CHAPTER 19

Multivariate Analysis: An Overview

Learning Objectives

After reading this chapter, you should understand . . .

1. How to classify and select multivariate techniques.
2. That multiple regression explains or predicts a metric dependent variable from a set of metric independent variables.
3. That discriminant analysis classifies people or objects into (categorical) groups using several metric predictors.
4. How multivariate analysis of variance assesses the relationship between two or more metric dependent variables and independent classificatory variables.
5. How structural equation modeling explains causality among constructs that cannot be directly measured—specifying causal relationships, connections, and unexplained variance among the constructs.
6. The ways conjoint analysis assists researchers to discover the importance of product or service attributes and the levels of features that are most desirable.
7. How principal components analysis extracts uncorrelated factors from an initial set of variables and factor analysis reduces the number of variables to discover the underlying constructs.
8. The use of cluster analysis techniques for grouping similar objects or people.
9. How perceptions of products or services are revealed numerically and geometrically by multidimensional scaling.

Bringing Research to Life

Dorrie Henry would have tolerated Henry Parker's habit of dropping in unexpectedly if he were not a bore, and a grabbing bore at that, one who had to seize you by the lapel or grasp your elbow while he shared his every vagrant thought. He was displaying his annoying habits at this very moment.

"I was driving by and saw two cars in your driveway and said, 'Henry, if Cousin Dorrie and her Jason are home on a Wednesday, then you had better stop in for a lemonade and a chat.'" This was supposed to be the day she caught up on her medical record keeping and Jason did tax reports for both of them. But here she was with Henry's arm draped on her shoulder and him waving his iced lemonade wildly to and fro.

She extricated herself by leveling with him. "Henry, I am not at all comfortable with you holding me so tightly." When she saw she had hurt his feelings, she softened her assertiveness with a little lie. "There is a strain of flu running around the clinic, you know, and though I am certainly immune, I would hate to pass it to you."

"Oh, sure, no problem, *doctor.* Anyway, *doctor,* I mostly want to fill your husband in on some late-breaking developments." In a single smooth motion he spun loose from his grip on Dorrie and surprised Jason with a lock on Jason's left forearm. Dorrie saw Jason's pupils first dilate and then contract, in a sure sign of annoyance, and she feared he would deal with Henry not as diplomatically as she had.

Jason had a name for Henry, "Ceteribus Parker," an allusion to *ceteribus paribus,* the Latin words for "all things being equal." It was Henry's annoying practice, while holding you in his firm grip (if you let him do so), to make amazingly improbable comparisons between people, groups, institutions, products, services, practices—anything and everything—by declaring the likes of "All things being equal, Mercury would seem to be a more congenial planet on which life might emerge than Earth." Meaning, if you allowed for its atmosphere being nonexistent, and its temperature being 1,380 degrees Fahrenheit, there was presumably *something* about its gravitational fields or length of day that fitted Henry's preferred cosmology. *"Ceteribus paribus,"* he once said, "my electric bill would be cheaper if I lived in Antarctica than in Death Valley." You cannot argue against that kind of pseudoscientific blather.

Now Henry was lecturing Jason about an appointment he had taken as the business's representative to the governing board of the public housing authority. "The best tenants are the Pantamarians," he declared. "All things being equal, they are the most law-abiding and hard-working tenants."

"You mean Panamanians," Jason stated indifferently. It wasn't even a question, just a flat accusation of error.

"No, no, not Panamanians. These folks are *Pantamarians.* They are English-speakers from little islands in the Caribbean. Never heard of Pantamarie before I was put on the Authority, but, I tell you, they are the most law-abiding tenants . . ."

". . . *ceteribus paribus,"* echoed Jason ironically, as the very same words slipped from Henry's mouth. Dorrie saw signs of Jason's increasing impatience, as the color flushed his neck and he struggled to free himself from her cousin's grip.

"Do be more specific," urged Jason. "Are you telling me that the Pantamarians—have I got that right? Pantamarians?—have the lowest crime rate in the Authority? You must have data—you take federal funds, don't you? So you must have data."

"Well," said Henry, evasively, "you have got to allow for these Pantamarians having very large families. And they did not get much schooling, back home."

"So what is not equal is their family size and education. Right? What else? What else is not equal?"

Jason had leaned forward into Henry's grip and was now staring icily into Dorrie's cousin's eyes. Henry let loose his grip, set down his beverage, and reached for a handful of cocktail napkins, which he began to dab at his brow, mouth, and neck.

"Oh, well, you know. They are young. And there are other things. You know. Other things." Henry's voice had trailed off to a mere whisper as Jason bore in conversationally.

"No, I don't know. But I have good news for you, Henry. You can be sure that the Authority staff has been keeping really good records. We can go down there right now—wonderful of you to drop in on a working day—and ask the staff to roll out its records. Family size, education, age, everything. You can bet you have all that and more in your computers down there at the Authority. The Federal Housing and Urban Development people won't give you a penny without it."

Henry stumbled into a chair. He was trembling.

"Be right back," said Jason. He reappeared almost at once, carrying his laptop. "Good news, Henry. There are statistical techniques called *multivariate analysis* that in fact make all other things equal. Look here: This is a data cable. Let's hop in the car and run down to the Authority. You flash your identification, and I suck the data out of its computer. We set crime rate as the dependent variable—you know what that means, don't you?—and country of origin as the independent variable. Then we apply a technique called *analysis of covariance,* correcting for the effects of education, age, household size, whatever.

"Or maybe we do a *factor analysis* with Caribbean country of origin, the population count for 2000, GDP per capita, teacher ratios, female life expectancy, births and deaths, and the infant mortality rate per 1,000 of the population, radios and phones per 100 people, hospital beds, age, and family size. Then we'd know which variables are worth studying.

"Better yet, Henry, we could take the results of our *factor analysis* and run a *multiple regression* with crime rate as the dependent variable and the new factors which we output from the factor analysis as our predictors.

"Wait, this is the best one yet," Jason said excitedly. "We take your famous Pantamarians and the same data for their neighboring country and see if we can correctly classify them with a *discriminant analysis.*"

"And *voilà!!!* Your Pantamarians are the most law-abiding tenants, or they aren't. *Ceteribus paribus!!!!*"

Henry grabbed at his chest. "In my pocket," he croaked. "My pill box." Dorrie moved fast and had placed a nitro pill under Henry's tongue before Jason realized what was happening.

After she'd stabilized Henry and called for Cousin Anita to take him to his family doctor, Jason remained remorse-free. "That's the beautiful part of understanding multivariate analysis," he asserted. "In 10 minutes I would have shown Henry up for the old blowhard he is."

Following this inexcusable thrust, Jason slept for three nights on the sofa.

Introduction

In recent years, multivariate statistical tools have been applied with increasing frequency to research problems. This recognizes that many problems we encounter are more complex than the problems bivariate models can explain. Simultaneously, computer programs have taken advantage of the complex mathematics needed to manage multiple variable relationships. Today, computers with fast processing speeds and versatile software bring these powerful techniques to researchers.

Throughout the functional areas of management, more and more problems are being addressed by considering multiple independent and/or multiple dependent variables. Sales managers base forecasts on various product history variables; marketers consider the complex set of buyer preferences and preferred product options; financial analysts classify levels of credit risk based on a set of predictors; and human resource managers devise future wage and salary compensation plans with multivariate techniques.

Many of the examples presented in this text could be considered multivariate problems. The revenue improvements for a physicians' group that decided to join a different insurance program were based on multiple factors. In another example, the aviation industry was attempting to control radiation risks for passengers and crew by altering the proximity of air routes to the poles, aircraft shielding, altitude, and other variables. The price of investment-grade wine was forecast based on spring and harvest rainfall and growing-season temperatures.

One author defines **multivariate analysis** as "those statistical techniques which focus upon, and bring out in bold relief, the structure of simultaneous relationships among three or more phenomena."[1] Our overview of multivariate analysis seeks to illustrate the meaning of this definition while building on your understanding of bivariate statistics from the last few chapters. Several common multivariate techniques and examples will be discussed.

Because a complete treatment of this subject would require a thorough consideration of the mathematics, assumptions, and diagnostic tools appropriate for each technique, our coverage is necessarily limited. Readers needing greater detail are referred to the suggested readings at the end of the chapter.

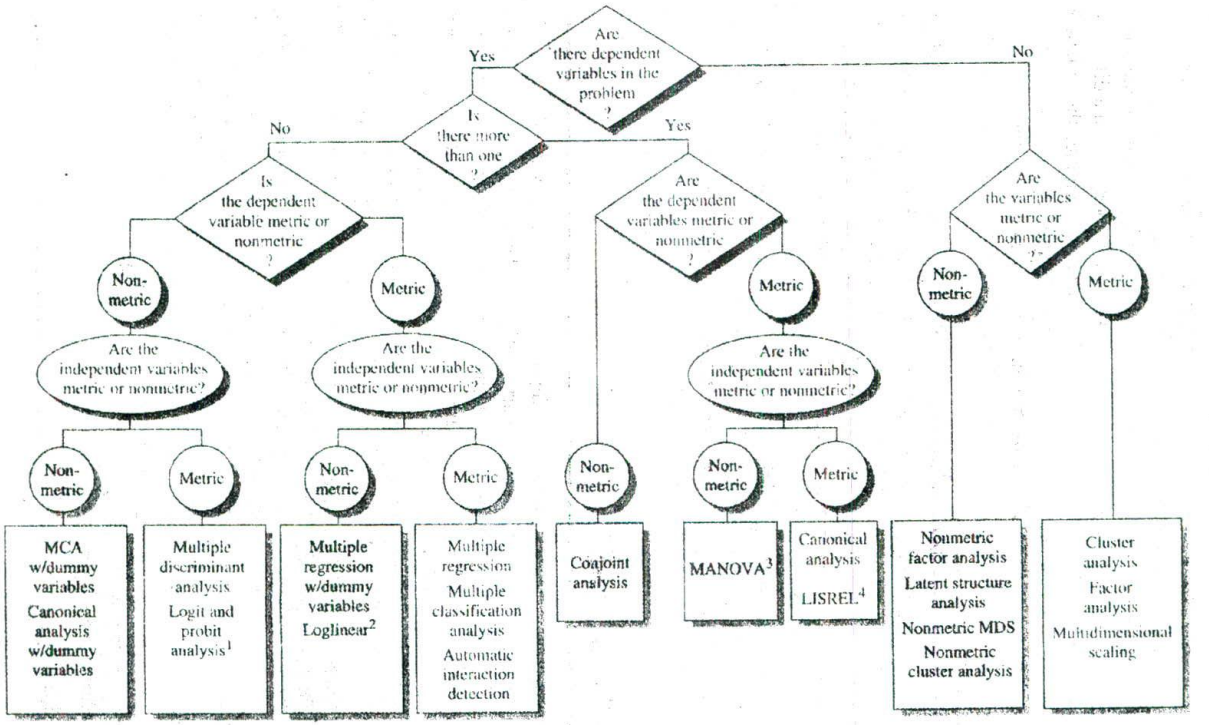
Selecting a Multivariate Technique

Multivariate techniques may be classified as **dependency** and **interdependency techniques.** Selecting an appropriate technique starts with an understanding of this distinction. If criterion and predictor variables exist in the research question, then we will have an assumption of dependence. Multiple regression, multivariate analysis of variance (MANOVA), and discriminant analysis are techniques where criterion or dependent variables and predictor or independent variables are present. Alternatively, if the variables are interrelated without designating some dependent and others independent, then interdependence of the variables is assumed. Factor analysis, cluster analysis, and multidimensional scaling are examples of interdependency techniques.

Exhibit 19–1 provides a diagram to guide in the selection of techniques. Let's take an example to show how you might make a decision. Every other year since 1978, the Roper organization has tracked public opinion toward business by providing a list of items that are said to be the responsibility of business. The respondents are asked whether business fulfills these responsibilities "fully, fairly well, not too well, or not at all well." The following issues make up the list:[2]

- Developing new products and services.
- Producing good-quality products and services.
- Making products that are safe to use.
- Hiring minorities.
- Providing jobs for people.
- Being good citizens of the communities in which they operate.

EXHIBIT 19–1 Selecting from the Most Common Multivariate Techniques



Notes:

[1]The independent variable is metric only in the sense that a transformed proportion is used.

[2]The independent variable is metric only when we consider that the number of cases in the cross-tabulation cell are used to calculate the logs.

[3]Factors may be considered nonmetric independent variables in that they organize the data into groups. We do not classify MANOVA and other multivariate analysis of variance models.

[4]LISREL refers to a linear structural equations model for latent variables. It is a family of models appropriate for confirmatory factor analysis, path analysis, time series analysis, recursive and nonrecursive models, and covariance structure models. Because it may handle dependence and interdependence, metric and nonmetric, it is arbitrarily placed in this diagram.

SOURCE: Partially adapted from T. C. Kinnear and J. R. Taylor, "Multivariate Methods in Marketing: A Further Attempt at Classification," *Journal of Marketing*, October 1971, p. 57; and J. F. Hair, Jr., Rolph E. Anderson, Ronald L. Tatham, and Bernie J. Grablowsky, *Multivariate Data Analysis* (Tulsa, OK: Petroleum Publishing Co., 1979), pp. 10–14.

- Paying good salaries and benefits to employees.
- Charging reasonable prices for goods and services.
- Keeping profits at reasonable levels.
- Advertising honestly.
- Paying their fair share.
- Cleaning up their own air and water pollution.

You have access to data on these items and wish to know if they could be reduced to a smaller set of variables that would account for most of the variation among respondents. In response to the first question in Exhibit 19–1, you correctly determine there are no dependent variables in the data set. You then check to see if the variables are **metric** or **nonmetric measures.** In the figure, *metric* refers to ratio and interval measurements, and *nonmetric* refers to data that are nominal and ordinal. Based on the measurement scale, which appears to have equal intervals, and preliminary findings that show a linear relationship between several variables, you decide the data are metric. This decision leads you to three options: multidimensional scaling, cluster analysis, or factor analysis. *Multidimensional scaling* develops a geometric picture or map of the locations of some objects relative to others. This map specifies how the objects differ. *Cluster analysis* identifies homogeneous subgroups or clusters. *Factor analysis* looks for patterns among the variables to discover if an underlying combination of the original variables (a factor) can summarize the original set. Based on your research objective, you select factor analysis.

Suppose you are interested in predicting family food expenditures from family income, family size, and whether the family's location is rural or urban. Returning to Exhibit 19–1, you conclude there is a singular dependent variable, family food expenditures. You decide this variable is metric since dollars are measured on a ratio scale. The independent variables, income and family size, also meet the criteria for metric data. However, you are not sure about the location variable since it appears to be a dichotomous nominal variable. According to the figure, your choices are automatic interaction detection (AID), multiple classification analysis (MCA), and multiple regression. You recall from Chapter 16 that AID was designed to locate the most important interaction effects and typically uses numerous independent variables in its sequential partitioning procedure. MCA handles weak predictors (including nominal variables), correlated predictors, and nonlinear relationships. Multiple regression is the extension of bivariate regression. You believe that your data exceed the assumptions for the first two techniques and that by treating the nominal variable's values as 0 or 1, you could use it as an independent variable in a multiple regression model. You prefer this to losing information from the other two variables—a certainty if you reduce them to nonmetric data.

In the next two sections, we will extend this discussion as we illustrate dependency and interdependency techniques.

Dependency Techniques

Multiple Regression

Multiple regression is used as a descriptive tool in three types of situations. First, it is often used to develop a self-weighting estimating equation by which to predict values for a criterion variable (DV) from the values for several predictor variables (IVs). Thus,

we might try to predict company sales on the basis of new housing starts, new marriage rates, annual disposable income, and a time factor. Another prediction study might be one in which we estimate a student's academic performance in college from the variables of rank in high school class, SAT verbal scores, SAT quantitative scores, and a rating scale reflecting impressions from an interview.

Second, a descriptive application of multiple regression calls for controlling for confounding variables to better evaluate the contribution of other variables. For example, one might wish to control the brand of a product and the store in which it is bought to study the effects of price as an indicator of product quality.[3] A third use of multiple regression is to test and explain causal theories. In this approach, often referred to as **path analysis,** regression is used to describe an entire structure of linkages that have been advanced from a causal theory.[4] In addition to being a descriptive tool, multiple regression is also used as an inference tool to test hypotheses and to estimate population values.

Method Multiple regression is an extension of the bivariate linear regression presented in Chapter 18. The terms defined in that chapter will not be repeated here. Although **dummy variables** (nominal variables coded 0, 1) may be used, all other variables must be interval or ratio. The generalized equation is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

where

β_0 = A constant, the value of Y when all X values are zero.

β_i = The slope of the regression surface or the response surface. The β represents the regression coefficient associated with each X_i.

ε = An error term, normally distributed about a mean of 0. For purposes of computation, the ε is assumed to be 0.

The regression coefficients are stated either in raw score units (the actual X values) or as **standardized coefficients** (X values restated in terms of their standard deviations). In either case, the value of the regression coefficient states the amount that Y varies with each unit change of the associated X variable when the effects of all other X variables are being held constant. When the regression coefficients are standardized, they are called **beta weights** (β), and their values indicate the relative importance of the associated X values, particularly when the predictors are unrelated. For example, in an equation where $\beta_1 = .60$ and $\beta_2 = .20$, one concludes that X_1 has three times the influence on Y as does X_2.

Example In a Snapshot later in this chapter, we describe an e-business that uses multivariate approaches to understand its target market in the global "hybrid mail" business. SuperLetter's basic service enables users to create a document on any PC and send it in a secure encrypted mode over the Internet to a distant international terminal near the addressee, where it will be printed, processed, and delivered via the local postal service. Spread like a "fish net" over the world's major commercial markets, the network connects corresponding parties, linking the world's "wired" with its "non-wired."

We use multiple regression in this example to evaluate the key drivers of customer usage for hybrid mail. Among the explanatory variables are customer perceptions of: (1) cost/speed valuation, (2) security (limits on changing, editing, or forwarding a document and document privacy), (3) reliability, (4) receiver technology (hard copy for

receivers with no e-mail or fax access), and (5) impact/emotional value (reducing e-mail spam clutter and official/important appearance). We have chosen the first three variables, all measured on 5-point scales, for this equation:

Y = customer usage

X_1 = cost/speed valuation

X_2 = security

X_3 = reliability

SPSS computed the model and the regression coefficients. Most statistical packages provide various methods for selecting variables for the equation. The equation can be built with all variables or specific combinations or you can select a method that sequentially adds or removes variables (forward selection, backward elimination, and stepwise selection). **Forward selection** starts with the constant and adds variables that result in the largest R^2 increase. **Backward elimination** begins with a model containing all independent variables and removes the variable that changes R^2 the least. **Stepwise selection,** the most popular method, combines forward and backward sequential approaches. The independent variable that contributes the most to explaining the dependent variable is added first. Subsequent variables are included based on their incremental contribution over the first variable and whether they meet the criterion for entering the equation (e.g., a significance level of .01). Variables may be removed at each step if they meet the removal criterion, which is a larger significance level than for entry.

The standard elements of a stepwise output are shown in Exhibit 19–2. In the upper portion of the exhibit there are three models. In Model 1, cost/speed is the first variable to enter the equation. This model consists of the constant and the variable cost/speed. Model 2 adds the security variable to cost/speed. Model 3 consists of all three independent variables. In the summary statistics for Model 1, you see that cost/speed explains 77 percent of customer usage (see the R^2 column). This is increased by 8 percent in Model 2 when security is added (see R^2 Change column). When reliability is added in Model 3, accounting for only 2 percent, 87 percent of customer usage is explained.

The other reported statistics have the following interpretations.

1. Adjusted R square for Model 3 = .871. R^2 is adjusted to reflect the model's goodness of fit for the population. The net effect of this adjustment is to reduce the R^2 from .873 to .871, thereby making it comparable to other R^2s from equations with a different number of independent variables.
2. Standard error of Model 3 = .4937. This is the standard deviation of actual values of Y about the regression line of estimated Y values.
3. Analysis of variance measures whether or not the equation represents a set of regression coefficients that, in total, are statistically significant from zero. The critical value for F is found in Appendix Table G–9, with degrees of freedom for the numerator equaling k, the number of independent variables, and for the denominator, $n - k - 1$, where n for Model 3 is 183 observations. Thus, d.f. = (3, 179). The equation is statistically significant at less than the .05 level of significance (see the column labeled "Significant F Change").
4. Regression coefficients for all three models are shown in the lower table of Exhibit 19–2. The column headed "B" shows the unstandardized regression coefficients for the equation. The equation may now be constructed as:

$$Y = -.093 + .448X_1 + .315X_2 + 254X_3$$

EXHIBIT 19–2 Multiple Regression Analysis of Hybrid Mail Customer Usage, Cost/Speed Valuation, Security, and Reliability

Model Summary

					Change Statistics				
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	R^2 Change	F Change	d.f.1	d.f.2	Sig. F Change
1	.879	.772	.771	.6589	.772	612.696	1	181	.000
2	.925	.855	.854	.5263	.083	103.677	2	180	.000
3	.935	.873	.871	.4937	.018	25.597	3	179	.000

1 Predictors: (constant), cost/speed.
2 Predictors: (constant), cost/speed, security.
3 Predictors: (constant), cost/speed, security, reliability.

Coefficients

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
Model		B	Std. Error	Beta			VIF
1	(Constant)	.579	.151		3.834	.000	
	Cost/Speed	.857	.035	.879	24.753	.000	1.000
2	(Constant)	9.501E-02	.130		.733	.464	
	Cost/Speed	.537	.042	.551	12.842	.000	2.289
	Security	.428	.042	.437	10.182	.000	2.289
3	(Constant)	–9.326E-02	.127		–.734	.464	
	Cost/Speed	.448	.043	.460	10.428	.000	2.748
	Security	.315	.045	.321	6.948	.000	3.025
	Reliability	.254	.050	.236	5.059	.000	3.067

Dependent variable: Customer usage.

5. The column headed "Beta" gives the regression coefficients expressed in standardized form. When these are used, the regression Y intercept is zero. Standardized coefficients are useful when the variables are measured on different scales. The beta coefficients also show the relative contribution of the three independent variables to the explanatory power of this equation. The cost/speed valuation variable explains more than either of the other two variables.
6. Standard error is a measure of the sampling variability of each regression coefficient.
7. The column headed "t" measures the statistical significance of each of the regression coefficients.

Again compare these to the table of t values in Appendix Table G–9, using degrees of freedom for one independent variable. All three regression coefficients are

judged to be significantly different from zero. Therefore, the regression equation shows the relationship between the dependent variable, customer usage of hybrid mail, and three independent variables: cost/speed, security, and reliability. The regression coefficients are both individually and jointly statistically significant. The independent variable cost/speed influences customer usage the most, followed by security and then reliability.

Collinearity—or **multicollinearity,** the situation where two or more of the independent variables are highly correlated—can have damaging effects on multiple regression. When this condition exists, the estimated regression coefficients can fluctuate widely from sample to sample, making it risky to interpret the coefficients as an indicator of the relative importance of predictor variables. Just how high can acceptable correlations be between independent variables? There is no definitive answer, but correlations at a .80 or greater level should be dealt with in one of two ways: (1) Choose one of the variables and delete the other, or (2) create a new variable that is a composite of the highly intercorrelated variables and use this new variable in place of its components. Making this decision with a correlation matrix alone is not always advisable. In the example just presented, Exhibit 19–2 contains a column labeled "Collinearity Statistics" that shows a variable inflation factor (VIF) index. This is a measure of the effect of the other independent variables on a regression coefficient. Large values, usually 10.0 or more, suggest collinearity or multicollinearity. With the three predictors in the hybrid mail example, multicollinearity is not a problem.

We discuss the correlation matrix, which displays multiple combinations of two variable relationships, in Chapter 18.

Another difficulty with regression occurs when researchers fail to evaluate the equation with data beyond those used originally to calculate it. A practical solution is to set aside a portion of the data (from a fourth to a third) and use only the remainder to compute the estimating equation. This is called a **holdout sample.** One then uses the equation on the holdout data to calculate an R^2. This can then be compared to the original R^2 to determine how well the equation predicts beyond its database.



SNAPSHOT Teeing Up a New Strategic Direction

NCR Country Club (NCRCC) has undergone a dramatic transformation within the last three years with the construction of a multimillion-dollar clubhouse and dining facility, but the changes have been built on the long-standing tradition of fine golf and dining. Started in 1954 as an employee benefit of the National Cash Register Co. but now an open-membership club, this country club located near Dayton (OH) hosts two 18-hole golf courses. The NCRCC South course, a par 71 championship course of 6,824 yards of heavily wooded rolling countryside, has played host to the PGA Championship (1996), the U.S. Open (1986), and the U.S. Mid-Amateur (1998) and is consistently ranked by *Golf Digest* as one of the top 100 courses in the U.S.

When its aging membership started to decrease and a one-year membership referral drive didn't dramatically reverse the trend, NCRCC turned to the McMahon Group, a research and strategic golf-course management specialist, for insight and direction. Through an extensive two-stage research design employing six focus groups of 10–15 people each, followed by 886 membership surveys, McMahon's research helped NCRCC design a new strategic direction. Sophisticated modeling and analysis led to new facilities for swimming and fitness that turned this proud golf and dining organization into a full-service club for 2,000 with amenities to serve its new target member (the under-46, golf-oriented household, with one or more children under 21 still living at home).

www.mcmahongroup.com

www.ncr.com

Discriminant Analysis

Researchers often wish to classify people or objects into two or more groups. One might need to classify persons as either buyers or nonbuyers, good or bad credit risks, or superior, average, or poor performers in some activity. The objective is to establish a procedure to find the predictors that best classify subjects.

Method **Discriminant analysis** joins a nominally scaled criterion or dependent variable with one or more independent variables that are interval or ratio scaled. Once the discriminant equation is found, it can be used to predict the classification of a new observation. This is done by calculating a linear function of the form

$$D_i = d_0 + d_1X_1 + d_2X_2 + \ldots + d_pX_p$$

where

D_i is the score on discriminant function i.

The d_is are weighting coefficients; d_0 is a constant.

The Xs are the values of the discriminating variables used in the analysis.

A single discriminant equation is required if the categorization calls for two groups. If three groups are involved in the classification, it requires two discriminant equations. If more categories are called for in the dependent variable, it is necessary to calculate a separate discriminant function for each pair of classifications in the criterion group.

While the most common use for discriminant analysis is to classify persons or objects into various groups, it can also be used to analyze known groups to determine the relative influence of specific factors for deciding into which group various cases fall. Assume we have supervisory ratings that enable us to classify administrators as successful or unsuccessful on administrative performance. We might also be able to secure test results on three measures: ability to work with others (X_1), motivation for administrative work (X_2), and general professional skill (X_3). Suppose the discriminant equation is:

$$D = .06X_1 + .45X_2 + .30X_3$$

Since discriminant analysis uses standardized values for the discriminant variables, we conclude from the coefficients that ability to work with others is less important than the other two in classifying administrators.[5]

Example An illustration of the method takes us back to the problem in the last chapter where Dean Merrill, a brokerage firm, is hiring MBAs for its account executives program. Over the years the firm has had indifferent success with the selection process. You are asked to develop a procedure to improve this. It appears that discriminant analysis is a perfect technique. You begin by gathering data on 30 MBAs who have been hired in recent years. Fifteen of these have been successful employees while the other 15 have been unsatisfactory. The personnel files provide the following information that can be used to conduct the analysis:

X_1 = Years of prior work experience.

X_2 = GPA in graduate program.

X_3 = Employment test scores.

An algorithm determines how well these three independent variables will correctly classify those who are judged successful from those judged unsuccessful. The classifi-

EXHIBIT 19–3 Discriminant Analysis Classification Results of MBA Hires at Dean Merrill

			Predicted Group Membership	
Actual Group		Number of Cases	0	1
Unsuccessful	0	15	13	2
			86.7%	13.3%
Successful	1	15	3	12
			20.0%	80.0%

Note: Percent of "grouped" cases correctly classified: 83.33%.

cation results are shown in Exhibit 19–3. This indicates that 25 of the 30 (30 – 3 – 2 = 25) cases have been correctly classified using these three variables.

The standardized and unstandardized discriminant function coefficients are as follows:

	Unstandardized	Standardized
X_1	.36084	.65927
X_2	2.61192	.57958
X_3	.53028	.97505
(constant)	12.89685	

These results indicate that X_3 (the employment test) has the greatest discriminating power. Several significance tests are also computed. One, Wilk's lambda, has a chi-square transformation for testing the significance of the discriminant function. It indicates the equation is statistically significant at the $\alpha = .0004$ level. Using the discriminant equation,

$$D = .659X_1 + .580X_2 + .975X_3$$

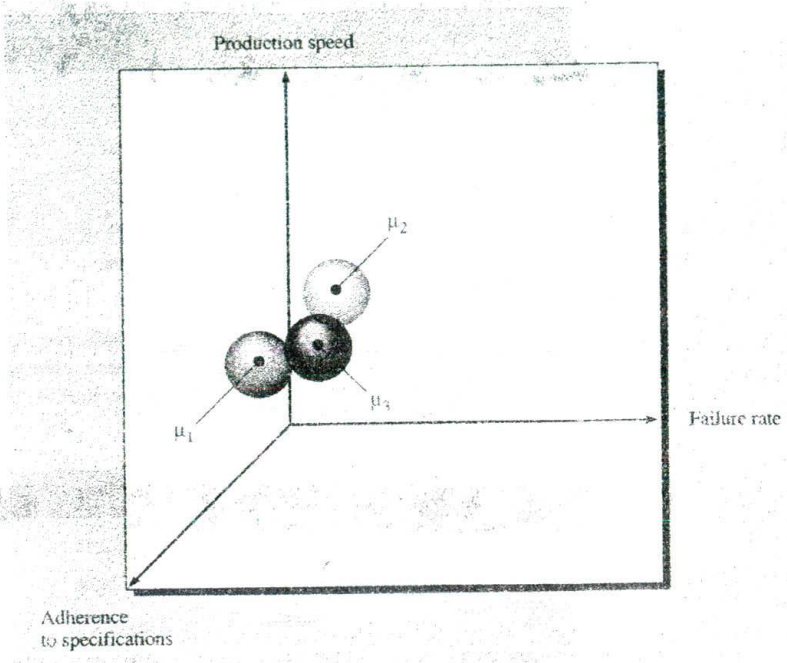
you can now predict whether future candidates are likely to be successful account executives.

MANOVA

Multivariate analysis of variance, or **MANOVA,** is a commonly used multivariate technique. MANOVA assesses the relationship between two or more dependent variables and classificatory variables or factors. In business research, MANOVA can be used to test differences among samples of employees, customers, manufactured items, production parts, and so forth.

Method MANOVA is similar to the univariate ANOVA described earlier, with the added ability to handle several dependent variables. If ANOVA is applied consecutively to a set of interrelated dependent variables, erroneous conclusions may result. MANOVA can correct this by simultaneously testing all the variables and their interrelationships. MANOVA employs sums-of-squares and cross-products (SSCP) matrices to test for differences among groups. The variance between groups is determined by

EXHIBIT 19–4 MANOVA Techniques Show These Three Centroids to Be Unequal in the CalAudio Study



partitioning the total SSCP matrix and testing for significance. The *F* ratio, generalized to a ratio of the within-group variance and total-group variance matrices, tests for equality among treatment groups.

MANOVA examines similarities and differences among the multivariate mean scores of several populations. The null hypothesis for MANOVA is that all of the **centroids** (multivariate means) are equal, H_0: $\mu_1 = \mu_2 = \mu_3 = \ldots \mu_n$. The alternative hypothesis is that the vectors of centroids are unequal, H_A: $\mu_1 \neq \mu_2 \neq \mu_3 \neq \ldots \mu_n$. Exhibit 19–4 shows graphically three populations whose centroids are unequal, allowing the researcher to reject the null hypothesis. When the null hypothesis is rejected, additional tests are done to better understand the data. Several alternatives may be considered:

1. Univariate *F* tests can be run on the dependent variables.
2. Simultaneous confidence intervals can be produced for each variable.
3. Stepdown analysis, like stepwise regression, can be run by computing *F* values successively. Each value is computed after the effects of the previous dependent variable are eliminated.
4. Multiple discriminant analysis can be used on the SSCP matrices. This aids in the discovery of which variables contribute to the MANOVA's significance.[6]

Example To illustrate, let's look at CalAudio, a firm that manufactures compact disk (CD) players. The plant manager is concerned about the quality of CD players coming off the manufacturing line. Two measures are used to assess quality in this example: adherence to product specifications and time before failure. Measured on a 0–100 scale

EXHIBIT 19–5 MANOVA Cell Means and Standard Deviations in CalAudio Study

VARIABLE	FACTOR	LEVEL	MEAN	STD. DEV.
FAILURE				
	METHOD	1	158.867	4.998
	METHOD	2	181.067	5.994
	For entire sample		169.967	12.524
SPECIFICATIONS				
	METHOD	1	89.800	2.077
	METHOD	2	94.800	2.178
	For entire sample		92.300	3.292
SPEED				
	METHOD	1	2.126	.061
	METHOD	2	2.599	.068
	For entire sample		2.362	.249

with 100 meeting all product specifications, the specification variable is averaging approximately 90. The mean time before failure is calculated in weeks; it is approximately 159 weeks, or three years.

The plant manager asks the industrial engineering department to devise a modified manufacturing procedure that will improve the quality measures but not change the production rate significantly. A new method is designed that includes more efficient parts handling and "burn-in" time where CD players are powered up and run at high temperatures.

Engineering takes a sample of 15 CD players made with the old manufacturing method and 15 made with the new method. The players are measured for their adherence to product specifications and are stress-tested to determine their time before failure. The stress test uses accelerated running conditions and adverse environmental conditions to simulate years of use in a short time.

Exhibit 19–5 shows the mean and standard deviation of the dependent variables (failure, specifications, and manufacturing speed) for each level of method.[7] Method 1 represents the current manufacturing process, and method 2 is the new process. The new method extended the time before failure to 181 weeks, compared to 159 weeks for the existing method. The adherence to specifications is also improved, up to 95 from 90. But the manufacturing speed is slower by approximately 30 minutes (.473 hour).

We have used diagnostics to check the assumptions of MANOVA except for equality of variance. Both levels of the manufacturing method variable produce a matrix, and the equality of these two matrices must be determined. Exhibit 19–6 contains homogeneity of variance tests for separate dependent variables and a multivariate test. The former are known as univariate tests. The multivariate test is a comparable version that tests the variables simultaneously to determine whether MANOVA should proceed.

The significance levels of Cochran's C and Bartlett-Box F do not allow us to reject any of the tests for the dependent variables considered separately. This means the two methods have equal variances in each dependent variable. This fulfills the univariate assumptions for homogeneity of variance. We then consider the variances and covariances simultaneously with Box's M, also found in Exhibit 19–6. Again, we are unable to reject the homogeneity of variance assumption regarding the matrices. This satisfies the multivariate assumptions.

EXHIBIT 19–6 MANOVA Homogeneity of Variance Tests in the CalAudio Study

VARIABLE	TEST	RESULTS
FAILURE		
	Cochran's *C* (14,2) =	.58954, *P* = .506 (approx.)
	Bartlett-Box *F* (1,2352) =	.44347, *P* = .506
SPECIFICATIONS		
	Cochran's *C* (14,2) =	.52366, *P* = .862 (approx.)
	Bartlett-Box *F* (1,2352) =	.03029, *P* = .862
SPEED		
	Cochran's *C* (14,2) =	.55526, *P* = .684 (approx.)
	Bartlett-Box *F* (1,2352) =	.16608, *P* = .684

Multivariate Test for Homogeneity of Dispersion Matrices

Box's *M* =	6.07877
F with (6,5680) DF =	.89946, *P* = .498 (approx.)
Chi-Square with 6 DF =	5.37320, *P* = .497 (approx.)

EXHIBIT 19–7 Bartlett's Test of Sphericity in the CalAudio Study

Statistics for WITHIN CELLS correlations

Log (Determinant) =	-3.92663
Bartlett's test of sphericity =	102.74687 with 3 D.F.
Significance =	.000
F(max) criterion =	7354.80161 with (3,28) D.F.

When MANOVA is applied properly, the dependent variables are correlated. If the dependent variables are unrelated, there would be no necessity for a multivariate test, and we could use separate *F* tests for failure, specifications, and speed much like the ANOVAs in Chapter 17. Bartlett's test of sphericity helps us decide if we should continue analyzing MANOVA results or return to separate univariate tests. In Exhibit 19–7, we will look for a determinant value that is close to 0. This implies that one or more dependent variables is a linear function of another. The determinant has a chi-square transformation that simplifies testing for statistical significance. Since the observed significance is below that set for the model ($\alpha = .05$), we are able to reject the null hypothesis and conclude there are dependencies among the failure, specifications, and speed variables.

We now move to the test of equality of means that considers the three dependent variables for the two levels of manufacturing method. This test is analogous to a *t*-test or an *F* test for multivariate data. The sums-of-squares and cross-products (SSCP) matrices are used. Exhibit 19–8 shows three tests, including the Hotelling T^2. All the tests provided are compared to the *F* distribution for interpretation. Since the observed

EXHIBIT 19–8 Multivariate Tests of Significance in the CalAudio Study

Multivariate Tests of Significance (S = 1, M = 1/2, N = 12)

Test Name	Value	Exact F	Hypoth. DF	Error DF	Sig. of F
Hotelling	51.33492	444.90268	3.00	26.00	.000
Pillai	.98069	444.90268	3.00	26.00	.000
Wilks	.01911	444.90268	3.00	26.00	.000

Note: F statistics are exact.

EXHIBIT 19–9 Univariate Tests of Significance in the CalAudio Study

Univariate F-Tests with (1,28) D.F.

Variable	Hypoth. SS	Error SS	Hypoth. MS	Error MS	F	Sig. of F
FAILURE	3696.30000	852.66667	3696.30000	30.45238	121.37967	.000
SPECS	187.50000	126.80000	187.50000	4.52857	41.40379	.000
SPEED	1.67560	.11593	1.67560	.00414	404.68856	.000

Note: F statistics are exact.

significance level is less than $\alpha = .05$ for the T^2 test, we reject the null hypothesis that said methods 1 and 2 provide equal results with respect to failure, specifications, and speed. Similar results are obtained from the Pillai trace and Wilks' statistic.

Finally, to detect where the differences lie, we can examine the results of univariate F tests in Exhibit 19–9. Since there are only two methods, the F is equivalent to t^2 for a two-sample t-test. The significance levels for these tests do not reflect that several comparisons are being made, and we should use them principally for diagnostic purposes. This is similar to problems that require the use of multiple comparison tests in univariate analysis of variance. Note, however, that there are statistically significant differences in all three dependent variables resulting from the new manufacturing method. Techniques for further analysis of MANOVA results were listed at the beginning of this section.

See Chapter 17's discussion of multiple comparison procedures.

LISREL[8]

First developed by Karl Jöreskog in 1973, **LISREL** (an acronym for *linear structural relationships*) is still a commonly accepted term for referring to both the software program and the general statistical method for modeling the analysis of covariance structures. While several other programs have been written since, with EQS and AMOS ranking among the most popular, LISREL is still the most widely referenced package for estimation of the covariance structure model, also frequently referred to as structural equation modeling (SEM). LISREL is a powerful alternative to other multivariate techniques, such as multiple regression, MANOVA, and canonical analysis—which are limited to representing only a single relationship between the dependent and independent variables. The major advantages of LISREL are that it can estimate multiple and interrelated dependence relationships, and that it can represent unobserved concepts, or *latent variables*, in those relationships and account for measurement error in the estimation process.

LISREL is a technique that allows for separate relationships for each of a set of dependent variables. In its most basic sense, LISREL provides an efficient estimation technique for a series of multiple regression equations projected simultaneously. The general LISREL model consists of two submodels: a measurement model and a structural model. The *measurement model* allows the researcher to use several observed variables as factors of a single unobserved independent or dependent variable. This provides the link between observed scores on measurement instruments and the underlying constructs they are designed to measure. Using confirmatory factor analysis (CFA), the researcher can evaluate the contribution of each manifest variable as well as incorporate how well the overall instrument measures the concept into the estimation of the relationships between dependent and independent variables.

The *structural model* is the "path" model that defines relationships among the unobserved variables. It specifies which latent variables cause changes in the values of other latent variables in the model. The development of the structural model requires the incorporation of theory, previous experience, or other guidelines to help the researcher discern which independent variables predict each dependent variable.

LISREL is usually viewed as a confirmatory rather than an exploratory procedure; however, its flexibility provides the researcher with a versatile modeling program that can be applied to a variety of research objectives. Three distinct strategies appropriate for LISREL include:

- The strictly confirmatory strategy.
- The competing models approach.
- The model development strategy.

In the *strictly confirmatory approach,* the researcher specifies a single model, which is tested using LISREL's goodness-of-fit tests to assess its statistical significance. This allows the researcher to discern whether the pattern of variances and covariances in the data is consistent with the specified structural model. However, research has shown this approach is subject to *confirmation bias* and tends to confirm that the model fits the data. Accordingly, other unexamined models may fit the data as well or better, and an accepted model is confirmed as being only one of several possible acceptable models.

Using the *competing models strategy,* the researcher may test several causal models against each other to determine which has the best fit. By examining models with different hypothetical structural relationships, the researcher comes much closer to comparing competing "theories." This is a much stronger test than a comparison of slight modifications of a single theory. An example is a comparison of equivalent models—alternatives that differ in proposed relationships but that have the same number of parameters and the same level of model fit.

The *model development strategy* differs from the strictly confirmatory and competing models approaches in that the researcher seeks to improve the model by modifying the structural and measurement models. In practice, much of the research combines confirmatory and exploratory purposes, especially in cases where theory provides only the framework for a model, which must then be empirically tested. The tested model is often found to be deficient in some way, and an alternative model is then tested based on changes suggested by the LISREL modification indexes. This is perhaps the most common approach found in the literature. However, this approach may be problematic if the post hoc models that are confirmed do not fit new data. One way to possibly avoid this problem is for researchers to use a *cross-validation* approach that uses a calibration data sample to develop the model and an independent validation sample for confirmation.

Method LISREL is a several-step process that begins with the development of a theoretical model based on causal relationships. In order to assume causality, the researcher must satisfy four general requirements:

1. There must be sufficient association between the two variables being considered.
2. The assumed cause must occur prior to the observed effect.
3. There must be a lack of viable alternative causal variables.
4. There must be a theoretical basis for the relationship.

Researchers must be careful to consider all key predictive variables in order to avoid **specification error,** a bias that overestimates the importance of the variables included in the model.

The second step is to construct a **path diagram** that allows the researcher to present the predictive and associative relationships among the constructs and indicators in the model. The path diagram includes various shapes, lines, and notation, and researchers using LISREL must understand how the geometric symbolism depicted in the schematic models relates to the regression or matrix equations. In path diagrams, three types of arrows are used to depict all of the relationships in the model. Straight arrows denote causal relationships from one variable to another; a curved arrow or line indicates a covariance between constructs; and a straight arrow with two heads shows a reciprocal relationship between constructs. Exhibit 19–10 illustrates some other key symbols frequently used in path diagrams.

The matrices used in LISREL equations are represented using Greek notation. A *matrix* is a collection of numbers written in rows and columns, and the numbers within the matrix are its *elements.* These elements represent the parameters in the model. A matrix with only one column but multiple rows is called a **vector.** Matrices are most commonly represented by uppercase Greek letters, and the elements of a matrix are denoted using lowercase Greek letters. The observed measures are indicated using Roman letters—independent variables are labeled *X-variables,* and dependent variables are labeled *Y-variables.* At the most, eight matrices and four vectors define a general LISREL model, although the actual number of matrices required will depend on the particular model specified.

EXHIBIT 19–10 Symbols Frequently Used in Path Diagrams

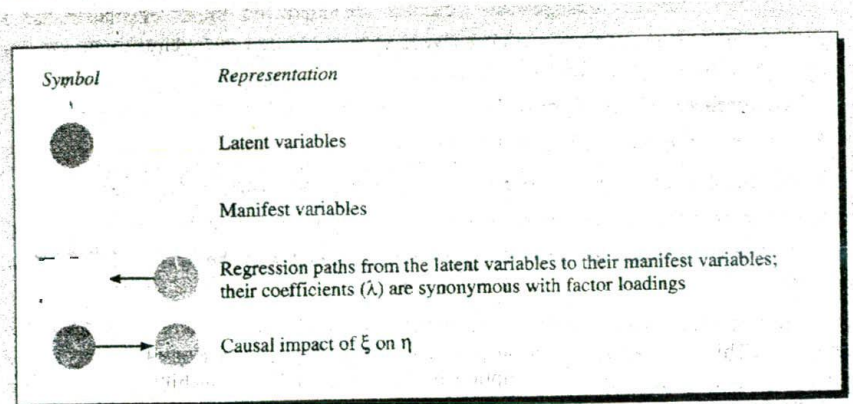


EXHIBIT 19–11 A Summary of Matrix and Greek Notation[9]

Greek Letter	Full Matrix	Matrix Elements	Type
Measurement Model			
Lambda-*X*	Λ_X	λ_X	Regression
Lambda-*Y*	Λ_Y	λ_Y	Regression
Theta delta	Θ_δ	θ_δ	Var/cov
Theta epsilon	Θ_ε	θ_ε	Var/cov
Nu	—	ν	Vector
Structural Model			
Gamma	Γ	γ	Regression
Beta	B	β	Regression
Phi	Φ	φ	Var/cov
Psi	Ψ	ψ	Var/cov
Xi	—	ξ	Vector
Eta	—	η	Vector
Zeta	—	ζ	Vector

For the general LISREL model, the measurement model is composed of two regression matrices, two variance-covariance matrices among errors of measurement, and one vector representing the endogenous factor. The structural model comprises two variance-covariance matrices (one among the exogenous factors and one among the residual errors associated with the endogenous factors) and three vectors representing the exogenous variables, endogenous variables, and errors associated with the endogenous variables, respectively. A summary of these matrices and vectors is presented in Exhibit 19–11.

In the path diagram, each of the constructs is specified as being exogenous (independent) or endogenous (dependent). Exogenous variables are not predicted by other variables, whereas endogenous variables are predicted by other constructs. The researcher must make the distinction between exogenous and endogenous constructs with respect to each of the following:

1. The number of factors (ξ or η).
2. The number of observed variables (X or Y).
3. Relationships between the observed variables and latent factors (λ_X or λ_Y).
4. Factor variances and covariances (φ).
5. Error variances (and possibly covariances) associated with the observed variables (Θ_δ or Θ_ε).

Path diagrams also require two basic assumptions. First, all causal relationships must be indicated. This requires a theoretical justification for including or excluding variables from the model. The second assumption is that the causal relationships are linear in nature. However, modifications of the LISREL equation, as in multiple regression, usu-

EXHIBIT 19–12 Path Analysis of *X* and *Y* Constructs[10]

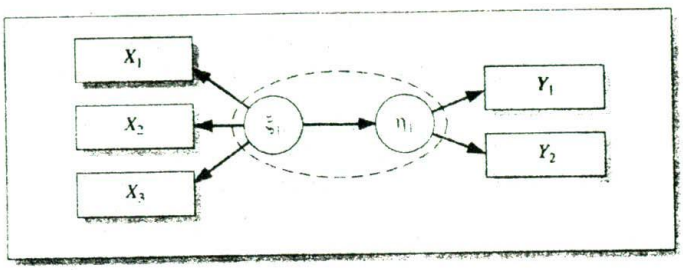
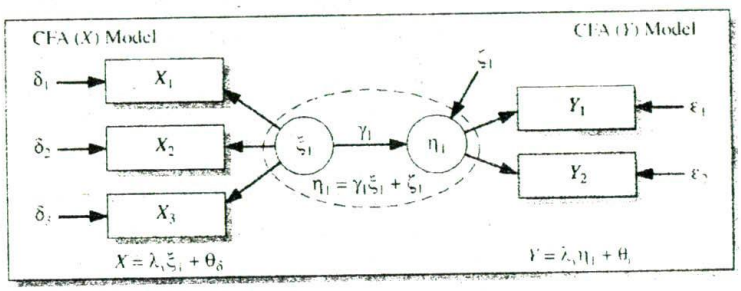


EXHIBIT 19–13 The LISREL CFA Model Relative to the LISREL Full Model[11]



ally allow for the model to remain robust against this assumption. An example of a simple path analysis is shown in Exhibit 19–12.

After the path diagram is hypothesized, the third stage in LISREL is to convert the path diagram into a more formal set of structural and measurement models. This is accomplished through a set of equations that define (1) the structural equations linking the constructs; (2) the measurement model specifying exogenous and endogenous variables; and (3) a set of matrices indicating any hypothetical covariances among the constructs or variables. The goal for this stage is to develop a connection between the operational definitions of the constructs and the theory for the proper test.

The measurement model, commonly referred to as a **confirmatory factor analysis (CFA)** model, is achieved similar to exploratory factor analysis (EFA) and details on its methodology are provided in that section of the chapter. The main difference between EFA and CFA is that in EFA there are no constraints on variable loading; accordingly, each variable has a loading on each factor. In CFA, the researcher specifies which variables, or *indicators*, define each construct. To develop the structural model, each endogenous construct becomes a dependent variable in a separate equation. Exhibit 19–13 illustrates that *relative to the structural model* there are two CFA models with a theoretical causal relationship, γ_1, between ξ_1 and η_1. δ and ε represent the measurement error associated with the observed variables, and ζ_1 is the residual error in the prediction of η_1 from ξ_1.

Next, the researcher must select the input matrix type and estimate the proposed model. At this point the researcher must test whether the data seriously violate any of

LISREL's four basic assumptions: independent observations, random sampling of respondents, linearity of all relationships, and multivariate normality. Because LISREL differs from other multivariate techniques in that it only uses the variance-covariance matrix as its input data, the researcher must run diagnostic tests for violations of these assumptions using a separate statistics package, such as PRELIS, SPSS, SAS, or other software.

During the analysis the researcher must select the estimation procedure used to yield the overall LISREL model. True to its name, *maximum likelihood estimation (MLE)* generates estimates that have the greatest probability of reproducing the observed data. MLE is by far the most common method used. This approach is advantageous over ordinary least squares (OLS) because MLE does not assume uncorrelated error terms and, accordingly, may be used for both recursive and nonrecursive models. Other estimation procedures, such as bootstrapping, simulation, and jackknifing—all of which generate samples for comparing models—are also appropriate in special circumstances.

The estimation procedure selected, as well as model misspecification error, model size, and departures from normality, will all affect the sample size required for a robust model. Model misspecification error is the omission of important constructs or indicators. The researcher should increase the sample size if this is a concern. An appropriate model size is 5–10 respondents per parameter; an absolute minimum sample size is one that is greater than the number of covariances in the input data matrix. However, if the data violate the assumption of normality, we recommend a ratio of 15 respondents per parameter.

After testing the assumptions, the researcher must identify the structural model. This includes considering the size of the covariance matrix in proportion to the number of estimated coefficients. The difference between the number of covariances and the actual number of coefficients in the proposed model is the *degrees of freedom*, calculated as:

$$\text{d.f.} = \tfrac{1}{2}[(p + q)(p + q + 1)] - t$$

where:

p = The number of endogenous indicators.

q = The number of exogenous indicators.

t = The number of estimated coefficients in the proposed model.

The *order condition* states that the model must be just-identified or over-identified, meaning the d.f. of the model must be equal to or greater than zero. The goal of the researcher is to achieve an acceptable fit with the largest number d.f. obtainable, which causes the model to be in its most generalizable state. In addition to meeting the order condition, the model also must meet the *rank condition*. That is, the researcher must algebraically determine if each parameter is uniquely estimated. A set of heuristics is available so that the researcher will not have to complete this task in its entirety.

Next, the researcher must evaluate the goodness-of-fit criteria. *Goodness-of-fit tests* are used to determine whether the model should or should not be rejected. If the model is not rejected, the researcher will continue the analysis and interpret the path coefficients in the model. LISREL currently provides at least 15 different goodness-of-fit measures, each of which can be categorized as one of three types of measures: (1) an absolute fit measure, (2) an incremental fit measure, or (3) a parsimonious fit measure. The type of fit index to report will be specific to the researcher's situation.

After the model is fit, the measurement model is reassessed with each construct evaluated for unidimensionality and composite reliability. Unidimensionality is an assumption for calculating reliability. Reliability measures, such as *Cronbach's alpha*,

do not ensure unidimensionality, but they do detect whether the indicators of a construct have an acceptable fit on a single factor model. A test for construct reliability—to verify that indicators are consistent in their measurement—is not available on LISREL but can be calculated easily with the equation:

$$\text{Construct reliability} = \Sigma(\text{standardized loading})^2/\Sigma(\text{standardized loading})^2 + \Sigma_{\varepsilon j}$$

In addition to the estimated coefficients, the researcher also considers the standard errors and t values for each coefficient. Because of the sensitivity of MLE with smaller sample sizes, the critical values should be conservative (a significance of either .025 or .01). And similar to multiple regression analysis, the overall R^2 is a comparative measure of fit for each LISREL equation.

As we said earlier in the section, the model can be compared with competing or nested models to find the best fit among a set of models and, if necessary, respecified to produce a model with better fit. However, at this point the researcher should be careful to evaluate only the empirical relationships—those which are not essential to the model's underlying theory. Relationships between constructs and indicators essential to the model's underlying theory should not be modified. This allows the researcher to compare several competing models with the same theoretical foundation. The researcher also can look for possible improvements by examining the residuals of the predicted covariance matrix. Residual values ±2.58 are considered statistically significant at the .05 level. Additionally, other tools, such as the *modification index* and the *unexpected change parameter,* can be used to assess goodness of overall model fit. However, each time modifications are made, the researcher must reevaluate the modified model.

Example Assume we wish to develop a model for employee performance. In conceptualizing our measurement model, we first consider a hypothetical two-factor model for employee performance with the two factors being *training* and *motivation.* These will be designated as exogenous constructs, since training and motivation are believed to have a causal effect on performance. For this example, training consists of two indicators: *formal education* and *on-the-job training.* Motivation is measured by three indicators: motivation test 1, motivation test 2, and the empirical observation of behavior as measured on a scale. A diagrammatic representation of the exogenous model is shown in Exhibit 19–14. Here, the two-factor CFA model consists of training and motivation, with each factor measured by two and three indicators, respectively. The curved two-headed arrow denotes that training and motivation are correlated.

Performance is considered to be an endogenous factor, in that it is believed to be caused by motivation and training. This variable is measured by *manager's observation* and by the *measurement of work output.* The schematic representation of this CFA model is presented in Exhibit 19–15.

The full measurement model consists of a pair of CFA models identical to those developed individually. LISREL allows the researcher to test and interpret the parameters of the measurement model in exactly the same way as the parameters of the individual CFA models were tested and interpreted. The full measurement model is expressed diagrammatically in Exhibit 19–16.

The structural model component would then causally relate performance to training and motivation, as well as training and motivation to their respective indicators using a system of linear structural equations. Remember that the researcher must make the distinction between the exogenous and endogenous variables, and there is no specification of causal relationships among latent variables in CFA modeling. Accordingly, the residual error (ζ) associated with the prediction of performance from motivation and training in the measurement model will be zero.

EXHIBIT 19–14 Path Diagram for Employee Performance (Exogenous Variable Model)

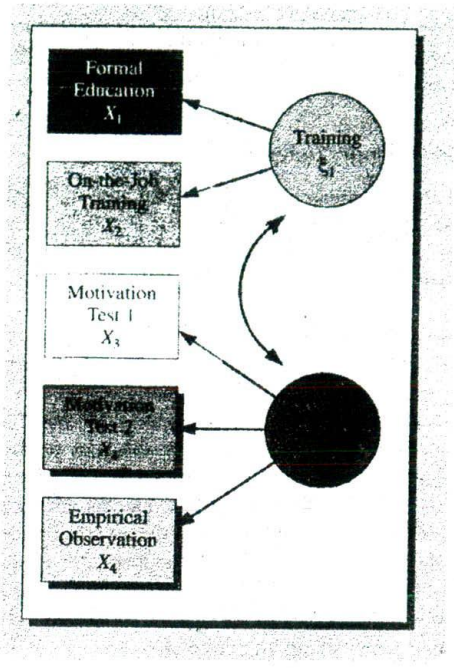


EXHIBIT 19–15 Path Diagram for Employee Performance (Endogenous Variable Model)

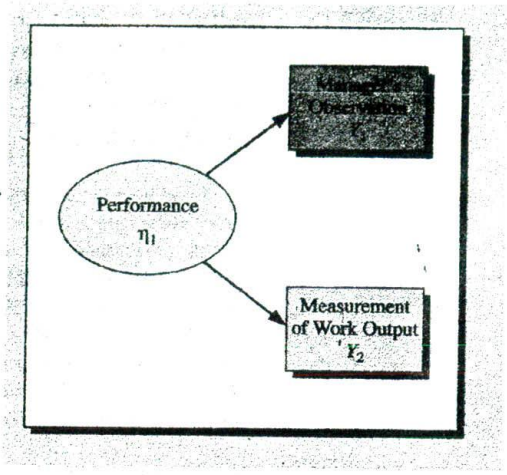
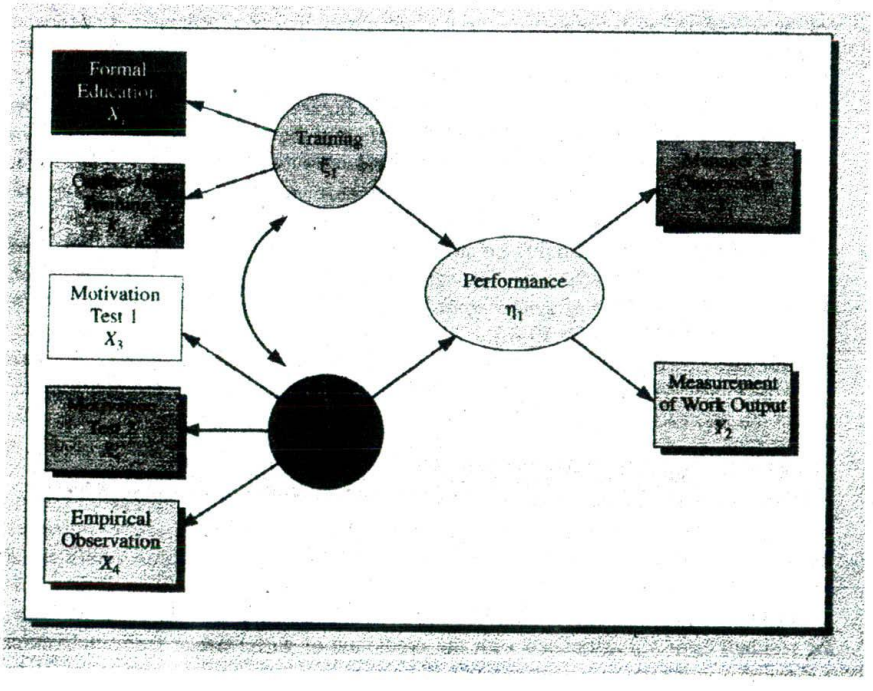


EXHIBIT 19–16 Path Diagram for Employee Performance (Full Measurement Model)



Conjoint Analysis

In management research, the most common applications for conjoint analysis are market research and product development. Consumers buying a MindWriter computer, for example, may evaluate a set of attributes to choose the product that best meets their needs. They may consider brand, speed, price, educational values, games, or capacity for work-related tasks. The attributes and their features require the buyer to make trade-offs in the final decision making.

Method **Conjoint analysis** typically uses input from nonmetric independent variables. Normally, we would use cross-classification tables to handle such data, but even multiway tables become quickly overwhelmed by the complexity. If there were three prices, three brands, three speeds, two levels of educational values, two categories for games, and two categories for work assistance, the model would have 216 decision levels ($3 \times 3 \times 3 \times 2 \times 2 \times 2$). A choice structure this size poses enormous difficulties for respondents and analysts. Conjoint analysis solves this problem with various optimal scaling approaches, often with loglinear models, to provide researchers with reliable answers that could not be obtained otherwise.

The objective of conjoint analysis is to secure *part-worths*, or **utility scores**, that represent the importance of each aspect of a product or service in the subjects' overall preference ratings. Utility scores are computed from the subjects' rankings or ratings of a set of cards. Each card in the deck describes one possible configuration of combined product attributes.

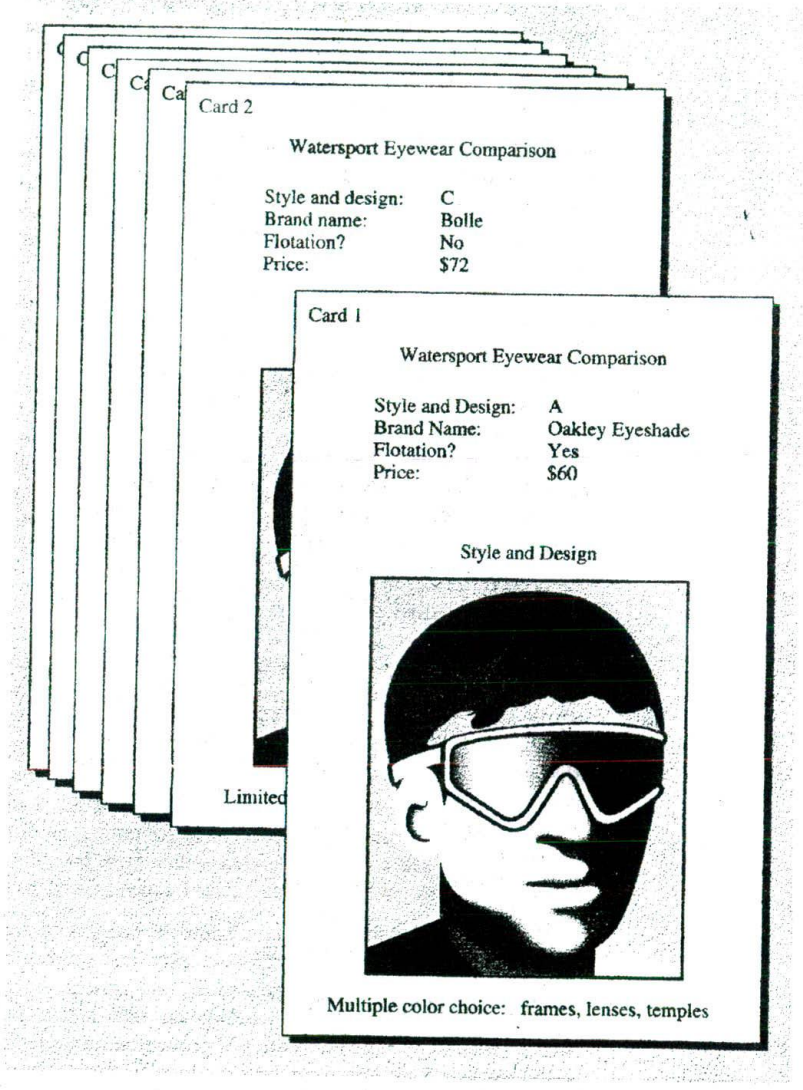
The first step in a conjoint study is to select the attributes most pertinent to the purchase decision. This may require an exploratory study such as a focus group, or it could be done by an expert with thorough market knowledge. The attributes selected are the independent variables, which are called *factors*. The possible values for an attribute are called *factor levels*. In the MindWriter example, the speed factor may have levels of 800 megahertz (MHz), 1 gigahertz, and 1.5 gigahertz. Speed, like price, approaches linear measurement characteristics since consumers typically choose higher speeds and lower prices. Other factors like brand are measured as discrete variables.

After selecting the factors and their levels, a computer program determines the number of product descriptions necessary to estimate the utilities. SPSS procedures ORTHOPLAN, PLANCARDS, and CONJOINT build a file structure for all possible combinations, generate the subset required for testing, produce the card descriptions, and analyze results. The command structure within these procedures provides for holdout sampling, simulations, and other requirements frequently used in commercial applications.[12]

Example Watersport enthusiasts know the dangers of ultraviolet (UV) light. It fades paint and clothing; yellows surfboards, skis, and sailboards; and destroys sails. More important, UV damages the eye's retina and cornea. At the beginning of the 1990s, Americans were spending $1.3 billion on 189 million pairs of sunglasses, most of which failed to provide adequate UV protection. Manufacturers of sunglasses for specialty markets have improved their products to such a degree that all of the companies in our example advertised 100 percent UV protection. Many other features influence trends in this market. For this example, we chose four factors from information contained in a review of sun protection products.[13]

Brand	Style		Flotation	Price
Bolle	A	Multiple color choices for frames, lenses, and temples	Yes	$100
Hobbies	B	Multiple color choices for frames, lenses, and straps	No	72
Oakley		(no hard temples)		60
Ski Optiks	C	Limited colors for frames, lenses, and temples		40

EXHIBIT 19–17 Concept Cards for Conjoint Sunglasses Study



This is a $4 \times 4 \times 3 \times 2$ design, or a 96-option full-concept study. The algorithm selected 16 cards to estimate the utilities for the full concept. Combinations of interest that were not selected can be estimated later from the utilities. In addition, four holdout cards were administered to subjects but evaluated separately. The cards shown in Exhibit 19–17 were administered to a small sample ($n = 10$). Subjects were asked to order their cards from most to least desirable. The data produced the results presented in Exhibits 19–18 and 19–19.

Exhibit 19–18 contains the results of the eighth subject's preferences. This individual was an avid boardsailor, and flotation was the most important attribute for her, followed by style and price and then brand. From her preferences, we can compute her total utility score:

EXHIBIT 19–18 Conjoint Results for Subject 8, Sunglasses Study

Subject name: 8

Importance	Utility (s.e.)	Factor	Level *
23.86	−1.4167(.3143)	STYLE	Style and design
	3.4583(.3685)	—	B
	−2.0417(.3685)		C
11.93	−1.4375(.4083)	BRAND	Brand Name
	.3125(.4083)		Bolle
	1.3125(.4083)		Hobbies
	−.1875(.4083)		Oakley
			Ski Optiks
45.01	10.3750(.4715)	FLOAT	Flotation?
	20.7500(.9429)	— — —	No
	B = 10.3750(.4715)	— — — — —	Yes
19.20	1.4750(.2108)	PRICE	Price *
	2.9500(.4217)	—	$100
	4.4250(.6325)	—	$72
	5.9000(.8434)	—	$60
	B = 1.4750(.2108)	—	$40
	−8.2083(.9163)	CONSTANT	

Pearson's r	= .994	Significance =	.0000
Pearson's r	= .990 for 4 holdouts	Significance =	.0051
Kendall's tau	= .967	Significance =	.0000
Kendall's tau	= 1.000 for 4 holdouts	Significance =	.0208

*Subject reversed decision once

(Style B) 3.46 + (Oakley brand) 1.31 + (flotation) 20.75
+ (price @ $40) 5.90 + (constant) − 8.21 = 23.21

If brand and price remain unchanged, a design that uses a hard temple with limited color choices (Style C) and no flotation would produce a considerably lower total utility score for this respondent. For example:

(Style C) − 2.04 + (Oakley brand) 1.31 + (no float) 10.38
+ (price @ $40) 5.90 + (constant) − 8.21 = 7.34

EXHIBIT 19–19 Conjoint Results for Sunglasses Study Sample ($n = 10$)

Importance	Utility	Factor	Level
		STYLE	Style and design
18.31	1.1583		A
	−1.9667		B
	.8083		C
		BRAND	Brand Name
7.62	.1938		Bolle
	−.7813		Hobbies
	.5187		Oakley
	.0688		Ski Optiks
		FLOAT	Flotation?
31.57	5.3875		No
	10.7750		Yes
	B = 5.3875		
		PRICE	Price
42.50	2.4175		$100
	4.8350		$72
	7.2525		$60
	9.6700		$40
	B = 2.4175		
	−3.4583	CONSTANT	

Pearson's r	=	.995	Significance =	.0000
Pearson's r	=	.976 for 4 holdouts	Significance =	.0120
Kendall's tau	=	.950	Significance =	.0000
Kendall's tau	=	1.000 for 4 holdouts	Significance =	.0208

We could also calculate other combinations that would reveal the range of this individual's preferences. Our prediction that respondents would prefer less expensive prices did not hold for the eighth respondent as revealed by one asterisk next to the price factor in Exhibit 19–18. She reversed herself once on price to get flotation. Other subjects also reversed once on price to trade off for other factors.

The results for the sample are presented in Exhibit 19–19. In contrast to individuals, the sample placed price first in importance, followed by flotation, style, and brand. Group utilities may be calculated just as we did for the individual. At the bottom of the printout we find Pearson's r and Kendall's tau. Each was discussed in Chapter 18. In this application, they measure the relationship between observed and estimated preferences. Since holdout samples (in conjoint, regression, discriminant, and other methods)

are not used to construct the estimating equation, the coefficients for the holdouts are often a more realistic index of the model's fit.

Conjoint analysis is an effective tool used by researchers to match preferences to known characteristics of market segments and design or target a product accordingly.

Interdependency Techniques

Factor Analysis

Factor analysis is a general term for several specific computational techniques. All have the objective of reducing to a manageable number many variables that belong together and have overlapping measurement characteristics. The predictor-criterion relationship that was found in the dependence situation is replaced by a matrix of intercorrelations among several variables, none of which is viewed as being dependent on another. For example, one may have data on 100 employees with scores on six attitude scale items.

Method Factor analysis begins with the construction of a new set of variables based on the relationships in the correlation matrix. While this can be done in a number of ways, the most frequently used approach is **principal components analysis.** This method transforms a set of variables into a new set of composite variables or principal components that are not correlated with each other. These linear combinations of variables, called **factors,** account for the variance in the data as a whole. The best combination makes up the first principal component and is the first factor. The second principal component is defined as the best linear combination of variables for explaining the variance *not* accounted for by the first factor. In turn, there may be a third, fourth, and *k*th component, each being the best linear combination of variables not accounted for by the previous factors.

The process continues until all the variance is accounted for, but as a practical matter it is usually stopped after a small number of factors has been extracted. The output of a principal components analysis might look like the hypothetical data shown in Exhibit 19–20.

Numerical results from a factor study are shown in Exhibit 19–21. The values in this table are correlation coefficients between the factor and the variables (.70 is the *r*

SNAPSHOT Insider Information

PricewaterhouseCoopers (PWC), a consulting company based in New York, wanted to position itself as a telecommunications specialist. An alliance with PointCast Network (now EntryPoint) was proposed in 1998 to launch a free, up-to-the-minute e-business providing specialized information to telecommunication decision makers. The result is Telecominsider.

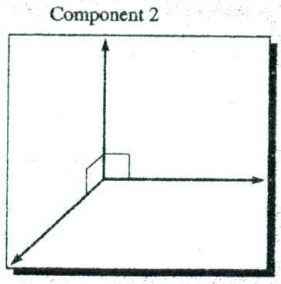
Why was PWC willing to foot the $50,000 in start-up capital? Through focus groups and surveys with PWC's desired target audience, telecommunication senior managers, PWC found executives were seeking convenience in accessing the information and premium content that would help them make business decisions. Analysis of multiple variables in its tracking research during October 1999 shows that of the 76,000 viewers to the Telecom-Insider site, 24 percent of click-throughs from the Telecom-Insider articles go to PWC's website. Telecominsider is now patched into cell phones, Palm Pilots, and pagers so users can have instant access to Telecominsider's information.

www.pwcglobal.com

www.telecominsider.com

www.entrypoint.com

EXHIBIT 19–20 Principal Components Analysis from a Three-Variable Data Set



Extracted Components	% of Variance Accounted for	Cumulative Variance
Component no. 1	63%	63%
Component no. 2	29	92
Component no. 3	8	100

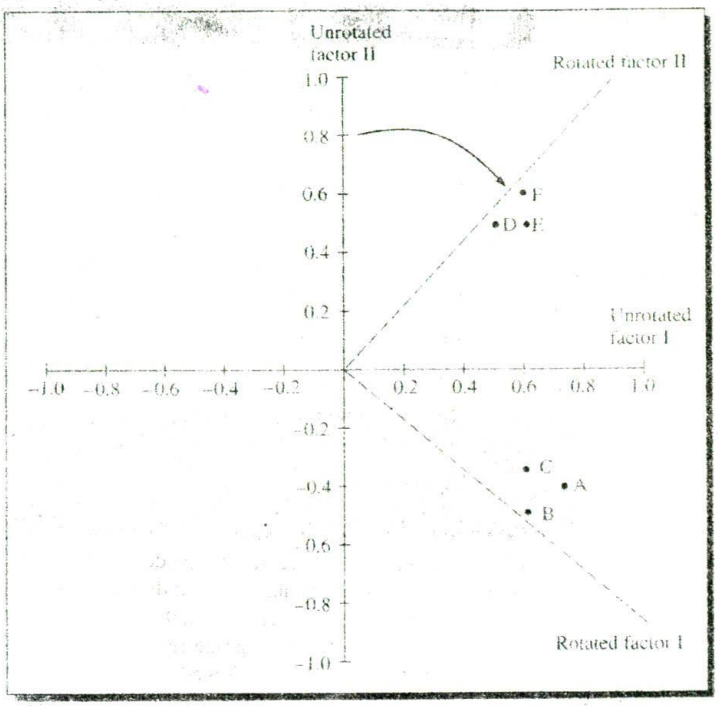
EXHIBIT 19–21 Factor Matrices

	A Unrotated Factors			B Rotated Factors	
Variable	I	II	h^2	I	II
A	.70	–.40	.65	**.79**	.15
B	.60	–.50	.61	**.75**	.03
C	.60	–.35	.48	**.68**	.10
D	.50	.50	.50	.06	**.70**
E	.60	.50	.61	.13	**.77**
F	.60	.60	.72	.07	**.85**
Eigenvalue	2.18	1.39			
Percent of variance	36.30	23.20			
Cumulative percent	36.30	59.50			

between variable A and factor I). These correlation coefficients are called **loadings.** Two other elements in Exhibit 19–21 need explanation. *Eigenvalues* are the sum of the variances of the factor values (for factor I the eigenvalue is $.70^2 + .60^2 + .50^2 + .60^2 + .60^2$). When divided by the number of variables, an eigenvalue yields an estimate of the amount of total variance explained by the factor. For example, factor I accounts for 36 percent of the total variance. The column headed h^2 gives the **communalities,** or estimates of the variance in each variable that is explained by the two factors. With variable A, for example, the communality is $.70^2 + (-.40)^2 = .65$, indicating that 65 percent of the variance in variable A is statistically explained in terms of factors I and II.

In this case, the unrotated factor loadings are not enlightening. What one would like to find is some pattern in which factor I would be heavily loaded (have a high *r*) on some variables and factor II on others. Such a condition would suggest rather "pure" constructs underlying each factor. You attempt to secure this less ambiguous condition

EXHIBIT 19–22 Orthogonal Factor Rotations



between factors and variables by **rotation.** This procedure can be carried out by either orthogonal or oblique methods, but only the former will be illustrated here.

To understand the rotation concept, consider that you are dealing only with simple two-dimensional rather than multidimensional space. The variables in Exhibit 19–21 can be plotted in two-dimensional space as shown in Exhibit 19–22. Two axes divide this space, and the points are positioned relative to these axes. The location of these axes is arbitrary, and they represent only one of an infinite number of reference frames that could be used to reproduce the matrix. As long as you do not change the intersection points and keep the axes at right angles, when an orthogonal method is used you can rotate the axes to find a better solution or position for the reference axes. "Better" in this case means a matrix that makes the factors as pure as possible (each variable loads onto as few factors as possible). From the rotation shown in Exhibit 19–22, it can be seen that the solution is improved substantially. Using the rotated solution suggests that the measurements from six scales may be summarized by two underlying factors (see the rotated factors section of Exhibit 19–21).

The interpretation of factor loadings is largely subjective. There is no way to calculate the meanings of factors; they are what one sees in them. For this reason, factor analysis is largely used for exploration. One can detect patterns in latent variables, discover new concepts, and reduce data. Factor analysis is also applied to test hypotheses with confirmatory models using LISREL.

EXHIBIT 19–23 Correlation Coefficients, Metro U MBA Study

Variable	Course	V1	V2	V3	V10
V1	Financial Accounting	1.00	.56	.17	–.01
V2	Managerial Accounting	.56	1.00	–.22	.06
V3	Finance	.17	–.22	1.00	.42
V4	Marketing	–.14	.05	–.48	–.10
V5	Human Behavior	–.19	–.26	–.05	–.23
V6	Organization Design	–.21	–.00	–.56	–.05
V7	Production	–.44	–.11	–.04	–.08
V8	Probability	.30	.06	.07	–.10
V9	Statistical Inference	–.05	.06	–.32	.06
V10	Quantitative Analysis	–.01	.06	.42	1.00

Example Student grades make for an interesting example. The director of Metro U's MBA program has been reviewing grades for the first-year students and is struck by the patterns in the data. His hunch is that distinct types of people are involved in the study of management, and he decides to gather evidence for this idea.

Suppose a sample of 21 grade reports is chosen for students in the middle of the GPA range. Three steps are followed:

1. Calculate a correlation matrix between the grades for all pairs of the 10 courses for which data exist.
2. Factor-analyze the matrix by the principal components method.
3. Select a rotation procedure to clarify the factors and aid in interpretation.

Exhibit 19–23 shows a portion of the correlation matrix. These data represent correlation coefficients between the 10 courses. For example, grades secured in V1 (Financial Accounting) correlated rather well (0.56) with grades received in course V2 (Managerial Accounting). The next best correlation with V1 grades is an inverse correlation (–.44) with grades in V7 (Production).

After the correlation matrix, the extraction of components is shown in Exhibit 19–24. While the program will produce a table with as many as 10 factors, you choose, in this case, to stop the process after three factors have been extracted. Several features in this table are worth noting. Recall that the communalities indicate the amount of variance in each variable that is being "explained" by the factors. Thus, these three factors account for about 73 percent of the variance in grades in the financial accounting course. It should be apparent from these communality figures that some of the courses are not explained well by the factors selected.

The eigenvalue row in Exhibit 19–24 is a measure of the explanatory power of each factor. For example, the eigenvalue for factor 1 is 1.83 and is computed as follows:

$$1.83 = (.41)^2 + (.01)^2 + \ldots + (.25)^2$$

The percent of variance accounted for by each factor in Exhibit 19–24 is computed by dividing eigenvalues by the number of variables. When this is done, one sees that the three factors account for about 43 percent of the total variance in course grades.

EXHIBIT 19–24 Factor Matrix Using Principal Factor with Iterations, Metro U MBA Study

Variable	Course	Factor 1	Factor 2	Factor 3	Communality
V1	Financial Accounting	.41	.71	.23	.73
V2	Managerial Accounting	.01	.53	−.16	.31
V3	Finance	.89	−.17	.37	.95
V4	Marketing	−.60	.21	.30	.49
V5	Human Behavior	.02	−.24	−.22	.11
V6	Organization Design	−.43	−.09	−.36	.32
V7	Production	−.11	−.58	−.03	.35
V8	Probability	.25	.25	−.31	.22
V9	Statistical Inference	−.43	.43	.50	.62
V10	Quantitative Analysis	.25	.04	.35	.19
Eigenvalue		1.83	1.52	.95	
Percent of variance		18.30	15.20	9.50	
Cumulative percent		18.30	33.50	43.00	

EXHIBIT 19–25 Varimax Rotated Factor Matrix, Metro U MBA Study

Variable	Course	Factor 1	Factor 2	Factor 3
V1	Financial Accounting	.84	.16	−.06
V2	Managerial Accounting	.53	−.10	.14
V3	Finance	−.01	.90	−.37
V4	Marketing	−.11	−.24	.65
V5	Human Behavior	−.13	−.14	−.27
V6	Organization Design	−.08	−.56	−.02
V7	Production	−.54	−.11	−.22
V8	Probability	.41	−.02	−.24
V9	Statistical Inference	.07	.02	.79
V10	Quantitative Analysis	−.02	.42	.09

In an effort to further clarify the factors, a varimax (orthogonal) rotation is used to secure the matrix shown in Exhibit 19–25. The heavy factor loadings for the three factors are as follows:

Factor 1		Factor 2		Factor 3	
Financial Accounting	.84	Finance	.90	Marketing	.65
Managerial Accounting	.53	Organization Design	−.56	Statistical Inference	.79
Production	−.54				

SNAPSHOT

The Mail as a "Super" E-Business

The world's postal system is projected to grow at a rate of 3.8 percent through 2005, according to its governing body, the Universal Postal Union (UPU). Hybrid mail will account for 6 percent, or 33 billion, of the world's 550 billion pieces of physical mail in 2005 according to the UPU. SuperLetter.com plans to be an e-business success story in this hybrid mail sector. According to founder and successful entrepreneur Christopher Schultheiss, "We are establishing the world's first global 'hybrid mail' network enabling users to create letters or documents on their personal computers, send them like email in a secure encrypted mode over the Internet to remote printers near the recipients, where they will be printed, folded, enveloped, franked with postage and delivered in the local mail."

Using a variety of multiple-variable analytic techniques, SuperLetter specifically identified its target market as professional and financial service firms, not-for-profit organizations, education, and immigrant/expatriate communities. SuperLetter will also draw from the $100 billion worldwide international courier market, like FedEx, UPS and DHL, now experiencing strong growth rates (15 percent in international volumes relative to single-digit domestic growth). But the greatest source of messaging is likely to come from the Internet itself. Focused primarily on international correspondence, SuperLetter bridges the gap between conventional door-to-door postal services, taking from 5 to 10 days for overseas delivery, and private express/courier services, which may take from 2 to 3 days. SuperLetter's basic international service delivers a letter from desk to door in 2 to 3 days for about one-tenth private express costs and under one-half of those costs for same day services.

www.superletter.com

Interpretation The varimax rotation appears to clarify the relationship among course grades, but as pointed out earlier, the interpretation of the results is largely subjective. We might interpret the above results as showing three kinds of students, classified as the accounting, finance, and marketing types. Other interpretations could be made as well.

A number of problems affect the interpretation of these results. Among the major ones are these:

1. The sample is small and any attempt at replication might produce a different pattern of factor loadings.
2. From the same data, another number of factors rather than three can result in different patterns.
3. Even if the findings are replicated, the differences may be due to the varying influence of professors or the way they teach the courses rather than to the subject content.
4. The labels may not truly reflect the latent construct that underlies any factors we extract.

This suggests that factor analysis can be a demanding tool to use. It is powerful, but the results must be interpreted with great care.

Cluster Analysis

Unlike techniques for analyzing the relationships between variables, **cluster analysis** is a set of techniques for grouping similar objects or people. Originally developed as a classification device for taxonomy, its use has spread because of classification work in medicine, biology, and other sciences. Its visibility in those fields and the availability of high-speed computers to carry out the extensive calculations have sped its adoption in engineering, economics, marketing, and a host of other areas.

Cluster analysis shares some similarities with factor analysis, especially when factor analysis is applied to people (*Q*-analysis) instead of to variables. It differs from discriminant analysis in that discriminant analysis begins with a well-defined group composed of two or more distinct sets of characteristics in search of a set of variables to separate them. Cluster analysis starts with an undifferentiated group of people, events, or objects and attempts to reorganize them into homogeneous subgroups.

Method Five steps are basic to the application of most cluster studies:

1. Selection of the sample to be clustered (e.g., buyers, medical patients, inventory, products, employees).
2. Definition of the variables on which to measure the objects, events, or people (e.g., financial status, political affiliation, market segment characteristics, symptom classes, product competition definitions, productivity attributes).
3. Computation of similarities among the entities through correlation, Euclidean distances, and other techniques.
4. Selection of mutually exclusive clusters (maximization of within-cluster similarity and between-cluster differences) or hierarchically arranged clusters.
5. Cluster comparison and validation.

Different clustering methods can and do produce different solutions. It is important to have enough information about the data to know when the derived groups are real and not merely imposed on the data by the method.

The example shown in Exhibit 19–26 shows a cluster analysis of individuals based on three dimensions: age, income, and family size. Cluster analysis could be used to segment the car-buying population into distinct markets. For example, cluster A might be targeted as potential minivan or sport-utility vehicle buyers. The market segment represented by cluster B might be a sports and performance car segment. Clusters C and D could both be targeted as buyers of sedans, but the C cluster might be the luxury buyer. This form of clustering or a hierarchical arrangement of the clusters may be used to plan marketing campaigns and develop strategies.

EXHIBIT 19–26 Cluster Analysis on Three Dimensions

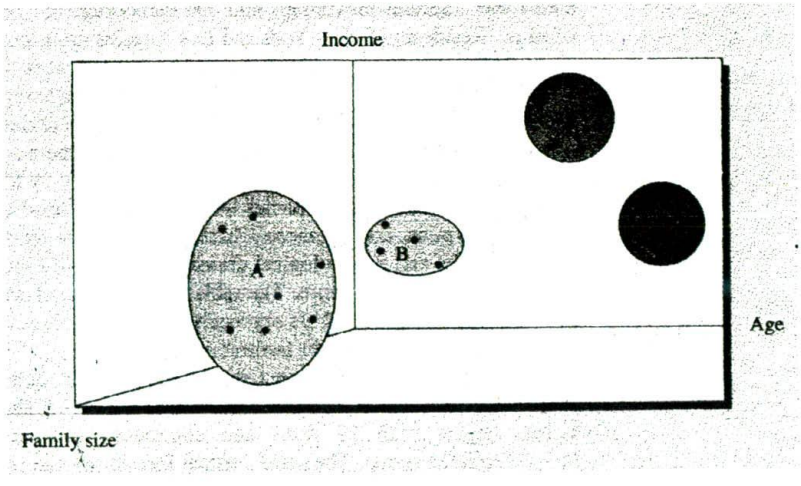


EXHIBIT 19–27 Film, Country, Genre, and Cluster Membership

Film	Country	Genre	Case	Number of Clusters			
				5	4	3	2
Cyrano de Bergerac	France	DramaCom	1	1	1	1	1
Il y a des Jours	France	DramaCom	4	1	1	1	1
Nikita	France	DramaCom	5	1	1	1	1
Les Noces de Papier	Canada	DramaCom	6	1	1	1	1
Leningrad Cowboys . . .	Finland	Comedy	19	2	2	2	2
Storia de Ragazzi . . .	Italy	Comedy	13	2	2	2	2
Conte de Printemps	France	Comedy	2	2	2	2	2
Tatie Danielle	France	Comedy	3	2	2	2	2
Crimes and Misdem . . .	USA	DramaCom	7	3	3	3	2
Driving Miss Daisy	USA	DramaCom	9	3	3	3	2
La Voce della Luna	Italy	DramaCom	12	3	3	3	2
Che Hora E	Italy	DramaCom	14	3	3	3	2
Attache-Moi	Spain	DramaCom	15	3	3	3	2
White Hunter Black . . .	USA	PsyDrama	10	4	4	3	2
Music Box	USA	PsyDrama	8	4	4	3	2
Dead Poets Society	USA	PsyDrama	11	4	4	3	2
La Fille aux All . . .	Finland	PsyDrama	18	4	4	3	2
Alexandrie, Encore . . .	Egypt	DramaCom	16	5	3	3	2
Dreams	Japan	DramaCom	17	5	3	3	2

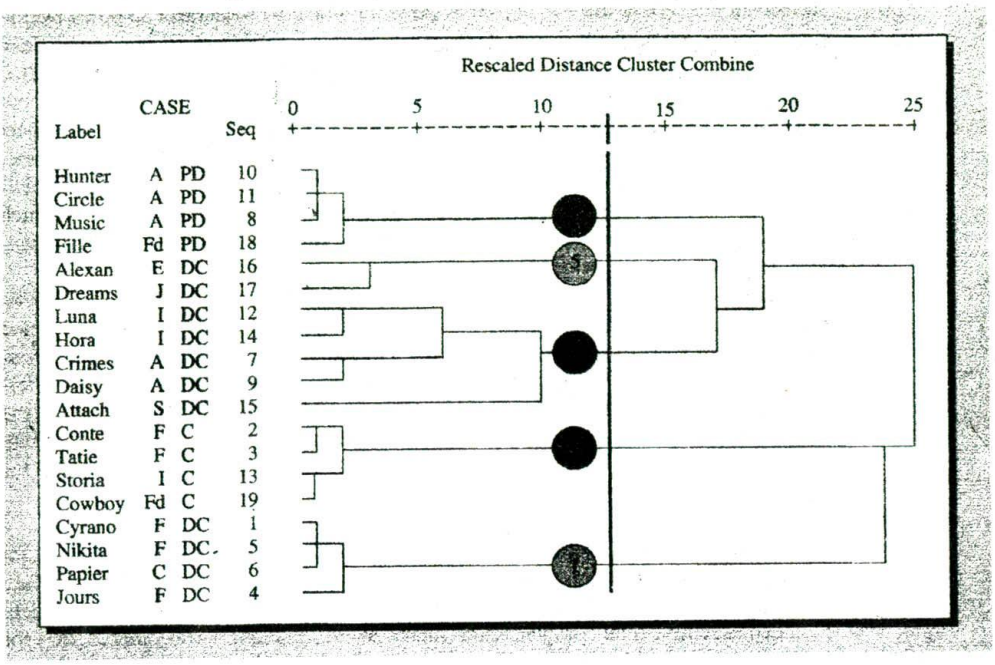
Example Serious movie fans find that Paris offers one of the world's best selections of films. Residents of New York and Los Angeles are often surprised to discover their cities are eclipsed by Paris's average of 300 films per week shown in over 100 locations.

We selected ratings from 12 cinema reviewers using sources ranging from *Le Monde* to international publications sold in Paris. The reviews reputedly influence box-office receipts, and the entertainment business takes them seriously.

The object of this cluster example was to classify 19 films into homogeneous subgroups. The production companies were American, Canadian, French, Italian, Spanish, Finnish, Egyptian, and Japanese. Three genres of film were represented: comedy, dramatic comedy, and psychological drama. Exhibit 19–27 shows the data by film name, country of origin, and genre. The table also lists the clusters for each film using the *average linkage method*. This approach considers distances between all possible pairs rather than just the nearest or farthest neighbor.

The sequential development of the clusters and their relative distances are displayed in a diagram called a *dendogram*. Exhibit 19–28 shows that the clustering procedure begins with 19 films and continues until all the films are again an undifferentiated group. The solid vertical line shows the point at which the clustering

EXHIBIT 19–28 Dendogram of Film Study Using Average Linkage Method



solution best represents the data. This determination was guided by coefficients provided by the SPSS program for each stage of the procedure. Five clusters explain this data set.

The first cluster shown in Exhibit 19–28 has three French-language films and one Canadian film, all of which are dramatic comedies. Cluster two consists of comedy films. Two French and two other European films joined at the first stage, and then these two groups came together at the second stage. Cluster three, composed of dramatic comedies, is otherwise diverse. It is made up of two American films with two Italian films adding to the group at the fourth stage. Late in the clustering process, cluster three is completed when a Spanish film is appended. In cluster four, we find three American psychological dramas combined with a Finnish film at the second stage. In cluster five, two very different dramatic comedies are joined in the third stage.

Cluster analysis classified these productions based on reviewers' ratings. The similarities and distances are influenced by film genre and culture (as defined by the translated language).

Multidimensional Scaling

Multidimensional scaling (MDS) creates a special description of a respondent's perception about a product, service, or other object of interest. This often helps the business researcher to understand difficult-to-measure constructs such as product quality or desirability. In contrast to variables that can be measured directly, many constructs are perceived and cognitively mapped in different ways by individuals. With MDS, items that are perceived to be similar will fall close together in multidimensional space, and items that are perceived to be dissimilar will be farther apart.

Method We may think of three types of attribute space, each representing a multidimensional map. First, there is *objective space*, in which an object can be positioned in terms of its measurable attributes: its flavor, weight, and nutritional value. Second, there is *subjective space*, where perceptions of the object's flavor, weight, and nutritional value may be positioned. Objective and subjective attribute assessments may coincide, but often they do not. A comparison of the two allows us to judge how accurately an object is being perceived. Individuals may hold different perceptions of an object simultaneously, and these may be averaged to present a summary measure of perceptions. In addition, a person's perceptions may vary over time and in different circumstances; such measurements are valuable to gauge the impact of various perception-affecting actions, such as advertising programs.

With a third map we can describe respondents' preferences using the object's attributes. This represents their ideal; all objects close to this ideal point are interpreted as preferred by respondents to those that are more distant. Ideal points from many people can be positioned in this preference space to reveal the pattern and size of preference clusters. These can be compared to the subjective space to assess how well the preferences correspond to perception clusters. In this way, cluster analysis and MDS can be combined to map market segments and then examine products designed for those segments.

Example We illustrate multidimensional scaling with a study of 16 companies from *Business Week*'s "Executive Compensation Scoreboard."[14] The companies chosen are from the natural resources (fuel) segment of the scoreboard. *Business Week* data included executive total compensation (salary, bonus, and long-term compensation for two years), shareholders' return (the year-end value based on $100 invested in corporate stock for two prior years), and the company's return on common equity (ROE) for a three-year period. We created a metric algorithm measuring the similarities among the 16 companies based on total executive compensation and the ROE. The matrix of similarities is shown in Exhibit 19–29. Higher numbers reflect the items that are more dissimilar.

EXHIBIT 19–29 Similarities Matrix of 16 Companies, Executive Compensation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0															
2	3.9	0														
3	4.7	6.7	0													
4	4.4	2.8	4.7	0												
5	14.0	12.4	18.5	15.2	0											
6	4.9	6.9	0.2	4.9	18.7	0										
7	0.8	3.7	4.1	3.7	14.5	4.3	0									
8	6.0	2.1	8.5	4.0	11.8	8.7	5.8	0								
9	4.3	6.9	1.1	5.3	18.3	1.2	3.8	8.9	0							
10	8.2	4.9	8.5	4.1	15.3	8.6	7.6	3.9	9.3	0						
11	8.6	8.7	4.7	5.9	21.1	4.5	7.8	9.7	5.7	7.7	0					
12	2.2	3.7	6.9	5.5	11.8	7.1	2.8	5.5	6.5	8.5	10.5	0				
13	8.4	9.8	3.7	7.2	22.0	3.5	7.8	11.2	4.5	10.0	2.9	10.6	0			
14	12.8	13.4	8.2	10.6	25.8	8.1	12.1	14.4	9.1	12.0	4.7	14.5	4.6	0		
15	19.1	18.2	23.8	21.0	6.2	24.0	19.7	17.8	23.4	21.5	26.9	16.9	27.4	31.5	0	
16	2.6	5.2	2.1	4.0	16.5	2.3	2.0	7.2	1.9	8.0	6.3	4.8	5.8	10.3	21.7	0

SOURCE: Similiarities matrix based on data from "Executive Compensation Scoreboard," *International Business Week*, May 7, 1990, pp. 74–75.

If we were using respondents and producing a matrix of similarities among the perception of objects, we might obtain ordinal data. Then the matrix would contain ranks with 1 representing the most similar pair and n indicating the most dissimilar pair.

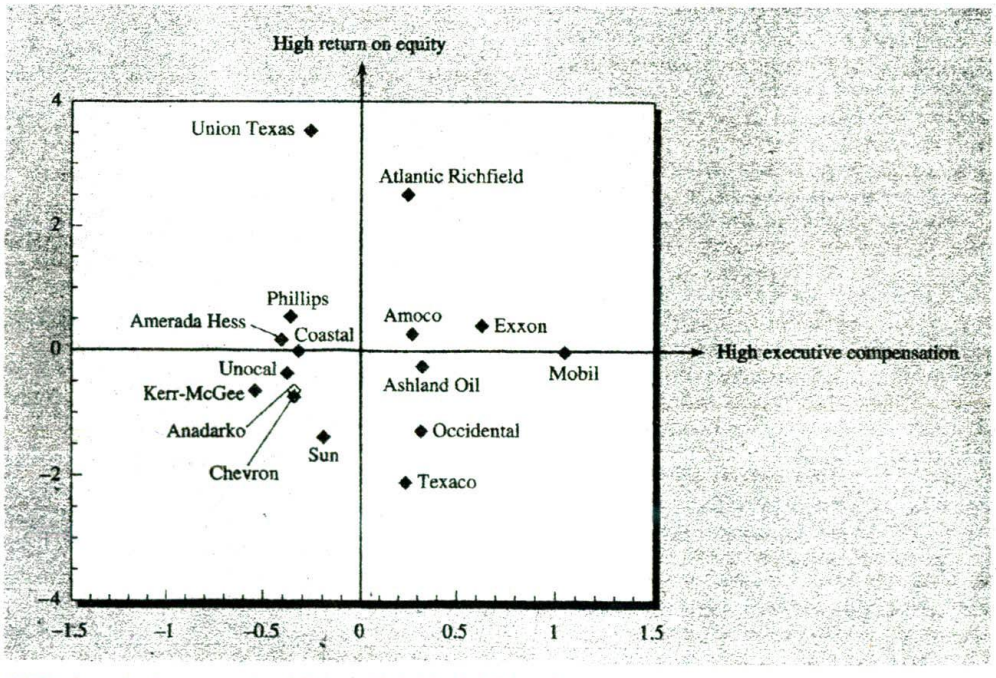
A computer program is used to analyze the data matrix and generate a spatial map.[15] The objective is to find a multidimensional spatial pattern that best reproduces the original order of the data. For example, the most similar pair (companies 3, 6) must be located in this multidimensional space closer together than any other pair. The least similar pair (companies 14, 15) must be the farthest apart. The computer program presents these relationships as a geometric configuration so all distances between pairs of points closely correspond to the original matrix.

Determining how many dimensions to use is complex. The more dimensions of space we use, the more likely the results will closely match the input data. Any set of n points can be satisfied by a configuration of $n - 1$ dimensions. Our aim, however, is to secure a structure that provides a good fit for the data and has the fewest dimensions. MDS is best understood using two or at most three dimensions.

Most algorithms include the calculation of a **stress index** (S-stress or Kruskal's stress) that ranges from the worst fit (1) to the perfect fit (0). This study, for example, had a stress of .001. Another index, R^2, is interpreted as the proportion of variance of transformed data accounted for by distances in the model. A result close to 1.0 is desirable.

In the executive compensation example, we conclude that two dimensions represent an acceptable geometric configuration, as shown in Exhibit 19–30. The distance

EXHIBIT 19–30 Multidimensional Scaling Plot of Natural Resource Companies' Return on Equity and Executive Compensation



SOURCE: Input data from *International Business Week*, May 7, 1990, pp. 74–75.

between Anadarko and Chevron (3, 6) is the shortest, while that between Texaco and Union Texas Petro Holdings (14, 15) is the longest. As with factor analysis, there is no statistical solution to the definition of the dimensions represented by the *X* and *Y* axes. The labeling is judgmental and depends on the insight of the researcher, analysis of information collected from respondents, or another basis. Respondents sometimes are asked to state the criteria they used for judging the similarities, or they are asked to judge a specific set of criteria. In this example, the horizontal dimension approximates the total executive compensation while the vertical dimension represents return on equity.

Consistent with raw data, Union Texas and Atlantic Richfield have high ROE but compensate their executives close to the sample mean. In contrast, Exxon and Mobil generated an ROE close to the sample's average while providing higher compensation for their executives. We could hypothesize that the latter two companies may be more difficult to run—are larger and more complex—but that would need to be confirmed with another study. The clustering of companies in attribute space shows that they are perceived to be similar along the dimensions measured.

MDS is most often used to assess perceived similarities and differences among objects. Using MDS allows the researcher to understand constructs that are not directly measurable. The process provides a spatial map that shows similarities in terms of relative distances. It is best understood when limited to two or three dimensions that can be graphically displayed.



Close-Up

Simalto+Plus™[16]

As part of MindWriter's CompleteCare project, Jason needs to assess customer satisfaction among MindWriter's corporate computer buyers. To identify and prioritize the areas of performance where investment in improvement will have the greatest pay-off, Jason decides to use a trade-off technique called Simalto+Plus™ (Simultaneous Multi-Level Trade-Off).[17]

Simalto+Plus™ is a conjoint-related technique used to predict consumers' purchasing behavior. It recognizes that since resources are limited, buyers seldom can have all the features of a product or service they want, and satisfying one set of needs is often at the expense of another. Simalto+Plus™ is distinguished from other conjoint techniques in that, rather than mathematically deriving correlation coefficients, Simalto+Plus™ is a rule-based expert system that operates similar to neural network analyses.

Neural networks use nodes, modeled after the neurons in the brain, to recognize patterns and linkages by summarizing values in a nonlinear manner, with values being expressed as connection weights. Simalto+Plus™ uses a pattern-recognition technique called *notice and prefer* which inductively identifies the relationships among the variables. Grid data are used as input, and Simalto+Plus™ learns from the patterns provided on an individual participant basis and then infers their relevance into a rule base. The approach is similar to that used in optical character reading when a document is scanned.

Instead of relying on a single algorithm, Simalto+Plus™ customizes its own rule set. This is necessary because participants will have provided only a relatively small number of patterns compared to the billions of possible combinations that could be developed on the grid. The underlying premise for the Simalto+Plus™ rules is that choice is most likely to occur for the specifications that cause the most individual satisfaction. For example:

1. If two service programs differ by only one feature, then the buyer will select the service program with the features that most closely match the buyer's preferences.
2. If service program specifications are of equal merit to the buyer, then the buyer will choose the service program that is less expensive.
3. If a designed service program becomes more expensive than the buyer's available budget, then the buyer will have lower probability of purchasing from a given vendor.

While those rules are simple, they, and other rules, form a system for making inferences and applying them as a set of "if . . . then" type predictions stated as the percentage preference for a specific arrangement of particular product or service features.

Because of the large range of product or service feature combinations that can be modeled, Simalto+Plus™ follows an analytic process to determine the product or service feature combinations that best meet consumers' pref-

erences. This process occurs in three phases. Phase 1 involves identifying key driving features and levels above the base product. This phase includes three steps: (1) current product profiling; (2) identifying the most important features; and (3) identifying unacceptable features. Phase 2 entails identifying winning potential products. This requires (1) reprioritizing the existing products' features; and (2) identifying bonused improvements. Phase 3 involves testing the relative brand value of the product or service (using a questionnaire) and determining the brand image using a Brand Image/Equity grid. The Simalto+Plus™ analytic process is summarized in Exhibit 19–31.

The core of Jason's research is a series of grid exercises (Exhibit 19–32) that deconstruct the MindWriter CompleteCare services into 30 separate attributes, each with between three and eight different levels of performance. For example, repair speed after receiving the computer at the CompleteCare facility might have four levels of performance: shipped next day, shipped by third day, shipped within five days, and shipped within seven days. For Jason's scales, the descriptions are provided in words, rather than numerically. Jason had previously validated the descriptions through focus groups and interviews with both consumers and MindWriter employees involved in different areas of MindWriter product design, service, and support.

Jason conducts the interviews with upper-level managers at the client-companies by telephone. The Simalto+Plus™ grid is faxed to participants prior to the interview with

EXHIBIT 19–31 Simalto+Plus™ Analytic Procedure

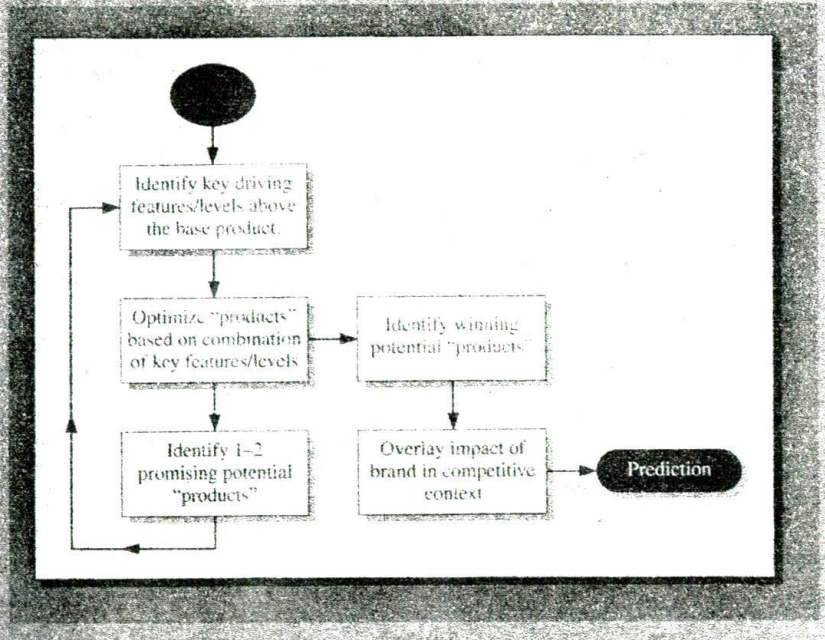
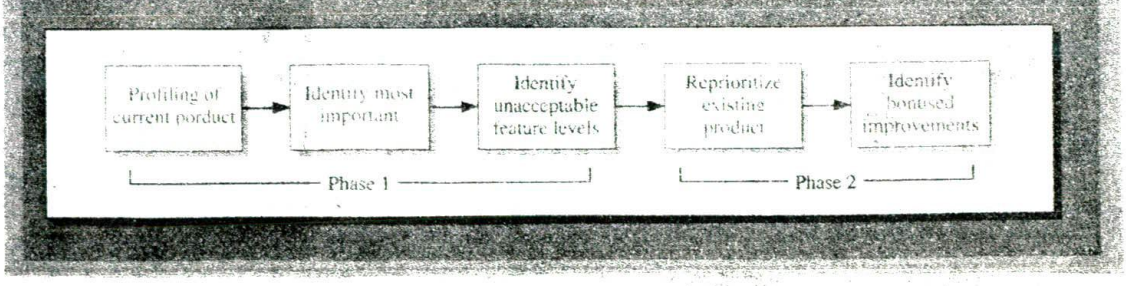


EXHIBIT 19–32 Simalto+Plus™ Grid Exercises



a brief description of how it will be used. The participants are asked to complete the grid as the questions are asked, while Jason also completes a copy on his end.

The first step (Phase I) in Jason's MindWriter Simalto+Plus™ research is to establish a benchmark measure of satisfaction among large corporations, MindWriter's high-end clients. During the interview, participants are asked to first identify, for each of the 30 attributes in the grid, the performance level that best represents the service they expect to receive from a quality business computer manufacturer. Next, participants are asked to identify, for each of the 30 attributes, the current level of service they obtained both from MindWriter and from the best other business computer vendor with whom they also do business. Using the profile of delivered service provided by MindWriter as a "benchmark" or starting point, participants are then asked to make a maximum of 10 improvements—shifts from the current service performance to a higher level of performance—based on any selection of product or service attributes and level changes. However, each attribute level is weighted by the approximate investment cost of implementation. Participants are allowed to make more than one improvement for a given product or service attribute, but they are limited to spending a preset number of improvement "points." Participants selecting more expensive service improvements can make fewer improvements in other areas. This "trade off" procedure allows MindWriter to identify, through improvement "votes," each participant's individual priorities.

Phase 3 of the Simalto+Plus™ process focuses on the importance of brand value and brand image in consumers' purchasing decisions. Instead of treating the brand as a product or service feature, Simalto+Plus™ looks at brand separately to provide a more comprehensive assessment of both relative brand value and brand image.

Relative brand value is determined through questions that ask how much more or less than the currently owned brand is the participant willing to pay to purchase a product of another brand. Brand image and equity are evaluated using an exercise similar to the Simalto+Plus™ grids used in phases one and two. The brand image/equity grid includes 15–20 brand image/equity traits, with brands being evaluated on each characteristic using a nonmetric "poor-to-excellent" scale (see Exhibit 19–33). The last stage is a *brand improvement* exercise in which participants award points to brand improvements to make a particular brand more acceptable. This is typically a two-part process used to generate first- and second-level improvements.

Following the phone interviews, Jason feeds the data from the Simalto+Plus™ grids into a PC-based expert system, a software program specially designed to translate the raw data into a predictive model. This model quantifies the overall impact of making single or multiple box improvements in any service feature area. In this process, each participant is a separate unit for the purposes of preference allocation. The predictive model involves no averaging. And, using the pattern of responses for the expected and current performance levels, Jason is able to demonstrate graphically where MindWriter is falling short of expectation in its current level of service and how MindWriter compares with its competition, the best other business computer vendors.

Through its "notice and prefer" process, Simalto+Plus™ allows Jason to build the predictive model to propose specific actions or performance improvements in a rank order of impact for individual improvements, while also demonstrating the closeness/distance between ranked improvements. However, it is important to note that this is not simply a matter of choosing the top-ranked individual improvements, as the selection of these may be closely correlated and would not add dramatically to overall perceptual gain. This is due to the way individual participants are treated as whole units in preference allocation. The optimum combination could well include an improvement outside the individual top 10.

EXHIBIT 19–33 Example Simalto+Plus™ Brand Image/Equity Grid

	Poor Couldn't be worse						Excellent Couldn't be better
Treats you like a valued customer							
Provides top quality customer service							
Offers good value							
Offers durable, reliable products							
Resolves problems quickly							

With Simalto+Plus™, Jason is able to identify combinations of several improvements that collectively would achieve the greatest impact. Simalto+Plus™ also illustrates how comparable satisfaction gains can be made with several different combinations of improvements. This is where the weighting points become especially effective in identifying the combination of improvements that will yield the best balance between satisfaction gain and investment cost.

Subsequently, Jason uses Simalto+Plus™ in association with clustering techniques to compare the optimal improvements appropriate for different groups of consumers, with clusters developed on the basis of distinctive differences in needs, current perceptions, and improvement priorities.

In sum, the Simalto+Plus™ analysis allows Jason to (1) provide MindWriter with clear guidance on what actions are needed and valued, (2) relate satisfaction to the match between expectation and delivered performance, and (3) demonstrate clearly whether MindWriter is doing better or worse than the best other business computer vendors. Simalto+Plus™ can be used for researching trade-offs for a variety of products and services. It also can be used to evaluate job design and compensation programs, as well as social service and government programs. In the bonused improvement exercise, dollar budgets can be used as an alternative to bonus "points."

Jason's next research assignment has him using Simalto+Plus™ to assist in the design of the ideal MindWriter laptop. Exhibits 19–34 and 19–35 are drafts of the grids he will use in this next multivariate exercise.

EXHIBIT 19–34 Example Simalto+Plus™ Grid with Features and Levels

PC Features	Levels for Each Feature								
Processor Speed	400 MHz	600 MHz	800 MHz	1.0 GHz	1.2 GHz	1.4 GHz	1.6 GHz	1.8 GHz	2.0 GHz
Hard Drive Capacity	8 GB	10 GB	15 GB	20 GB	30 GB	40 GB	60 GB	80 GB	100 GB
Memory—RAM	64 MB	128 MB	192 MB	256 MB	320 MB	384 MB	448 MB	512 MB	
CD-ROM Drive	None $0 **current**	48x Max CD—ROM Drive add $50	8x/4x/32x CD—RW Drive add $80	16x/10x/40x CD—CD-RW Drive add $100	24x/10x/40x CD—CD-RW Drive add $140	CD-RW and DVD Combination Drive add $250 **reprioritized**			

EXHIBIT 19–35 Example Simalto+Plus™ Grid with Features and Levels: Bonused Improvements

PC Features	Levels for Each Feature								
Processor Speed	433 MHz $0 current	600 MHz add $25	800 MHz add $40		1.2 GHz add $75	1.4 GHz add $90	1.6 GHz add $125	1.8 GHz add $165	2.0 GHz add $210
Hard Drive Capacity	8 GB $0 current		15 GB add $40	20 GB add $50	30 GB add $65	40 GB add $80	60 GB add $100	80 GB add $140	100 GB add $180
Memory—RAM	64 GB $0 current	128 MB add $20	192 MB add $40		320 MB add $120	384 MB add $160	448 MB add $200	512 MB add $240	
CD-ROM Drive	None $0 current	48x Max CD—ROM Drive add $50	8x/4x/32x CD—RW Drive add $80	16x/10x/40x CD—CD-RW Drive add $100	24x/10x/40x CD—CD-RW Drive add $140				

SUMMARY



1. Multivariate techniques are classified into two categories: dependency and interdependency. When a problem reveals the presence of criterion and predictor variables, we have an assumption of dependence. If the variables are interrelated without designating some dependent and others independent, then interdependence of the variables is assumed. The choice of techniques is guided by the number of dependent and independent variables involved and whether they are measured on metric or nonmetric scales.

2. Multiple regression is an extension of bivariate linear regression. When a researcher is interested in explaining or predicting a metric dependent variable from a set of metric independent variables (although dummy variables may also be used), multiple regression is often selected. Regression results provide information on the statistical significance of the independent variables, the strength of association between one or more of the predictors and the criterion, and a predictive equation for future use.

3. Discriminant analysis is used to classify people or objects into groups based on several predictor variables. The groups are defined by a categorical variable with two or more values, whereas the predictors are metric. The effectiveness of the discriminant equation is based not only on its statistical significance but also on its success in correctly classifying cases to groups.

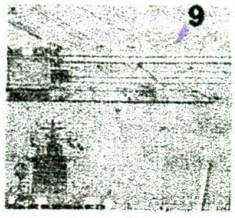
4. Multivariate analysis of variance, or MANOVA, is one of the more adaptive techniques for multivariate data. MANOVA assesses the relationship between two or more metric dependent variables and classificatory variables or factors. MANOVA is most commonly used to test differences among samples of people or objects. In contrast to ANOVA, MANOVA handles multiple dependent variables, thereby simultaneously testing all the variables and their interrelationships.

5. The LISREL technique is extremely useful in explaining causality among constructs that cannot be directly measured. LISREL has two parts, a measurement model and a structural equation model. The measurement model is used to relate the observed, recorded, or measured variables to the latent variables (constructs). The structural equation model specifies causal relationships, causal effects, and unexplained variance among the constructs.

6. Conjoint analysis is a technique that typically handles nonmetric independent variables. Conjoint analysis allows the researcher to determine the importance of product or service attributes and the levels or features that are most desirable. Respondents provide preference data by ranking or rating cards that describe products. These data become utility weights of product characteristics by means of optimal scaling and loglinear algorithms.

7. Principal components analysis extracts uncorrelated factors that account for the largest portion of variance from an initial set of variables. Factor analysis also attempts to reduce the number of variables and discover the underlying constructs that explain the variance. A correlation matrix is used to derive a factor matrix from which the best linear combination of variables may be extracted. In many applications, the factor matrix will be rotated to simplify the factor structure.

8. Unlike techniques for analyzing the relationships between variables, cluster analysis is a set of techniques for grouping similar objects or people. The cluster procedure starts with an undifferentiated group of people, events, or objects and attempts to reorganize them into homogeneous subgroups.



Multidimensional scaling (MDS) is often used in conjunction with cluster analysis or conjoint analysis. It allows a respondent's perception about a product, service, or other object of attitude to be described in a spatial manner. MDS helps the business researcher to understand difficult-to-measure constructs such as product quality or desirability, which are perceived and cognitively mapped in different ways by different individuals. Items judged to be similar will fall close together in multidimensional space and are revealed numerically and geometrically by spatial maps.

KEY TERMS

backward elimination 615
beta weights 614
centroids 620
cluster analysis 640
collinearity 617
communalities 636
confirmatory factor analysis (CFA) 627
conjoint analysis 631
dependency techniques 611
discriminant analysis 618
dummy variables 614
factor analysis 635
factors 635
forward selection 615
holdout sample 617
interdependency techniques 611
LISREL 623
loadings 636
metric measures 613
multicollinearity 617
multidimensional scaling (MDS) 643
multiple regression 613
multivariate analysis 611
multivariate analysis of variance (MANOVA) 619
nonmetric measures 613
path analysis 614
path diagram 625
principal components analysis 635
rotation 637
specification error 625
standardized coefficients 614
stepwise selection 615
stress index 645
utility scores (part-worths) 631
vector 625

EXAMPLES

Company	Scenario	Page
Business Week's "Executive Compensation Scoreboard"	Multidimensional scaling of 16 (fuel segment) companies based on executive compensation and return on equity.	644
CalAudio*	Using MANOVA to assess the manufacturing quality of CD players.	620
Dean Merrill*	Using discriminant analysis to predict whether future candidates will be successful account executives.	618
EntryPoint	Formed an alliance with PWC to launch an e-business, TelecomInsider, which provides timely decision-making information to telecommunication managers.	635
McMahon Group	A research and golf course management specialist helps NCRCC design a new strategic vision.	617
Metro University*	Factor analysis evaluates commonalities among curriculum specialties using student grades.	638
MindWriter*	Selecting attribute levels with conjoint analysis.	631
Motion picture industry	Cluster analysis of films into homogeneous subgroups based on genre and country of origin.	642–643
NCR Country Club	A prestigious country club transforms its facilities, image, and target members through research.	617

PricewaterhouseCoopers	A widely respected consulting firm enters a strategic alliance with EntryPoint to provide instant information and website click-throughs.	635
Sunglasses manufacturers	Comparison of the desirability of four manufacturers' products using "full concept" conjoint analysis.	631
SuperLetter.com	A hybrid mail e-business uses diverse multivariate techniques to understand its customer base.	614, 640

*Due to the confidential and proprietary nature of most research, the names of some companies have been changed.

DISCUSSION QUESTIONS

Terms in Review

1. Distinguish among multidimensional scaling, cluster analysis, and factor analysis.
2. Describe the differences between dependency techniques and interdependency techniques. When would you choose a dependency technique?

Making Research Decisions

3. How could discriminant analysis be used to provide insight into MANOVA results where the MANOVA has one independent variable (a factor with two levels)?
4. Describe how you would create a conjoint analysis study of off-road vehicles. Restrict your brands to three, and suggest possible factors and levels. The full-concept description should not exceed 256 decision options.
5. What type of multivariate method do you recommend in each of the following cases and why?
   a. You want to develop an estimating equation that will be used to predict which applicants will come to your university as students.
   b. You would like to predict family income using such variables as education and stage in family life cycle.
   c. You wish to estimate standard labor costs for manufacturing a new dress design.
   d. You have been studying a group of successful salespeople. You have given them a number of psychological tests. You want to bring meaning out of these test results.
6. Sales of a product are influenced by the salesperson's level of education and gender, as well as consumer income, ethnicity, and wealth.
   a. Formulate this statement as a multiple regression model (form only, without parameter estimation).
   b. Specify dummy variables.
   c. If the effects of consumer income and wealth are not additive alone, and an interaction is expected, specify a new variable to test for the interaction.
7. What multivariate technique would you use to analyze each of the following problems? Explain your choice.
   a. Employee job satisfaction (high, normal, low) and employee success (0–2 promotions, 3–5 promotions, 5+ promotions) are to be studied in three different departments of a company.
   b. Consumers making a brand choice decision between three brands of coffee are influenced by their own income levels and the extent of advertising of the brands.
   c. Consumer choice of color in fabrics is largely dependent on ethnicity, income levels, and the temperature of the geographical area. There is detailed areawide demographic data on income levels, ethnicity, and population, as well as the weather bureau's historical data

on temperature. How would you identify geographical areas for selling dark-colored fabric? You have sample data for 200 randomly selected consumers: their fabric color choice, income, ethnicity, and the average temperature of the area where they live.

From Concept to Practice

8. An analyst sought to predict the annual sales for a home-furnishing manufacturer using the following predictor variables:

X_1 = Marriages during the year.

X_2 = Housing starts during the year.

X_3 = Annual disposable personal income.

X_4 = Time trend (first year = 1, second year = 2, and so forth).

Using data for 24 years, the analyst calculated the following estimating equation:

$$Y = 49.85 - .068X_1 + .036X_2 + 1.22X_3 - 19.54X_4$$

The analyst also calculated an $R^2 = .92$ and a standard error of estimate of 11.9. Interpret the above equation and statistics.

9. A researcher was given the assignment of predicting which of three actions would be taken by the 280 employees in the Desota plant that was going to be sold to its employees. The alternatives were to:

a. Take severance pay and leave the company.

b. Stay with the new company and give up severance pay.

c. Take a transfer to the plant in Chicago.

The researcher gathered data on employee opinions, inspected personnel files and the like, and then did a discriminant analysis. Later, when the results were in, she found the results listed below. How successful was the researcher's analysis?

	Predicted Decision		
Actual Decision	A	B	C
A	80	5	12
B	14	60	14
C	10	15	70

10. You are working with a consulting group that has a new project for the Palm Grove School System. The school system of this large county has individuals with purchasing, service, and maintenance responsibilities. They were asked to evaluate the vendor/distribution channels of products that the county purchases.

The evaluations were on a 10-point metric scale for the following variables:

Delivery speed—Amount of time for delivery once the order has been confirmed.
Price level—Level of price charged by the product suppliers.
Price flexibility—Perceived willingness to negotiate on price.
Manufacturer's image—Manufacturer or supplier's image.
Overall service—Level of service necessary to preserve a satisfactory relationship between buyer and supplier.
Sales force—Overall image of the manufacturer's sales representatives.
Product quality—Perceived quality of a particular product.

The data are found at www.mhhe.com/business/cooper8.

Your task is to complete an exploratory factor analysis on the survey data. The purpose for the consulting group is twofold: (1) to identify the underlying dimensions of these data; and (2) to create a new set of variables for inclusion into subsequent assessments of the vendor/distribution channels.

Issues to consider in your analysis:

a. Methodology: (a) desirability of principal components versus principal axis factoring, (b) decisions on criteria for number of factors to extract, (c) rotation of the factors, (d) factor loading significance, and (e) interpretation of the rotated matrix.

b. Prepare a report summarizing your findings and interpreting your results.

WWW Exercises

Vist our website for Internet exercises related to this chapter at www.mhhe.com/business/cooper8

CASES



MASTERING TEACHER LEADERSHIP



PERFORMANCE EVALUATIONS



MEDICAL LABORATORIES



WASTE PAPER



NCR: TEEING UP A NEW STRATEGIC DIRECTION

*All cases indicating a video icon are located on the Instructor's Videotape Supplement. All nonvideo cases are in the case section of the textbook. All cases indicating a CD icon offer a data set, which is located on the accompanying CD.

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