Chapter 17

MODELING COMMUNICATION BEHAVIOR

The language of modeling reflects different research traditions. Hence, many scholars lump together path models, structural equation models, causal models, and the like. A modern trend is to call these things *models* or *causal models* in general. The models all share a common focus in examining the flow of suspected mediating variables that may explain important phenomena.

The phrase "path analysis" can be traced back at least as far as 1921, when Sewell Wright (1921, 1934) illustrated how to identify complex models based on information revealed from correlations. Over the years, at least two general categories of models have been developed.

- **Path analysis** is "a kind of multivariate analysis in which causal relations among several variables are represented by graphs (path diagrams) showing the 'paths' along which causal influences travel" (Vogt, 2005, p. 230). In this sort of model, all the variables are **observed variables**, also known as **manifest variables**.
- **Structural equation models** "describe causal relationships among latent variables and include coefficients for endogenous variables" (Vogt, 2005, p. 281). As stated in Chapter 16, **latent variables** are underlying factors or dimensions that are not observed directly. These latent variables are also known as unmeasured variables, constructs, or factors. Structural equation models are "a melding of factor analysis and path analysis into one comprehensive statistical methodology" (Kaplan, 2000, p. 3). These structural equation models (SEM for short) actually have two models, a **measurement model** that identifies the ways individual measures are related to latent variables (often considered basic constructs under investigation), and a **structural model** that illustrates and tests the hypothesized relationships among variables.

Researchers often combine the methods to examine a structural equation model that is composed of a combination (or "hybrid") of observed and latent variables. Different approaches often are divided into two categories: traditional path models and structural equation models. Although structural equation modeling was originally developed to analyze latent composite variables (e.g., Bentler, 1980; Jöreskog, 1973), most modeling in communication research has been restricted to studies of observed variables only. In fact, a content analysis of structural equation model studies in communication from 1995 through 2000 found that fewer than 7% of the structural equation models involved latent composite variables only (Holbert & Stephenson, 2002). Slightly more than 35% of the studies involved models with combinations of latent and observable variables. Thus, standard path analysis with observed variables remains a popular tool for modern communication researchers.

THE GOALS OF MODELING

Structural equation modeling and path modeling are elegant ways to examine many hypotheses. Rather than rely on hypotheses that are stated in words alone, the models *exhibit* relationships of interest.

Presentation of a Map of Relationships

The first part of a path model involves a diagram of relationships. Models may show both direct and indirect effects. In multiple regression analysis, a single output measure is identified (in the absence of interactions or suppressor variables) as a result of direct paths from predictors. In essence, multiple regression correlation is a form of path modeling. Yet, when there are moderating variables, it makes sense to consider increasingly complicated models, called path models. Researchers often find it efficient to describe relationships with a picture, rather than as a series of propositions (though propositions may be derived from any model). For instance, if there were a model with five variables, there could be one comprehensive picture of the process, or the researcher could make potentially 10 separate statements about the relationships of variables taken a pair at a time (computed as $\frac{p(p-1)}{2}$, where p is the number of variables).

Of course, identifying and picturing paths may be easier said than done. First, past research that has used modeling has proven notorious for failure to cross-validate. Studies that take data at one point in time to obtain a random draw of events across conditions are called **cross-sectional** studies. As a general rule, cross-sectional studies (which are most common in communication studies) do not provide evidence for the cross-validation for models. Second, it may be difficult to form a picture of many relationships among variables because the past research has produced unclear results. Third, it may be difficult to form a picture of relationships because there may be a bewilderingly large number of causes for many communication phenomena. None of these limitations, however, should stop thoughtful researchers. Preparing models that can be tested is justification enough to explore this approach. Sometimes just imagining possible causal relationships can be helpful to stimulate thinking in productive directions.

Predictions From Causal Ordering of Variables

Researchers often hypothesize about causal order among relationships. When researchers advance problem questions that deal with multiple variables arranged in some sort of cause-and-effect arrangement, modeling may be particularly invited. For causal claims, the "cause" variables should precede the others that are identified as effects. But this stipulation does not mean that models are simply time-series analyses in which the same variable is measured at different time periods.

A comment about causality is appropriate here. Although structural equation modeling is frequently associated with the label "causal modeling" (Asher, 1983), most models are based on simple associations, and the term "cause" is used to define types of models that attempt to specify order, rather than assertions of ultimate causes. There are no assumptions of strict deterministic causality or exact predictions. For those interested in drawing hard-and-fast causal relationships, it is wise to be warned that "conclusions drawn from causal modeling with correlational data must be confined to the following limitation: The results of causal modeling are valid and unbiased only if the assumed model adequately represents the real causal processes" (Mertler & Vannatta, 2002, p. 199, citing Tate, 1992). Causal modeling is

Special Discussion 17.1

Assessing Cause

In his effort to assess causal relationships as a form of inductive reasoning, John Stuart Mill developed five ways that observations could be examined to discover whether the relationship between them is causal or accidental. Called Mill's canons of causality, they include these elements that are suitable to help assess whether correlations reported in path models really are evidence of causality in "causal modeling."

The Method of Agreement: "*If two or more instances of the phenomenon under investigation have only one circumstance in common, the circumstance in which alone all the instances agree is the cause (or effect) of the given phenomenon*" (Mill, 1872/1959, p. 255). Hence, if the path coefficients come from experiments that share only one common independent variable, the common element is likely to be the cause.

The Method of Difference: "*If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance in common save one, that one occurring only in the former: the circumstances in which alone the two instances differ is the effect, or the cause, or an indispensable part of the cause, of the phenomenon*" (Mill, 1872/1959, p. 256). If the path coefficients come from experiments where the effect occurred in the presence of the experimental variable and not when the experimental variable was absent, the common independent variable is likely to be the cause. This method is the basis of causal claims from experiments.

The Joint Method of Agreement and Difference: "*If two or more instances in which the phenomenon occurs have only one circumstance in common, while two or more instances in which it does not occur have nothing in common save the absence of that circumstance, the circumstance in which alone the two sets differ is the effect, or cause, or an indispensable part of the cause, of the phenomenon*" (Mill, 1872/1959, p. 259). The method combines the first two methods to make strong assertions of causality.

The Method of Residues: "*Subduct from any phenomenon such part as is known by previous inductions to be the effect of certain antecedents, and the residue of the phenomenon is the effect of the remaining antecedents*" (Mill, 1872/1959, p. 260). If all the alternative pathways to a variable can be eliminated as causes on the basis of other proof, the remaining path suspected as causal is the cause.

The Method of Concomitant Variation: "*Whatever phenomenon varies in any manner whenever another phenomenon varies in some particular manner, is either a cause or an effect of that phenomenon, or is connected with it through some fact of causation*" (Mill, 1872/1959, p. 263). In path analysis, this canon indicates that a high path coefficient means that some causal forces are operating.

Though these canons are helpful, there are some difficulties with this form (and any form) of inductive reasoning. Inductive reasoning can only lead to conclusions that have a high probability of being true. Furthermore, the methods work best when careful control is practiced and when all the possible antecedent circumstances are controlled or otherwise carefully taken into account. In essence, the cause cannot be identified until the researcher already knows all of the possible causes. Researchers may not be ready to make such claims.

best considered a search for "proximate" causes in which variables that trigger others can be found. There is no search for final causes. Instead, the "causal modeling techniques examine whether a pattern of intercorrelations among variables 'fits' the researcher's underlying theory of which variables are causing other variables" (Mertler & Vannatta, 2002, p. 199).

Despite such concerns, however, there are occasions when causal patterns can be inferred even though one has correlational data. First, if a variable suspected of being a cause occurs first in a sequence, then it is possible that it is a cause of other effects. If variables occur simultaneously, it is difficult to argue that one is the cause and another is an effect. Thus, researchers constructing causal models feel increasingly confident if they can submit that causal variables occurred before the effect variables. Second, if it is clearly impossible for a variable to have been the cause of another, it can be eliminated as a competing path. For instance, sex of the subject cannot be the effect of one's level of communication apprehension; communication apprehension does not determine whether a person is male or female. Third, if **spurious correlations** ("nonsense" correlations between variables that appear related but are, in fact, not causally associated) can be eliminated from the list of possible causal forces, a remaining causal claim may become viable.

HOW TO DO A MODELING STUDY

Many steps are involved in examining structural equation or path models. Although the process can be elaborate, only the major steps are listed here.

Step 1: Develop a Theoretically or Conceptually Based Ordering of Variables

The order of variables should be developed based on past research, theory development, or conceptualizations based in research. Ultimately, the purpose of any model is to predict dependent variables. These models may be most useful when researchers take into account some mediating processes.

In these models, variables are of two forms:

- **Exogenous variables** (also known as "prior variables") are variables that have no predictors. Their values are dependent on systems "from outside the system being studied. A causal system says nothing about its exogenous variables. Their values are given, not analyzed" (Vogt, 2005, p. 110). Their values are assumed to be measured without error.
- **Endogenous variables** are predicted by other variables. Their variability is assumed to be explained by their predictors. A dependent variable is sometimes distinguished as a special form of endogenous variable that is the final object of prediction in the model.

Researchers selecting variables for their models must take into account the potential difficulty created by multicollinearity, or high levels of interrelationship among independent predictor variables.

> Multicollinearity is literally built into a set of structural equations. If X_1 causes X_2 and X_2 causes X_3, it is all but inevitable that X_1 and X_2 are correlated. If X_1 is a strong cause of X_2, it may be difficult, if not impossible, to disentangle the causal effects of X_1 and X_2 on X_3 with a small sample. (Kenny, 1979, p. 85)

If two predictors have intercorrelations greater than the average of their reliabilities, no claims of discriminant validity can be made for the measurements (Campbell & Fiske, 1959). Thus, the usefulness of redundant multiple indicators for the same cause is greatly limited.

Special Discussion 17.2

Causal Analysis Through Corresponding Regressions

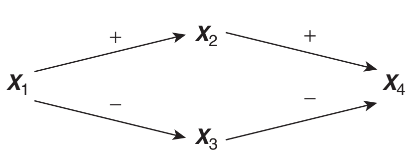
The search for causality using the method of concomitant variation has stimulated some researchers to look for traces left by corresponding regressions. One interesting and controversial approach was initiated by Chambers (1986), who started with the observation that although causally related variables should have high positive correlations, not all the scores in a distribution would share that pattern. When dependent variables' scores were divided into high, moderate, and low scores, it was found that moderate scores were associated with either high or low values of the independent variable. Furthermore, Monte Carlo studies revealed that when a causal relation is present, the variance of the dependent variable scores associated with moderately scoring independent variables is lower than the variance of the independent variable scores associated with the moderately scoring dependent variables.

This information led Chambers (1991) to suggest a way to infer a presence of a causal relationship: When there are two variables, the researcher may run two regressions, with the first variable as independent in the first and the second as dependent, and then with independent and dependent variables switched in the second regression. For each case, the researcher follows these steps:

1. The residuals in the dependent variable predicted scores are computed for each event in the study.
2. The deviations of the independent variable around its mean are identified for each event in the study.
3. The deviations are correlated.
4. The first three steps are repeated with the independent and dependent variables reversed.
5. The two correlations may be compared. When the actual cause of dependent variable effects is the independent variable, the correlation should be higher than when the noncausal factor is the independent variable. The reason is that the moderate dependent variable values should be more closely associated with moderate independent variable values when the actual cause is used as a predictor. The overall correlations should be inverse because when predictor variable scores are extreme, dependent variable residuals should decline (increased variability occurs among moderate scores). In an application of this method to an example in the social sciences, Chambers (1991, p. 66) recommended that researchers faced with the absence of any inverse correlations assume that there are no causal relationships among the chief variables of interest.

This approach assumes the following: bivariate causality in which one of the measured variables is the cause, moderate sample sizes of at least 50 events, correlations in the range of .2 to .9, and additivity of error terms in determining the dependent variable. These assumptions (especially the first one) are not casual ones, and the approach is not universally accepted.

Although some researchers do not include hypotheses in their exploration of path models, they eventually find themselves engaging in statistical hypothesis testing nonetheless. Hence, a typical hypothesis in a modeling study posits that one variable affects another. For instance, in the causal model shown on the left, researchers might examine if there is a significant regression of variable X_4 on variables X_2 and X_3.



Such a hypothesis might be stated verbally as

H_1: X_2 increases X_4 or H_1: $\rho_{42} > 0$.

The null hypothesis to be tested would be

H_0: $\rho_{42} \leq 0$, which states that the relationship between variables X_4 and X_2 is equal to 0 or some negative value below 0.

Other hypotheses include the following statements:

H_2: X_3 decreases X_4, or H_2: $\rho_{43} < 0$. The null hypothesis would be

H_0: $\rho_{43} \geq 0$, which states that the relationship between variables X_4 and X_3 is equal to 0 or some positive value above 0.

H_3: X_1 decreases X_2, or H_3: $\rho_{21} < 0$. The null hypothesis would be

H_0: $\rho_{21} \geq 0$, which states that the relationship between variables X_2 and X_1 is equal to 0 or some positive value above 0.

H_4: X_1 increases X_3, or H_1: $\rho_{31} > 0$. The null hypothesis would be

H_0: $\rho_{31} \leq 0$, which states that the relationship between variables X_3 and X_1 is equal to 0 or some negative value below 0.

For path models, some sources (Causality Lab, 2004) recommend that researchers present hypotheses in a single graphic display. The path parameters and their directions (indicated by positive and negative signs to indicate direct and inverse relationships) may receive special attention. Hypothesis testing may be completed by conducting statistical tests of the fit of the model to the data. Unlike some other hypothesis tests, the researchers are *not* hoping for statistically significant differences. In this situation, researchers actually speculate that the model does *not* deviate from the data. Rejecting this null hypothesis would mean rejection of the model.

Step 2: Construct the Model

Path models start with a structural equation. As has been seen, the paths themselves are part of a causal model that is expressed diagrammatically. Although it is not strictly required that a diagram be displayed, there are many advantages in doing so, not the least of which is an economy of presentation.

Many computer programs contain protocols for labeling model elements. Some of the most frequently used symbols are identified here.

- *X*s identify observed or measured variables. In many structural equation modeling programs, these measured variables are placed in boxes.
- *z*s often are used to identify observed or measured variables. These *z* symbols indicate that the variable is in the form of a standard score or *z* score with a mean of 0 and a

standard deviation of 1. Representing variables as *z* scores can make the process of understanding predictive equations increasingly clear. In this chapter, *X*s are used to indicate both variables and variable values.

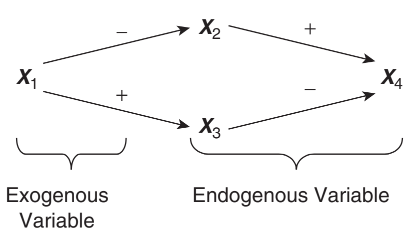
- Latent variables are identified by variables placed in circles or ovals.

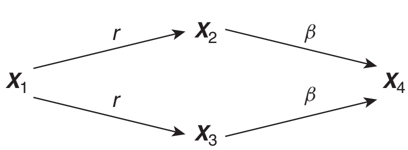
Identify Predictive Links

Models are drawn to identify direct and indirect effects. **Direct effects** are indicated by straight arrows drawn from a variable (assumed to be a cause) to another variable (which is the effect). These paths may lead from an exogenous variable, but not to one. If there is more than one exogenous variable, a curved line (often with arrows) is drawn to identify that there is no causal relationship. Curved arrows also may be drawn to indicate relationships among covariances for which causality is not claimed. Naturally, exogenous variables are initially presumed to be uncorrelated, but if there is reason for expressing an association between them, it would be indicated in the statement of the coefficients.

Indirect effects are influences on variables as mediated by the presence of another endogenous variable. Sometimes the mediating variable is called an "intervening variable" (though that term has some extra meaning of its own), sometimes it is called a "moderator variable," and sometimes it is not given a special name at all. Nevertheless, the ability to be isolated for indirect effects is one of the great advantages of using structural equation modeling techniques. A mediated path (indicated by the absence of a direct path between two variables) to other exogenous variables does not mean that there is no relationship. At the very most, it indicates that a partial relationship is absent when other predictors with direct paths are held constant. As an illustration, at one time it was theorized that evidence produced attitude change in persuasive messages by increasing the credibility of the source, which in turn affected attitude change. The model (Evidence Use → Source Credibility → Attitude Change) predicted an indirect effect of evidence on attitude change.

The simple model previously shown has one exogenous variable (X_1) and three endogenous variables (X_4 also may be known as a dependent variable). The directions of the relationships are indicated by the plus and minus signs representing direct and inverse relationships, respectively. Although the arrows indicate direct effects (not to be confused with "direct relationships") between pairs of variables, the X_2 and X_3 endogenous variables also reveal that there are indirect paths between X_1 and X_4. Once all the effects are diagramed, it becomes easy to report total effects.





The **path coefficients**, *p* coefficients, or structural coefficients are links between the variables involved in direct effects. The paths are symbolized by such terms as p_{34}, p_{31}, p_{42}, and so forth. As a matter of tradition, the variable predicted is listed first because this variable is the one that is *regressed* against the predict*or* variables. When there is one predictor of an exogenous variable, the path coefficient is the zero-order correlation (*r*) between variables. When a variable has two or more predictors, the paths are in the form of beta weights. As the diagram at the left shows, these path coefficients are simply applications of regression analyses. These paths may be interpreted as the amount of change in one variable that is associated with a standard deviation change in the other.

Although models may be categorized in several ways, two basic forms of models are recursive and nonrecursive. In **recursive models**, all paths move in one direction only (e.g., A → B). There are no feedback loops (no A⇄B) and no reciprocal patterns between pairs of variables (no A ↔ B). To fit a nonrecursive model to the data, "ordinary least squares regression will provide good estimates of the parameters when the necessary assumptions are made about the properties of the residual terms" (Asher, 1983, p. 15). For other models, including nonrecursive models, estimation methods beyond ordinary least squares must be enlisted.

In a path diagram, other symbols typically are used, with specific meanings.

- An arrow → with a single direction indicates the direct effect of one variable on another.
- A curved line indicates the covariance or correlation between pairs of error terms or the correlation between a pair of exogenous variables. A curved line indicates that a causal interpretation is not invited for the relationship.

Some rules generally are followed for constructing models (Mertler & Vannatta, 2002, p. 207). First, a path may pass through a given variable only once. Second, "no path may go backward on an arrow after going forward on another arrow (although it is acceptable to go forward on an arrow after *first* going backward" (p. 207). Third, only one bidirectional arrow can appear on a single path.

Specify Error Terms

In addition to the observed and latent variables, some measure of residual error in prediction also has to be included. By implication, this error term reveals the influence of other direct predictors not in the model. For path models, error terms reveal the absence of predictability for each R^2 or r in the model. In structural equation models, the error terms also are called **disturbances** (and the disturbance term is the residual term described in Chapter 13). Error terms are symbolized as arrows (sometimes with dotted lines) connected to the predicted endogenous variables. These terms usually are identified with numbered subscripts as e_1, e_2, e_3, or e_4 to indicate that they are involved in predicting values for particular predicted variables. Because these terms deal with prediction error and not measurement error, they are not presented for exogenous variables. Because each endogenous variable has a disturbance term, the implication is drawn that each structural equation has a disturbance or error term.

Several assumptions are made about the error terms:

- That residuals (differences between the observed and predicted values of the dependent variable) are normally distributed.
- That variability of the residuals holds the same relationship pattern through the entire range of the variables.
- That residuals are independent of the exogenous variables and from each other.
- That there is a linear relationship between observed and predicted values of the dependent variable (this assumption also means that the residuals have a mean of zero).

Naturally, the assumptions can be assessed rather than just presumed.

Step 3: Gather Reliable Data of Relationships Related to Theory

Because structural equation modeling extends multiple regression correlation, it stands to reason that the requirements of sampling adequacy also apply here. In the first place, the sampling should be a random sample of adequate size. With nonrandom samples, selection bias may jeopardize the model's overall validity (Muthen & Jöreskog, 1983). Traditional advice recommends sample sizes of at least 104 events plus the number of independent variables (Tabachnick & Fidell, 2001, p. 117). Other guidelines have advised at least 15 events per predictor variable (J. P. Stevens, 2002, p. 143). For structural equation modeling, increased sample sizes are routinely advised. Various experts advise 100 events with highly reliable measures and 200 with moderately reliable measures (Hoyle & Kenny, 1999), 150 (J. C. Anderson & Gerbing, 1988), and 200 (Chou & Bentler, 1995).

Step 4: Test the Model

Much of the statistical work in structural equation modeling involves checking assumptions, assessing variance explained, and assessing the model's fit to the data.

Check Assumptions

In addition to assumptions previously mentioned, several routinely tested assumptions underlie the use of structural equation models.

- Variability of the residuals is assumed to hold the same relationship pattern through the entire range of the variables (homoscedasticity).
- Data are assumed to be sampled independently of each other; with independence, residuals are independent of the exogenous variables and from each other (thus, the covariances of errors are zero).
- A linear relationship between observed and predicted values of the dependent variable is assumed. This assumption also means that the residuals have a mean of zero.

The assumptions of homoscedasticity and of independence of residuals can be examined by looking at charts of data distributions. Furthermore, because of the use of least squares methods, the residuals are, in fact, uncorrelated with the exogenous variables.

> In structural modeling, this result requires that the disturbances be uncorrelated with the causes of the endogenous variables . . . the assumption of uncorrelated errors implies that: 1. The endogenous variable must not cause any of the variables that cause it; that is, there is no reverse causation. 2. The causal variables must be measured without error and with perfect validity. 3. None of the unmeasured causes must cause any of the causal variables; that is, there are no common causes, or third variables. (Kenny, 1979, p. 65)

Although modest violations of homoscedasticity may not greatly affect statistical test results, violating the independence assumption can make a great difference. Independence can be ensured by taking care in the sampling process; hence, researchers are well advised to explain how their sampling ensured independence of observations. Avoiding reverse causation can be addressed by design choices and ruling out arrangements that could result in a reverse sequence.[1]

"Perfect" measurement may not be completely possible, but it may be very closely approximated. For instance, when a variable is an experimental manipulation, such as the number of deliberate repetitions used by a speaker, the measurement may be assumed (aside from some philosophic nit-picking) to have reliability of 1. Measurement of such variables as participant age, sex, and academic major may be very close to reliability of 1.0. Observed correlation coefficients may be corrected for attenuation of measurement (see Schmidt & Hunter, 1996). Not only does the correction permit researchers to address the question of measurement reliability, but "correction for attenuation due to error of measurement produces a point estimate closer to the population value of the population corrected effect size" (Boster, 2002, p. 483).

Under specific circumstances, two other assumptions may be added.

- When hypotheses about regression equations are involved, the assumption of normal distribution of errors (residuals) is included (Kenny, 1979, p. 62). Although statistical tests are robust to violations of this assumption, it may be checked by consulting charts of residuals, much as is ordinarily done in multiple regression analysis.
- When variables are studied in a single cross-section analysis, the **equilibrium** assumption is made that "if X_1 is assumed to cause X_2 with a lag of k units, and if X_1 and X_2 are contemporaneously measured at time t, equilibrium exists if $X_1 = X_2$; that is, X_1 did not change between times $t - k$ and t" (Kenny, 1979, p. 66). In short, the cross section is assumed to capture the causality if the causal variable has not shown change from one time to another. Except for cross-validation studies, this assumption typically remains untested.

Depending on the specific tools at work, the researcher may find that there are other assumptions that must be made. Sometimes assumptions about unidirectional causation and independent errors require examining subsets ("blocks") of endogenous variables and their associated errors. Such a model is called block recursive.

Variance Explained

Researchers typically report the overall effect sizes for each exogenous variable. Because the SEM approach is an extension of multiple regression correlation, it makes sense to use that option to get the job done. Both corrected and uncorrected R^2 coefficients usually are reported.

Check Deviations From Predicted Expectations

Testing the fit of a structural equation model involves both inspecting parameters and applying specific statistical tools such as confidence intervals, goodness-of-fit tests, and various indices. Other tests involve looking at deviations from expectations.

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[1]Obviously, lack of reverse causation, perfect measurement, and lack of common causes are rather stringent assumptions. Reverse causation can be ruled out by theory or logic; for example, variables measured at one point in time do not cause variables measured earlier in time. "If reverse causation cannot be ruled out, however, a nonhierarchical model must be specified, the parameters of which cannot be estimated by an ordinary regression analysis. . . ." The common cause problem can be solved by measuring the third variables (although these variables must be perfectly measured), but it is still logically impossible to demonstrate that all third variables have been excluded if the multiple correlation is less than one. (Kenny, 1979, p. 66)

Sound models tend to have relatively small residual errors. Thus, researchers often look at these errors to check whether the model has disturbances that suggest the operation of other forces. Bollen (2002, p. 617) explains:

> Some authors describe ε_i [the disturbance term or residual error] as a random variable that has three components: (*a*) an inherent, unpredictable random component present in virtually all outcomes, (*b*) a component that consists of a large number of omitted variables that influence Y_i, and (*c*) random measurement error in Y_i (e.g., Johnston, 1984, pp. 14–15; Maddala, 1983, p. 32).

Other authors would add a fourth component, such as would occur if a researcher assumes a linear relation when a curvilinear one is more appropriate (e.g., Hanushek & Jackson, 1977, pp. 12–13; Weisberg, 1980, p. 6). Thus, researchers often look at the disturbance terms early in assessing model fit because they may provide circumstantial evidence that the model has omitted other, important variables.[2]

Many statistical tools for testing goodness of fit have been developed for use in structural equation modeling. As reviewed in Chapter 16, there are many approaches. These tools attempt to examine whether models have "verisimilitude," or the appearance of truth (see review in Meehl & Waller, 2002). The most popular tool used to assess fit is an application of chi-square called the **likelihood ratio test** and the GFI (goodness-of-fit index). These models, it should be remembered, are only estimates of relationships. As one author (Cudeck, 1991) explains, "A 'correctly specified model' is, always has been, and always will be a fiction. . . . All that can be hoped is that a model captures some reasonable approximation to the truth" (p. 261). Hence, instead of alleging "proof" for their models, researchers claim that their models are "supported" or are "found tenable."

Step 5: Revise the Model

Among articles in communication journals from 1995 to 2000, models using observed variables alone failed to fit the data 20.5% of the time. Of models involving combinations of observed and latent variables, 79.5% failed to fit the data (Holbert & Stephenson, 2002). Thus, researchers often revisit their models to see if other specifications make sense.

On other occasions, the question is not whether the model fits, but which of several competing models best fits the data (J. C. Anderson & Gerbing, 1988). Sometimes researchers find that a model can be improved by adding a direct path between variables that have higher correlations than is predicted for them. Sometimes variables can be deleted as a way to improve a model. Other guidelines have been suggested over the years. To create equivalent models with improved fit, researchers may examine the possibility of inverting the order of variables or permitting residuals to be correlated (Stelzl, 1986). In addition, for "just-identified" models (a term to be defined subsequently), a replacing rule may be applied to permit interchanging direct paths, reciprocal paths, and correlated residuals when there are direct paths leading to other variables in the model (Lee & Hershberger, 1990, 1991).

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[2]Bollen (2002, pp. 617–619) suggests that increases in disturbances may indicate latent variables that exhibit nonrandom influences. Although there are some technical difficulties with calling observed disturbances indications of latent variables, there is little doubt that large residuals may indicate that variables not included in a model exhibit nonrandom influences.

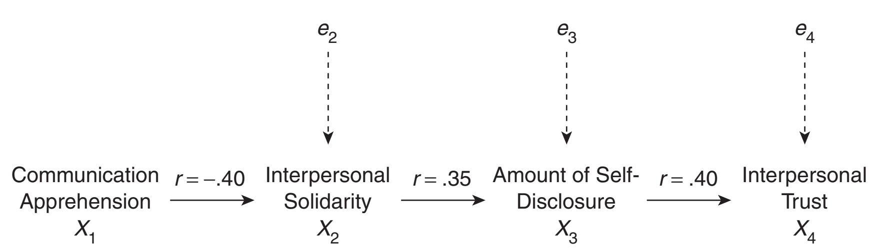
PATH MODELS

Although the term "path model" is often used interchangeably with any modeling, we already have identified it as part of the tradition that examines structural equation modeling with observed or manifest variables. Although structural equation model testing has been streamlined by computer programs, it is helpful to remember that no computer (yet) can construct a path model; so path modeling requires some serious thinking about causes for phenomena. Path models are most concerned with the roles of moderator variables and indirect or mediated paths.

Designing of Models

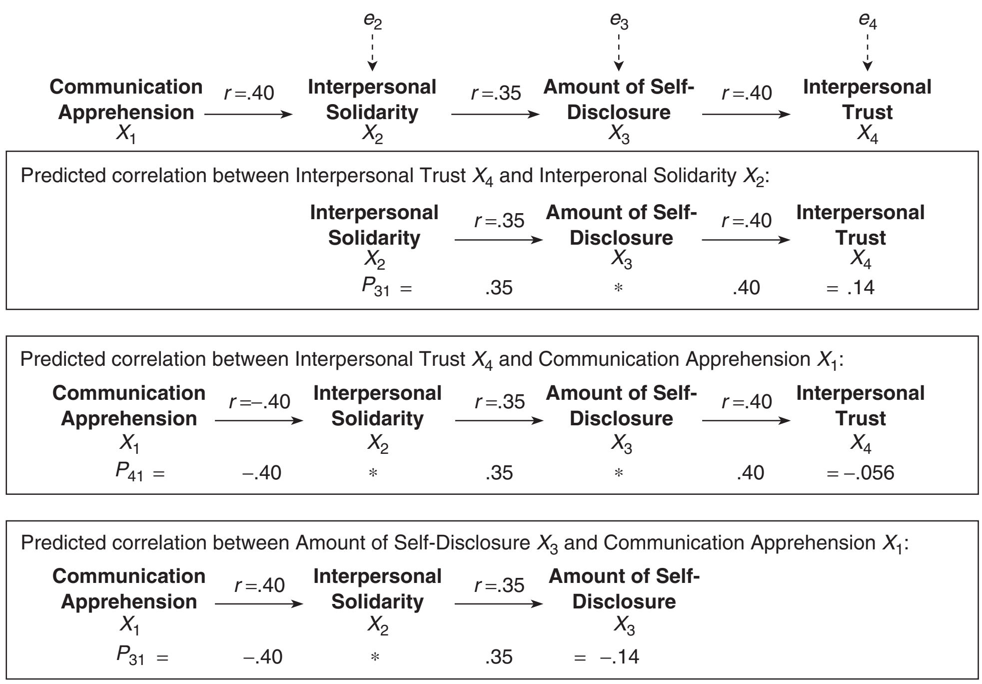
For any path model that describes data, the researcher expects relationships between moderator and dependent variables (identified as endogenous variables that are last in a sequence) to be greater than relationships between exogenous and dependent variables. Furthermore, adjacent variables should have larger relationships than variables that are mediated by several endogenous variables. An illustration might make this process increasingly understandable. The model identified as "Figure 17.1: Path Model 1" hypothesizes that receivers' levels of communication apprehension influence their levels of interpersonal trust with acquaintances. Yet, this communication apprehension effect occurs by inversely influencing perceptions of interpersonal solidarity with others, which affects the amount of self-disclosure they share with their acquaintances. A model of these relationships may be found in Path Model 1 shown below. Pearson product moment correlations have been placed above each direct path.

Figure 17.1 Path Model 1



Starting with the interpersonal trust variable, the size of the correlation coefficients between it and other variables should decline as one moves to the variables further and further to the left. A moderator variable should be more closely associated with the dependent variable than an exogenous variable is. In fact, the dependent variable's association with the exogenous variable would be considered spurious. In this simple path model, the theoretically expected correlations between any two variables are simply the products of all the paths between them in addition to any error terms. Thus, Table 17.1 shows how the predicted paths for this simple model would be computed. The diagram shows terms e_1, e_2, and e_3. As will be explained subsequently, these elements are the disturbance (or residual error) terms for predicting each endogenous variable. Diagrams typically omit disturbance terms for exogenous variables because they involve measurement error rather than prediction error.

Table 17.1



Computing Coefficients and Testing Models

After a model is selected for examination, researchers specify the nature of the causes within the model for each variable. This information permits computing the theoretically expected path coefficients among variables in the model. To illustrate a path model where each variable is not predicted by one variable alone, consider the case of the researcher using the previously identified variables. As shown in Figure 17.2, the researcher might hypothesize a different arrangement with two exogenous variables, interpersonal solidarity and interpersonal attraction. These two variables are assumed to be uncorrelated, even though the actual correlation coefficient between them is .09.

Computing Path Coefficients

Defining structural equations that identify the source of variation for each variable is essential to computing path coefficients. The two exogenous variables, interpersonal solidarity and interpersonal attraction, are not predicted by other variables but are caused by *e*, the error or disturbance term, which is assumed to equal zero. As mentioned previously, disturbance terms for exogenous variables indicate measurement error, rather than prediction error; hence, it is not necessary to insert error terms for the exogenous variables on path diagrams. Because X_1 is explained by no variables except elements outside the model, its predicted values may be symbolized as $z_1 = e_1$. This statement is called the **structural equation** for variable X_1. Because interpersonal attraction X_2 also is an exogenous variable, its structural equation is $z_2 = e_2$.

For the amount of self-disclosure, variable X_3, there are two paths (one each from X_1 and X_2) forming the prediction. Hence, the structural equation for X_3 is $z_3 = p_{32}z_2 + p_{31}z_1 + e_3$. Because the interpersonal trust variable, X_4, is predicted by only variable X_3, the structural equation for variable X_4 is $z_4 = z_3 + e_4$. To figure out what path coefficients are expected to be, researchers apply either of two rules.

- The so-called first law of path analysis states that to derive the correlation of any variable with an endogenous variable Y,

  $$r_{YZ} = \sum p_{YXi} r_{XiZ},$$

  where

  p_{YXi} is the path from variable X_i to Y and

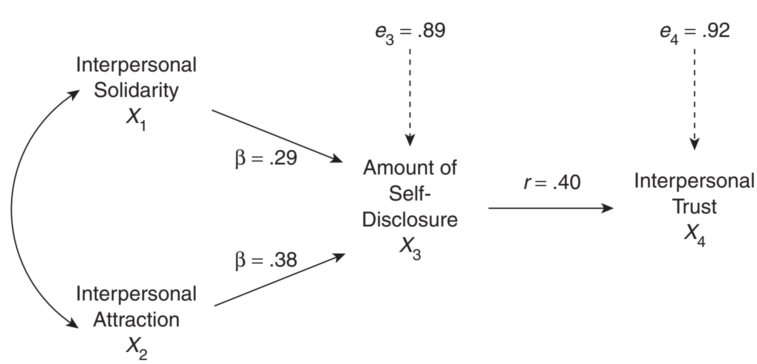
  p_{XiZ} is the path indicating the correlation between X_i and Z, and the set of X_i variables that includes all the causes of variable Y (from Kenny, 1979, p. 36).

  In other words, the correlation between two variables is obtained by adding the products of each structural parameter for every variable that causes the effects on the endogenous variables. "A simple procedure to employ is to write all the path coefficients of the endogenous variable including the disturbance. Next to each path write the correlation of the exogenous variable of that path with the variable Z. Multiply each path and correlation and sum the products" (Kenny, 1979, p. 36).
- The **tracing rule** states that the correlation of any variable with an endogenous variable Y is equal to the sum of all the products of the paths between the two variables. All traced paths between the two variables are included, provided that (a) no variable is entered more than once and (b) no variable is entered in one direction and exited in the same direction (Kenny, 1979, pp. 37–42).

The two rules produce the same results and, hence, researchers may view them as convenient substitutes for each other. Even so, the tracing rule approach is more prone to clerical errors on the part of the researcher than is the approach using the first law of path analysis.

As an example, consider how the predicted correlations can be found for Path Model 2 in Figure 17.2. Because there are no reciprocal causes or feedback loops, the model is clearly

Figure 17.2 Path Model 2



recursive.[3] A friendly word of advice: The material in the rest of this section is really pretty easy, but you have to follow it slowly—one step at a time—to see the common sense that is involved.

- For the relationship between interpersonal solidarity (X_1) and the amount of self-disclosure in the relationship (X_3), there is a direct path. But X_3 has two predictors, which must be taken into account. To compute the expected correlation, one multiplies structural equations. You may remember from Chapter 5 that to compute a population correlation using the original z score method, one takes the average of the products of the z scores for all the events in the sample, $\frac{\sum z_x z_Y}{N}$ or $\frac{1}{N}\sum z_x z_Y$. Thus, to find the value of this predicted equation, one multiplies the structural equation values together for each event and then divides by N. In this case, the correlation is predicted as $\frac{1}{N}\sum z_1 z_3$. Because the error terms are uncorrelated with other elements in the model, their coefficients are 0 and the structural equation for z_3 simplifies to $p_{32}z_2 + p_{31}z_1$. Once this element is substituted, the formula for the predicted correlation between X_1 and X_3 becomes $\frac{1}{N}\sum z_1(p_{32}z_2 + p_{31}z_1)$. When the terms are multiplied out, the equation becomes

$$\frac{\sum p_{32}z_2z_1}{N} + \frac{\sum p_{31}z_1^2}{N},$$

which is equivalent to

$$\left(\frac{\sum p_{32}}{N} * \frac{\sum z_2z_1}{N}\right) + \left(\frac{\sum p_{32}}{N} * \frac{\sum z_1^2}{N}\right).$$

[3]Another way to isolate whether a model is recursive is to take all the structural equations for the model and place them in a matrix, with any residual error terms placed on the right. If a matrix of zeros appears in the upper or lower diagonal (depending on the form of notation used), the model is recursive (see Asher, 1983, pp. 88–89). For instance, a model to be presented shortly includes the following structural equations: $X_6 = p_{65}z_5 + e_6$; $X_5 = p_{54}z_4 + e_5$; $X_4 = p_{43}z_3 + p_{42}z_2 + p_{41}z_1 + e_4$; $X_3 = p_{32}z_2 + p_{31}z_1 + e_3$; $X_2 = e_2$; and $X_1 = e_1$. Inserting them into a matrix of coefficients yields the pattern shown below. Because all the entries in the upper diagonal are 0, the system is recursive.

X_1	X_2	X_3	X_4	X_5	X_6	e
1	0	0	0	0	0	e_1
0	1	0	0	0	0	e_2
$-p_{31}z_1$	$-p_{32}z_2$	1	0	0	0	e_3
$-p_{41}z_1$	$-p_{42}z_2$	$-p_{43}z_3$	1	0	0	e_4
0	0	0	$-p_{54}z_4$	1	0	e_5
0	0	0	0	$-p_{65}z_5$	1	e_6

At this point, you may notice that $\frac{\sum z_2 z_1}{N}$ is the formula for the Pearson product-moment correlation r between variables X_2 and X_1.[4]

You also may notice that $\frac{\sum z_1^2}{N}$ is the average of squared standard scores. Because the standard scores already are deviations from a mean of zero, the squared z values also are the squared deviations of z scores from their means. The mean of the sum of these values is also known as the population variance of z scores. The population variance of z is 1 because z scores have standard deviations of 1. Thus, this term in the formula becomes a constant equal to 1.

Thus, the equation further simplifies to

$$\left(\frac{\sum p_{32}}{N} * r_{21}\right) + \left(\frac{\sum p_{32}}{N} * 1\right).$$

In addition, if all the values of p_{32} or p_{31} are the same (as they are when using the same path scores), the average of the paths is equal to the original path coefficients. Therefore, the predicted path coefficient formula reduces to $p_{31} = p_{32}r_{12} + p_{31}$. Inserting the appropriate numbers, the coefficient becomes (–.38 * .09) + .29 = .26.

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[4]Here is the idea. The chapter on correlations (Chapter 5) explained that the earliest formula for correlation is the mean of the products of the z scores for the two variables. So, for variable X and variable Y, the formula is $\rho_{XY} = \frac{\sum z_X z_Y}{N}$. This formula is a population formula because the standard deviation used to compute z scores has N in the denominator. With sample standard deviations used, the formula here divides not by N, but by $n - 1$. If the path equation for Variable 4 (z_4) is inserted in place of z_y, the formula becomes

$$\rho_{X4} = \frac{\sum z_X(p_{43}z_x + e_4)}{N}.$$

This formula translates to

$$\rho_{X4} = \frac{\sum(p_{43}z_x z_x + e_4 z_x)}{N} = \frac{\sum p_{43}z_X^2}{N} + \frac{\sum e_4 z_x}{N}.$$

But an assumption of the model is that there is no correlation between z and e. So, the formula becomes

$$\frac{\sum p_{43}z_X^2}{N} + 0.$$

In addition, the population variance of $\left(z\ \frac{\sum z_X^2}{N}\right)$ is 1 because z scores have standard deviations of 1. The term $\frac{\sum p_{43}z_X^2}{N}$ is equivalent to $\frac{\sum p_{43}}{N} * \frac{\sum z_X^2}{N}$, which means that the formula becomes:

$$\left(\frac{\sum p_{43}}{N} * \frac{\sum z_X^2}{N}\right) + 0 \cdot$$

Hence, the formula may be cast as $\rho_{X4} = \left(\frac{\sum p_{43}}{N} * 1\right) + 0$. Because the path ($p_{43}$) is constant, the sum of these elements divided by N also is the value of the path, which simplifies to $p_{X4} = p_{43}$. Thus, when there is only one predictor for a variable, the expected path is the correlation between the two variables.

- The predicted correlation between interpersonal attraction (X_2) and amount of self-disclosure (X_3) is computed from the product of the two structural equations for variables X_2 ($z_2 = e_2$) and X_3 ($z_3 = p_{32}z_2 + p_{31}z_1 + e_3$). Using methods similar to those described to identify the correlation for the relationship between X_1 and X_3, one may take the average of the products of the z scores for all the events in the sample, $\frac{1}{N}\sum z_x z_Y$ or $\frac{1}{N}\sum z_2 z_3$. As we have seen, because the error terms are uncorrelated with other elements in the model, their coefficients are 0 and the structural equation for z_3 simplifies to $p_{32}z_2 + p_{31}z_1$. After substitutions, the formula for the predicted correlation between X_2 and X_3 becomes $\frac{1}{N}\sum z_1(p_{32}z_2 + p_{31}z_1)$. When the terms are multiplied, the equation becomes

$$\frac{\sum p_{32}z_2^2}{N} + \frac{\sum p_{31}z_1z_2}{N} = \left(\frac{\sum p_{32}}{N} * \frac{\sum z_2^2}{N}\right) + \left(\frac{\sum p_{31}}{N} * \frac{\sum z_1z_2}{N}\right),$$

which is equivalent to $p_{32} = p_{32} + p_{31}r_{12}$. Inserting the numbers, the coefficient becomes –.38 + (.09 * .29) = –.35.

- For the predicted correlations between interpersonal solidarity (X_1) and interpersonal trust (X_4), one multiplies each of the paths by the path between Variable 3 and Variable 4. Because the intermediate formulae already have been computed, the process simplifies to $p_{41} = p_{34}(p_{32}r_{12} + p_{31}) = p_{34}p_{32}r_{12} + p_{34}p_{31}$. Inserting the values, this path is revealed to be (.40 * –.38 * .09) + (.40 * .29) = .10.
- For the predicted correlations between interpersonal attraction (X_3) and interpersonal trust (X_4), one multiplies each of the paths by the path between Variable 3 and Variable 4. Because the intermediate formulae already have been computed, the process simplifies to $p_{42} = p_{34}p_{32} = p_{34}(p_{32} + p_{31}r_{12}) = p_{34}p_{32} + p_{34}p_{31}r_{12}$. Inserting the values, this path is revealed to be (.40 * –.38) + (.40 * .29 * .09) = –.14.

The results of these predictions may be placed in a table such as Table 17.2. A cursory look at the table shows relatively small differences between the observed and predicted equations. You will notice that when a path consists of a single predictor, the predicted direct path is constrained to equal its predicted value.

Table 17.2

Lower Diagonal: Predicted Correlations[a]	*Upper Diagonal: Observed Correlations* X_1	X_2	X_3	X_4
X_1: Interpersonal solidarity	1	.09	.29	.11
X_2: Interpersonal attraction	.00(.09)	1	–.35	–.03
X_3: Amount of self-disclosure	.26(.03)	–.35(.00)	1	.40
X_4: Interpersonal trust	.10(.01)	–.14(.11)	.40(.00)[b]	1

a. Absolute differences between observed and predicted values in parentheses.

b. The predicted correlation is constrained to equal its observed value.

Computing R *and Residuals for Each Predicted Variable*

Researchers regularly report the percentage of variance explained for both the dependent variable and the other endogenous variables. Variance explained is not a test of the fit of the model to the data, because models that fit the data well may not account for large portions of variance (Bielby & Hauser, 1977). Nevertheless, it is a piece of descriptive information that reveals the usefulness of the model. In the case of endogenous variables with multiple predictors, the multiple regression correlation term, R^2, is most typically reported. For endogenous variables with single predictors, the simple r^2 is reported because it is equivalent to R^2 in these circumstances. Thus, in Path Model 2, the R for the prediction of interpersonal trust is equal to the Pearson product-moment r of .40 which, when transformed into a coefficient of determination (r^2), indicates that 16% of the variance in trust can be explained by a knowledge of the amount of self-disclosure. In this case, R for the prediction of the amount of self-disclosure is .45, whose coefficient of determination R^2 is .20, indicating that 20% of the variance in the amount of self-disclosure could be explained by a knowledge of interpersonal solidarity and interpersonal attraction ratings.

To compute disturbance terms in predicting each endogenous variable, the formula $\sqrt{1-R^2}$ may be used. These values may be placed on a path model diagram next to the e symbols near the predicted variables. Disturbance terms are omitted for the exogenous variables because this residual error value identifies prediction error, not measurement error.

Checking Fit of the Model to the Data

Once the predicted path coefficients have been computed, some steps have to be made to ensure that they are comparable to the actual correlations among variables. There are several options (see Bollen & Long, 1993).

Perhaps the most direct way involves constructing confidence intervals around observed correlations and examining whether the predicted correlations fall within that range. If the differences are smaller than the confidence interval, the observed correlation is within the limits of random sampling error of the predicted correlation. Hence, the prediction is said to fit the data. This method permits researchers to target specific details about the location of any predictive shortcomings. The formula for a two-tailed 95% confidence interval around a correlation coefficient is $\pm\frac{1.96}{\sqrt{n}}$. If observed and predicted correlations differ by more than $\frac{1.96}{\sqrt{n}}$ (in either direction, because it is a two-tailed test), then the model does not fit the data.

Other tests rely on a global examination of fit. Although very popular, they may leave the researcher knowing that there is a misspecification in the model, but not knowing where.[5] Inspecting other modification indices may help, however. Two of the most popular tools for traditional path modeling are the likelihood ratio chi-square test and the root mean square approximation RMSEA. Other related tools, such as the goodness-of-fit index, are associated

[5]In different—but instructive—research, a comparison of several techniques was examined to determine if error variances of misspecified models could be detected when using a z test, a Wald test, a likelihood ratio chi-square test, a Lagrangian multiplier test, and confidence intervals. Researchers found that "the use of confidence intervals as well as four other proposed tests yielded similar results when testing whether the error variance was greater than or equal to zero" (Chen, Bollen, Paxton, Curran, & Kirby, 2001, p. 468).

with the measures supported by specific programs (e.g., Amos, LISREL, EQS) designed for the analysis of covariance matrices.

The likelihood ratio chi-square test is a global test and takes the form $\chi^2 = N\,\Phi$ where Φ is equal to $ln\ |\mathbf{C^*}| - ln\ |\mathbf{S}| + \text{trace}\ (\mathbf{SC^{*-1}}) - m$ (where **C*** is the maximum likelihood estimate of the population covariance matrix, assuming the null hypothesis; **S** is the covariance matrix of the sample). The trace is the sum of the diagonal elements of a matrix. Though it seems most suitable for models involving 75 to 200 events, for moderate to small samples it leads to excessive rejection of null hypotheses (and hence, false claims that a model does not fit) (see Neill & Dunn, 1975; Steiger, 1980, p. 248). Others observe that as samples grow beyond 200 events, the test "is almost always statistically significant. Chi square is also affected by the size of the correlation in the model: the larger the correlations, the poorer the fit" (Kenny, 2003, ¶ 2).

The **root mean square error of approximation** (**RMSEA**) is most often reserved for analysis of covariance matrices, but it also has applications when correlations are used. This measure is based on the RMR (root mean square residual), which is the square root of the average squared amount by which the observed and expected sample variances and covariances differ. But such estimates do not adjust for the number of paths in the model. The RMSEA takes the square root of the F_0 values that have been divided by the number of degrees of freedom for testing the model. Taking the square root of the resulting ratio gives the population root mean square error of approximation, or RMSEA (though its developers [Steiger & Lind, 1980] referred to it as RMS). This approach "can be interpreted as a root mean square standardized measure of badness of fit of a particular model . . ." (Steiger, 1998, p. 413). To accept a model, a general rule of thumb is that the RMSEA should be below .05 or .06 (Hu & Bentler, 1999). The RMSEA coefficient is *not* a probability statement. Indeed, one of its developers (Steiger, 2000) chided others who use it as a form of statistical hypothesis testing.

When path models have troubled fit to data, researchers sometimes rely on repairs of convenience regardless of whether there is a theoretic justification for doing so. For instance, a researcher with a sample of 200 participants examined the tenability of Path Model 3. Structural equations were defined and predicted correlations were computed.[6] It might be

[6]With this complex model, the structural equations were $z_6 = z_5 + e_6$; $z_5 = z_4 + e_5$; $z_4 = p_{41}z_1 + p_{42}z_2 + p_{43}z_3 + e_4$; $z_3 = p_{31}z_1 + p_{32}z_2 + e_3$; $z_2 = e_2$; and $z_1 = e_1$. Thus, the predicted correlations for X_6 and X_5 as well as for X_5 and X_4 were equal to their observed values. That is, $p_{65} = r_{65}$ and $p_{54} = r_{54}$. Other paths also were computed:

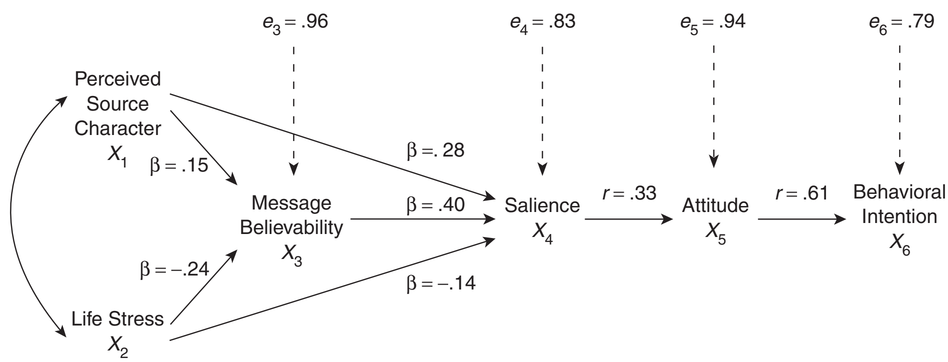
$$p_{64} = p_{65}p_{54}.$$

Because multiple sources predict Variable 4 and Variable 3, and because the tracing rule requires each variable to be entered only once and that no variable is both entered and exited through an arrowhead on the path, the path analyst must take care not to violate these rules preventing inappropriate duplications.

$$\begin{gathered}
p_{63} = p_{65}p_{54}p_{43} + p_{65}p_{54}p_{42}r_{23} + p_{65}p_{54}p_{41}r_{13};\\
p_{62} = p_{65}p_{54}p_{42} + p_{65}p_{54}p_{43}r_{23} + p_{65}p_{54}p_{41}r_{12};\\
p_{61} = p_{65}p_{54}p_{41} + p_{65}p_{54}p_{43}r_{13} + p_{65}p_{54}p_{42}r_{12};\\
p_{53} = p_{54}p_{43} + p_{54}p_{42}r_{23} + p_{54}p_{41}r_{13};\\
p_{52} = p_{54}p_{42} + p_{54}p_{43}r_{23} + p_{54}p_{41}r_{12};\\
p_{51} = p_{54}p_{41} + p_{54}p_{43}r_{13} + p_{54}p_{42}r_{12};\\
p_{43} = p_{43} + p_{41}r_{13} + p_{42}r_{12};\\
p_{42} = p_{42} + p_{41}r_{12} + p_{43}r_{32};\\
p_{41} = p_{41} + p_{43}r_{13} + p_{42}r_{12};\\
p_{32} = p_{32} + p_{31}r_{12};\ \text{and}\\
p_{31} = p_{31} + p_{32}r_{12}.
\end{gathered}$$

mentioned that some path analysts believe that examining predicted relationships with direct paths do not help test model fit, since the predicted correlations are simply the direct paths after accounting for spurious correlations. These predicted values involving direct paths always are close to the observed correlations. In this example, such instances are identified on Figure 17.3 as predicted correlations including a direct path. Other cases, where an endogenous variable is predicted from only one variable, are identified as predicted correlations that are constrained to equal their observed values.

Figure 17.3 Path Model 3



For this model, confidence intervals revealed that one observed correlation was much higher than predicted. The 95% confidence interval was $\pm\frac{1.96}{\sqrt{n}} = \pm\frac{1.96}{\sqrt{200}} = \pm .138 \approx .14$.

As Table 17.3 shows, the difference between the predicted and the observed correlations between life stress (X_2) and behavioral intentions (X_4) was larger (though inverse) than the confidence interval.

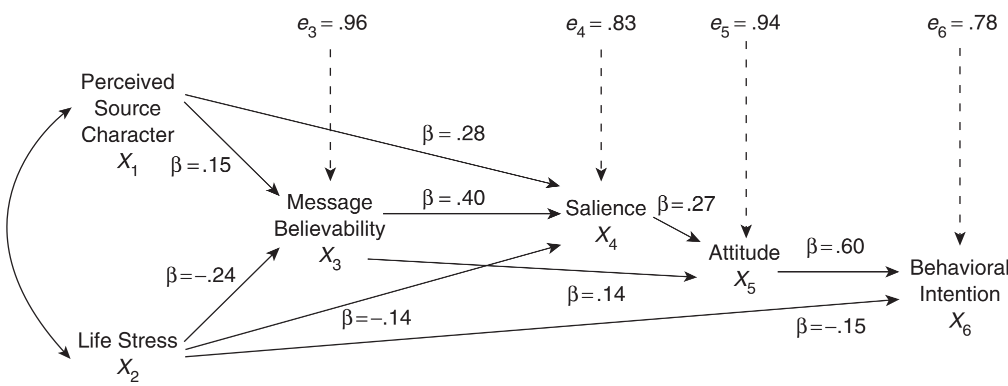
Table 17.3

Lower Diagonal: Predicted Correlations[a]	*Upper Diagonal: Observed Correlations* X_1	X_2	X_3	X_4	X_5	X_6
X_1: Source character	1	.05	.14	.33	.10	.16
X_2: Life stress	.00 (.05)	1	−.23	−.22	−.09	−.20
X_3: Message believability	.14[c](.00)	−.23[c](.00)	1	.47	.26	.04
X_4: Topic salience	.33[c](.00)	−.22[c](.00)	.47[c](.00)	1	.33	.24
X_5: Attitude	.11 (.01)	−.07 (.02)	.16 (.10)	.33[b]	1	.61
X_6: Behavioral intention	.07 (.09)	−.04 (.16)	.09 (.05)	.20(.04)	.61[b]	1

a. Absolute differences between observed and predicted values in parentheses.
b. The predicted correlation is constrained to equal its observed value.
c. Predicted correlation includes a direct path between varriables.

There also was a sizable difference between the observed and predicted correlations for the relationship between message believability (X_3) and attitudes (X_5). Furthermore, the source character ratings showed a somewhat odd pattern. Rather than coefficients declining as they moved further away from adjacent variables, there sometimes was a jump in predicting behavioral intentions. The researcher would have to reject the model. The RMSEA was .11, and the χ^2 value was 35.67 with 8 degrees of freedom ($p < .05$; critical value 15.51).

Some researchers might fiddle with the model in hopes of making it work. For instance, direct paths could be added between message believability and attitude, and between life stress and behavior intentions. But there are two difficulties with this strategy. First, the two predictor variables of attitude (believability and salience) had a higher correlation with each other than with the attitude measure. The beta weights would be .27 from the salience measure and .14 from the belivevability measure. Second, as shown below, it makes no theoretic sense, even if it worked.



Furthermore, it did not really work in this case. Enlisting the Amos program for further analysis, the chi-square likelihood ratio was 21.622, which, with 6 degrees of freedom, was statistically significant. Furthermore, in this revised model the predicted correlation between believability and behavioral intentions became too high (.20) to fit the data (the observed correlation was .04; the deviation was .16). Another direct path could be added, of course, but the model would soon become so unwieldy that its usefulness in summarizing relationships would become doubtful. By reducing the number of indirect effects that may be examined, the process rapidly becomes a model of direct effects that do not require modeling at all.

Overfitting

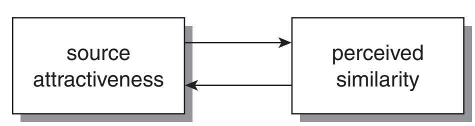
Researchers sometimes force a model to fit by including so many direct and mediated paths that little predictive error is possible to identify. This problem is called **overfitting** (and should not be confused with overidentification, which is not a defect in path analysis). This tendency often leads to developing path models that do not cross-validate and that fail to advance understanding. There is more than one reason such a condition emerges. The researcher may capitalize on chance findings, especially when small samples are used. Furthermore, measurement imperfections may prevent clear isolation of relationships.

Researchers frequently find evidence to support more than one path model to describe a data set. Experience with path analysis usually reveals that models with small numbers of paths tend to cross-validate more often than complex models. There are some guidelines to decide which models deserve the most serious attention. First, if competing models fit the data equally well, the one that accounts for the greatest variation in predicted variables should be preferred. Second, if two fitting models account for roughly the same proportions of variance in predicted variables, the one that is simplest should be advanced.

Identification of the Model

Path analysis estimates of the structural model (not the measurement model) cannot be completed for models that are not identified. A parameter that can be predicted or estimated to have one unique (deliberate redundancy here) value is said to be **identified**. Hence, models composed of identified equations also are considered to be identified. A parameter that cannot be predicted or estimated to have one value is said to be **unidentified** or **underidentified.** Naturally, the model with which it is associated also is considered unidentified or underidentified. A problem of identification exists when there are more unknown elements than can be estimated from the available (known) data. "In other words, it occurs when there are too many unknowns in a causal model for a solution to be possible" (Vogt, 2005, p. 149). Any sound path model must be identified such that the unknown parameters can be shown as unique functions of the identified elements of the model. There are three types of models.

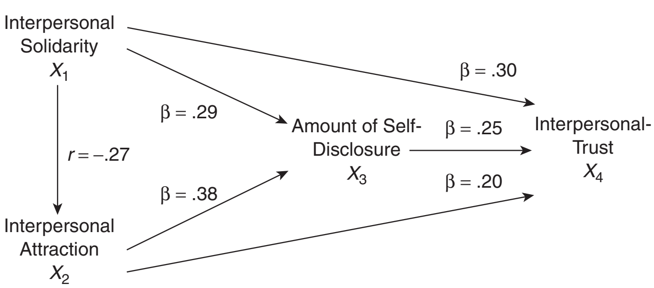
- An **underidentified model** is composed of one or more unidentified equations. Underidentification exists when it is impossible to provide a unique identification for all parameters. For instance, imagine that there is a correlation of .64 between source attractiveness and perceived similarity. If the researcher suggests a reciprocal relationship between these variables, the model is in good shape *if* the researcher has separate correlations for each of the paths. If the researcher does not have such information, there is a problem. A correlation of .64 could be attributable to the product of two correlations (one from source attractiveness and one from perceived similarity), each one of which is .80 (.80 * .80 = .64). Or the correlation of .64 could be the product of a correlation of .91 and another of .70. Or the correlation of .64 could be the product of a correlation of .852 and another of.752. There is no single best answer to identify the parameter. Thus, the model remains underidentified. Structural equations for underidentified models cannot be estimated.



- A **just identified** (or "exactly identified") model is one for which there are as many known as unknown parameters. A model is *just identified* if the number of structural equations in the model matches the number of correlations (or covariances). So, a solution may be found for each parameter. The possible number of correlations between pairs of variables is equal to $\frac{p(p-1)}{2}$, where p is the number of variables in the model.

As an example of a just identified model, consider Path Model 4 (Figure 17.4). Interestingly, this just identified model has a path between every pair of variables. There are direct effects for each variable except for the one exogenous variable. There is only one estimate of a parameter available to the researcher. Because there are no indirect paths to explore, the researcher might find this model of limited interest.

Figure 17.4 Path Model 4



- An **overidentified model** is one for which an unknown parameter can be solved (or predicted) inmore than one way. Though different equations could be used to estimate parameters, as far back as 1960, Wright solved this challenge by recommending the use of multiple regression methods that remain in use today. Researchers find that overidentified models are most valuable because

> over identifying restrictions also increase the efficiency of parameter estimation (Goldberger, 1973). If there are two estimates of the same parameter, those estimates can be pooled to obtain a new estimate whose variance is less than or equal to the variance of either original parameter estimate. (Kenny, 1979, p. 45)

To assess identification, researchers compare two numbers. The first number is the possible number of correlations between pairs of observed variables; the second is the actual total of model parameters. This sum is produced by adding the number of observed paths, the number of correlations between pairs of exogenous variables (computed as $\frac{\text{number of exogenous variables} * (\text{number of exogenous variables} - 1)}{2}$), and any correlations between pairs of errors, excluding the paths to error terms.

- If the actual total model parameters are greater than the possible number of correlations between pairs of observed variables, the model is underidentified.
- If the actual total model parameters are smaller than the possible number of correlations between pairs of observed variables, the model is overidentified.
- If the actual total model parameters are the same as the possible number of correlations, the model may be just identified (provided that the pattern of underidentification and overidentification of other variables does not lead to underidentification for the model).

In the examples examined in this chapter, Path Model 3 has 7 paths, 1 correlation between exogenous variables, and 0 correlations among error terms, for total model parameters of 8. The total possible number of correlations is 15. Because the total possible correlations are greater than the total model parameters, Path Model 3 is overidentified. Path Model 4 has

6 paths, 0 correlations between exogenous variables, and 0 correlations among error terms, for total model parameters of 6. The total possible number of correlations is 6. Because the total possible correlations equals the total model parameters, Path Model 4 may be "just identified."

USING THE AMOS PROGRAM

Amos[7] (**A**nalysis of **MO**ment **S**tructures) was introduced in the last chapter as a method to complete confirmatory factor analysis. Amos also permits creating and testing general structural equation models, which is the primary focus of attention here. The comprehensiveness of AMOS combined with the convenience of its wide availability through SPSS (which has now dropped LISREL) surely will contribute to the further popularity of AMOS and structural equation modeling.

The Approach of Amos

Amos allows researchers to use diagrams or programming in the Sax Basic Language,[8] which is compatible with the language known as Visual Basic for Applications™.[9] The graphical approach will be emphasized in this discussion because of its obvious efficiency.

The details of using the drawing area and handling basic commands were explained in Chapter 16 and will not be reviewed here. Amos also allows researchers to create diagrams and prepare path models for analysis, testing, and even presentation. Once a diagram has been drawn of the model, Amos develops simultaneous equations among variables by use of optimizing methods such as maximum likelihood estimation. Structural relationships may be between observed variables (manifest variables) or unobserved variables (latent variables). In traditional path modeling, observed variables are explored and their measurement properties are established separately. In contrast, Amos encourages exploring relationships among latent variables or constructs whose measurement composition is verified as part of the model. Because Amos involves confirmatory factor analysis methods, it is most properly considered to be a theory-testing method, rather than a theory exploration tool.

As described in Chapter 16, structural equation models in general, and Amos in particular, assume multivariate normal distributions. Although this assumption is not necessary when considering exogenous variables that are measured without error, it applies to all latent variables, as well as to measurement errors for observed exogenous variables and to endogenous variables. Though imperfect, Mardia's coefficient of multivariate kurtosis (Mardia, 1970, 1974) is included in Amos output.

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[7]Amos is a registered trademark of the Amos Development Corporation.

[8]Sax Basic Language is a registered trademark of Polar Engineering and Consulting.

[9]Visual Basic and Visual Basic for Applications are registered trademarks of the Microsoft Corporation.

Phases of Model Development With Amos

Amos requires researchers to define the forms of the variables in the study. In particular, they must specify whether a variable is

- an observed variable that is a measurement on a given item or scale,
- a latent variable or underlying factor that is not observed directly, or
- a term to identify error terms.

After the researcher has identified such information, a model may be sketched out and contrasted with the data.

To illustrate how this process is completed, an example will be explored. In this case, a researcher suspected that the credibility of the message and the perceptions of source character would be good predictors of whether women would take some action to help lower their risks of breast cancer. In the study, women participants rated the character of a well-known public figure and then read a message attributed to that source. Afterward, participants completed scales to assess message credibility. Finally, two 5-point Likert-type scales ("I intend to learn more about breast cancer" [learnabo] and "I intend to complete a breast cancer self-examination" [selfexam]) were completed to measure individuals' intentions to acquire additional medical information about breast cancer. The message credibility scales were "the message was believable" (believe) and "the message content was accurate" (acconten). Source credibility scales were "the source of the message is trustworthy" (trust) and "the source of the message is virtuous" (virtue).[10]

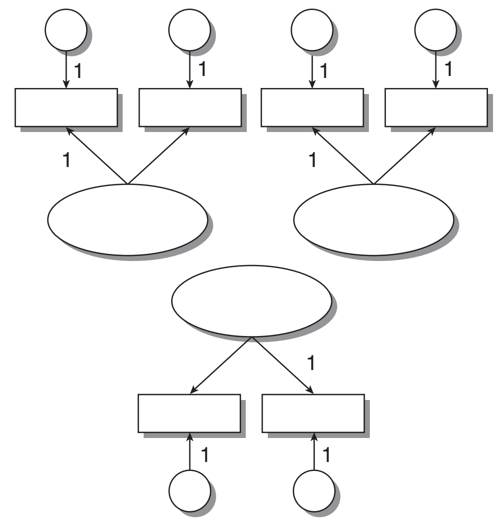
After starting the *Amos Graphics* program (the *Amos Basic* program could have been used if the researcher wished to use Amos Basic programming language), the researcher began to enter a path model on the drawing area. The researcher clicked the *Select Data Files* icon to select a data file for active use, following the same steps as used in the confirmatory factor analysis setup described in Chapter 16. In SPSS, input may be in the form of raw data or matrices of covariances or correlations. If a correlation matrix is input, the types of variables are identified in a column marked "rowtype," and the variable names are listed in available columns and in the "varname" column. Using this format also required including the sample size, means, and standard deviations for the variables.

	rowtype	varname_	believe	acconten	learnabo	selfexam	trust	virtue
1	n		280.00	280.00	280.00	280.00	280.00	280.00
2	corr	believe	1.00	.	.	.	.	.
3	corr	acconten	.60	1.00	.	.	.	.
4	corr	learnabo	.52	.37	1.00	.	.	.
5	corr	selfexam	.40	.32	.59	1.00	.	.
6	corr	trust	.15	.12	.42	.40	1.00	.
7	corr	virtue	.17	.08	.28	.33	.63	1.00
8	stddev		1.59	1.35	1.23	1.43	1.70	1.86
9	mean		4.53	4.92	5.21	4.85	4.09	5.24

[10]The number of observed variables is kept small for purposes of illustration. In reality, most researchers would have more than two items to measure an underlying or latent dimension.

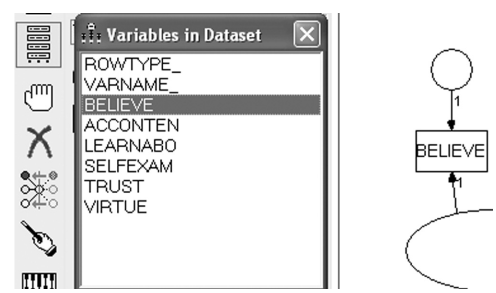
Constructing the Diagram

Because there were three latent or unobserved variables, they would be placed on the drawing by clicking on the oval *Draw unobserved variables* icon and drawing three ovals in the middle of the page (two on one row and one on another). Afterward, clicking the *Draw unobserved variables* icon would deactivate it. To add the two measured variables for each of the latent variables, the *Draw indicator variable* icon was used, similar to the way it was described in the discussion of confirmatory factor analysis. Each time the left mouse button is clicked, a manifest (or observed) variable, along with a place for its error term, is attached. Two indicator paths were added to each latent variable. The diagrams may be rotated using the *Rotate the indicators of a latent variable* tool (each click on a parent oval moves the indicator variables by 90 degrees). Something resembling the diagram on the top right was drawn.

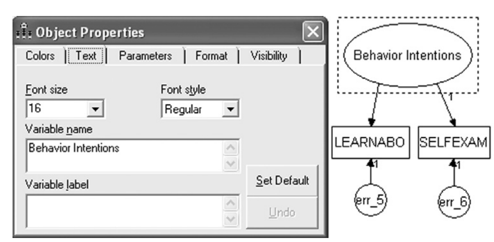


Any movement of objects could be completed by using the *Move objects* icon, which, not surprisingly, moves a highlighted item. Numbers have been inserted into some paths. To identify the regression model, the scale of the unobserved or latent variable must be defined. This step may be accomplished by setting the variance of the path coefficient from a latent to an observed variable at some positive value. In this case, the *Draw indicator variable* tool automated this task by constraining a parameter at 1.

After clicking on the *List variables in dataset* icon, variable names were inserted into rectangles by clicking and dragging the desired names to the rectangles. For instance, the observed variable BELIEVE was highlighted and dragged to the first box, as shown in the middle on the right.



Latent variables were labeled by double-clicking on the ovals and making insertions in the "Variable names" field of the *Object Properties* dialog box. In this case, the "behavior intentions" latent variable was identified as composed of LEARNABO and SELFEXAM. The other two latent variables were labeled "message credibility" (composed of BELIEF and ACCONTEN scales) and "source credibility" (composed of TRUST and VIRTUE scales).



The error terms were labeled as well. Some researchers prefer to use labels that are familiar to LISREL users (delta [δ] for the error terms associated with the exogenous indicators, epsilon [ε] for error terms associated with latent endogenous variables, and zeta [ζ] terms for structural disturbances). In this example, however, the researcher simply numbered error terms from "err_1" through "err_8."

Special Discussion 17.3

LISREL* is a clever program that combines confirmatory factor analysis and path modeling using the language of structural equation modeling. In the past, because of its support by SPSS, it was the tool of choice by structural equation modelers in academic life. Other programs, particularly Amos, have begun to eclipse its popularity.

There are two fundamental equations in LISREL (Jöreskog & Sörbom, 1986, p. I.6). The first is the structural equation model, and the second is the measurement model. Each will be considered in turn.

$$\text{Structural Equation Model: } \boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta}$$

where

$\boldsymbol{\eta}$ (eta) is "the names of all the endogenous concepts in a column vector" (Hayduk, 1987, pp. 90–91) of $m \times 1$ dimension, where m is the number of endogenous concepts;

$\mathbf{B}\boldsymbol{\eta}$ is an $(m \times m)$ matrix containing the structural coefficients (β) multiplied by the $\boldsymbol{\eta}$ $(m \times 1)$ matrix;

$\boldsymbol{\Gamma}$ (uppercase gamma) is an $(m \times n)$ matrix containing the structural coefficients (γ [lowercase gamma]), which is multiplied by the $\boldsymbol{\xi}$ (*xi*, pronounced "ksi" and rhymes with "sigh") $(n \times 1)$ vector of exogenous concepts; and

$\boldsymbol{\zeta}$ (zeta) is an $m \times 1$ vector of exogenous concepts.

In addition,

the covariances among exogenous concepts are an $n \times n$ matrix $\boldsymbol{\Phi}$ (phi);

the covariances among the residual errors (ε) in the conceptual model are an $m \times m$ vector ψ (*psi*, pronounced "sigh");

$\mathbf{y}$ is "a vector of observed endogenous *indicators*" (Hayduk, 1987, p. 91) of $p \times 1$ dimension, where p is the number of endogenous indicators;

$\boldsymbol{\Lambda}_y$ (lambda) is a $(p \times m)$ matrix containing the structural coefficients of y multiplied by the $\boldsymbol{\eta}$ $(m \times 1)$ vector of endogenous concepts; and

$\boldsymbol{\varepsilon}$ (epsilon) is a $p \times 1$ vector of errors in the measurement model for y.

In addition, $\boldsymbol{\theta}_{\boldsymbol{\varepsilon}}$ (theta sub epsilon) is a $(p \times p)$ vector of the covariances among the errors of exogenous concepts.

$$\text{Measurement Model for } \mathbf{x} = \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta}$$

$$\text{Measurement Model for } \mathbf{y} = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\varepsilon}$$

where

$\mathbf{x}$ is "a vector of observed exogenous *indicators*" (Hayduk, 1987, p. 91) of $q \times 1$ dimension, where q is the number of exogenous indicators;

$\boldsymbol{\Lambda}_x$ (lambda) is a $(q \times n)$ matrix containing the structural coefficients of x multiplied by the $\boldsymbol{\xi}$ $(n \times 1)$ vector of exogenous concepts; and

$\boldsymbol{\delta}$ (delta) is a $q \times 1$ vector of errors in the measurement model for x.

In addition, $\boldsymbol{\theta}_{\boldsymbol{\delta}}$ (theta sub delta) is a $(q \times q)$ vector of the covariances among the errors of exogenous concepts.

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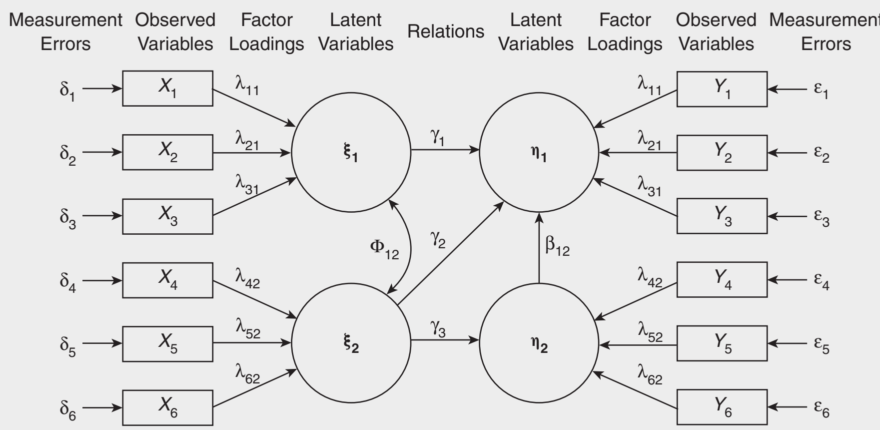
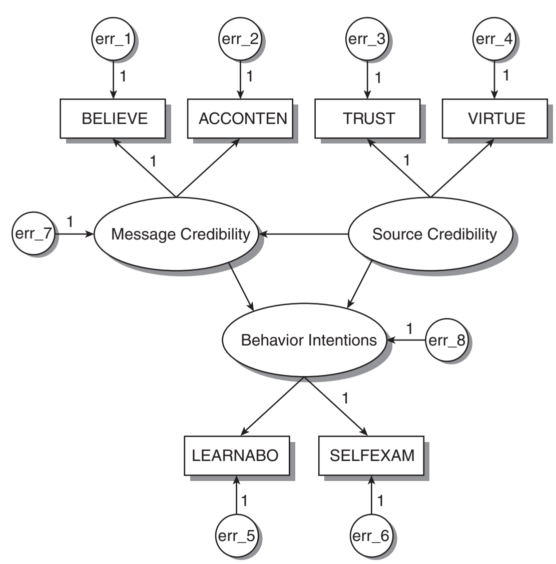
*LISREL is a registered trademark of Scientific Software Inc.

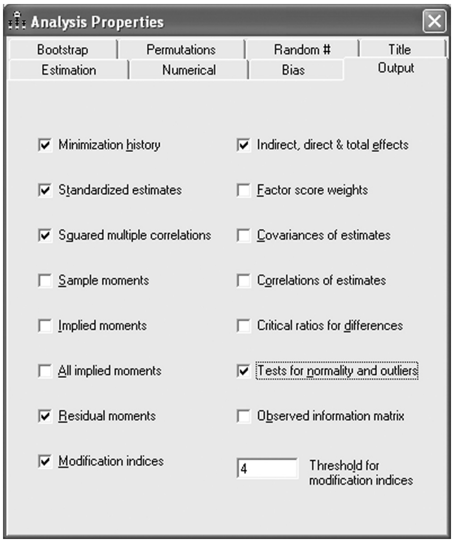
Thus, to use LISREL, the researcher must identify the variables that are manifest (observed) and those that are latent. Then, the program is used to identify parameters and examine evidence of the fit of the model to the data. LISREL is best suited for the analysis of covariance structures yielding latent variables or factors, but it can be used for examining correlation structures. It also may be used to examine relations among manifest variables by substituting observable variables for the values of variables otherwise presumed to be latent. Furthermore, LISREL is strong when linking a set of latent *X* and *Y* variables. When a string of mediated paths is involved, the model is strained and routinely produces rejection of sound models. An example of such a model may be found in the figure shown below. One might imagine that LISREL requires data at the interval or ratio level, but LISREL also supports a module called PRELIS, which is a set of alternative procedures for non-normal ordinal measures.



Clicking the arrow toolbar permitted the researcher to draw the arrows between any two endogenous latent variables. The researcher was interested in a direct path (an arrow with a single point) from source credibility to message credibility and another path to behavior intentions. Furthermore, a direct path is predicted from message credibility to behavior intentions.

Each endogenous variable predicted by another endogenous variable must have an error term. In this example, there were two endogenous variables predicted by other endogenous variables, "message believability" and "behavior intentions." To add such error terms, the researcher clicked on the *Add a unique variable to an existing variable* icon. While this button was active, clicking on the "message credibility" oval added another latent variable for the error term. Unfortunately, it was placed next to the other manifest variables associated with this variable. Hence, the researcher may have needed to move it using the *Move objects* icon. When completed, the model looks similar to the figure on the right.



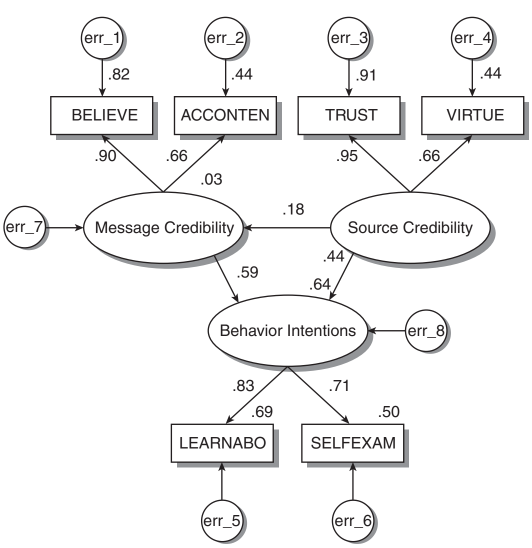


Examining Model Characteristics and Parameters

Specific output was requested for the example we are describing. Clicking on the *Analysis properties* icon produced a dialog box to control output. On the *Estimation* tab, the researcher found several options to minimize discrepancies in the model's estimates. Maximum likelihood estimation is the default for computing model parameters. This approach has the advantages of consistency, efficiency, and normality as sample size increases (Keeping, 1995, p. 123). Furthermore, likelihood ratio chi-square tests of model fit usually are presented, and the use of a maximum likelihood solution is most often recommended.

On the *Output* tab, the researcher found another series of choices. In addition to the ones selected for confirmatory factor analysis in the last chapter, several other output options usually are considered. Some of the boxes include the following categories of options.

- *Squared multiple correlations:* multiple correlations (when multiple predictors are involved) and correlations (when multiple predictors are involved) among endogenous variables and their predictor variables.
- *Residual moments:* differences between the sample and implied covariance matrices or the differences between sample and implied means (if means and intercepts are included in the model).
- *Indirect, direct & total effects:* all effects divided into categories (when the *Standardized estimates* box also is checked, the standardized as well as the unstandardized direct, indirect, and total effects are included).



Afterward, the researcher clicked the *Calculate estimates* icon. Examining the output model by clicking on the *View the output path diagram* involved clicking the right button at the top center of the page. The diagram appeared with a complete set of coefficients. Depending on whether the researcher clicked the *standardized estimate* statement in the middle column of the Amos control field, these parameter estimates may be unstandardized or standardized, as is shown in the diagram to the left.

The paths shown on the diagram revealed standardized regression coefficients (beta weights). In addition, because standardizing the output sets the intercept at zero, error terms are uncorrelated, and exogenous variables have measurement errors of 0.

Clicking the *View text* icon revealed the output divided into sections, though the *Text Output* subprogram must be operating to display it. After an *Analysis Summary* listing the type of model and the sample size, a *Variable Summary* report lists all the variables in the model and classifies them as observed or unobserved (latent) and endogenous or exogenous. Error terms are listed under the category of "unobserved, exogenous variables." A *Parameter Summary* includes the number of parameters that are fixed, labeled, or unlabeled. A table also reports whether the parameters involve covariances, variances, means, or intercepts.

The next section includes *Notes for Model (Default model)*, which reports critical information about model composition and identification. The section for this model is found in Table 17.4. In this case, the estimated parameters were fewer than the number of "distinct sample moments." Hence, the model was overidentified and was suitable for structural equation modeling. In short, the model could be tested. In contrast, a "just identified" model would always show perfect fit as an artifact. If the model were underidentified or unidentified, a warning would appear and the researcher would receive information about the sort of parameter estimation problems that are present. The output also states that the estimation method successfully achieved a local minimum value. The likelihood ratio chi-square test was not statistically significant. In this case, with alpha risk of .05, the critical value of likelihood ratio chi-square was 12.59. The observed test statistic (9.016) was not greater than this value. Thus, the null hypothesis that the model does not differ from the data set could not be rejected. Unlike most statistical significance testing, path modelers do *not* want to find significant differences between the paths and the data. Hence the model may be accepted. Of course, model fit actually means that the model *permits* reproducing the correlation or covariance matrix. In this case, that assumption continues to hold. Other measures of fit also were used, and, as will be seen, they revealed the same patterns.

Table 17.4

Computation of Degrees of Freedom (Default model)

Number of distinct sample moments:	21
Number of distinct parameters to be estimated:	15
Degrees of freedom (21 - 15):	6

Result (Default model)

Minimum was achieved
Chi-square = 9.016
Degrees of freedom = 6
Probability level = .173

The *Estimates* output provided tables of the unstandardized and the standardized parameter estimations for the model. The unstandardized values (except for those whose values are constrained) were tested to see if their diffences from zero were statistically significant. In this case, all of them were, as indicated by p values below .05. When the exact probability is lower than .000, three asterisks are placed in the column for p values. The standardized regression weights are among the most important to examine. These paths are most typically placed on

Table 17.5

Regression Weights (Group number 1—Default model)

		Estimate	*S.E.*	*C.R.*	*P*	*Label*
Message Credibility	<---	Source Credibility	.162	.063	2.582	.010
Behavior Intentions	<---	Message Credibility	.418	.063	6.664	***
Behavior Intentions	<---	Source Credibility	.277	.052	5.339	***
TRUST	<---	Source Credibility	1.000			
VIRTUE	<---	Source Credibility	.757	.108	6.978	***
BELIEVE	<---	Message Credibility	1.000			
ACCONTEN	<---	Message Credibility	.625	.077	8.164	***
LEARNABO	<---	Behavior Intentions	1.005	.096	10.512	***
SELFEXAM	<---	Behavior Intentions	1.000			

published path models. The standardized regression weights for this model are found in Table 17.6.

Table 17.6

Standardized Regression Weights (Group number 1—Default model)

			Estimate
Message Credibility	<---	Source Credibility	.183
Behavior Intentions	<---	Message Credibility	.591
Behavior Intentions	<---	Source Credibility	.442
TRUST	<---	Source Credibility	.955
VIRTUE	<---	Source Credibility	.660
BELIEVE	<---	Message Credibility	.903
ACCONTEN	<---	Message Credibility	.664
LEARNABO	<---	Behavior Intentions	.830
SELFEXAM	<---	Behavior Intentions	.711

Table 17.7 reports the variances, standard errors, and critical ratios of parameters, and the probability of differences of observed variances being explicable by random sampling error.

The R^2 for the prediction of (other than exogenous) variables also was reported. As a measure of behavioral intentions about breast cancer health care, this model predicted 64% of the shared variance (see Table 17.8).

Table 17.7

Variances (Group number 1—Default model)

	Estimate	*S.E.*	*C.R.*	*P*	*Label*
Source Credibility	2.624	.411	6.381	***	
err_7	1.985	.293	6.772	***	
err_8	.370	.088	4.185	***	
err_1	.465	.216	2.153	.031	
err_2	1.014	.119	8.499	***	
err_3	.256	.333	.770	.441	
err_4	1.946	.251	7.739	***	
err_6	1.009	.115	8.808	***	
err_5	.468	.087	5.399	***	

Table 17.8

Squared Multiple Correlations (Group number 1—Default model)

	Estimate
Message Credibility	.033
Behavior Intentions	.640
LEARNABO	.689
SELFEXAM	.505
VIRTUE	.436
TRUST	.911
ACCONTEN	.441
BELIEVE	.815

Examining Model Fit

The standardized residual covariances also were reported because the researcher checked the *Request residual moments* option. These residuals appear in Table 17.9. Ideally, these standardized residuals should reflect a standard normal distribution. As a rule, the values should be below 1.96 in a tenable model. A difference greater than 1.96 indicates that the residuals are beyond a chance expectation at a decision rule of .05. The modification indices were not computed because

Table 17.9

Standardized Residual Covariances (Group number 1—Default model)

	LEARNABO	*SELFEXAM*	*VIRTUE*	*TRUST*	*ACCONTEN*	*BELIEVE*
LEARNABO	.000					
SELFEXAM	.000	.000				
VIRTUE	−.346	1.163	.000			
TRUST	−.248	.418	.000	.000		
ACCONTEN	−.009	.046	−.003	.067	.000	
BELIEVE	.244	−.475	1.013	−.126	.000	.000

there was no significant deviation from acceptable fit and because any changes would not reduce the chi-square value by the minimum of 4.0. If a model fails to fit the data, the modification indices indicate which paths, if altered by relaxing initial assumptions, would lead to greatest changes in the value of the likelihood ratio chi-square test.

Table 17.10

Model	*NPAR*	*CMIN*	*DF*	*P*	*CMIN/DF*
Default model	15	9.016	6	.173	1.503
Saturated model	21	.000	0		
Independence model	6	559.603	15	.000	37.307

Model	*RMR*	*GFI*	*AGFI*	*PGFI*
Default model	.063	.990	.965	.283
Saturated model	.000	1.000		
Independence model	.777	.559	.382	.399

Model	*RMSEA*	*LO 90*	*HI 90*	*PCLOSE*
Default model	.042	.000	.096	.524
Independence model	.361	.335	.387	.000

This section ended with minimization history followed by indices of model fit. The Amos program produces more than 20 model fit indices, though the development of such tests is active and there may be as many as 100 different tests available. Only a handful will be interpreted here to explore the health model. Many of these tests were described in Chapter 16 and will not be reviewed again here. The fit of the model to the data is revealed in Table 17.10.

- CMIN is the minimum discrepancy $\hat{C}$ and is an application of the chi-square test. Because no statistically significant difference was noted, the breast cancer health model seemed to fit the data.
- CMIN/DF adjusts CMIN for model complexity. A value below 2 indicates acceptable fit. This model clearly fit the data, as indicated by a value of 1.503.
- RMR is the root mean square residual, described in this chapter's section on "Checking Fit of the Model to the Data." Ideal fit is indicated by RMR values approaching zero. Though it is a judgment call, a value below .08 (which was found in this example) is considered acceptable fit. This measure is not available for models with manifest variables only.
- GFI is the *G*oodness of *F*it *I*ndex, which is computed as $GFI = 1 - \frac{\hat{F}}{\hat{F}_b}$, where $\hat{F}$ is the minimum value of the discrepancy function and $\hat{F}_b$ is the discrepancy function for the null model where all parameters except for the variances have values set at 0. The

highest GFI is 1.0, indicating a perfect fit of the model to the data. The GFI for the health model was .99, a value that suggested strong fit. GFI is not available to assess models with manifest variables only.

- AGFI is the *A*djusted *G*oodness of *F*it *I*ndex, which adjusts the GFI for the degrees of freedom for the hypothesized model. It is computed as $AGFI = 1 - (1 - GFI)\frac{d_b}{d}$, where $d_b = \sum_{g=1}^{G} p^{*(g)}$. The most positive value indicating perfect fit is 1.0, but values may go below zero. The breast cancer health model had a very high AGFI (.965) and, hence, the evidence of fit seemed consistent with other measures. The AGFI is not available to assess models with manifest variables only.

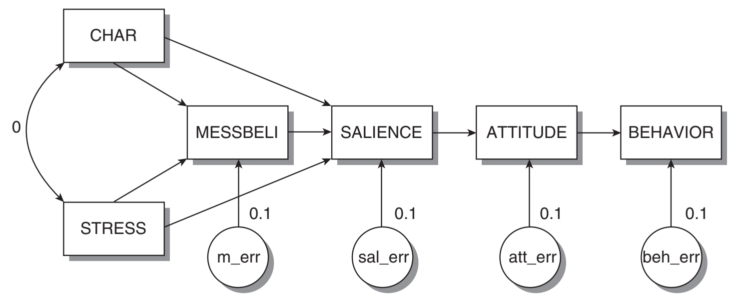
It might be mentioned that the measures just identified have been criticized for being biased upward with increasing sample sizes. Hence, other measures have been recommended.

- PGFI is the *P*arsimony *G*oodness of *F*it *I*ndex, which adjusts the GFI for the degrees of freedom for the null model. The PGFI is computed as $PGFI = GFI\frac{d}{d_b}$, where d is degrees of freedom for the hypothesized model and $d_b = \sum_{g=1}^{G} p^{*(g)}$ is the degrees of freedom for the null model, called the *baseline* model. The PGFI differs from the AGFI in whether the null or hypothesized degrees of freedom are used to standardize comparison values. In this case, the value of .283 suggested reasonable fit to the data. The PGFI is not available for assessing models with manifest variables only.
- RMSEA, as previously described in this chapter, is the *R*oot *M*ean *S*quare *E*rror of *A*pproximation. As previously described, values below .05 are taken as support for claims of fit of the model to the data. In this case, the RMSEA was .042, which was within acceptable limits.
- PCLOSE is a statistical significance test of the RMSEA. Rejecting the null hypothesis asserts that the population RMSEA is greater than .05. In this case, the probability value of .524 indicated no statistically significant difference between the observed RMSEA and an RMSEA ≤ .05. Thus, the model was supported.

As explained in Chapter 16, these measures of fit often are based on the same statistical approach. Hence, when the health communication model "passes" 20 tests, it does not mean we have 10 times as much proof as for a model that "passes" 2 tests. Thus, the tests of fit should be taken as imperfect indicators of model fit to the data, especially because many seem to report variations of the same basic information.

Using Amos for Models With Observed Variables Only

Amos is a versatile program that also analyzes models with observed variables only, without much difficulty. As an example, the path model dealing with source character and life stress may be analyzed using this program. After inputting the diagram from the previously described model, the result was as is shown on page 485. As the model indicated, all key variables were placed in rectangles to indicate that they were observed variables. Only error terms for each of the endogenous variables were placed in ovals. The two exogenous variables were assumed to be unrelated. Thus, the curved line between the exogenous variables indicated this lack of association.



After clicking on the *Analysis properties* icon, the researchers selected options for output. Some output is provided for models composed of latent variables only. Some other measures of model fit are omitted because they apply to covariance matrices for unobserved variables. Clicking the *Calculate estimates* icon produced the formal analysis. To secure a diagram with parameters included, the researcher clicked the *View the output path diagram* button, which is located on the right side of the pair of buttons at the top of the page. As shown on the right, clicking on the *Standardized estimated* bar on the parameter format field produces a diagram with standardized parameters included. Within the limits of rounding error, the results mirrored the analysis of these data using traditional path modeling methods. The numbers above the rectangles were the r^2 or R^2 coefficients for each endogenous variable. These elements also were reported in the text version of the output, as shown in Table 17.11. In addition to the description of the model, the results showed a statistically significant chi-square likelihood ratio test (as indicated by a probability level below .05). Thus, the model did not seem to fit the data.

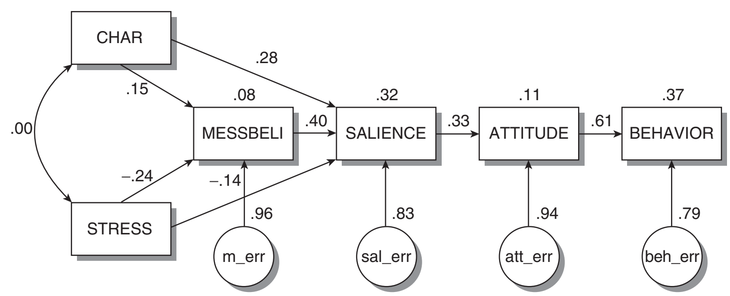


Table 17.11

Notes for Model (Default model)

Computation of Degrees of Freedom (Default model)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	19
Degrees of freedom (27 − 19):	8

Result (Default model)

Minimum was achieved
Chi-square = 35.674
Degrees of freedom = 8
Probability level = .000

The modification indices examine the parameters that are constrained to equal a constant value and estimate the amount by which the chi-square test of model discrepancy would be reduced if the constraints on the parameter were removed. Additional modification indices are computed for paths that are not part of the model, except for paths that would require making an exogenous variable into an endogenous variable or that would make an indirect path from a variable back to itself (creating a nonrecursive model). As Table 17.12 shows, the modification indices revealed some interesting results. The first box reports on the effects of relaxing assumptions about the parameters constrained to be zero (including the assumption of uncorrelated error terms). The second box reports on the impact of other nonexistent paths. In particular, examining the modification indices reported for parameters constrained to be zero, the largest modification index was 13.589, indicating that the chi-square test statistic would decrease by at least this amount if the covariance between the error terms for behavior and message believability were allowed to take a nonzero value. The column marked "Par Change" indicates the estimated amount by which the parameter value would drop (–.221) if this path were permitted (because the original value was constrained to equal zero, the reported "Par Change" also is the actual estimated covariance). Even if this change were made, however, the chi-square test statistic still would have been statistically significant. So, the changes would have made little difference. Examining the unpredicted paths, some changes might produce changes in chi-square values, but none of them would make sense given the theoretic foundation of the model. Hence, the examination of the modification indices revealed little evidence that the model could be saved by relaxing assumptions or adding paths.

Table 17.12

			M.I.	*Par Change*
m_err	<---	beh_err	13.589	–.221
STRESS	<---	beh_err	9.355	–1.521
CHAR	<---	beh_err	4.355	.485
			M.I.	*Par Change*
STRESS	<---	beh_err	9.355	–1.521
CHAR	<---	beh_err	4.355	.485
MESSBELI	<---	beh_err	13.589	–1.370
BEHAVIOR	<---	m_err	13.589	–.061

The indices of fit showed the model's inadequacy (see Table 17.13). Not only was the CMIN (the chi-square likelihood ratio) test statistically significant, but the CMIN/DF measure was far above 2. The RMSEA was greater than .05, and the PCLOSE test revealed that the RMSEA was beyond the .05 threshold for acceptable models. In general, when an apparently unacceptable model is found, the Hoelter's critical *N* can be instructive. This statistic reveals the sample size at which the model would have been accepted (at the .05 or .01 level). Because most measures of fit are sensitive to sample size, this statistic reveals how large the sample would be *just below* the point at which the model would have been rejected

Table 17.13

Model	*NPAR*	*CMIN*	*DF*	*P*	*CMIN/DF*
Default model	19	35.674	8	.000	4.459
Saturated model	27	.000	0		
Independence model	12	323.724	15	.000	21.582

Model	*RMSEA*	*LO 90*	*HI 90*	*PCLOSE*
Default model	.111	.076	.150	.003
Independence model	.272	.246	.298	.000

Model	*HOELTER .05*	*HOELTER .01*
Default model	122	158
Independence model	22	27

by statistics based on comparisons with random sampling error. The stronger the model, the larger this number is. In this case, the model would have been rejected with any sample above 122. Given the recommendation by Hoelter (1983) that a critical *N* of at least 200 is expected of acceptable models, the researcher must reject the model.

As can be seen, employing Amos for models with all observed variables can be quite useful. In this case, an unacceptable model was identified both with traditional path analysis and with Amos's use of structural equation modeling. As a revision of the model, the researcher might add paths or delete troublesome variables. In this case, if the behavioral intentions measure were removed, the model's fit to the data would improve substantially. In fact, when this step was taken, the CMIN chi-square likelihood ratio dropped to a statistically insignificant 5.173 with 4 degrees of freedom. Furthermore, all tests of fit were supportive of the revised model.