cross-tabulation of two nonmetric or categorical variables in which the entries are the frequencies of responses that fall into each cell of the matrix. For example, if three brands were rated on four attributes, the brand-by-attribute contingency table would be a three-row by four-column table. The entries would be the number of times a brand (e.g., Coke) was rated as having an attribute (e.g., sweet taste).

Decompositional method Perceptual mapping method associated with MDS techniques in which the respondent provides only an overall evaluation of *similarity* or *preference* between *objects*. This set of overall evaluations is then decomposed into a set of dimensions that best represent the objects' differences.

Degenerate solution MDS solution that is invalid because of (1) inconsistencies in the data or (2) too few objects compared with the number of dimensions specified by the researcher. Even though the computer program may indicate a valid solution, the researcher should disregard the degenerate solution and examine the data for the cause. This type of solution is typically portrayed as a circular pattern with illogical results.

Derived measures Procedure to obtain respondents' perceptions of *similarities data*. Derived similarities are typically based on a series of scores given to stimuli by respondents, which are then combined in some manner. The semantic differential scale is frequently used to elicit such scores.

Dimensions Features of an *object*. A particular object can be thought of as possessing both *perceived/subjective* dimensions (e.g., expensive, fragile) and *objective* dimensions (e.g., color, price, features).

Disaggregate analysis Approach to MDS in which the researcher generates *perceptual maps* on a respondent-by-respondent basis. The results may be difficult to generalize across respondents. Therefore, the researcher may attempt to create fewer maps by some process of *aggregate analysis*, in which the results of respondents are combined.

Disparities Differences in the computer-generated distances representing *similarity* and the distances provided by the respondent.

Ideal point Point on a perceptual map that represents the most preferred combination of perceived attributes (according to the respondents). A major assumption is that the position of the ideal point (relative to the other objects on the perceptual map) would define relative *preference* such that objects farther from the ideal point should be preferred less.

Importance–performance grid Two-dimensional approach for assisting the researcher in labeling dimensions. The vertical axis is the respondents' perceptions of the importance (e.g., as measured on a scale of "extremely important" to "not at all important"). The horizontal axis is performance (e.g., as measured on a scale of "excellent performance" to "poor performance") for each brand or product/service on various attributes. Each object is represented by its values on importance and performance.

Index of fit Squared correlation index (R^2) that may be interpreted as indicating the proportion of variance of the *disparities* (optimally scaled data) that can be accounted for by the MDS procedure. It measures how well the raw data fit the MDS model. This index is an alternative to the *stress measure* for determining the number of dimensions. Similar to measures of covariance in other multivariate techniques, measures of .60 or greater are considered acceptable.

Initial dimensionality A starting point in selecting the best spatial configuration for data. Before beginning an MDS procedure, the researcher must specify how many *dimensions* or features are represented in the data.

Object Any stimulus that can be compared and evaluated by the respondent, including tangible entities (product or physical object), actions (service), sensory perceptions (smell, taste, sights), or even thoughts (ideas, slogans).

Objective dimension Physical or tangible characteristics of an *object* that have an objective basis of comparison. For example, a product has size, shape, color, weight, and so on.

Perceived dimension A respondent's subjective attachment of features to an *object* represent its intangible characteristics. Examples include "quality," "expensive," and "good-looking." These perceived dimensions are unique to the individual respondent and may bear little correspondence to actual *objective dimensions*.

Perceptual map Visual representation of a respondent's perceptions of *objects* on two or more *dimensions*. Usually this map has opposite levels of dimensions on the ends of the X and Y axes, such as "sweet" to "sour" on the ends of the X axis and "high-priced" to "low-priced" on the ends of the Y axis. Each object then has a spatial position on the perceptual map that reflects the relative *similarity* or *preference* to other objects with regard to the dimensions of the perceptual map.

Preference Implies that *objects* are judged by the respondent in terms of dominance relationships; that is, the stimuli are ordered in preference with respect to some property. Direct ranking, paired comparisons, and preference scales are frequently used to determine respondent preferences.

Preference data Data used to determine the *preference* among *objects*. Can be contrasted to *similarities data,* which denotes the similarity among objects, but has no "good-bad" distinction as seen in preference data.

Projections Points defined by perpendicular lines from an object to a *vector*. Projections are used in determining the *preference* order with vector representations.

Similarities data Data used to determine which *objects* are the most similar to each other and which are the most dissimilar. Implicit in similarities measurement is the ability to compare all pairs of objects. Three procedures to obtain similarities data are paired comparison of objects, *confusion data*, and *derived measures*.

Similarity See *similarities data.*

Similarity scale Arbitrary scale, for example, from −5 to +5, that enables the representation of an ordered relationship between objects from the most similar (closest) to the least similar (farthest apart). This type of scale is appropriate only for representing a single dimension.

Spatial map See *perceptual map*.

Stress measure Proportion of the variance of the *disparities* (optimally scaled data) not accounted for by the MDS model. This type of measurement varies according to the type of program and the data being analyzed. The stress measure helps to determine the appropriate number of *dimensions* to include in the model.

Stretched Transformation of an MDS solution to make the *dimensions* or individual elements reflect the relative weight of preference.

Subjective clustering See *confusion data*.

Subjective dimension See *perceived dimension*.

Subjective evaluation Method of determining how many *dimensions* are represented in the MDS model. The researcher makes a subjective inspection of the spatial maps and asks whether the configuration looks reasonable. The objective is to obtain the best fit with the least number of dimensions.

Unfolding Representation of an individual respondent's *preferences* within a common (aggregate) stimulus space derived for all respondents as a whole. The individual's preferences are "unfolded" and portrayed as the best possible representation within the aggregate analysis.

Vector Method of portraying an ideal point or attribute in a perceptual map. Involves the use of *projections* to determine an *object's* order on the vector.

WHAT IS MULTIDIMENSIONAL SCALING?

Multidimensional scaling (MDS), also known as perceptual mapping, is a procedure that enables a researcher to determine the perceived relative image of a set of objects (firms, products, ideas, or other items associated with commonly held perceptions). The purpose of MDS is to transform consumer judgments of overall similarity or **preference** (e.g., preference for stores or brands) into distances represented in multidimensional space.

Comparing Objects

Multidimensional scaling is based on the comparison of **objects** (e.g., product, service, person, aroma). MDS differs from other multivariate methods in that it uses only a single, overall measure of similarity or preference. To perform a multidimensional scaling analysis, the researcher performs three basic steps:

1. Gather measures of similarity or preference across the entire set of objects to be analyzed.
2. Use MDS techniques to estimate the relative position of each object in multidimensional space.
3. Identify and interpret the axes of the dimensional space in terms of perceptual and/or objective attributes.

Assume that objects A and B are judged by respondents to be the most similar compared with all other possible pairs of objects (AC, BC, AD, and so on). MDS techniques will position objects A and B so that the distance between them in multidimensional space is smaller than the distance between any other two pairs of objects. The resulting **perceptual map**, also known as a **spatial map**, shows the relative positioning of all objects, as shown in Figure 10-1.

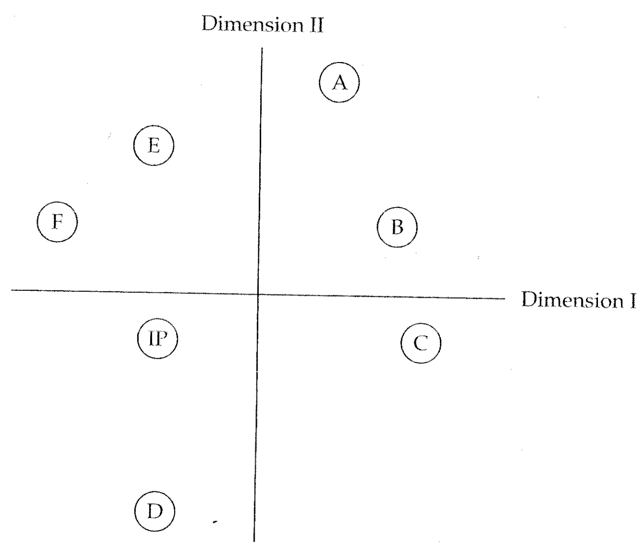


FIGURE 10-1 Illustration of a Multidimensional Map of Perceptions of Six Industrial Suppliers (A to F) and the Ideal Point (IP)

Dimensions: The Basis for Comparison

What is the basis for the relative position of each object? Why were A and B more similar than any other pair of objects (e.g., A and D)? What do the axes of the multidimensional space represent? Before we attempt to answer any of these questions, we first must recognize that any object can be thought of as having **dimensions** that represent an individual's perceptions of attributes or combinations of attributes. These dimensions may represent a single attribute/perception or idea, or they may be a composite of any number of attributes (e.g., reputation).

OBJECTIVE VERSUS SUBJECTIVE DIMENSIONS When characterizing an object, it is also important to remember that individuals may use different types of measures in making these judgments. For example, one measure is an **objective dimension,** which has quantifiable (physical or observable) attributes. Another type of measure is a **perceived dimension** (also known as a **subjective dimension**), in which individuals evaluate the objects based on perceptions. In this case, the perceived dimension is an interpretation by the individual that may or may not be based on objective dimensions.

For example, management may view their product (a lawn mower) as having two color options (red and green), a two-horsepower motor, and a 24-inch blade, which are the objective dimensions. However, customers may (or may not) focus on these attributes. Customers may focus on a perceived dimension, such as the mower being expensive-looking or fragile.

Two objects may have the same physical characteristics (objective dimensions) but be viewed differently because the objects are perceived to differ in quality (a perceived dimension) by many customers. Thus, the following two differences between objective and perceptual dimensions are important:

- *Individual differences:* The dimensions perceived by customers may not coincide with (or may not even include) the objective dimensions assumed by the researcher. We expect that each individual may have different perceived dimensions, but the researcher must also accept that the objective dimensions may also vary substantially. Individuals may consider different sets of objective characteristics as well as vary the importance they attach to each dimension.
- *Interdependence:* The evaluations of the dimensions (even if the perceived dimensions are the same as the objective dimensions) may not be independent and may not agree. Both perceived and objective dimensions may interact with one another to create unexpected evaluations. For example, one soft drink may be judged sweeter than another because the first has a fruitier aroma, although both contain the same amount of sweetener.

RELATING OBJECTIVE AND SUBJECTIVE DIMENSIONS The challenge to the researcher is to understand how both the perceived dimensions and objective dimensions relate to the axes of the multidimensional space used in the perceptual map, if possible. It is similar to the interpretation of the variate in many other multivariate techniques (e.g., "labeling" the factors from factor analysis), but differs in that the researcher never directly uses any attribute ratings (e.g., ratings of quality, attractiveness, etc.) when obtaining the similarity ratings among objects. Instead, the researcher collects only similarity or preference.

Using only the overall measures (similarity or preference) requires that the researcher first understand the correspondence between perceptual and objective dimensions with the axes of the perceptual map. Then, additional analysis can identify which attributes predict the position of each object in both perceptual and objective space.

A note of caution must be raised, however, concerning the interpretation of dimensions. Because this process is as much an art as a science, the researcher must resist the temptation to allow personal perception to affect the qualitative dimensionality of the perceived dimensions. Given the level of researcher input, caution must be taken to be as objective as possible in this critical, yet still rudimentary, area.

A SIMPLIFIED LOOK AT HOW MDS WORKS

To facilitate a better understanding of the basic procedures in multidimensional scaling, we first present a simple example to illustrate the basic concepts underlying MDS and the procedure by which it transforms similarity judgments into the corresponding spatial positions. We will follow the three basic steps described previously.

Gathering Similarity Judgments

The first step is to obtain similarity judgments from one or more respondents. Here we will ask respondents for a single measure of similarity for each pair of objects.

Market researchers are interested in understanding consumers' perceptions of six candy bars that are currently on the market. Instead of trying to gather information about consumer's evaluations of the candy bars on a number of attributes, the researchers instead gather only perceptions of overall similarities or dissimilarities. The data are typically gathered by having respondents give simple global responses to statements such as these:

- Rate the similarity of products A and B on a 10-point scale.
- Product A is more similar to B than to C.
- I like product A better than product B.

Creating a Perceptual Map

From these simple responses, a perceptual map can be drawn that best portrays the overall pattern of **similarities** among the six candy bars. We illustrate the process of creating a perceptual map with the data from a single respondent, although this process could also be applied to multiple respondents or to the aggregate responses of a group of consumers.

The data are gathered by first creating a set of 15 unique pairs of the six candy bars ($6 \times 5 \div 2 = 15$ pairs). After tasting the candy bars, the respondent is asked to rank the 15 candy bar pairs, where a rank of 1 is assigned to the pair of candy bars that is most similar and a rank of 15 indicates the pair that is least alike. The results (rank orders) for all pairs of candy bars for one respondent are shown in Table 10-1. This respondent thought that candy bars D and E were the most similar, candy bars A and B were the next most similar, and so forth until candy bars E and F were the least similar.

If we want to illustrate the similarity among candy bars graphically, a first attempt would be to draw a single **similarity scale** and fit all the candy bars to it. In this one-dimensional portrayal of similarity, distance represents similarity. Thus, objects closer together on the scale are more similar and those farther away less similar. The objective is to position the candy bars on the scale so that the rank orders are best represented (rank order of 1 is closest, rank order of 2 is next closest, and so forth).

TABLE 10-1 Similarity Data (Rank Orders) for Candy Bar Pairs

Candy Bar	A	B	C	D	E	F
A	—	2	13	4	3	8
B		—	12	6	5	7
C			—	9	10	11
D				—	1	14
E					—	15
F						—

Note: Lower values indicate greater similarity, with 1 the most similar pair and 15 the least similar pair.

Let us try to see how we would place some of the objects. Positioning two or three candy bars is fairly simple. The first real test comes with four objects. We choose candy bars A, B, C, and D. Table 10-1 shows that the rank order of the pairs is as follows: AB < AD < BD < CD < BC < AC (each pair of letters refers to the distance [similarity] between the pair). From these values, we must place the four candy bars on a single scale so that the most similar (AB) are the closest and the least similar (AC) are the farthest apart. Figure 10-2a contains a one-dimensional perceptual map that matches the orders of pairs. If the person judging the similarity between the candy bars had been thinking of a simple rule of similarity that involved only one attribute (dimension), such as amount of chocolate, then all the pairs could be placed on a single scale that reproduces the similarity values.

Although a one-dimensional map can accommodate four objects, the task becomes increasingly difficult as the number of objects increases. The interested reader is encouraged to attempt this task with six objects. When a single dimension is employed with the six objects, the actual ordering varies substantially from the respondent's original rank orders.

Because one-dimensional scaling does not fit the data well, a two-dimensional solution should be attempted. It allows for another scale (dimension) to be used in configuring the six candy bars.

The procedure is quite tedious to attempt by hand. The two-dimensional solution produced by an MDS program is shown in Figure 10-2b. This configuration matches the rank orders of Table 10-1 exactly, supporting the notion that the respondent most probably used two dimensions in evaluating the candy bars. The conjecture that at least two attributes (dimensions) were considered is based on the inability to represent the respondent's perceptions in one dimension. However, we are still not aware of what attributes the respondent used in this evaluation.

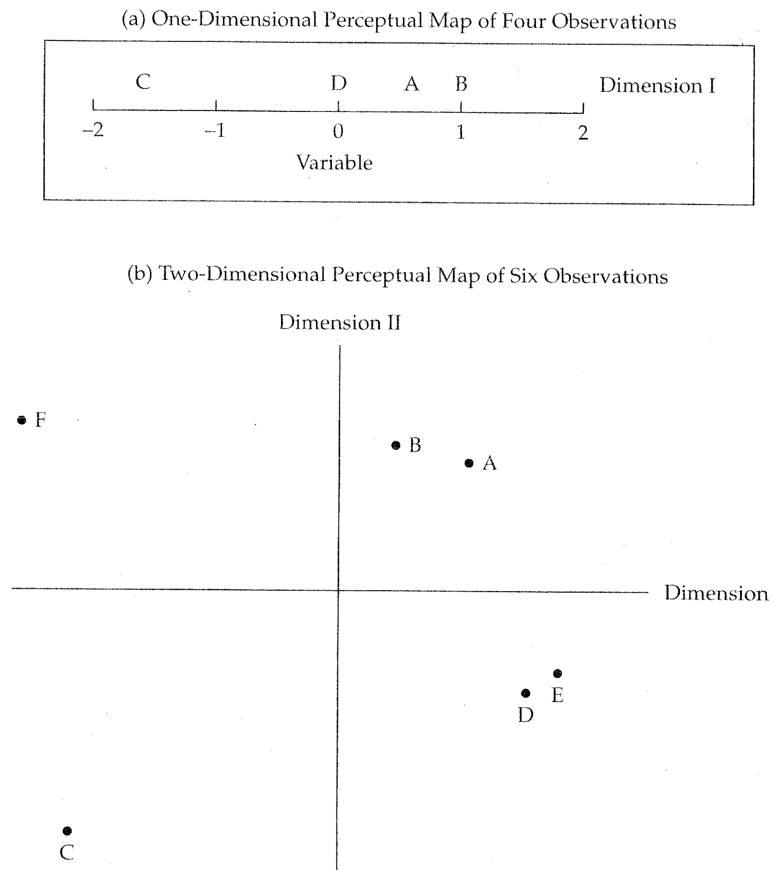


FIGURE 10-2 One- and Two-Dimensional Perceptual Maps

Interpreting the Axes

Although we have no information as to what these dimensions are, we may be able to look at the relative positions of the candy bars and infer what attribute(s) the dimensions represent.

For example, suppose that candy bars A, B, and F were a form of combination bar (e.g., chocolate and peanuts, chocolate and peanut butter), and C, D, and E were strictly chocolate bars. We could then infer that the horizontal dimension represents the type of candy bar (chocolate versus combination). When we look at the position of the candy bars on the vertical dimension, other attributes may emerge as the descriptors of that dimension as well.

MDS enables researchers to understand the similarity between objects (e.g., candy bars) by asking only for overall similarity perceptions. The procedure may also assist in determining which attributes actually enter into the perceptions of similarity. Although we do not directly incorporate the attribute evaluations into the MDS procedure, we can use them in subsequent analyses to assist in interpreting the dimensions and the impacts each attribute has on the relative positions of the candy bars.

COMPARING MDS TO OTHER INTERDEPENDENCE TECHNIQUES

Multidimensional scaling can be compared to the other interdependence techniques such as factor and cluster analysis based on its approach to defining structure:

- *Factor analysis:* Defines structure by grouping variables into variates that represent underlying dimensions in the original set of variables. Variables that highly correlate are grouped together.
- *Cluster analysis:* Defines structure by grouping objects according to their profile on a set of variables (the cluster variate) in which objects in close proximity to each other are grouped together.

MDS differs from factor and cluster analysis in two key aspects: (1) a solution can be obtained for each individual and (2) it does not use a variate.

Individual as the Unit of Analysis

In MDS, each respondent provides evaluations of all objects being considered, so that a solution can be obtained for each individual that is not possible in cluster analysis or factor analysis. As such, the focus is not on the objects themselves but instead on how the individual perceives the objects. The structure being defined is the perceptual dimensions of comparison for the individual(s). Once the perceptual dimensions are defined, the relative comparisons among objects can also be made.

Lack of a Variate

Multidimensional scaling, unlike the other multivariate techniques, does not use a variate. Instead, the variables that make up the variate (i.e., the perceptual dimensions of comparison) are inferred from global measures of similarity among the objects. In a simple analogy, it is like providing the dependent variable (similarity among objects) and figuring out what the independent variables (perceptual dimensions) must be. MDS has the advantage of reducing the influence of the researcher by not requiring the specification of the variables to be used in comparing objects, as was required in cluster analysis. It also has the disadvantage that the researcher is not really sure what variables the respondent is using to make the comparisons.

A DECISION FRAMEWORK FOR PERCEPTUAL MAPPING

Perceptual mapping encompasses a wide range of possible methods, including MDS, and all these techniques can be viewed through the model-building process introduced in Chapter 1. These steps represent a decision framework, depicted in Figure 10-3 (stages 1–3) and Figure 10-5 (stages 4–6, see page 563) within which all perceptual mapping techniques can be applied and the results evaluated.

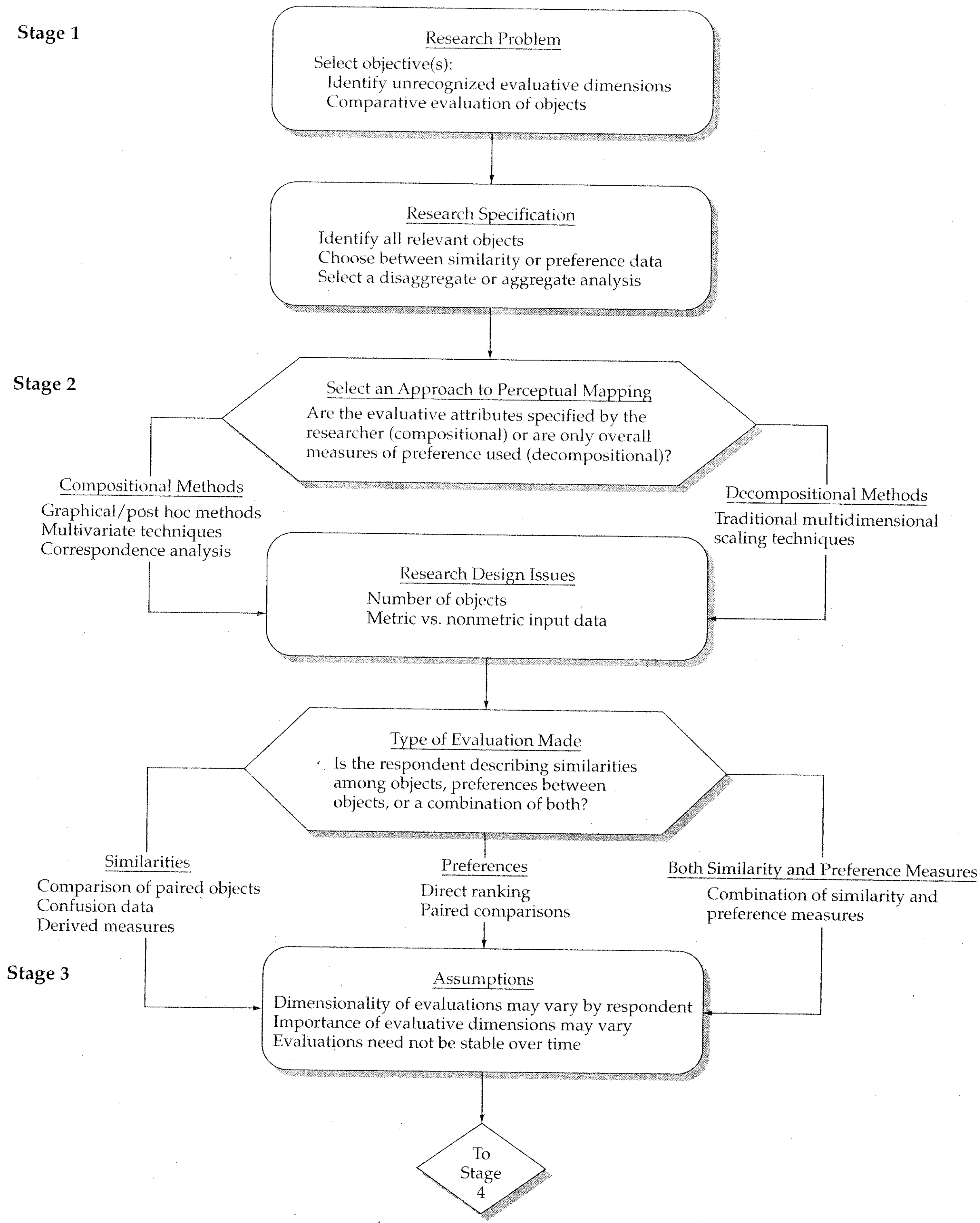


FIGURE 10-3 Stages 1–3 in the Multidimensional Scaling Decision Diagram

STAGE 1: OBJECTIVES OF MDS

Perceptual mapping, and MDS in particular, is most appropriate for achieving two objectives:

1. An exploratory technique to identify unrecognized dimensions affecting behavior
2. A means of obtaining comparative evaluations of objects when the specific bases of comparison are unknown or undefined

In MDS, it is not necessary to specify the attributes of comparison for the respondent. All that is required is to specify the objects and make sure that the objects share a common basis of comparison. This flexibility makes MDS particularly suited to image and positioning studies in which the dimensions of evaluation may be too global or too emotional and affective to be measured by conventional scales. MDS methods combine the positioning of objects and subjects in a single overall map, making the relative positions of objects and consumers for segmentation analysis much more direct.

Key Decisions in Setting Objectives

The strength of perceptual mapping is its ability to infer dimensions without the need for defined attributes. The flexibility and inferential nature of MDS places a greater responsibility on the researcher to correctly define the analysis. The conceptual as well as practical considerations essential for MDS to achieve its best results are addressed through three key decisions:

1. Selecting the objects that will be evaluated
2. Deciding whether similarities or preferences are to be analyzed
3. Choosing whether the analysis will be performed at the group or individual level

IDENTIFICATION OF ALL RELEVANT OBJECTS TO BE EVALUATED The most basic, but important, issue in perceptual mapping is the defining of the objects to be evaluated. The researcher must ensure that all relevant firms, products, services, or other objects are included, because perceptual mapping is a technique of relative positioning. Relevancy is determined by the research questions to be addressed.

For example, a study of soft drinks must include both sugar-based and sugar-free soft drinks, unless the research question explicitly excludes one type or another. Likewise, a study of soft drinks would not include fruit juices.

The perceptual maps resulting from any of the methods can be greatly influenced by either the omission of objects or the inclusion of inappropriate ones [6, 13]. If irrelevant or noncomparable objects are included, the researcher is forcing the technique not only to infer the perceptual dimensions that distinguish among comparable objects but also to infer those dimensions that distinguish among noncomparable objects as well. This task is beyond the scope of MDS and results in a solution that addresses neither question well. Likewise, omitting a relevant object may prevent the true depiction of the perceptual dimensions.

SIMILARITIES VERSUS PREFERENCE DATA Having selected the objects for study, the researcher must next select the basis of evaluation: similarity versus preference. To this point, we discussed perceptual mapping and MDS mainly in terms of similarity judgments. In providing **similarities data**, the respondent does not apply any "good–bad" aspects of evaluation in the comparison. The good–bad assessment is done, however, within **preference data**, which assumes that differing combinations of perceived attributes are valued more highly than other combinations.

Both bases of comparison can be used to develop perceptual maps, but with differing interpretations:

- Similarity-based perceptual maps represent attribute similarities and perceptual dimensions of comparison but do not reflect any direct insight into the determinants of choice.

- Preference-based perceptual maps do reflect preferred choices but may not correspond in any way to the similarity-based positions, because respondents may base their choices on entirely different dimensions or criteria from those on which they base comparisons.

Without any optimal base for evaluation, the decision between similarities and preference data must be made with the ultimate research question in mind, because they are fundamentally different in what they represent.

AGGREGATE VERSUS DISAGGREGATE ANALYSIS In considering similarities or preference data, we are taking respondent's perceptions of stimuli and creating representations (perceptual maps) of stimulus proximity in t-dimensional space (where the number of dimensions t is less than the number of stimuli). At issue, however, is the level of analysis (individual or group) at which the data is analyzed. Each approach has both strengths and weaknesses.

Disaggregate Analysis. One of the distinctive characteristics of MDS techniques is their ability to estimate solutions for each respondent, a method known as a **disaggregate analysis.** Here the researcher generates perceptual maps on a subject-by-subject basis (producing as many maps as subjects). The advantage is the representation of the unique elements of each respondent's perceptions. The primary disadvantage is that the researcher must identify the common dimensions of the perceptual maps across multiple respondents.

Aggregate Analysis. MDS techniques can also combine respondents and create a single perceptual map through an **aggregate analysis**. The aggregation may take place either before or after scaling the subjects' data. Three basic approaches to this type of analysis are aggregating before the MDS analysis, aggregate individual results, and INDSCAL.

- ***Aggregating Before the MDS Analysis*** The simplest approach is for the researcher to find the average evaluations for all respondents and then obtain a single solution for the group of respondents as a whole. It is also the most typical type of aggregate analysis. To identify subgroups of similar respondents and their unique perceptual maps, the researcher may cluster analyze the subjects' responses to find a few average or representative subjects and then develop perceptual maps for the cluster's average respondent.
- ***Aggregate Individual Results*** Alternatively, the researcher may develop maps for each individual and cluster the maps according to the coordinates of the stimuli on the maps. It is recommended, however, that the previous approach of finding average evaluations be used rather than clustering the individual perceptual maps because minor rotations of essentially the same map can cause problems in creating reasonable clusters by the second approach.
- ***INDSCAL: A Combination Approach*** A specialized form of aggregate analysis is available with INDSCAL (individual differences scaling) [2] and its variants, which have characteristics of both disaggregate and aggregate analyses. An INDSCAL analysis assumes that all individuals share a common or group space (an aggregate solution) but that the respondents individually weight the dimensions, including zero weights, when totally ignoring a dimension. The analysis proceeds in two steps:

  1. As a first step, INDSCAL derives the perceptual space shared by all individuals, just as do other aggregate solutions.
  2. However, individuals are also portrayed in a special group space map where each respondent's position is determined by the respondent's weights for each dimension. Respondents positioned closely together employ similar combinations of the dimensions from the common group space. Moreover, the distance of the individual from the origin is an approximate measure of the proportion of variance for that subject

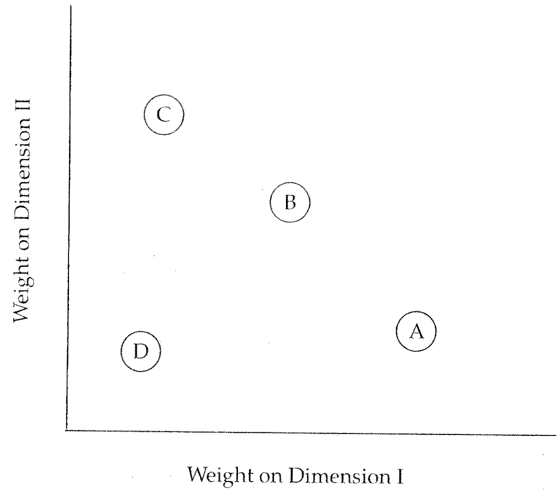


FIGURE 10-4 Respondents' Weights in an INDSCAL Disaggregate Analysis

accounted for by the solution. Thus, a position farther from the origin indicates better fit. Being at the origin means "no fit" because all weights are zeros. If two or more subjects or groups of subjects are at the origin, separate group spaces need to be configured for each of them.

As an example, let us assume we derived a two-dimensional aggregate solution (see step 1). INDSCAL would also derive weights for each dimension, which would allow for each respondent to be portrayed in a two-dimensional graph (see Figure 10-4). For respondent A, almost all of the solution was oriented around dimension I, whereas the opposite is seen for respondent C. Respondents B and D have a balance between the two dimensions.

We also determine the fit for each respondent given the respondent's distance from the origin. Respondents A, B, and C are relatively similar in their distance from the origin, indicating comparable fit. Respondent D, however, has a substantially lower level of fit given its close proximity to the origin.

In an INDSCAL analysis, the researcher is presented with not only an overall representation of the perceptual map but also the degree to which each respondent is represented by the overall perceptual map. These results for each respondent can then be used to group respondents and even identify different perceptual maps in subsequent analyses.

Selecting a Disaggregate Versus Aggregate Analysis. The choice of aggregate or disaggregate analysis is based on the study objectives. If the focus is on an understanding of the overall evaluations of objects and the dimensions employed in those evaluations, an aggregate analysis is the most suitable. However, if the objective is to understand variation among individuals, particularly as a prelude to segmentation analysis, then a disaggregate approach is the most helpful.

STAGE 2: RESEARCH DESIGN OF MDS

Although MDS looks quite simple computationally, the results, as with other multivariate techniques, are heavily influenced by a number of key issues that must be resolved before the research can proceed. We cover four of the major issues, ranging from discussions of research design (selecting the approach and objects or stimuli for study) to specific methodological concerns (metric versus nonmetric methods) and data collection methods.

RULES OF THUMB 10-1

Objectives of MDS

- MDS is an exploratory technique well suited for:
  - Identifying unrecognized dimensions used by respondents in making comparisons between objects (brands, products, stores, etc.)
  - Providing an objective basis for comparison between objects based on these dimensions
  - Identifying specific attributes that may correspond to these dimensions
- An MDS solution requires identification of all relevant objects (e.g., all competing brands within a product category) that set the boundaries for the research question
- Respondents provide one or both types of perceptions:
  - Perceptual distances where they indicate how similar/dissimilar objects are to each other, or
  - "Good–bad" assessments of competing objects (*preference* comparisons) that assist in identifying combinations of attributes that are valued highly
- MDS can be performed at the individual or group level:
  - Disaggregate (individual) analysis:
    - Allows for construction of perceptual maps on a respondent-by-respondent basis
    - Assesses variation among individuals
    - Provides a basis for segmentation analysis
  - Aggregate (group) analysis:
    - Creates perceptual maps of one or more groups
    - Helps understand overall evaluations of objects and/or dimensions employed in those evaluations
    - Should be found by using the average evaluations of all respondents within a group

Selection of Either a Decompositional (Attribute-Free) or Compositional (Attribute-Based) Approach

Perceptual mapping techniques can be classified into one of two types based on the nature of the responses obtained from the individual concerning the object:

- The **decompositional method** measures only the overall impression or evaluation of an object and then attempts to derive spatial positions in multidimensional space that reflect these perceptions. This technique is typically associated with MDS.
- The **compositional method** is an alternative approach that employs several of the multivariate techniques already discussed that are used in forming an impression or evaluation based on a combination of specific attributes.

Each approach has advantages and disadvantages that we address in the following sections. Our discussion here centers on the distinctions between the two approaches and then we focus primarily on the decompositional methods in the remainder of the chapter.

DECOMPOSITIONAL OR ATTRIBUTE-FREE APPROACH Commonly associated with the techniques of MDS, decompositional methods rely on global or overall measures of similarity from which the perceptual maps and relative positioning of objects are formed. Because of the relatively simple task presented to the respondent, decompositional methods have two distinct advantages:

1. They require only that respondents give their overall perceptions of objects. Respondents do not have to detail the attributes or the importance of each attribute used in the evaluation.
2. Because each respondent gives a full assessment of similarities among all objects, perceptual maps can be developed for individual respondents or aggregated to form a composite map.

Decompositional methods have disadvantages as well, primarily related to the inferences required of the researcher to evaluate the perceptual maps:

1. The researcher has no objective basis provided by the respondent on which to identify the basic dimensions used to evaluate the objects (i.e., the correspondence of perceptual and objective dimensions). In many instances, the usefulness to managers of attribute-free studies is restricted because the studies provide little guidance for specific action. For example, the inability to develop a direct link between actions by the firm (the objective dimension) and market positions of their products (the perceptual dimension) many times diminishes the value of perceptual mapping.
2. Little guidance, other than generalized guidelines or a priori beliefs, is available to determine both the dimensionality of the perceptual map and the representativeness of the solution. Although some overall measures of fit are available, they are nonstatistical, and thus decisions about the final solution involve substantial researcher judgment.

Characterized by the generalized category of MDS techniques, a wide range of possible decompositional techniques is available. Selection of a specific method requires decisions regarding the nature of the respondent's input (rating versus ranking), whether similarities or preferences are obtained, and whether individual or composite perceptual maps are derived. Among the most common multidimensional scaling programs are KYST, MDSCAL, PREFMAP, MDPREF, INDSCAL, ALSCAL, MINISSA, POLYCON, and MULTISCALE. Detailed descriptions of the programs and sources for obtaining them are available [1, 2, 3, 4, 5, 6, 11, 16, 17].

COMPOSITIONAL OR ATTRIBUTE-BASED APPROACH Compositional methods include some of the more traditional multivariate techniques (e.g., discriminant analysis or factor analysis), as well as methods specifically designed for perceptual mapping, such as correspondence analysis. A principle common to all of these methods, however, is the assessment of similarity in which a defined set of attributes is considered in developing the similarity between objects. The various techniques included in the set of compositional methods can be grouped into one of three basic groups:

1. *Graphical or post hoc approaches.* Included in this set are analyses such as semantic differential plots or **importance–performance grids,** which rely on researcher judgment and univariate or bivariate representations of the objects.
2. *Conventional multivariate statistical techniques.* These techniques, especially factor analysis and discriminant analysis, are particularly useful in developing a dimensional structure among numerous attributes and then representing objects on these dimensions.
3. *Specialized perceptual mapping methods.* Notable in this class is **correspondence analysis**, (see Chapter 11) developed specifically to provide perceptual mapping with only qualitative or nominally scaled data as input.

Compositional methods in general have two distinct advantages stemming from their defined attributes used in comparison:

- First is the explicit description of the dimensions of perceptual space. Because the respondent provides detailed evaluations across numerous attributes for each object, the evaluative criteria represented by the dimensions of the solution are much easier to ascertain.
- Also, these methods provide a direct way of representing both attributes and objects on a single map, with several methods providing the additional positioning of respondent groups. This information offers unique managerial insight into the competitive marketplace.

Yet the explicit description of the dimensions of comparison also has disadvantages:

- The similarity between objects is limited to only the attributes rated by the respondents. Omitting salient attributes eliminates the opportunity for the respondent to incorporate them, which would be available if a single overall measure were provided.

- The researcher must assume some method of combining these attributes to represent overall similarity, and the chosen method may not represent the respondents' thinking.
- The data collection effort is substantial, especially as the number of choice objects increases.
- Results are not typically available for the individual respondent.

Even though compositional models follow the concept of a variate depicted in many of the other multivariate techniques we have discussed in other sections of the text, they represent a distinctly different approach, with advantages and disadvantages, when compared to the decompositional methods. It is a choice that the researcher must make based on the research objectives of each particular study.

SELECTING BETWEEN COMPOSITIONAL AND DECOMPOSITIONAL TECHNIQUES Perceptual mapping can be performed with both compositional and decompositional techniques, but each technique has specific advantages and disadvantages that must be considered in view of the research objectives:

- If perceptual mapping is undertaken in the spirit of either of the two basic objectives discussed earlier (see stage 1), the decompositional or attribute-free approaches are the most appropriate.
- If, however, the research objectives shift to the portrayal among objects on a defined set of attributes, then the compositional techniques become the preferred alternative.

Our discussion of compositional methods in past chapters illustrated their uses and application along with their strengths and weaknesses. The researcher must always remember the alternatives that are available in the event the objectives of the research change. Thus, we focus here on the decompositional approaches, followed by a discussion of correspondence analysis, a widely used compositional technique particularly suited to perceptual mapping. As such, we also consider as synonymous the terms *perceptual mapping* and *multidimensional scaling* unless necessary distinctions are made.

Objects: Their Number and Selection

Before undertaking any perceptual mapping study, the researcher must address two key questions dealing with the objects being evaluated. These questions deal with issues concerning the basic task (i.e., ensuring the comparability of the objects) as well as the complexity of the analysis (i.e., the number of objects being evaluated).

SELECTING OBJECTS The key question when selecting objects is: Are the objects really comparable? An implicit assumption in perceptual mapping is that common characteristics, either objective or perceived, are present and may be used by the respondent for evaluations. Therefore, it is essential that the objects being compared have some set of underlying attributes that characterize each object and form the basis for comparison by the respondent. It is not possible for the researcher to force the respondent to make comparisons by creating pairs of noncomparable objects. Even if responses are given in such a forced situation, their usefulness is questionable.

THE NUMBER OF OBJECTS A second issue concerns the number of objects to be evaluated. In deciding how many objects to include, the researcher must balance two desires: a smaller number of objects to ease the effort on the part of the respondent versus the required number of objects to obtain a stable multidimensional solution. These opposing considerations each impose limits on the analysis:

- A suggested guideline for stable solutions is to have more than four times as many objects as dimensions desired [8]. Thus, at least five objects are required for a one-dimensional perceptual map, nine objects for a two-dimensional solution, and so on.

- When using the method of evaluating pairs of objects for similarity, the respondent must make 36 comparisons of the nine objects—a substantial task. A three-dimensional solution suggests at least 13 objects be evaluated, necessitating the evaluation of 78 pairs of objects.

Therefore, a trade-off must be made between the dimensionality accommodated by the objects (and the implied number of underlying dimensions that can be identified) and the effort required on the part of the respondent.

The number of objects also affects the determination of an acceptable level of fit. Many times the estimate of fit is inflated when fewer than the suggested number of objects are present for a given dimensionality. Similar to the overfitting problem we found in regression, falling below the recommended guidelines of at least four objects per dimension greatly increases the chances of a misleading solution.

For example, an empirical study demonstrated that when seven objects are fit to three dimensions with random similarity values, acceptable stress levels and apparently valid perceptual maps are generated more than 50 percent of the time. If the seven objects with random similarities were fit to four dimensions, the stress values decreased to zero, indicating perfect fit, in half the cases [12]. Yet in both instances, no real pattern of similarity emerged among the objects.

Thus, we must be aware of the risks associated with violating the guidelines for the number of objects per dimension and the impact this has on both the measures of fit and the validity of the resulting perceptual maps.

Nonmetric Versus Metric Methods

The original MDS programs were truly nonmetric, meaning that they required only nonmetric input, but they also provided only nonmetric (rank-order) output. The nonmetric output, however, limited the interpretability of the perceptual map. Therefore, all MDS programs used today produce metric output. The metric multidimensional positions can be rotated about the origin, the origin can be changed by adding a constant, the axes can be flipped (reflection), or the entire solution can be uniformly stretched or compressed, all without changing the relative positions of the objects.

Because all programs today produce metric output, the differences in the approaches are based only on the input measures of similarity.

- Nonmetric methods, distinguished by the nonmetric input typically generated by rank-ordering pairs of objects, are more flexible in that they do not assume any specific type of relationship between the calculated distance and the similarity measure. However, because nonmetric methods contain less information for creating the perceptual map, they are more likely to result in degenerate or suboptimal solutions. This problem arises when wide variations occur in the perceptual maps between respondents or the perceptions between objects are not distinct or well defined.
- Metric methods assume that input as well as output is metric. This assumption enables us to strengthen the relationship between the final output dimensionality and the input data. Rather than assuming that only the ordered relationships are preserved in the input data, we can assume that the output preserves the interval and ratio qualities of the input data. Even though the assumptions underlying metric programs are more difficult to support conceptually in many cases, the results of nonmetric and metric procedures applied to the same data are often similar.

Thus, selection of the input data type must consider both the research situation (variations of perceptions among respondents and distinctiveness of objects) and the preferred mode of data collection.

Collection of Similarity or Preference Data

As already noted, the primary distinction among MDS programs is the type of input data (metric versus nonmetric) and whether the data represent similarities or preferences. Here we address issues associated with making similarity-based and preference judgments. For many of the data collection methods, either metric (ratings) or nonmetric (rankings) data may be collected. In some instances, however, the responses are limited to only one type of data.

SIMILARITIES DATA When collecting similarities data, the researcher is trying to determine which items are the most similar to each other and which are the most dissimilar. The terms of dissimilarities and similarities often are used interchangeably to represent measurement of the differences between objects. Implicit in similarity measurement is the ability to compare all pairs of objects.

If, for example, all pairs of objects of the set A, B, C (i.e., AB, AC, BC) are rank-ordered, then all pairs of objects can also be compared. Assume that the pairs were ranked AB = 1, AC = 2, and BC = 3 (where 1 denotes most similar). Clearly, pair AB is more similar than pair AC, pair AB is more similar than pair BC, and pair AC is more similar than pair BC.

Several procedures are commonly used to obtain respondents' perceptions of the similarities among stimuli. Each procedure is based on the notion that the relative differences between any pair of stimuli must be measured so that the researcher can determine whether the pair is more or less similar to any other pair. We discuss three procedures commonly used to obtain respondents' perceptions of similarities: comparison of paired objects, confusion data, and derived measures.

Comparison of Paired Objects. By far the most widely used method of obtaining similarity judgments is that of paired objects, in which the respondent is asked simply to rank or rate the similarity of all pairs of objects. If we have stimuli A, B, C, D, and E, we could rank pairs AB, AC, AD, AE, BC, BD, BE, CD, CE, and DE from most similar to least similar.

If, for example, pair AB is given the rank of 1, we would assume that the respondent sees that pair as containing the two stimuli that are the most similar, in contrast to all other pairs (see example in preceding section).

This procedure would provide a nonmetric measure of similarity. Metric measures of similarity would involve a rating of similarity (e.g., from 1 "very similar" to 10 "not at all similar"). Either form (metric or nonmetric) can be used in most MDS programs.

Confusion Data. Measuring similarity by pairing (or confusing) stimulus *I* with stimulus *J* is known as **confusion data**. Also known as **subjective clustering**, a typical procedure for gathering these data when the number of objects is large is as follows:

- Place the objects whose similarity is to be measured on small cards, either descriptively or with pictures.
- The respondent is asked to sort the cards into stacks so that all the cards in a stack represent similar candy bars. Some researchers tell the respondents to sort into a fixed number of stacks; others say to sort into as many stacks as the respondent wants.
- The data from each respondent is then aggregated into a similarities matrix similar to a **cross-tabulation table**. Each cell contains the number of times each pair of objects was included in the same stack. These data then indicate which products appeared together most often and are therefore considered the most similar.

Collecting data in this manner allows only for the calculation of aggregate similarity, because the responses from all individuals are combined to obtain the similarities matrix.

Derived Measures. Similarity based on scores given to stimuli by respondents are known as **derived measures**. The researcher defines the dimensions (attributes) and the respondent rates each object on each dimension. From these ratings, the similarity of each object is calculated by such methods as a correlation between objects or some form of index of agreement.

For example, subjects are asked to evaluate three stimuli (cherry, strawberry, and lemon-lime soda) on a number of attributes (diet versus nondiet, sweet versus tart, and light tasting versus heavy tasting) using semantic differential scales. The responses would be evaluated for each respondent (e.g., correlation or index of agreement) to create similarity measures between the objects.

Three important assumptions underlie this approach:

1. The researcher selects the appropriate dimensions to measure.
2. The scales can be weighted (either equally or unequally) to achieve the similarities data for a subject or group of subjects.
3. All individuals have the same weights.

Of the three procedures discussed, the derived measure is the least desirable in meeting the spirit of MDS—that the evaluation of objects be made with minimal influence by the researcher.

PREFERENCES DATA Preference implies that stimuli should be judged in terms of dominance relationships; that is, the stimuli are ordered in terms of the preference for some property. It enables the researcher to make direct statements of which is the more preferred object (e.g., brand A is preferred over brand C). The two most common procedures for obtaining preference data are direct ranking and paired comparisons.

Direct Ranking. Each respondent ranks the objects from most preferred to least preferred. This method of gathering nonmetric similarity data is popular because it is easy to administer for a small to moderate number of objects. It is quite similar in concept to the subjective clustering procedure discussed earlier, only in this case each object must be given a unique rank (no ties).

Paired Comparisons. A respondent is presented with all possible pairs and asked to indicate which member of each pair is preferred. Then, overall preference is based on the total number of times each object was the preferred member of the paired comparison. In this way, the researcher gathers explicit data for each comparison. This approach covers all possible combinations and is much more detailed than just the direct rankings. The principal drawback to this method is the large number of tasks involved with even a relatively small number of objects. For example, 10 objects result in 45 paired comparisons, which are too many tasks for most research situations. Note that paired comparisons are also used in collecting similarity data, as noted in the example at the beginning of the chapter, but there the pairs of objects are ranked or rated as to the degree of similarity between the two objects in the pair.

PREFERENCE DATA VERSUS SIMILARITY DATA Both similarity and preference data provide a basis for constructing a perceptual map that can depict the relative positions of the objects across the perceived (inferred) dimensions. Selecting between the two approaches lies in the objectives to be achieved:

- Similarity-based perceptual maps are best suited to understanding the attributes/dimensions that describe the objects. In this approach, the focus is on characterizing the nature of each object and its composition relative to the other objects.
- Preference data enable the researcher to view the location of objects on a perceptual map for which distance implies differences in preference. This procedure is useful because an individual's perception of objects in a preference context may be different from that in a similarity context. That is, a particular dimension may be useful in describing the similarities between two objects but may not be consequential in determining preference.

The differing bases for comparison in the two approaches many times result in quite different perceptual maps. Two objects could be perceived as different in a similarity-based map but be

RULES OF THUMB 10-2

Research Design of MDS

- Perceptual maps can be generated through decompositional or compositional approaches:
  - Decompositional approaches are the traditional and most common MDS method, requiring only overall comparisons of similarity between objects
  - Compositional approaches are used when the research objectives involve comparing objects on a defined set of attributes
- The number of objects to be evaluated is a trade-off between:
  - A small number of objects to facilitate the respondents' task
  - Four times as many objects as dimensions desired (i.e., five objects for one dimension, nine objects for two dimensions, etc.) to obtain a stable solution

similar in a preference-based spatial map, resulting in two quite different maps. For example, two different brands of candy bars could be far apart in a similarity-based map but, with equivalent preference, be positioned close to each other on a preference map. The researcher must choose the map that best matches the objectives of the analysis.

STAGE 3: ASSUMPTIONS OF MDS ANALYSIS

Multidimensional scaling has no restraining assumptions on the methodology, type of data, or form of the relationships among the variables, but MDS does require that the researcher accept three tenets concerning perception:

1. *Variation in dimensionality.* Respondents may vary in the dimensionality they use to form their perceptions of an object (although it is thought that most people judge in terms of a limited number of characteristics or dimensions). For example, some might evaluate a car in terms of its horsepower and appearance, whereas others do not consider these factors at all but instead assess it in terms of cost and interior comfort.
2. *Variation in importance.* Respondents need not attach the same level of importance to a dimension, even if all respondents perceive this dimension. For example, two respondents perceive a soft drink in terms of its level of carbonation, but one may consider this dimension unimportant whereas the other may consider it very important.
3. *Variation over time.* Judgments of a stimulus in terms of either dimensions or levels of importance are likely to change over time. In other words, one may not expect respondents to maintain the same perceptions for long periods of time.

In spite of the differences we can expect between individuals, MDS methods can represent perceptions spatially so that all of these differences across individuals are accommodated. This capability enables MDS techniques to not only help a researcher understand each separate individual but also to identify the shared perceptions and evaluative dimensions within the sample of respondents.

STAGE 4: DERIVING THE MDS SOLUTION AND ASSESSING OVERALL FIT

Today the basic MDS programs available in the major statistical programs can accommodate the differing types of input data and types of spatial representations, as well as the varying interpretational alternatives. Our objective here is to provide an overview of MDS to enable a ready understanding of the differences among these programs. However, as with other multivariate techniques, development in both application and knowledge is continual. Thus, we refer the user interested in specific program applications to other texts devoted solely to multidimensional scaling [8, 9, 10, 12, 15].

Determining an Object's Position in the Perceptual Map

The first task of stage 4 involves the positioning of objects to best reflect the similarity evaluations provided by the respondents (see Figure 10-5). Here the MDS techniques determine the optimal locations for each object in a specified dimensionality. The solutions for each dimensionality (two dimensions, three dimensions, etc.) are then compared to select a final solution defining the number of dimensions and each object's relative position on those dimensions.

CREATING THE PERCEPTUAL MAP MDS programs follow a common three-step process for determining the optimal positions in a selected dimensionality:

1. Select an initial configuration of stimuli (S_k) at a desired **initial dimensionality** (t). Various options for obtaining the initial configuration are available. The two most widely used are configurations either applied by the researcher based on previous data or generated by selecting pseudorandom points from an approximately normal multivariate distribution.
2. Compute the distances between the stimuli points and compare the relationships (observed versus derived) with a measure of fit. Once a configuration is found, the interpoint distances between stimuli (d_{ij}) in the starting configurations are compared with distance measures ($\hat{d}_{ij}$) derived from the similarity judgments (s_{ij}). The two distance measures are then compared by a measure of fit, typically a measure of stress. (Fit measures are discussed in a later section.)
3. If the measure of fit does not meet a selected predefined stopping value, find a new configuration for which the measure of fit is further minimized. The program determines the directions in which the best improvement in fit can be obtained and then moves the points in the configuration in those directions in small increments.

The need for a computer program versus hand calculations becomes apparent as the number of objects and dimensions increases. Let us look at a typical MDS analysis and see what is actually involved.

With 10 products to be evaluated, each respondent must rank all 45 possible pairs of objects from most similar (1) to least similar (45). With these rank orders, we proceed to attempt to define the dimensionality and positions of each object.

1. First, assume that we are starting with a two-dimensional solution. Although we could define any number of dimensions, it is easiest to visualize the process in a simple two-dimensional situation.
2. Place 10 points (representing the 10 products) randomly on a sheet of graph paper (representing the two dimensions) and then measure the distances between every pair of points (45 distances).
3. Calculate the goodness-of-fit of the solution by measuring the rank-order agreement between the Euclidean (straight-line) distances of the plotted objects and the original 45 ranks.
4. If the straight-line distances do not agree with the original ranks, move the 10 points and try again. Continue to move the objects until you get a satisfactory fit among the distances between all objects and the ranks indicating similarity.
5. You can then position the 10 objects in three-dimensional space and follow the same process. If the fit of actual distances and similarity ranks is better, then the three-dimensional solution may be more appropriate.

As you can see, the process quickly becomes intractable with increases in the number of objects and dimensions. Computers execute the calculations and allow for a more accurate and

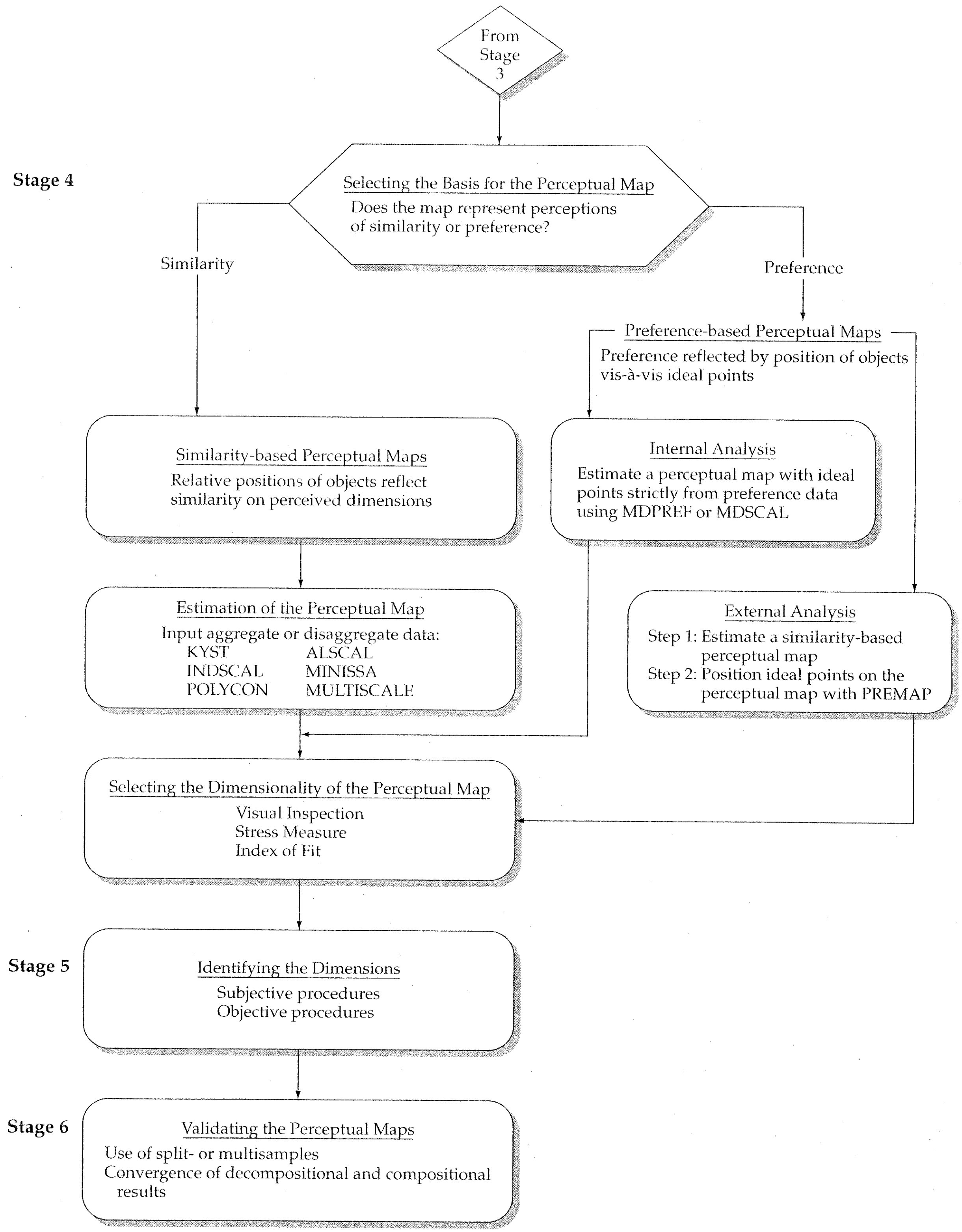


FIGURE 10-5 Stages 4–6 in the Multidimensional Scaling Decision Diagram

detailed solution. The program calculates the best solution across any number of dimensions, thus providing a basis to compare the various solutions.

The primary criterion in all instances for finding the best representation of the data is preservation of the ordered relationship between the original rank data and the derived distances between points. Any measure of fit (e.g., stress) is simply a measure of how well (or poorly) the ranks based on the distances on the map agree with the ranks given by the respondents.

AVOIDING DEGENERATE SOLUTIONS In evaluating a perceptual map, the researcher should always be aware of **degenerate solutions**. Degenerate solutions are derived perceptual maps that are not accurate representations of the similarity responses. Most often they are caused by inconsistencies in the data or an inability of the MDS program to reach a stable solution. They are characterized most often by either a circular pattern, in which all objects are shown to be equally similar, or a clustered solution, in which the objects are grouped at two ends of a single dimension. In both cases, MDS is unable to differentiate among the objects for some reason. The researcher should then reexamine the research design to see where the inconsistencies occur.

Selecting the Dimensionality of the Perceptual Map

As seen in the previous section, MDS defines the optimal perceptual map in a number of solutions of varying dimensionality. With these solutions in hand, the objective of the next step is the selection of a spatial configuration (perceptual map) in a specific number of dimensions. The determination of how many dimensions are actually represented in the data is generally reached through one of three approaches: subjective evaluation, scree plots of the stress measures, or an overall index of fit.

SUBJECTIVE EVALUATION The spatial map is a good starting point for the evaluation. The number of maps necessary for interpretation depends on the number of dimensions. A map is produced for each combination of dimensions. One objective of the researcher should be to obtain the best fit with the smallest possible number of dimensions. Interpretation of solutions derived in more than three dimensions is extremely difficult and usually is not worth the improvement in fit. The researcher typically makes a **subjective evaluation** of the perceptual maps and determines whether the configuration looks reasonable. This evaluation is important because at a later stage the dimensions will need to be interpreted and explained.

STRESS MEASURES A second approach is to use a **stress measure**, which indicates the proportion of the variance of the **disparities** (differences in distances between objects on the perceptual map and the similarity judgments of the respondents) not accounted for by the MDS model. This measurement varies according to the type of program and the data being analyzed. Kruskal's [11] stress is the most commonly used measure for determining a model's goodness-of-fit. It is defined by:

$$\text{Stress} = \sqrt{\frac{(d_{ij} - \hat{d}_{ij})^2}{(d_{ij} - \bar{d}_{ij})^2}}$$

where

$$\begin{aligned}
\bar{d} &= \text{average distance}(\Sigma d_{ij}/n) \text{ on the map} \\
\hat{d}_{ij} &= \text{derived distance from the perceptual map} \\
d_{ij} &= \text{original distance based on similarity judgments}
\end{aligned}$$

The stress value becomes smaller as the derived $\hat{d}_{ij}$ approaches the original d_{ij}. Stress is minimized when the objects are placed in a configuration so that the distances between the objects best match the original distances.

A problem found in using stress, however, is analogous to that of R^2 in multiple regression in that stress always improves with increased dimensions. (Remember that R^2 always increases with additional variables.) A trade-off must then be made between the fit of the solution and the number of dimensions. As was done for the extraction of factors in factor analysis, we can plot the stress value against the number of dimensions to determine the best number of dimensions to utilize in the analysis [12].

For example, in the scree plot in Figure 10-6, the elbow indicates substantial improvement in the goodness-of-fit when the number of dimensions is increased from 1 to 2. Therefore, the best fit is obtained with a relatively low number of dimensions (two).

INDEX OF FIT A squared correlation index is sometimes used as an **index of fit**. It can be interpreted as indicating the proportion of variance of the disparities accounted for by the MDS procedure. In other words, it is a measure of how well the raw data fit the MDS model.

The R^2 measure in multidimensional scaling represents essentially the same measure of variance as it does in other multivariate techniques. Therefore, it is possible to use similar measurement criteria. That is, measures of .60 or better are considered acceptable. Of course, the higher the R^2, the better the fit.

Incorporating Preferences into MDS

Up to this point, we have concentrated on developing perceptual maps based on similarity judgments. However, perceptual maps can also be derived from preferences. The objective is to determine the preferred mix of characteristics for a set of stimuli that predicts preference, given a set configuration of objects [7, 8]. In doing so, a joint space is developed portraying both the objects (stimuli) and the subjects (ideal points). A critical assumption is the homogeneity of perception across individuals for the set of objects. This homogeneity enables all differences to be attributed to preferences, not perceptual differences.

IDEAL POINTS The term **ideal point** has been misunderstood or misleading at times. We can assume that if we locate (on the derived perceptual map) the point that represents the most preferred combination of perceived attributes, we have identified the position of an ideal object. Equally, we can assume that the position of this ideal point (relative to the other products on the derived perceptual map) defines relative preferences so that products farther from the ideal should be less preferred. Thus, an ideal point is positioned so that the distance from the ideal conveys changes in preference.

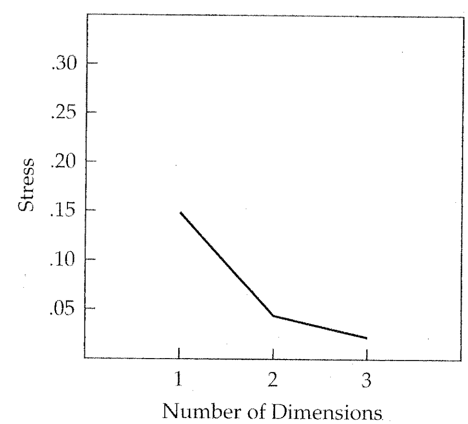


FIGURE 10-6 Use of a Scree Plot to Determine the Appropriate Dimensionality

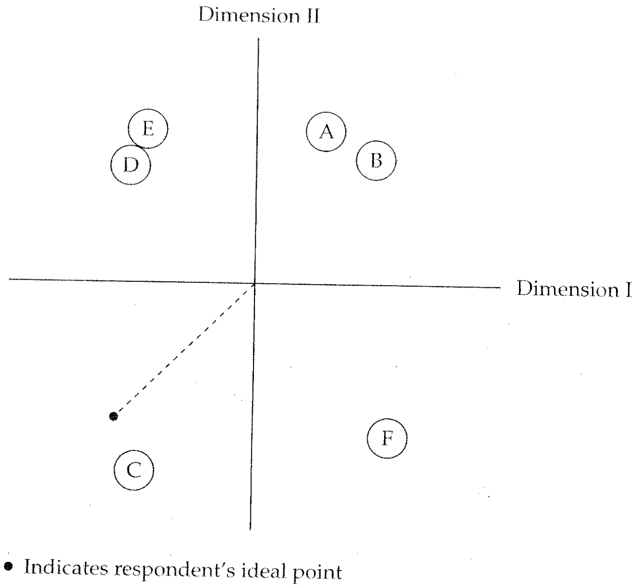


FIGURE 10-7 A Respondent's Ideal Point Within the Perceptual Map

Consider, for example, Figure 10-7. When preference data on the six candy bars (A to F) were obtained from a respondent, their ideal point (indicated by the dot) was positioned so that increasing the distance from it indicated declining preference. Based on this perceptual map, this respondent's preference order is C, F, D, E, A, B. To imply that the ideal candy bar is exactly at that point or even beyond (in the direction shown by the dashed line from the origin) can be misleading. The ideal point simply defines the ordered preference relationship (most preferred to least preferred) among the set of six candy bars for that respondent.

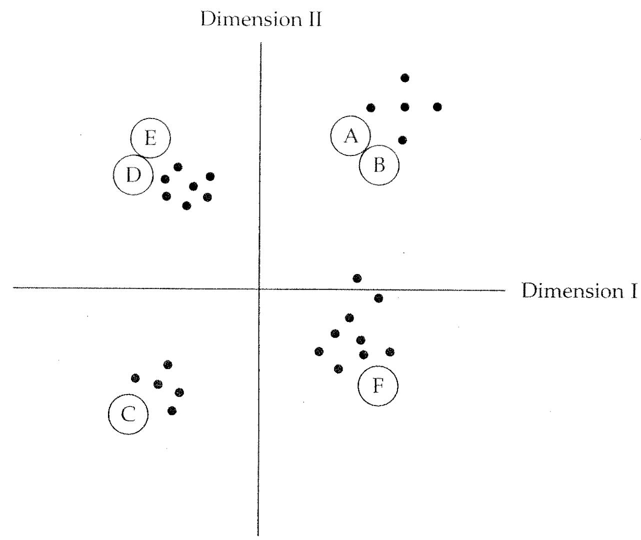
Although ideal points individually may not offer much insight, clusters of them can be useful in defining segments. Many respondents with ideal points in the same general area represent potential market segments of persons with similar preferences, as indicated in Figure 10-8.

DETERMINING IDEAL POINTS Two approaches generally work to determine ideal points: explicit and implicit estimation. The primary difference between the two approaches is the type of evaluative response requested of the respondent. We discuss each approach in the following sections.

Explicit Estimation. Explicit estimation proceeds from the direct responses of subjects, typically asking the subject to rate a hypothetical ideal on the same attributes on which the other stimuli are rated. Alternatively, the respondent is asked to include among the stimuli used to gather similarities data a hypothetical ideal stimulus (e.g., brand, image).

When asking respondents to conceptualize an ideal of anything, we typically run into problems. Often the respondent conceptualizes the ideal at the extremes of the explicit ratings used or as being similar to the most preferred product from among those with which the respondent has had experience. Also, the respondent must think in terms not of similarities but of preferences, which is often difficult with relatively unknown objects. Often these perceptual problems lead the researcher to use implicit ideal point estimation.

Implicit Estimation. Several procedures for implicitly positioning ideal points are described in the following section. The basic assumption underlying most procedures is that derived measures of ideal points' spatial positions are maximally consistent with individual respondents' preferences.



• Indicates a single respondent's ideal point

FIGURE 10-8 Incorporating Multiple Ideal Points in the Perceptual Map

Srinivasan and Schocker [18] assume that the ideal point for all pairs of stimuli is determined so that it violates with least harm the constraint that it be closer to the most preferred in each pair than it is to the least preferred.

Summary. In summary, ideal point estimation can be approached in many ways, and no single method has been demonstrated as best in all cases. The choice depends on the researcher's skills and the MDS procedure selected.

IMPLICIT POSITIONING OF THE IDEAL POINT Implicit positioning of the ideal point from preference data can be accomplished through either an internal or an external analysis:

- Internal analysis of preference data refers to the development of a spatial map shared by both stimuli and subject points (or vectors) solely from the preference data.
- External analysis of preference uses a prespecified configuration of objects and then attempts to place the ideal points within this perceptual map.

Each approach has advantages and disadvantages, which are discussed in the following sections.

Internal Analysis. Internal analyses must make certain assumptions in deriving a combined perceptual map of stimuli and ideal points. The objects' positions are calculated based on **unfolding** preference data for each individual. The results reflect perceptual dimensions that are **stretched** and weighted to predict preference. One characteristic of internal estimation methods is that they typically employ a vector representation of the ideal point (see the following section for a discussion of vector versus point representations), whereas external models can estimate either vector or point representations.

As an example of this approach, MDPREF [3] or MDSCAL [11], two of the more widely used programs, enable the user to find configurations of stimuli and ideal points. In doing so, the researcher must assume the following:

1. No difference between respondents
2. Separate configurations for each respondent
3. A single configuration with individual ideal points

By gathering preference data, the researcher can represent both stimuli and respondents on a single perceptual map.

External Analysis. External analysis of preference data refers to fitting ideal points (based on preference data) to stimulus space developed from similarities data obtained from the same subjects. For example, we might scale similarities data individually, examine the individual maps for commonality of perception, and then scale the preference data for any group identified in this fashion. If this procedure is followed, the researcher must gather both preference and similarities data to achieve external analysis.

PREFMAP [4] was developed solely to perform external analysis of preference data. Because the similarity matrix defines the objects in the perceptual map, the researcher can now define both attribute descriptors (assuming that the perceptual space is the same as the evaluative dimensions) and ideal points for individuals. PREFMAP provides estimates for a number of different types of ideal points, each based on different assumptions as to the nature of preferences (e.g., vector versus point representations, or equal versus differential dimension weights).

Choosing Between Internal and External Analysis. It is generally accepted [8, 9, 15] that external analysis is clearly preferable to internal analysis. This conclusion is based on computational difficulties with internal analysis procedures and on the confounding of differences in preference with differences in perception. In addition, the saliencies of perceived dimensions may change as one moves from perceptual space (Are the stimuli similar or dissimilar?) to evaluative space (Which stimulus is preferred?).

We discuss the procedure of external estimation in our example of perceptual mapping with MDS at the end of this chapter.

POINT VERSUS VECTOR REPRESENTATIONS The discussion of perceptual mapping of preference data emphasized an ideal point that portrays the relationship of an individual's preference ordering for a set of stimuli. The previous section discussed the issues relating to the type of data and analysis used in estimating and placing the ideal point. The remaining issue focuses on the manner in which the other objects in the perceptual map relate to the ideal point to reflect preference. The two approaches (point versus vector representation) are discussed next.

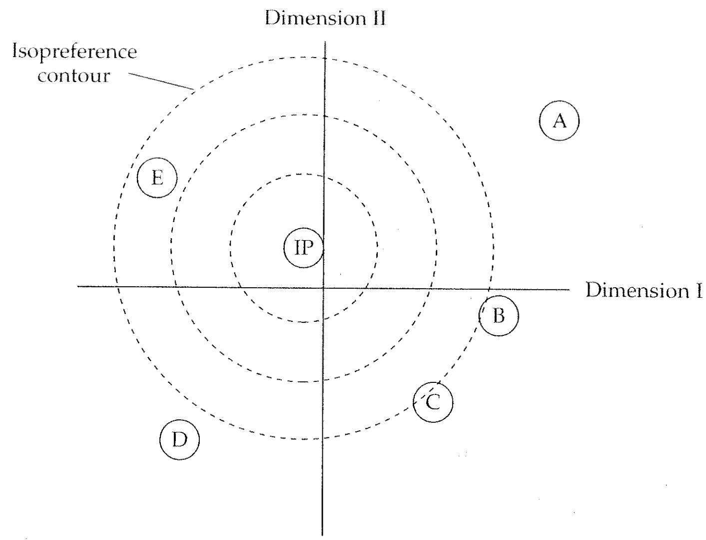
Point Representation. The most easily understood method of portraying the ideal point is to use the straight-line (Euclidean) distance measure of preference ordering from the ideal point to all the points representing the objects. We are assuming that the direction of distance from the ideal point is not critical, only the relative distance.

An example is shown in Figure 10-9. Here, the ideal point as positioned indicates that the most preferred object is E, followed by C, then B, D, and finally A. The ordering of preference is directly related to the distance from the ideal point.

Vector Representation. The ideal point can also be shown as a **vector**. To calculate the preferences in this approach, perpendicular lines (also known as **projections**) are drawn from the objects to the vector. Preference increases in the direction the vector is pointing. The preferences can be read directly from the order of the projections.

Figure 10-10 illustrates the vector approach for two subjects with the same set of stimuli positions. For subject 1, the vector has the direction of lower preference in the bottom left-hand corner to higher preference in the upper right-hand corner. When the projection for each object is made, the preference order (highest to lowest) is A, B, C, E, and D. However, the same objects have a quite different preference order for subject 2. For subject 2 the preference order ranges from the most preferred, E, to the least preferred, C. In this manner, a separate vector can represent each subject.

The vector approach does not provide a single ideal point, but it is assumed that the ideal point is at an infinite distance outward on the vector.

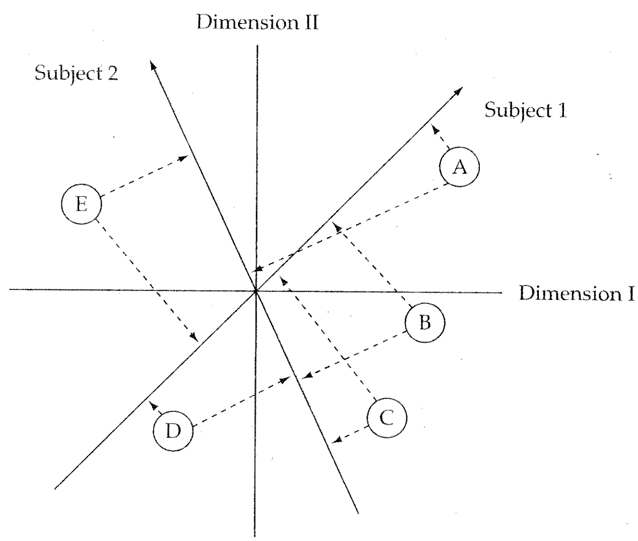


Preference order (highest to lowest): E > C > B > D > A

(A) Object (IP) Ideal Point

FIGURE 10-9 Point Representation of an Ideal Point

Although either the point or vector representations can indicate what combinations of attributes are more preferred, these observations are often not borne out by further experimentation. For example, Raymond [14] cites an example in which the conclusion was drawn that people would prefer brownies on the basis of degree of moistness and chocolate content. When the food technicians applied this result in the laboratory, they found that their brownies made to the



Preference order (highest to lowest): Subject 1: A > B > C > E > D
Subject 2: E > A > D > B > C

FIGURE 10-10 Vector Representations of Two Ideal Points: Subjects 1 and 2

experimental specification became chocolate milk. One cannot always assume that the relationships found are independent or linear, or that they hold over time, as noted previously. However, MDS is a beginning in understanding perceptions and choice that will expand considerably as applications extend our knowledge of both the methodology and human perception.

STAGE 5: INTERPRETING THE MDS RESULTS

Once the perceptual map is obtained, the two approaches—compositional and decompositional—again diverge in their interpretation of the results. The differences in interpretation are based on the amount of information directly provided in the analysis (e.g., the attributes incorporated in the compositional analysis versus their absence in the decompositional analysis) and the generalizability of the results to the actual decision-making process.

- For *compositional methods*, the perceptual map can be directly interpreted with the attributes incorporated in the analysis. The solution, however, must be validated against other measures of perception, because the positions are totally defined by the attributes specified by the researcher. For example, discriminant analysis results might be applied to a new set of objects or respondents, assessing the ability to differentiate with these new observations.
- For *decompositional methods*, the most important issue is the description of the perceptual dimensions and their correspondence to attributes. Evaluations of similarity or preference are done without regard to attributes, thus avoiding a specification error issue. The risk, however, is that the perceptual dimensions are not correctly translated in that the dimensions used in the evaluations are not reflected by the attributes chosen for their interpretation. Descriptive techniques to label the dimensions, as well as to integrate preferences (for objects and attributes) with the similarity judgments, are discussed later. Again, in line with their objectives, the decompositional methods provide an initial look into perceptions from which more formalized perspectives may emerge.

Because other chapters in this text deal with many of the compositional techniques, the remainder of this chapter focuses on decompositional methods, primarily the various techniques used in multidimensional scaling. A notable exception is the discussion of a compositional approach—correspondence analysis—that, to a degree, bridges the gap between the two approaches in its flexibility and methods of interpretation.

Identifying the Dimensions

As discussed in Chapter 3 relating to interpreting factors in factor analysis, identifying underlying dimensions is often a difficult task. Multidimensional scaling techniques have no built-in procedure for labeling the dimensions. The researcher, having developed the maps with a selected dimensionality, can adopt several procedures, either subjective or objective.

SUBJECTIVE PROCEDURES Interpretation must always include some element of researcher or respondent judgment, and in many cases this level of judgment proves adequate for the questions at hand. A quite simple, yet effective, method is labeling (by visual inspection) the dimensions of the perceptual map by the respondent. Respondents may be asked to interpret the dimensionality subjectively by inspecting the maps, or a set of experts may evaluate and identify the dimensions. Although it makes no attempt to quantitatively link the dimensions to attributes, this approach may be the best available if the dimensions are believed to be highly intangible or affective or emotional in content, so that adequate descriptors cannot be devised.

In a similar manner, the researcher may describe the dimensions in terms of known (objective) characteristics. In this way, the correspondence is made between objective and perceptual dimensions directly, although these relationships are not a result of respondent feedback but of the researcher's judgment.

OBJECTIVE PROCEDURES As a complement to the subjective procedures, a number of more formalized methods have been developed. The most widely used method, PROFIT (PROperty FITting) [1], collects attribute ratings for each object and then finds the best correspondence of each attribute to the derived perceptual space. The attempt is to identify the determinant attributes in the similarity judgments made by individuals. Measures of fit are given for each attribute, as well as their correspondence with the dimensions. The researcher can then determine which attributes best describe the perceptual positions and are illustrative of the dimensions. The need for correspondence between the attributes and the defined dimensions diminishes with the use of metric output, because the dimensions can be rotated freely without any changes in interpretation.

SELECTING BETWEEN SUBJECTIVE AND OBJECTIVE PROCEDURES For either subjective or objective procedures, the researcher must remember that although a dimension can represent a single attribute, it usually does not. A more common procedure is to collect data on several attributes, associate them either subjectively or empirically with the dimensions where applicable, and determine labels for each dimension using multiple attributes, similar to factor analysis. Many researchers suggest that using attribute data to help label the dimensions is the best alternative. The problem, however, is that the researcher may not include all the important attributes in the study. Thus, the researcher can never be totally assured that the labels represent all relevant attributes.

Both subjective and objective procedures illustrate the difficulty of labeling the axes. This task is essential because the dimensional labels are required for further interpretation and use of the results. The researcher must select the type of procedure that best suits both the objectives of the research and the available information. Thus, the researcher must plan for the derivation of the dimensional labels as well as the estimation of the perceptual map.

STAGE 6: VALIDATING THE MDS RESULTS

Validation in MDS is as important as in any other multivariate technique. Because of the highly inferential nature of MDS, this effort should be directed toward ensuring the generalizability of the results both across objects and to the population. As will be seen in the following discussion, MDS presents particularly problematic issues in validation, both from a substantive as well as methodological perspective.

Issues in Validation

Any MDS solution must deal with two specific issues that complicate efforts to validate the results:

- The only output of MDS that can be used for comparative purposes involves the relative positions of the objects. Thus, although the positions can be compared, the underlying dimensions have no basis for comparison. If the positions vary, the researcher cannot determine whether the objects are viewed differently, the perceptual dimensions vary, or both.
- Systematic methods of comparison have not been developed and integrated into the statistical programs. The researcher is left to improvise with procedures that may address general concerns but are not specific to MDS results.

As a result, researchers must strive in their validation efforts to maintain comparability between solutions while providing an empirical basis for comparison.

Approaches to Validation

Any approach to validation attempts to assess generalizability (e.g., similarity across different samples) while maintaining comparability for comparison purposes. The issues discussed in the previous section, however, make these requirements difficult for any MDS solution. Several approaches for validation that meet each requirement to some degree are discussed next.

SPLIT-SAMPLE ANALYSIS The most direct validation approach is a split- or multisample comparison, in which either the original sample is divided or a new sample is collected. In either instance, the researcher must then find a means of comparing the results. Most often the comparison between results is done visually or with a simple correlation of coordinates. Some matching programs are available, such as FMATCH [16], but the researcher still must determine how many of the disparities are due to differences in object perceptions, differing dimensions, or both.

COMPARISON OF DECOMPOSITIONAL VERSUS COMPOSITIONAL SOLUTIONS Another approach is to obtain a convergence of MDS results by applying both decompositional and compositional methods to the same sample. The decompositional method(s) could be applied first, along with interpretation of the dimensions to identify key attributes. Then one or more compositional methods, particularly correspondence analysis, could be applied to confirm the results. The researcher must realize that this is not true validation of the results in terms of generalizability, but does confirm the interpretation of the dimension. From this point, validation efforts with other samples and other objects could be undertaken to demonstrate generalizability to other samples.

OVERVIEW OF MULTIDIMENSIONAL SCALING

Multidimensional scaling represents a distinctive approach to multivariate analysis when compared to other methods in this text. Whereas other techniques are concerned with accurately specifying the attributes comprising independent and/or dependent variables, multidimensional scaling takes a quite different approach. It gathers only global or holistic measures of similarity or preference and then empirically infers the dimensions (both character and number) that reflect the best explanation of an individual's responses either separately or collectively. In this approach, the variate used in many other techniques becomes the perceptual dimensions inferred from the analysis. As such, the researcher does not have to be concerned with such issues as specification error, multicollinearity,

RULES OF THUMB 10-3

Deriving and Validating an MDS Solution

- Stress measures (lower values are better) represent an MDS solution's fit
- Researchers can identify a degenerate MDS solution that is generally problematic by looking for:
  - A circular pattern of objects suggesting that all objects are equally similar, or
  - A multiclustered solution in which objects are grouped at two ends of a single continuum
- The appropriate number of dimensions for a perceptual map is based on:
  - A subjective judgment as to whether a solution with a given dimensionality is reasonable
  - Use of a scree plot to identify the elbow where a substantial improvement in fit occurs
  - Use of R^2 as an index of fit; measures of .6 or higher are considered acceptable
- External analysis, such as is performed by PREFMAP, is considered preferable in generating ideal points relative to internal analysis
- The most direct validation method is a split-sample approach
  - Multiple solutions are generated by either splitting the original sample or collecting new data
  - Validity is indicated when the multiple solutions match

or statistical characteristics of the variables. The challenge to the researcher, however, is to interpret the variate; without a valid interpretation the primary objectives of MDS are compromised.

The application of MDS is appropriate when the objective is more oriented toward understanding overall preferences or perceptions rather than detailed perspectives involving individual attributes. One technique, however, combines the specificity of attribute-level analysis within MDS-like solutions. That method, correspondence analysis, is discussed in the following section where the similarities and differences with traditional MDS techniques are highlighted.

AN ILLUSTRATION OF MDS

To demonstrate the use of MDS techniques, we examine data gathered in a series of interviews by company representatives of a cross-section of potential customers. The discussion will proceed by following the six-step process described earlier. The examples discussed here are complemented by the compositional technique of correspondence analysis (CA) in Chapter 11. Readers are encouraged to review that technique as well. The application of both compositional and decompositional techniques enables the researcher to gain unique insights from each technique while also establishing a basis of comparison between each method. Data sets for both techniques are available on the Web at www.pearsonhighered.com/hair or www.mvstats.com.

Stage 1: Objectives of MDS

A common use of perceptual mapping is to explore a firm's image and competitiveness. This includes addressing the perceptions of a set of firms in the market as well as investigating attributes underlying those firms' positions. Information regarding preferences among potential customers can be added to the analysis, if desired. In this example, HBAT uses perceptual mapping techniques to identify the position of HBAT in a perceptual map of major competitors in the market, with an understanding of the dimension comparisons used by potential customers. It then analyzes those market positions to identify the relevant attributes that contribute to HBAT's position, as well as those of its competitors.

Particular interest is focused on assessing the dimensions of evaluation that may be too subjective or affective to be measured by conventional scales. Moreover, the intent is to create a single overall perceptual map by combining the positioning of objects and subjects and making the relative positions of objects and consumers for segmentation analysis much more direct.

In achieving these objectives, the researcher must address three fundamental issues that dictate the basic character of the results: (1) the objects to be considered for comparison, (2) the use of similarity and/or preference data, and (3) the use of disaggregate or aggregate analysis. Each of these issues will be addressed in the following discussion.

IDENTIFYING OBJECTS FOR INCLUSION A critical decision for any perceptual mapping analysis is the selection of the objects to be compared. Given that judgments are made based on the similarity of one object to another, the inclusion or exclusion of objects can have a marked impact. For example, excluding a firm with distinguishing characteristics unique to other firms may help reveal firm-to-firm comparisons or even dimensions not otherwise detected. Likewise, the exclusion of distinctive or otherwise relevant firms may affect the results in a similar manner.

In our example, the objects of study are HBAT and its nine major competitors. To understand the perceptions of these competing firms, mid-level executives of firms representing potential customers are surveyed on their perceptions of HBAT and the competing firms. The resulting perceptual maps hopefully portray HBAT's positioning in the marketplace.

BASING THE ANALYSIS ON SIMILARITY OR PREFERENCE DATA The choice of similarity or preference data depends on the basic objectives of the analysis. Similarity data provide the most direct comparison of objects based on their attributes, whereas preference data allow for a direct assessment of respondent sentiment toward an object. It is possible through use of multiple techniques to combine the two types of data if both are gathered.

For this analysis, emphasis will be placed on gathering similarity for use in the MDS techniques. Preference data will be used in supplementary analyses to assess preference ordering among objects.

USING A DISAGGREGATE OR AGGREGATE ANALYSIS The final decision involves whether to use aggregate or disaggregate analyses individually or in common. Aggregate analyses provides for an overall perspective on the entire sample in a single analysis, with perceptual maps representing the composite perceptions of all respondents. Disaggregate analyses allow for an individualized analysis, where all respondents can be analyzed separately and even portrayed with their own personal perceptual map. It is also possible to combine these two types of analysis such that results for individuals are displayed in conjunction with the aggregate results.

In this HBAT example, most analyses will be presented at the aggregate level, although in certain instances the disaggregate results will be examined to provide diagnostic information about the consistency of the individual results. The aggregate results more closely match the research objectives, which are an overall portrayal of HBAT versus its major competitors. If subsequent research were to focus more on segmentation or targeting issues that directly involve individuals, then disaggregate analyses would be more appropriate.

Stage 2: Research Design of the Perceptual Mapping Study

With the objectives defined for the perceptual mapping analyses, HBAT researchers must next address a set of decisions focusing on research design issues that define the methods used and the specific firms to be studied. By doing so, they also define the types of data that need to be collected to perform the desired analyses. Each of these issues is discussed in the following section.

SELECTING DECOMPOSITIONAL OR COMPOSITIONAL METHODS The choice between decompositional (attribute-free) or compositional (attribute-based) methods revolves around the level of specificity the researcher desires. In the decompositional approach, the respondent provides only overall perceptions or evaluations in order to provide the most direct measure of similarity. However, the researcher is left with little objective evidence of how these perceptions are formed or upon what basis they are made. In contract, the compositional approach provides some points of references (e.g., attributes) when assessing similarities, but then we must be aware of the potential problems when relevant attributes are omitted.

In this example, a combination of decompositional and compositional techniques is employed. First, a traditional MDS technique using overall measures of similarity provides a perceptual map of HBAT and its nine competitors. Then analyses incorporating preference data into the perceptual maps, as well as methods of describing the dimensions of the perceptual map in terms of firm attributes, are provided as supplementary analyses available on the text's Web sites (www.pearsonhighered.com/hair or www.mvstats.com).

SELECTING FIRMS FOR ANALYSIS In selecting firms for analysis, the researcher must address two issues. First, are all of the firms comparable and relevant for the objectives of this study? Second, is the number of firms included enough to portray the dimensionality desired? The design of the research to address each issue is discussed here.

This study includes nine competitors, plus HBAT, representing all the major firms in this industry and collectively having more than 85 percent of total sales. Moreover, they are considered representative of all of the potential segments existing in the market. All of the remaining firms not included in the analysis are considered secondary competitors to one or more of the firms already included.

By including 10 firms, researchers can be reasonably certain that perceptual maps of at least two dimensions can be identified and portrayed. Although the inclusion of this many firms results in a somewhat extensive evaluation task on the part of respondents, it was deemed necessary to include this set of firms to provide researchers a multidimensional framework representative of the entire industry structure.

NONMETRIC VERSUS METRIC METHODS The choice between nonmetric and metric methods is based jointly on the type of analyses to be performed (e.g., compositional versus decompositional), as well as the actual programs to be used. In the HBAT study, metric methods are used. The multidimensional scaling analyses are performed exclusively with metric data (similarities, preferences, and attribute ratings). Perceptual mapping with nonmetric data can be performed by correspondence analysis (see Chapter 11).

DATA COLLECTION The primary decision in constructing the perceptual map is whether to utilize similarities or preferences. To make this decision, the researcher must understand the research objectives: Does the analysis focus on understanding how the objects compare on the antecedents of choice (i.e., similarities based on attributes of the objects) or on the outcomes of choice (i.e., preferences)? In selecting one approach, the analyst must then infer the other through additional analysis. For example, if similarities are chosen as the input data, the researcher is still unsure as to what choices would be made in any type of decision. Likewise, if preferences are analyzed, the researcher has no direct basis for understanding the determinants of choice unless additional analysis is performed.

The HBAT study is composed of in-depth interviews with 18 mid-level management personnel from different firms. From the research objectives, the primary goal is to understand the similarities of firms based on firms' attributes. Thus, focus is placed on similarity data for use in the multidimensional scaling analysis and nonmetric attribute ratings for the correspondence analysis. In the course of the interviews, however, additional types of data were collected for use in supplementary MDS analyses, including attribute ratings of firms and preferences for each firm.

Similarity Data. The starting point for data collection for the MDS analysis was obtaining the perceptions of the respondents concerning the similarity or dissimilarity of HBAT and nine competing firms in the market.

Similarity judgments were made with the comparison-of-paired-objects approach. The 45 pairs of firms [$(10 \times 9)/2$] were presented to the respondents, who indicated how similar each was on a 9-point scale, with 1 being "not at all similar" and 9 being "very similar." The results are tabulated for each respondent in a lower triangular matrix (see the HBAT_MDS data set for specific example). Note that the use of larger values indicating greater similarity was done to ease the burden on the respondents. But the values will need to be "reversed" during analysis, because increasing values for the similarity ratings indicate greater similarity, the opposite of a distance measure of similarity that is used in the MDS techniques.

Attribute Ratings. In addition to the similarity judgments, ratings of each firm on a series of attributes were obtained to provide some objective means of describing the dimensions identified in the perceptual maps. These ratings would be used in the supplementary MDS techniques to assist in interpreting the dimensions of the perceptual map.

For the metric ratings used in MDS, each firm was rated on a set of attributes using a 6-point scale, ranging from Low (1) to High (6). The ratings indicate the extent to which each attribute is descriptive of a firm. The attributes include 8 of the 10 attributes identified as composing the four factors in Chapter 3: X_6, Product Quality; X_8, Technical Support; X_{10}, Advertising; X_{12}, Salesforce Image; X_{13}, Competitive Pricing; X_{14}, Warranty & Claims; X_{16}, Order & Billing; and X_{18}, Delivery Speed. Two of the attributes from the original set of 10 were eliminated in this analysis. First, X_7, relating to E-Commerce, was not used because about one-half of the firms did not have an e-commerce presence. Also, X_9, Complaint Resolution, which is largely experience-based, was also omitted because evaluation by noncustomers was difficult for the respondents.

Preference Evaluations. The final type of data assessed the preferences of each respondent in a specific choice context. These data are to be used in conjunction with the perceptual maps derived in multidimensional scaling to provide insight into the correspondence of similarity and preference judgments through a set of supplementary analyses.

Respondents ranked the firms in order of preference for a "typical" buying situation. Although choice criteria may vary given the type of buying context (e.g., straight rebuy versus new purchase), respondents were asked to provide an overall preference for each firm. The respondents indicated preferences with a simple ordinal ranking of firms, where they identified most preferred (rank order = 1), the next most preferred (rank order = 2), and so on, until all 10 firms were ranked.

Stage 3: Assumptions in MDS

The assumptions of MDS deal primarily with the comparability and representativeness of the objects being evaluated and the respondents. The techniques themselves place few limitations on the data, but their success is based on several characteristics of the data.

With regard to the sample, the sampling plan emphasized obtaining a representative sample of HBAT customers. Moreover, care was taken to obtain respondents of comparable position and market knowledge. Because HBAT and the other firms serve a fairly distinct market, all the firms evaluated in the perceptual mapping should be known, ensuring that positioning discrepancies can be attributed to perceptual differences among respondents.

Stage 4: Deriving MDS Results and Assessing Overall Fit

The process of developing a perceptual map can vary markedly in terms of the types of input data and associated analyses performed. In this section, we first discuss the process of developing a perceptual map based on similarity judgments. Then, with the perceptual map established, we discuss the supplementary analyses for incorporating preference judgments into the existing perceptual map.

DEVELOPING AND ANALYZING THE PERCEPTUAL MAP The estimation of the perceptual map starts with the type of input data and the model estimation (aggregate versus disaggregate) chosen. Methods such as the INDSCAL [2] approach are flexible in that they can produce aggregate results (i.e., a single perceptual map across all respondents) but also provide information on the individual respondents relating to the consistency across respondents.

The INDSCAL method of multidimensional scaling in SPSS was used to develop both a composite, or aggregate, perceptual map as well as the measures of the differences between respondents in their perception. The 45 similarity judgments from the 18 respondents were input as separate matrices (see the HBAT_MDS data set), but mean scores across respondents were calculated to illustrate the general pattern of similarities (see Table 10-2). The bottom rows of the table detail the firms with the highest and lowest similarity values for each firm. These relationships are illustrative of the basic patterns that should be identified in the resulting map (i.e., highly similar firms should be located closer together and dissimilar firms farther apart). For example, HBAT is most similar to firm A and least similar to firms C and G.

Establishing the Appropriate Dimensionality. The first analysis of the MDS results is to determine the appropriate dimensionality and portray the results in a perceptual map. To do so, the researcher should consider both the indices of fit at each dimensionality and the researcher's ability to interpret the solution.

Table 10-3 shows the indices of fit for solutions of two to five dimensions (a one-dimensional solution was not considered a viable alternative for 10 firms). As the table shows, substantial improvement in the stress measure occurs when moving from two to three dimensions, after which the improvement diminishes somewhat and remains consistent as we increase in the number of dimensions. Balancing this improvement in fit against the increasing difficulty of interpretation, the two- or three-dimensional solutions seem the most appropriate. For purposes of illustration, the two-dimensional solution is

TABLE 10-2 Mean Similarity Ratings for HBAT and Nine Competing Firms

	Firm									
Firm	**HBAT**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
HBAT	0.00									
A	6.61	0.00								
B	5.94	5.39	0.00							
C	2.33	2.61	3.44	0.00						
D	2.56	2.56	4.11	6.94	0.00					
E	4.06	2.39	2.17	4.06	2.39	0.00				
F	2.50	3.50	4.00	2.22	2.17	4.06	0.00			
G	2.33	2.39	3.72	2.67	2.61	3.67	2.28	0.00		
H	2.44	4.94	6.61	2.50	7.06	5.61	2.83	2.56	0.00	
I	6.17	6.94	2.83	2.50	2.50	3.50	6.94	2.44	2.39	0.00

Maximum and Minimum Similarity Ratings

	HBAT	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
Maximum similarity	A	I	H	D	H	H	I	B	D	A
Minimum similarity	C, G	E, G	E	F	F	B	C	F	I	H

Note: Similarity ratings are on a 9-point scale (1 = Not at All Similar, 9 = Very Similar).

selected for further analyses, but the methods we discuss here could just as easily be applied to the three-dimensional solution. The researcher is encouraged to explore other solutions to assess whether any substantively different conclusions would be reached based on the dimensionality selected.

Creating the Perceptual Map. With the dimensionality established at two dimensions, the next step is to position each object (firm) in the perceptual map. Remember that the basis for the map (in this case similarity) defines how objects can be compared.

The two-dimensional aggregate perceptual map is shown in Figure 10-11. To see how the similarity values are represented, let us examine some of the relationships between HBAT and other firms. In Table 10-2, we saw that HBAT is most similar to firm A and least similar to firms C and G. As we view the perceptual map, we can see those relationships depicted—HBAT is closest to firm A and farthest away from firms C and G. Similar comparisons for other highly similar pairs of firms (E and G, D and H, and F and I) show that they are closely positioned in the perceptual map as well.

TABLE 10-3 Assessing Overall Model Fit and Determining the Appropriate Dimensionality

	Average Fit Measures[a]			
Dimensionality of the Solution	**Stress**[b]	**Percent Change**	R^2[c]	**Percent Change**
5	.20068	—	.6303	—
4	.21363	6.4	.5557	11.8
3	.23655	10.7	.5007	9.9
2	.30043	27.0	.3932	21.5

[a] Average across 18 individual solutions.
[b] Kruskal's stress formula.
[c] Proportion of original similarity ratings accounted for by scaled data (distances) from the perceptual map.

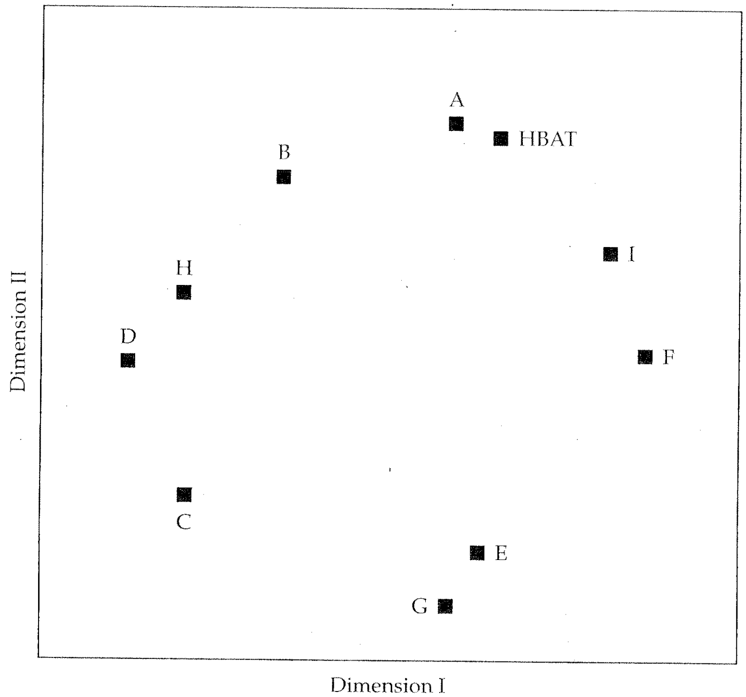


FIGURE 10-11 Perceptual Map of HBAT and Major Competitors

Differences can also be distinguished between forms based on the dimensions of the perceptual map. For example, HBAT differs from firms E and G primarily on dimension II, whereas dimension I differentiates HBAT most clearly from firms C, D, and H in one direction and firms F and I in another direction. All of these differences are reflected in their relative positions in the perceptual map, and similar comparisons can be made among all sets of firms. To understand the sources of these differences, however, the researcher must interpret the dimensions.

ASSESSING MODEL FIT The researcher should also assess model fit by examining how well the results portray the individual respondents. In doing so, the researcher should identify any potential outliers and check the assumption of homogeneity of respondents. These two additional analyses provide the researcher with some assessment of the results at the respondent level. This will allow for a better understanding of how the perceptions of individuals are combined into the aggregate results as well as a means of identifying the individuals who are candidates for possible deletion due to their inconsistency with the remaining sample.

Assessing Potential Outliers. In the process of selecting the appropriate dimensionality, an overall measure of fit (stress) was examined. However, this measure does not depict in any way the fit of the solution to individual comparisons. Such an analysis can be done visually through a scatterplot of actual distances (scaled similarity values) versus fitted distances from the perceptual map. Each point represents a single similarity judgment between two objects, with poor fit depicted as outlying points in the graph. Outliers are a set of similarity judgments that reflect consistently poor fit for an object or individual respondent. If a consistent set of objects or individuals is identified as outliers, they can be considered for deletion.

A measure of model fit is also provided for each individual so that the researcher has a quantitative perspective on each respondent. Lower values of stress indicate better fit, as do higher R^2 values. Although there are not absolute standards in assessing these measures, they do provide a sound comparative measure between respondents, such that individuals with relatively poor model fit can be identified and potentially eliminated from the analysis.

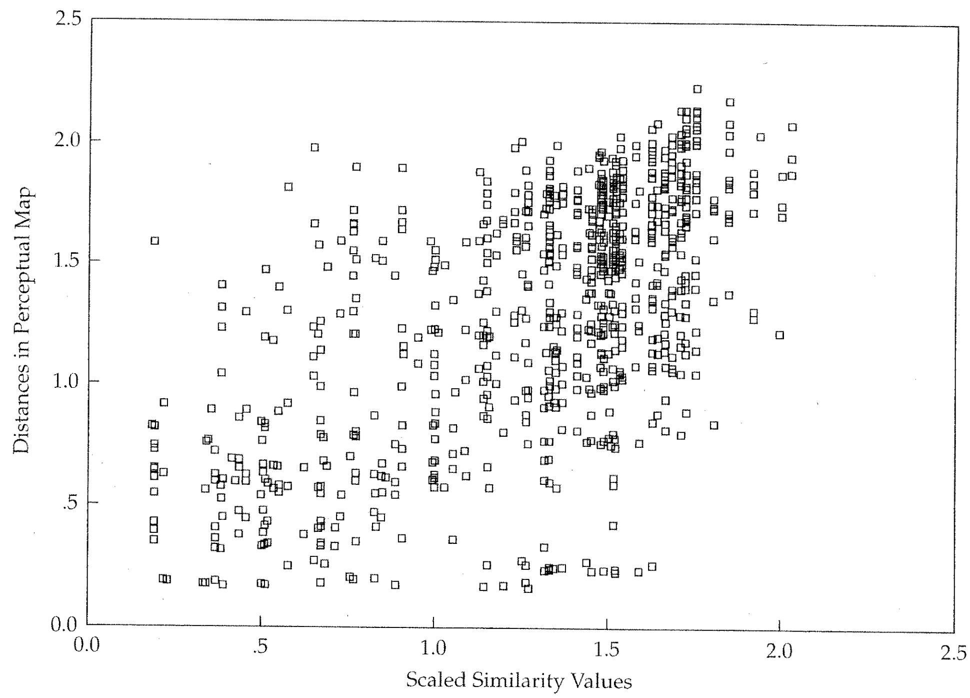


FIGURE 10-12 Scatterplot of Linear Fit

Figure 10-12 represents the scatterplot of similarity values versus the derived distances from the MDS program. Each point represents a separate similarity value. Points falling closer to the 45-degree diagonal are those with the best "fit" in the perceptual map, whereas points farther from the diagonal exhibit greater differences between the actual and derived similarity portrayed in the perceptual map. In examining the most outlying points in this analysis, we find that they are not associated with specific individuals to the extent that deletion of that individual would improve the overall solution.

Table 10-4 also provides measures of fit (stress and R^2) for each individual. For example, respondent 7 has low stress and a high R^2 value, indicating good overall model fit of the overall model to that respondent's perceptions of similarity. Likewise, respondent 9 has relatively high stress and a low R^2 value. This would be a potential candidate to see if the overall solution could be improved by eliminating a single respondent.

Testing the Assumption of Homogeneity of Respondents. In addition to developing the composite perceptual map, INDSCAL also provides the means for assessing one of the assumptions of MDS—the homogeneity of respondents' perceptions. Weights are calculated for each respondent indicating the correspondence of the respondent's own perceptual space and the aggregate perceptual map. These weights provide a measure of comparison among respondents, because respondents with similar weights have similar individual perceptual maps. INDSCAL also provides a measure of fit for each subject by correlating the computed scores and the respondent's original similarity ratings.

Table 10-4 contains the weights and measures of fit for each respondent, and Figure 10-13 is a graphical portrayal of the individual respondents based on their weights. Examination of the weights (Table 10-4) and Figure 10-13 reveals that the respondents are quite homogeneous in their perceptions, because the weights show few substantive differences on either dimension and no distinctive clusters of individuals emerge. In Figure 10-13, all of the individual weights fall roughly on a straight line, indicating a consistent weight between dimensions I and II.

The distance of each individual weight from the origin also indicates its level of fit with the solution. Better fits are shown by farther distances from the origin. Thus, respondents 4, 7, and 10 have the highest fit, and respondents 1 and 9 have the lowest fit. Combined with the earlier discussion

TABLE 10-4 Measures of Individual Differences in Perceptual Mapping: Respondent-Specific Measures of Fit and Dimension Weights

	Measures of Fit		*Dimension Weights*	
Subject	**Stress**[b]	R^{2c}	**Dimension I**	**Dimension II**
1	.358	.274	.386	.353
2	.297	.353	.432	.408
3	.302	.378	.395	.472
4	.237	.588	.572	.510
5	.308	.308	.409	.375
6	.282	.450	.488	.461
7	.247	.547	.546	.499
8	.302	.332	.444	.367
9	.320	.271	.354	.382
10	.280	.535	.523	.511
11	.299	.341	.397	.429
12	.301	.343	.448	.378
13	.292	.455	.497	.456
14	.302	.328	.427	.381
15	.290	.371	.435	.426
16	.311	.327	.418	.390
17	.281	.433	.472	.458
18	.370	.443	.525	.409
Average[a]	.300	.393		

[a]Average across 18 individual solutions.
[b]Kruskal's stress formula.
[c]Proportion of original similarity ratings accounted for by scaled data (distances) from the perceptual map.

of stress and R^2 values, no individual emerges as a definite candidate for elimination due to a poor fit in the two-dimensional solution.

SUPPLEMENTARY ANALYSES: INCORPORATING PREFERENCES IN THE PERCEPTUAL MAP Up to this point we dealt only with judgments of firms based on similarity, but many times we may wish to extend the analysis to the decision-making process and to understand the respondents' preferences for the objects. To do so requires additional analyses that attempt to correspond preferences with the similarity-based perceptual maps. Additional programs, such as PREFMAP, can be used to perform this analysis. Although not available in SPSS, preference mapping can be accomplished by more specialized MDS programs, such as NewMDSX [17] and the Marketing Engineering package by Lilien and Rangaswamy [5]. Supplementary analyses using PREFMAP are provided on the text's Web sites (www.pearsonhighered.com/hair or www.mvstats.com), where the preferences of a set of respondents are incorporated into the similarity-based perceptual map.

Stage 5: Interpretation of the Results

Once the perceptual map is established, we can begin the process of interpretation. Because the MDS procedure uses only the overall similarity judgments, HBAT also gathered ratings of each firm on a series of eight attributes descriptive of typical strategies followed in this industry. The ratings for each firm were then averaged across the respondents for a single overall rating used in describing each firm.

As described in stage 2, the eight attributes included were X_6, Product Quality; X_8, Technical Support; X_{10}, Advertising; X_{12}, Salesforce Image; X_{13}, Competitive Pricing; X_{14}, Warranty & Claims; X_{16}, Order & Billing; and X_{18}, Delivery Speed. These attributes represent the individual

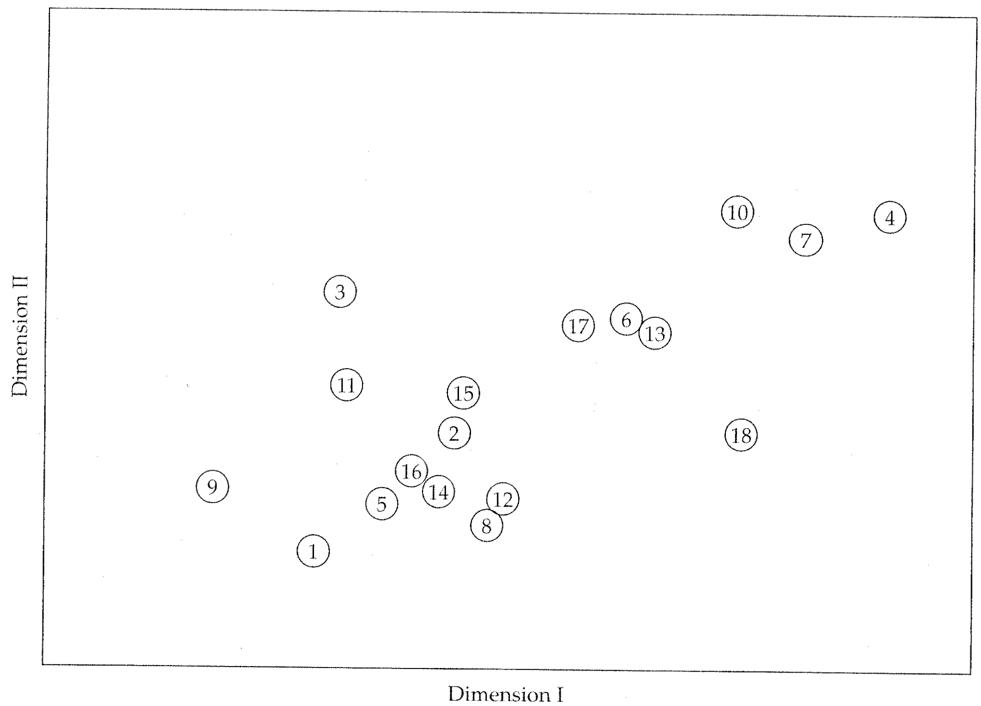


FIGURE 10-13 Individual Subject Weights

variables composing the four factors developed in Chapter 3, exclusive of X_7, E-Commerce; and X_9, Complaint Resolution. The mean scores for each firm are shown in Table 10-5.

A SUBJECTIVE APPROACH TO INTERPRETATION The researcher can undertake several subjective approaches to interpretation. First, the firms can be profiled in terms of their attribute ratings, with distinguishing attributes identified for each firm. In this manner, each firm is characterized on a set of attributes, with the researcher then relating the attributes to the association among firms, if possible. Interpreting the dimensions is more complicated in that the researcher must relate the positions of firms to the dimensions in terms of their characteristics. In both approaches, however, the researcher relies on personal judgment to identify the distinguishing characteristics and then relate them to both firm positions and the resulting interpretation of the dimensions.

TABLE 10-5 Interpreting the Perceptual Map

	ORIGINAL ATTRIBUTE RATINGS									
		Firm								
Variables	**HBAT**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
X_6 Product Quality	5.33	3.72	6.33	5.56	6.39	4.72	5.28	5.22	7.33	5.11
X_8 Technical Support	4.17	1.56	6.06	8.22	7.72	4.28	3.89	6.33	7.72	5.06
X_{10} Advertising	4.00	1.83	6.33	7.67	6.00	5.78	5.50	6.11	7.50	4.17
X_{12} Salesforce Image	6.94	7.17	7.67	3.22	4.78	5.11	6.56	1.61	8.78	3.17
X_{13} Competitive Pricing	6.94	5.67	3.39	3.67	3.67	6.94	6.44	7.22	4.94	6.11
X_{14} Warranty & Claims	5.11	1.22	5.78	7.89	6.56	3.83	4.28	6.94	8.67	4.72
X_{16} Order & Billing	5.16	3.47	6.41	5.88	6.06	4.94	5.29	4.82	8.35	4.65
X_{18} Delivery Speed	4.00	3.39	7.33	6.11	7.50	4.22	7.17	4.33	8.22	5.56

These approaches are best suited for use in situations where the objects and basic characteristics are well established. Then the researcher uses general knowledge of existing relationships among attributes and objects to assist in the interpretation. In situations where the researcher must develop these relationships and associations from the analysis itself, the objective approaches described in the following section are recommended, because they provide a systematic method of identifying the basic issues involved in the interpretation of objects and dimensions.

Perceptions of HBAT and the nine other firms were gathered for eight attributes (see earlier discussion), with profiles of each firm presented in Table 10-5. These perceptions can be used in a subjective manner to attempt to identify the unique attributes of each firm as well as to understand the characteristics represented by each dimension. For example, the firms with the highest perceptions on X_8 are C, D, and H, all located on the left side of the perceptual map, whereas firms with lower perceptions are generally on the right side of the perceptual map. This would indicate that dimension I (the *x*-axis) could be characterized in terms of X_8. Similar analysis of X_{12} indicates that firms with higher values are located toward the top of the perceptual map whereas those with lower scores are toward the bottom. Thus, dimension II would be partially characterized by X_{12}. Although this approach is limited, it does provide some reasonable basis for describing the characteristics of each of the dimensions.

SUPPLEMENTARY ANALYSIS: OBJECTIVE APPROACHES TO INTERPRETATION To provide an objective means of interpretation, additional programs, such as PROFIT [1], can be used to match the ratings to the firm positions in the perceptual map with attribute ratings for each object. The objective is to identify the determinant attributes in the similarity judgments made by individuals to determine which attributes best describe the perceptual positions of the firms and the dimensions. As was seen in the case of incorporating respondent preferences, a number of specialized MDS programs can assist in the interpretation of the dimensions of the perceptual map (NewMDSX [17] and Marketing Engineering program [5]). The interested reader is referred to the text's Web sites (www.pearsonhighered.com/hair or www.mvstats.com), where additional analyses employ PROFIT to assist in interpretation of the dimensions.

OVERVIEW OF THE DECOMPOSITIONAL RESULTS The decompositional methods employed in this perceptual mapping study illustrate the inherent trade-off and resulting advantages and disadvantages of attribute-free multidimensional scaling techniques. As advantages, the use of overall similarity judgments provides a perceptual map based only on the relevant criteria chosen by each respondent. The respondent can make these judgments based on any set of criteria deemed relevant on a single measure of overall similarity. However, this must be weighed against the problems encountered when interpreting the perceptual map in terms of specific attributes. The researcher is required to infer the bases for comparison among objects without direct confirmation from the respondent.

The researcher using these methods must examine the research objectives and decide whether the benefits accrued from perceptual maps developed through the attribute-free approaches outweigh the limitations imposed in interpretation. We can examine the results from the HBAT analysis to assess the trade-off, benefits, and costs.

HBAT can derive substantive insights into the relative perceptions of HBAT and the other nine firms. In terms of perceptions, HBAT is most associated with firm A and somewhat with firms B and I. Some competitive groupings (e.g., F and I, E and G) must also be considered. None of the firms are so markedly distinct as to be considered an outlier. HBAT can be considered average on several attributes (X_6, X_{16}, and X_{18}), but has lower scores on several attributes (X_8, X_{10}, and X_{14}) countered by a high score on attribute X_{12}.

These results provide HBAT insight into not only its perceptions, but also the perceptions of the other major competitors in the market. Remember, however, that the researcher is not assured of understanding what attributes were actually used in the judgment, just that these attributes may be descriptive of the objects.

Stage 6: Validation of the Results

Perhaps the strongest internal validation of this analysis is to assess the convergence between the results from the separate decompositional and compositional techniques. Each technique employs different types of consumer responses, but the resulting perceptual maps are representations of the same perceptual space and should correspond. If the correspondence is high, the researcher can be assured that results reflect the problem as depicted. The researcher should note that this type of convergence does not address the generalizability of the results to other objects or samples of the population.

To make this comparison, we draw upon the results of the correspondence analysis performed in a comparable analysis (see Chapter 11). The perceptual maps from the two approaches are shown in Figure 10-14. The comparison of the decompositional and compositional methods can take two approaches: examining the relative positioning of objects and interpreting the axes. Let us start by examining the positioning of the firms. When the results of each approach are rotated to obtain the same perspective, they show quite similar patterns of firms reflecting two groups: firms B, H, D, and C versus firms E, F, G, and I. Even though the relative distances among firms do vary between the two perceptual maps, we still see HBAT associated strongly with firms A and I in each perceptual map. Correspondence analysis produces more distinction between the firms, but its objective is to define firm positions as a result of differences; thus, it will generate more distinctiveness in its perceptual maps.

The interpretation of axes and distinguishing characteristics also shows similar patterns in the two perceptual maps. For the MDS method, if we rotate the axes then dimension I becomes associated with Customer Service and Product Value (X_6, X_{13}, X_{16}, and X_{18}), whereas dimension II reflects marketing and technical support (X_8, X_{10}, and X_{12}). The remaining attributes are not associated strongly with either axis.

To make a comparison with correspondence analysis, we must first reorient the axes. As we can see, the dimensions flip between the two analyses. The firm groupings remain essentially the same, but

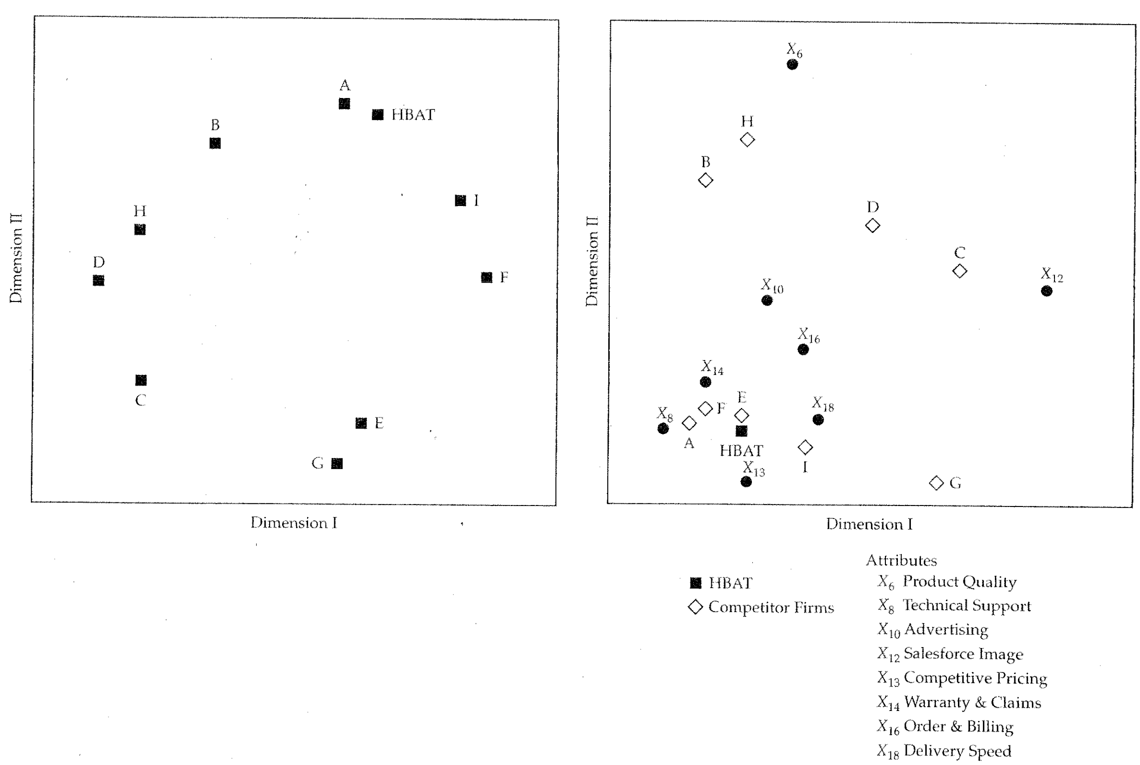


FIGURE 10-14 Comparison of Perceptual Maps from MDS and Correspondence Analysis

they are in different positions on the perceptual map. In correspondance analysis, the dimensions reflect somewhat the same elements, with the highest loadings being X_{18} (Delivery Speed) on dimension I and X_{12} (Salesforce Image) on dimension II. This compares quite favorably with the decompositional results except that the other attributes are somewhat more diffused on the dimensions.

Overall, although some differences do exist, owing to the characteristics of each approach, the convergence of the two results does provide some internal validity to the perceptual maps. Perceptual differences may exist for a few attributes, but the overall patterns of firm positions and evaluative dimensions are supported by both approaches. The disparity of the price flexibility attribute illustrates the differences in the two approaches.

The researcher has two complementary tools in the understanding of consumer perceptions. The decompositional method determines position based on overall judgments, with attributes applied only as an attempt to explain the positions. The compositional method positions firms according to the selected set of attributes, thus creating positions based on the attributes. Moreover, each attribute is weighted equally, thus potentially distorting the map with irrelevant attributes. These differences do not make either approach better or optimal, but instead must be understood by the researcher to ensure selection of the method most suited to the research objectives.

A Managerial Overview of MDS Results

Perceptual mapping is a unique technique providing overall comparisons not readily possible with any other multivariate method. As such, its results present a wide range of perspectives for managerial use. The most common application of the perceptual maps is for the assessment of image for any firm or group of firms. As a strategic variable, image can be quite important as an overall indicator of market presence or position.

In this study, we found that HBAT is most closely associated with firms A and I, and most dissimilar from firms C, E, and G. Thus, when serving the same product markets, HBAT can identify those firms considered similar to or different from its image. With the results based not on any set of specific attributes, but instead on respondents' overall judgments, they present the benefit of not being subject to a researcher's subjective judgments as to the attributes to include or how to weight the individual attributes, in keeping with the true spirit of assessing image. However, MDS technologies are less useful in guiding strategy because they are less helpful in prescribing how to change image. The global responses that are advantageous for comparison now work against us in explanation.

Although MDS techniques can augment the explanation of the perceptual maps, they must be viewed as supplemental and be expected to show greater inconsistencies than if integral to the process. Thus, additional research may assist in helping to explain the relative positions. To this end, correspondence analysis (see Chapter 11) can provide some insight into the attributes underlying the perceptual map. The researcher should note that neither technique has the absolute answer, but that each can be used to capitalize on their relative benefits. When used in this manner, the expected differences in the two approaches can actually provide unique and complementary insights into the research question.

Summary

Multidimensional scaling is a set of procedures that may be used to display the relationships tapped by data representing similarity or preference. It has been used successfully (1) to illustrate market segments based on preference judgments, (2) to determine which products are more competitive with each other (i.e., are more similar), and (3) to deduce what criteria people use when judging objects (e.g., products, companies, advertisements). This chapter helps you to do the following:

Define multidimensional scaling and describe how it is performed. Multidimensional scaling (MDS), also known as perceptual mapping, is a procedure that enables a researcher to determine the perceived relative image of a set of objects (firms, products, ideas, or other items associated with commonly held perceptions). The purpose of MDS is to transform consumer judgments of overall similarity or preference (e.g., preference for stores or brands) into distances represented in multidimensional space.

To perform a multidimensional scaling analysis, the researcher performs three basic steps: (1) gathers measures of similarity or preference across the entire set of objects to be analyzed, (2) uses MDS techniques to estimate the relative position of each object in multidimensional space, and (3) identifies and interprets the axes of the dimensional space in terms of perceptual and/or objective attributes. The perceptual map, also known as a spatial map, shows the relative positioning of all objects.

Understand the differences between similarity data and preference data. After choosing objects for study, the researcher must next select the basis of evaluation: similarity versus preference. In providing similarities data, the respondents do not apply any "good–bad" aspects of evaluation in the comparison, but with preference data good–bad assessments are done. In short, preference data assumes that differing combinations of perceived attributes are valued more highly than other combinations. Both bases of comparison can be used to develop perceptual maps, but with differing interpretations: (1) similarity-based perceptual maps represent attribute similarities and perceptual dimensions of comparison, but do not reflect any direct insight into the determinants of choice; and (2) preference-based perceptual maps do reflect preferred choices but may not correspond in any way to the similarity-based positions, because respondents may base their choices on entirely different dimensions or criteria from those on which they base comparisons. With no optimal base for evaluation, the decision between similarities and preference data must be made with the ultimate research question in mind because they are fundamentally different in what they represent.

Select between a decompositional or compositional approach. Perceptual mapping techniques can be classified into one of two types based on the nature of the responses obtained from the individual concerning the object: (1) the decompositional method measures only the overall impression or evaluation of an object and then attempts to derive spatial positions in multidimensional space that reflect these perceptions (it uses either similarity or preferences data and is the approach typically associated with MDS) and (2) the compositional method, which employs several of the multivariate techniques already discussed that are used in forming an impression or evaluation based on a combination of specific attributes. Perceptual mapping can be performed with both compositional and decompositional techniques, but each technique has specific advantages and disadvantages that must be considered in view of the research objectives. If perceptual mapping is undertaken either as an exploratory technique to identify unrecognized dimensions or as a means of obtaining comparative evaluations of objects when the specific bases of comparison are unknown or undefined, the decompositional, or attribute-free, approaches are the most appropriate. In contrast, if the research objectives include the portrayal among objects on a defined set of attributes, then the compositional techniques are the preferred alternative.

Determine the comparability and number of objects. Before undertaking any perceptual mapping study, the researcher must address two key questions dealing with the objects being evaluated. These questions deal with ensuring the comparability of the objects as well as selecting the number of objects to be evaluated. The first question when selecting objects is: Are the objects really comparable? An implicit assumption in perceptual mapping is that of common characteristics, either objective or perceived, used by the respondent for evaluations. Thus, it is essential that the objects being compared have some set of underlying attributes that characterize each object and form the basis for comparison by the respondent. It is not possible for the researcher to force the respondent to make comparisons by creating pairs of noncomparable objects. A second question concerns the number of objects to be evaluated. In deciding how many objects to include the researcher must balance two desires: a smaller number of objects to ease the effort on the part of the respondent versus the required number of objects to obtain a stable multidimensional solution. Often a trade-off must be made between the number of underlying dimensions that can be identified and the effort required on the part of the respondent to evaluate them.

Understand how to create a perceptual map. Three steps are involved in creating a perceptual map based on the optimal positions of the objects. The first step is to select an initial configuration of stimuli at a desired initial dimensionality. The two most widely used approaches for obtaining the initial configuration are either to base it on previous data or to generate one by selecting pseudorandom points from an approximately normal multivariate distribution. The second step is to compute the distances between the stimuli points and compare the relationships (observed versus derived) with a measure of fit. Once a configuration is found, the interpoint distances between stimuli in the starting configurations are compared with distance measures derived from the similarity judgments. The two distance measures are then compared by a measure of fit, typically a measure of stress. The third step is necessary if the measure of fit does not meet a selected predefined stopping value. In such cases, you find a new configuration for which the measure of fit is further minimized. The software determines the directions in which the best improvement in fit can be obtained and then moves the points in the configuration in those directions in small increments.

MDS can reveal relationships that appear to be obscured when one examines only the numbers resulting from a study. Visual perceptual maps emphasize the relationships between the stimuli under study. One must be cautious when using this technique. Misuse is common. The researcher should become familiar with the technique before using it and should view the output as only the first step in the determination of perceptual information.

Questions

1. How does MDS differ from other interdependence techniques (cluster analysis and factor analysis)?
2. What is the difference between preference data and similarities data, and what impact does it have on the results of MDS procedures?
3. How are ideal points used in MDS procedures?
4. How do metric and nonmetric MDS procedures differ?
5. How can the researcher determine when the optimal MDS solution has been obtained?
6. How does the researcher identify the dimensions in MDS? Compare this procedure with the procedure for factor analysis.
7. Compare and contrast CA and MDS techniques.

Suggested Readings

A list of suggested readings illustrating issues and applications of multivariate techniques in general is available on the Web at www.pearsonhighered.com/hair or www.mvstats.com.

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