

Structural Equation Modeling With AMOS, EQS, and LISREL: Comparative Approaches to Testing for the Factorial Validity of a Measuring Instrument

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Using a confirmatory factor analytic (CFA) model as a paradigmatic basis for all comparisons, this article reviews and contrasts important features related to 3 of the most widely-used structural equation modeling (SEM) computer programs: AMOS 4.0 (Arbuckle, 1999), EQS 6 (Bentler, 2000), and LISREL 8 (Jöreskog & Sörbom, 1996b). Comparisons focus on (a) key aspects of the programs that bear on the specification and testing of CFA models—preliminary analysis of data, and model specification, estimation, assessment, and misspecification; and (b) other important issues that include treatment of incomplete, nonnormally-distributed, or categorically-scaled data. It is expected that this comparative review will provide readers with at least a flavor of the approach taken by each program with respect to both the application of SEM within the framework of a CFA model, and the critically important issues, previously noted, related to data under study.

Of major importance in both the development and use of assessment instruments is the extent to which they “do” measure that which they are purported to measure; in other words, the extent to which their factorial structures are valid. This concern becomes even more critical when an instrument is used within a culture that differs from the one in which it was developed and normed. Indeed, the issue holds regardless of whether the instrument is used in its original linguistic form, or as a translated or adapted version.

One of the most rigorous methodological approaches to testing for the validity of factorial structures is the use of confirmatory factor analysis (CFA) within the framework of structural equation modeling (SEM). As such, the researcher postulates the underlying structure of a measuring instrument *a priori*, and then tests for the validity of this structure statistically. Given that CFA applications were only made possible less than 30 years ago, this methodology, compared with traditional statistical procedures, can be considered a relatively recent phenomenon. In sharp contrast to the sparseness of appropriate computer programs by which to implement CFA procedures in the 1970s and 1980s, however, researchers today have several SEM programs from which to choose (AMOS—Arbuckle, 1999; CALIS—SAS Institute, 1992; EQS—Bentler, 2000; LISREL—Jöreskog & Sörbom, 1996a, 1996b; Mplus—Muthén & Muthén, 1998; Mx—Neale, Boker, Xie, & Maes, 1999; and RAMONA—Browne & Mels, 1999). I limit my comparative review, however, to the three most popular and widely-used of these programs.

The intent of this article is to compare features of the AMOS, EQS, and LISREL computer programs that are pertinent to the application of CFA procedures in testing for the factorial validity of a measuring instrument. More specifically, the comparison focuses on (a) preliminary analyses, (b) model specification, estimation, goodness-of-fit, and misspecification, and (c) treatment of missing, nonnormal, and categorical data. It is important to emphasize that a comprehensive summary of each program would extend well beyond the intended scope of this article and, thus, is not considered here. Rather, the primary aim is to provide readers with at least a flavor of the general *modus operandi* related to each program, as well as with a glimpse of particular features associated with each.¹

For purposes of illustration, I have chosen to base my comparisons on a study that sought to validate scores on the Maslach Burnout Inventory (MBI; Maslach & Jackson, 1981, 1986) for elementary school teachers (Byrne, 1993). Although the purposes of the original study were fourfold, only analyses bearing on the factorial validity of the MBI for the calibration sample of elementary teachers ($n = 580$) are of interest in this article. Readers interested in a more extensive discussion and illustration of various SEM applications using AMOS, EQS, and LISREL are referred to Byrne (1994, 1998, 2001); those interested in more details related to the study from which the present example is drawn are referred to the original article (Byrne, 1993).

In outlining this review of the AMOS, EQS, and LISREL programs, I first present a brief and general overview of both the programs and the measuring instru-

¹It needs to be noted that, should research interests focus on the extent to which the factorial structure of instruments are equivalent across groups (e.g., cultures and gender), the CFA procedure illustrated in this article represents only the initial stage of a more complex process. For more detailed discussions and demonstrations of multigroup invariance testing, readers are referred to Byrne (1994, 1998, 2001) and Little (1997).

ment under study. Next, focusing on each analytic stage involved in testing for the validity of MBI scores, I then compare the particular approach used by each program in addressing this process. Finally, I describe the method followed by each program in addressing the issues of missing data, nonnormality of data, and the analysis of categorical variables.

THE PROGRAMS

AMOS

The name, AMOS, is an acronym for “Analysis of Moment Structures” or, in other words, the analysis of mean and covariance structures. Version 4.0 of the program provides the framework for all comparisons made in this article. An interesting aspect of AMOS is that, although developed within the Microsoft Windows interface, the program allows researchers to choose from two completely different modes of model specification. Use of the one approach, AMOS Graphics, allows the researcher to work directly from a path diagram; use of the other, AMOS Basic, to work directly from equation statements. Given (a) the wide array of drawing tools available, (b) the fact that they have all been carefully designed with SEM conventions in mind, and (c) the ease and speed with which a publication-quality path diagram can be formulated, it seems likely that most researchers will opt for the AMOS Graphics approach to analyses. For this reason, then, all comparisons presented in this article are based on the latter.

AMOS Graphics provides the user with all the tools that will ever be needed in creating and working with SEM path diagrams. Each tool is represented by an icon (or button) and performs one particular function. A palette displaying 66 of these icons is shown in Figure 1. In addition to the icons, however, all options related to analyses are also available from drop-down menus. Estimates derived from the analyses can be presented in either text or table (i.e., spreadsheet) format, as well as displayed graphically in a path diagram. (Readers wishing greater detail related to the operation of both the icons and the drop-down menus, within the framework of various SEM applications, are referred to Byrne, 2001.)

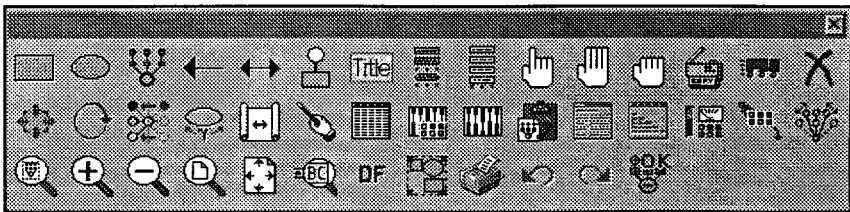


FIGURE 1 AMOS: Palette of selected drawing tool icons.

EQS

The EQS program has two major elements. The first of these is a graphical interface within the Windows environment; the second element represents the standard EQS program which conforms to conventions and procedures described in the manual (Bentler, 2000). This combination provides the user with a multiplicity of ways by which to manage, visually inspect, and analyze data, draw path diagrams, and almost automatically, build an input file containing the model specifications and equations necessary to run EQS. It is important to note that a Macintosh version of the program is also available. Comparisons related to EQS, in this article, are based on Version 6 (Bentler, 2000; Bentler & Wu, 2000).

The heart of the EQS program is the Bentler-Weeks representation system which argues, in the very broadest sense, that all variables in a model can be categorized as either dependent or independent variables. That is to say, any variable having a unidirectional arrow aiming at it represents a dependent variable; any variable having only unidirectional arrows leading away from it is considered to be an independent variable. This simple representation system makes the decomposition of a path model into structural equations very easy indeed. In specifying a model to be tested, the EQS user can do so by submitting either an input file, or a path diagram that has been created using the "Diagrammer" feature of EQS. Estimates derived from SEM analyses can be presented textually in an output file, or graphically on the path diagram.

LISREL

LISREL, an acronym for LInear Structural RELations, is grounded in the Jöreskog-Keesling-Wiley approach to representing systems of structural equations (Bentler, 1980). Thus, its command language is couched in the statistical language of matrix algebra which is dominated by the use of Greek letters. Within the framework of the LISREL program, a full latent variable model, based on the analysis of covariance structures, may be defined by a maximum of eight matrices and four vectors; analysis of means structures involves an additional four matrices. Nonetheless, a simple CFA model, such as the one illustrated in this article, is represented by only three matrices (factor loading matrix, Λ ; factor variance/covariance matrix, Φ ; and error variance/covariance matrix, Ψ). To specify a model within the context of an input file, the user must have a comprehensive understanding of both the matrices and their related LISREL notation. All comparisons of LISREL with AMOS and EQS are based on version 8.20 (Jöreskog & Sörbom, 1996b).

In an effort to make the LISREL program more user-friendly, Jöreskog and Sörbom (1993) introduced a new command language, termed SIMPLIS, which is intended to simplify both the creation of input files and the manner by which re-

sults are reported in the output file; hence, the acronym SIMPLis. The major difference between the two command languages is that SIMPLis commands are formulated using the everyday language of English and there is no need to comprehend either the various LISREL models and submodels, or the Greek and matrix notations. Nonetheless, users can request the standard LISREL output should that be their preference. For a more detailed explanation of both LISREL and SIMPLis, and their application to several different SEM models, readers are referred to Byrne (1998). Although LISREL also has a graphical interface by which users can submit a specified model for analysis or to retrieve a path diagram fully labeled with its estimated values, I have found it to be much less sophisticated and easy to work with than either the AMOS or EQS programs.

Given LISREL's inability to perform preanalytic and supplementary tasks associated with the analysis of SEM models, the program has a companion package called PRElis (Jöreskog & Sörbom, 1996a), which was designed specifically to serve as a preprocessor for LISREL; hence, the acronym PRElis. However, because it can be used effectively to manipulate and save data files, and to provide an initial descriptive overview of data, it can also function as a stand-alone program, or in conjunction with other programs. For a demonstration of numerous and various PRElis applications, readers are referred to Byrne, 1998.

THE MEASURING INSTRUMENT UNDER STUDY

The MBI (Maslach & Jackson, 1981, 1986) is a 22-item instrument designed to measure three dimensions of burnout which the authors term Emotional Exhaustion (EE), Depersonalization (DP), and Reduced Personal Accomplishment (PA). Items are structured on a 7-point Likert-type scale that ranges from 0 (*feeling has never been experienced*) to 6 (*feeling experienced daily*); the EE subscale comprises nine items, the DP subscale five, and the PA subscale eight. Although the original version of the MBI (Maslach & Jackson, 1981) was constructed from data based on samples of workers from a wide range of human service organizations, a later version (Maslach and Jackson, 1986), in collaboration with Richard L. Schwab, was designed specifically for use with teachers. This version parallels the original version of the MBI with the exception that the generic term "recipients," used in reference to clients, was replaced by "students."

THE HYPOTHESIZED MODEL

The CFA model depicting the three-factor structure of the MBI hypothesized a priori that (a) responses to the MBI could be explained by three factors, (b) each item would have a nonzero loading on the burnout factor it was designed to measure,

and zero loadings on all other factors, (c) the three factors would be correlated, and (d) measurement error terms would be uncorrelated. Because the labeled schematic representation of this model will necessarily vary with the program used, these path diagrams are presented separately relative to the AMOS, EQS, and LISREL programs.

TESTING THE HYPOTHESIZED MODEL

Preliminary Analyses of Data

Given (a) the strong underlying assumption of multivariate normality demanded of the SEM methodology, with violation of this assumption leading to the incorrect interpretation of findings, and (b) the fact that case outliers can often seriously distort model fit, it behooves researchers to scour their data prior to any testing of a specified model. Although the three programs reviewed here can provide the user with information bearing on these issues, they do so to varying degrees and in varying ways.

AMOS. Descriptive statistics related to nonnormality, as well as to detection of outliers, can be requested via an “Analysis Properties” dialogue box which is ac-



cessed, either by clicking on the related icon, or via the drop-down menu. These descriptive statistics include minimum and maximum values, as well as univariate skewness and kurtosis values, together with their related critical ratios. Outlier information identifies cases that are farthest from the centroid by reporting their Mahalanobis distance values.

EQS. By default, EQS always reports the univariate (mean, standard deviation, skewness, kurtosis), as well as multivariate (Mardia's coefficient and normalized estimate) sample statistics; the latter relate to kurtosis only. EQS also prints out, automatically, the five cases contributing most to the normalized multivariate kurtosis estimate. Nonetheless, it is possible that none of the five cases is actually an outlier. Pinpointing an outlier is based on the estimate for one case relative to those for the other four cases; there is no absolute value on which to make this decision.

LISREL. Information related to the sample statistics must be obtained by using PRELIS. If the data are of continuous scale, the program will provide the following univariate statistics: mean, standard deviation, skewness, kurtosis, and minimum and maximum frequency values; each skewness and kurtosis score is accompanied by its related z -statistic and probability value. In addition, the output

also includes a histogram related to each scale score. When data are of ordinal scale, PRElis provides information related to variable thresholds, bar chart of univariate distributions, bivariate distributions, and correlations (Pearson product-moment, polychoric, polyserial,) together with their test statistics.

Model Specification

AMOS. The hypothesized three-factor model of MBI structure, formulated using the AMOS drawing tool palette, is shown in Figure 2. This path diagram represents the only specification input required for analyses using the AMOS (graphics) program (i.e., no input file, per se, is required).² By convention, in the schematic presentation of structural equation models, measured (or observed) variables are shown in rectangles and unmeasured (or latent) variables in ellipses (or circles). Thus, in reviewing the model depicted in Figure 2, we see that there are three latent constructs (or factors), namely, EE, DP, and PA. The 22 observed variables (Item 1 through Item 22) serve as indicators of their respective underlying latent factor. Associated with each observed variable is an error term (err1 through err22); because errors of measurement are unobserved, AMOS path diagrams, unlike those associated with most other SEM programs, model these parameters as circled enclosures by default. The one-way arrows in the model represent structural regression coefficients, thereby indicating the impact of one variable on another. Accordingly, the one-way arrows leading from each MBI factor to its congeneric set of MBI items suggest that scores on the latter are “caused” by each of the related factors; these regression coefficients represent the factor loadings. Likewise, the one-way arrows pointing from the error terms to the items indicate that the reliability of these observed variables is influenced by random measurement error. Finally, the curved two-way arrows connecting each of the MBI factors indicate their intercorrelation. It is important to note that the “1”s assigned to the first of each set of factor loading coefficients, and to the regression coefficients associated with each error term, are imposed automatically by the program;³ they represent a fixed value of 1.00 and as such, are not to be estimated. The “1”s associated with the factor loadings address the issues of model identification and scaling of the unobserved factors, whereas those associated with the error terms represent values that are considered to be known; only the error variances are of interest. (For an elaborated discussion of these issues, see Bollen, 1989; Byrne, 1994, 1998, 2001).

²Should a user prefer to work from an input file, rather than from a path diagram, he or she can do so by working in AMOS Basic, the alternative program.

³Although the program automatically assigns a fixed value of 1.00 to the first of each set of factor loading regression paths, the user is free to redirect the assignment of this value (or some alternate value) to a different loading within the same set of indicator variables.

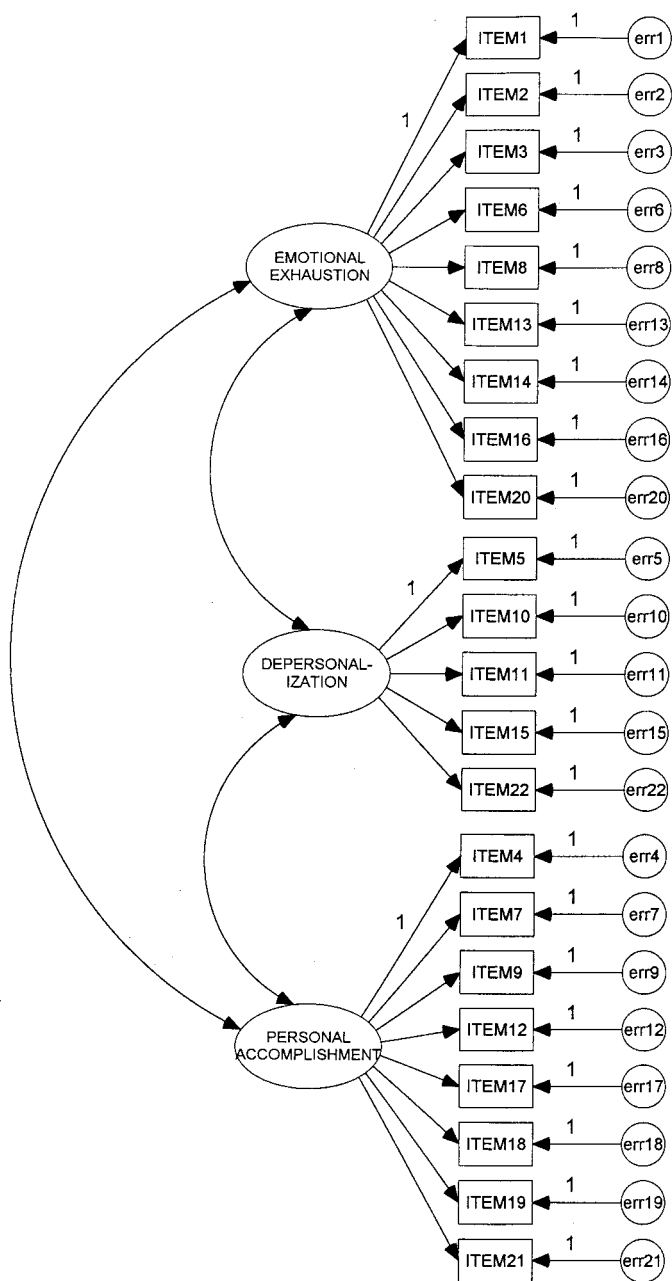


FIGURE 2 AMOS: Hypothesized model of Maslach Burnout Inventory structure.

In addition to the path diagram, however, the program needs specifications bearing on the data. This information is readily provided, either by clicking on the



“Data File” icon, or by pulling down the “File” menu and selecting “Data Files.” Of additional note is that the graphical specification shown here will yield only minimal default output. Given that one would likely wish, also, to obtain standardized estimates and modification indexes, this additional information must be conveyed to the program. This task is very easily accomplished simply by clicking on the “Analysis Properties” icon (illustrated earlier) to access the dialogue box in which you may request this additional information.

EQS. The hypothesized MBI model, structured using the EQS diagrammer and labelled with EQS notation, is presented in Figure 3. On screen, the program actually color-codes the model such that, in the present case for example, dependent variables (Items; the observed variables) are yellow, independent variables (“F”s; the factors) are gray, freely estimated paths and covariances are black, and fixed paths (first factor loading of each congeneric set of observed variables; error terms) are blue. The simplicity of EQS notation makes it very easy to see at a glance exactly which variables and coefficients are explicitly modeled, and how many parameters are to be estimated. As such, the program, by default, designates all observed variables as “V”s (unless otherwise labelled, as is the case in Figure 3), all latent constructs (which EQS regards as factors) as “F”s, and all errors of measurement as “E”s. Thus, in reviewing Figure 3, and following the SEM symbol conventions noted earlier, we can discern 22 observed variables (Item 1 through Item 22), three factors (F_1 through F_3), three covariances (two-way arrows), and 44 regression coefficients (one-way arrows)—22 leading from the “F”s to the “V”s (the factor loadings), and 22 indicating the impact of random measurement error on the “V”s. In the Bentler-Weeks terminology, then, there are 22 dependent variables and 25 independent variables.

Model specification, in EQS, can be accomplished either by means of an EQS-generated model, as shown in Figure 3, or by means of an input file. The input file pertinent to Figure 3 is presented in Table 1. All information describing the model and data are expressed in specific statements within particular paragraphs. Each statement is separated by a semicolon, and each paragraph begins with a slash. Within each paragraph, asterisks represent estimated parameters. For example, in the “/EQUATIONS” paragraph, the statement, $V2 = +*F1 + 1E2$, indicates that the factor loading of Item 2 ($V2$) on EE ($F1$) is to be freely estimated. In contrast, however, note that no asterisks accompany the first of each set of factor loading coefficients, nor any of the regression paths associated with the error terms, for purposes noted earlier. In contrast to AMOS and LISREL, standardized parameter estimates are automatically provided in the EQS output. Given the simplicity of the EQS file structure, with the exception of the Lagrange Multiplier Test (LMT) paragraph,

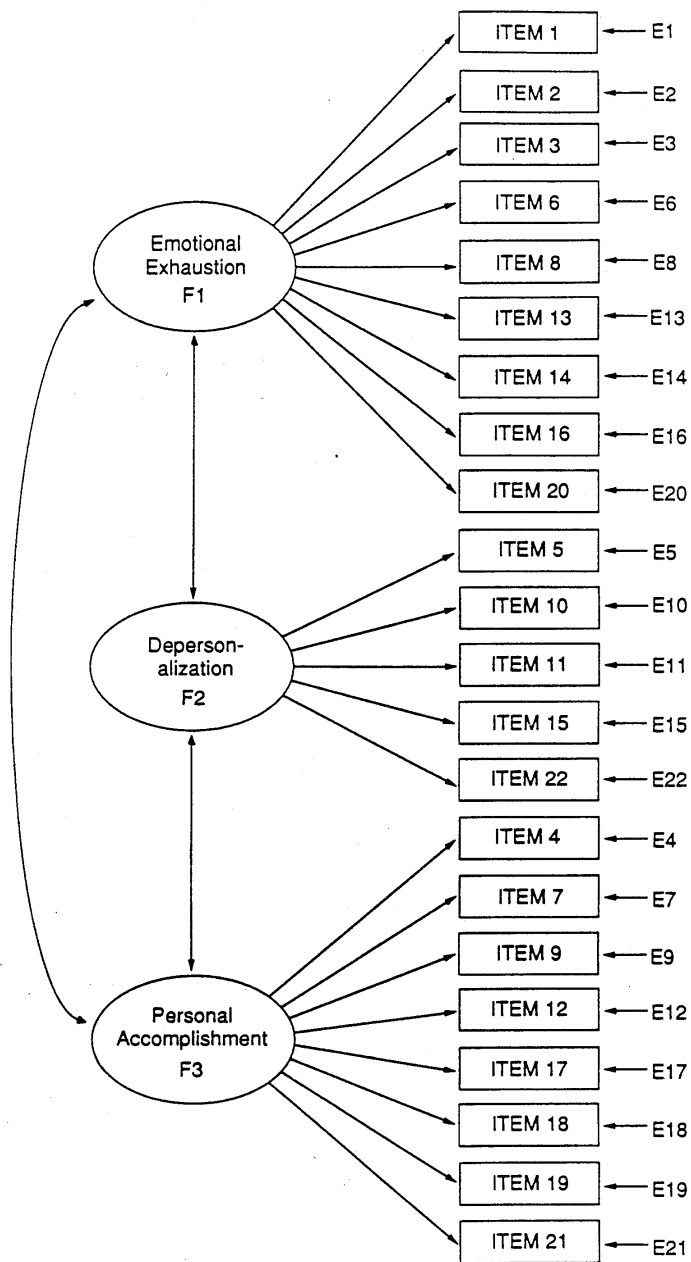


FIGURE 3 EQS: Hypothesized model of Maslach Burnout Inventory structure.

TABLE 1
EQS Input for Initially Hypothesized Model of MBI Structure

```

/TITLE
Testing for Validity of the MBI "CVEL1"
/SPECIFICATIONS
DATA= c:\eqs6\files\cvel1.ess ; VARIABLES=22; CASES=580; GROUPS=1;
METHODS=ROBUST; MATRIX=RAW; ANALYSIS=COVARIANCE;
/LABELS
V1=ITEM1; V2=ITEM2; V3=ITEM3; V4=ITEM4; V5=ITEM5; V6=ITEM6;
V7=ITEM7; V8=ITEM8; V9=ITEM9; V10=ITEM10; V11=ITEM11; V12=ITEM12;
V13=ITEM13; V14=ITEM14; V15=ITEM15; V16=ITEM16; V17=ITEM17;
V18=ITEM18; V19=ITEM19; V20=ITEM20; V21=ITEM21; V22=ITEM22;
/EQUATIONS
V1 = + 1F1 + 1E1;
V2 = + *F1 + 1E2;
V3 = + *F1 + 1E3;
V4 = + 1F3 + 1E4;
V5 = + 1F2 + 1E5;
V6 = + *F1 + 1E6;
V7 = + *F3 + 1E7;
V8 = + *F1 + 1E8;
V9 = + *F3 + 1E9;
V10 = + *F2 + 1E10;
V11 = + *F2 + 1E11;
V12 = + *F3 + 1E12;
V13 = + *F1 + 1E13;
V14 = + *F1 + 1E14;
V15 = + *F2 + 1E15;
V16 = + *F1 + 1E16;
V17 = + *F3 + 1E17;
V18 = + *F3 + 1E18;
V19 = + *F3 + 1E19;
V20 = + *F1 + 1E20;
V21 = + *F3 + 1E21;
V22 = + *F2 + 1E22;
/VARIANCES
F1 to F3 = *;
E1 to E20 = *;
/COVARIANCES
F1 to F3 = *;
/PRINT
FIT=ALL;
TABLE=EQUATION;
/LMTEST
SET=PEE,GVF;
/END

```

Note. MBI = Maslach Burnout Inventory; LMTEST = Lagrange Multiplier Test.

the information provided in Table 1 is likely self-explanatory. The LMTest advises the program that modification indexes are requested in the event that the model may not be well-fitting. (This topic is addressed later in the article.) An interesting, and extremely time-saving feature of the EQS program, is its special “Build EQS” feature. As the user responds, interactively, to questions posed on dialogue boxes associated with this option, the program builds the input file automatically.

LISREL. The hypothesized MBI model labeled with LISREL notation is schematically portrayed in Figure 4. Consistent with an all-X CFA model, the observed variables (i.e., MBI items) are represented by “X”s, the exogenous factors

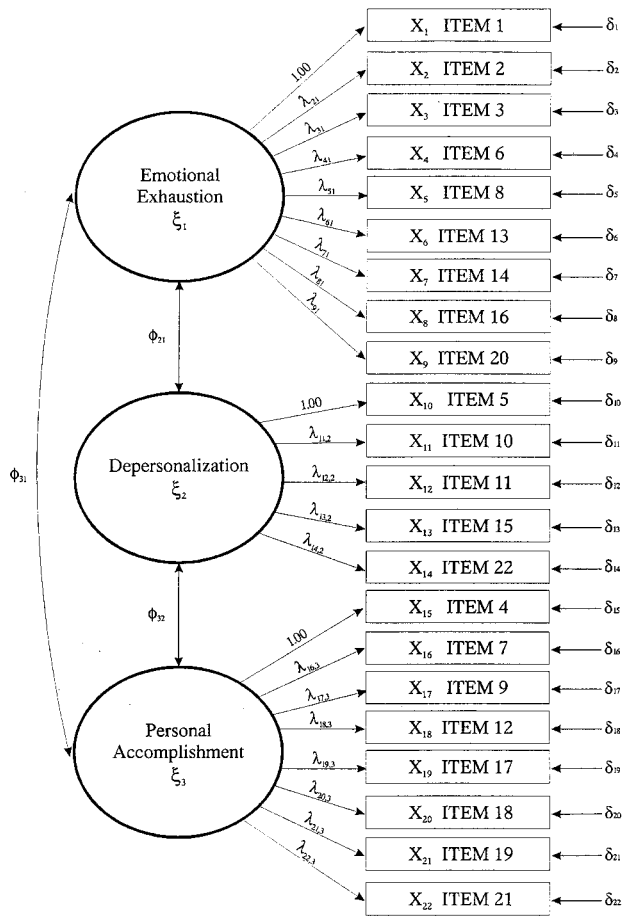


FIGURE 4 LISREL: Hypothesized model of Maslach Burnout Inventory structure.

by γ 's, the factor loading regression coefficients by β 's, the error terms by δ 's, and the factor covariances by ψ 's.

The input file describing the model in Figure 4 is presented in Table 2. Aside from the title and comments and item label information, some degree of explanation is in order here. In addition to specifying the number of indicator variables ($NI = 22$) and sample size ($NO = 580$), the Data (DA) line indicates that the covariance matrix ($MA = CM$) is to be analyzed (this option was default in both AMOS and EQS). The Select (SE) line reorders the observed variables in accord with their links to the factors; the Model (MO) line states that there are 22 observed variables (NX), three factors (NK), and that the factor loading matrix (LX) is full and fixed (FU, FI), the factor variance and covariance matrix (PH) is symmetric and free (SY, FR), and the error variance and covariance matrix (TD) is diagonal and free. The LK line indicates that the labels for the factors follow (EE, DP, PA). The labels are then followed by further model specification indicating which parameters in the fixed lambda matrix are to be freely estimated. The Value line (VA) specifies which parameters are to be fixed to 1.0. Finally, the request for standardized estimates (SC) must be specified on the Output (OU) line.

TABLE 2
LISREL Input for Initially Hypothesized Model of MBI Structure

! Testing for the Validity of the MBI "CVEL1I"																					
! Elementary Teachers - Calibration Sample																					
! Initially Hypothesized Model																					
DA NI=22 NO=580 MA=CM																					
LA																					
ITEM1 ITEM2 ITEM3 ITEM4 ITEM5 ITEM6 ITEM7 ITEM8 ITEM9 ITEM10																					
ITEM11 ITEM12 ITEM13 ITEM14 ITEM15 ITEM16 ITEM17 ITEM18 ITEM19																					
ITEM20 ITEM21 ITEM22																					
CM=CVEL1.CMM																					
SE																					
1 2 3 6 8 13 14 16 20 5 10 11 15 22 4 7 9 12 17 18 19 21																					
MO NX=22 NK=3 LX=FU,FI PH=SY,FR TD=DI,FR																					
LK																					
EE DP PA																					
FR LX(2,1) LX(3,1) LX(4,1) LX(5,1) LX(6,1) LX(7,1) LX(8,1) FR LX(9,1)																					
FR LX(11,2) LX(12,2) LX(13,2) LX(14,2)																					
FR LX(16,3) LX(17,3) LX(18,3) LX(19,3) LX(20,3) LX(21,3) LX(22,3)																					
VA 1.0 LX(1,1) LX(10,2) LX(15,3)																					
OU SC																					

Note. MBI = Maslach Burnout Inventory; DA = data; NI = number of indicator variables; EE = emotional exhaustion; DP = depersonalization; PA reduced personal accomplishment; SC = standardized estimates.

TABLE 3
SIMPLis Input for Initially Hypothesized Model of MBI Structure

! Testing for the Validity of the MBI "CVEL1I"
! Elementary teachers—Calibration Sample
! Initially Hypothesized Model
OBSERVED VARIABLES:
ITEM1 ITEM2 ITEM3 ITEM4 ITEM5 ITEM6 ITEM7 ITEM8 ITEM9 ITEM10
ITEM11 ITEM12 ITEM13 ITEM14 ITEM15 ITEM16 ITEM17 ITEM18 ITEM19
ITEM20 ITEM21 ITEM22
COVARIANCE MATRIX from FILE CVEL1.CMM
SAMPLE SIZE: 580
LATENT VARIABLES:
EE DP PA
EQUATIONS:
ITEM1 = 1*EE
ITEM2 = EE
ITEM3 = EE
ITEM6 = EE
ITEM8 = EE
ITEM13 = EE
ITEM14 = EE
ITEM16 = EE
ITEM20 = EE
ITEM5 = 1*DP
ITEM10 = DP
ITEM11 = DP
ITEM15 = DP
ITEM22 = DP
ITEM4 = 1*PA
ITEM7 = PA
ITEM9 = PA
ITEM12 = PA
ITEM17 = PA
ITEM18 = PA
ITEM19 = PA
ITEM21 = PA
LISREL OUTPUT: SC MI
END OF PROBLEM

Note. MBI = Maslach Burnout Inventory; EE = emotional exhaustion; DP depersonalization; PA = reduced personal accomplishment; SC = standardized estimates.

The related SIMPLis input file is shown in Table 3. Although the content here is fairly straightforward, explanation is perhaps needed regarding two aspects of the file. First, the expression, 1*, indicates a parameter to be constrained to a value of 1.00. Thus, for example, the equation ITEM1 = 1*EE, indicates that the factor loading of Item 1 on EE factor is not estimated, but rather, is fixed to a value of 1.00; likewise for the first loading relative to the remaining two factors (DP, PA).

Second, this input file has requested that the output be consistent with the usual LISREL file. The keyword, *MI*, indicates that modification indexes are requested (these parameters are default in LISREL). This topic is reviewed later in the article under the issue of model misspecification.

Model Estimation

For each of the AMOS, EQS, and LISREL programs, maximum likelihood estimation is default. Nonetheless, other methods of estimation are available to users who may wish such alternatives. With AMOS, this information is conveyed to the program by selecting the “Estimation” tab in the “Analysis Properties” dialogue box and then checking off the estimation procedure desired; with EQS, it is specified in the Method (ME) statement of the input file, and with LISREL, it is specified on the OU line with the selected method following the ME command.

Model Assessment

Of primary interest in SEM is the extent to which a hypothesized model “fits,” or adequately describes, the sample data. Ideally, evaluation of model fit should derive from a variety of perspectives and be based on several criteria that can assess model fit from a diversity of perspectives. In particular, these focus on the adequacy of (a) the model as a whole, and (b) the parameter estimates.

Model as a Whole

As a consequence of much research in the development of goodness-of-fit statistics that address the sensitivity of the χ^2 statistic to sample size, all three programs now report a smorgasbord of fit indexes. Those appearing in Version 6 of EQS, however, differ substantially from the other two programs in that they include two separate sets of fit statistics—one based on the traditional maximum likelihood χ^2 statistic, and one based on a corrected χ^2 value called the Satorra-Bentler scaled statistic (Satorra & Bentler, 1988). This second set of fit statistics, termed *robust statistics*, is an extremely important feature of the EQS program and serves to set it apart from other current SEM programs. Essentially, computation of the scaled statistic allows EQS to address the issue of multivariate kurtosis in the data by means of a correction to both the χ^2 statistic and the standard errors. As this article goes to press, neither AMOS nor LISREL report these important goodness-of-fit statistics. In addition to goodness-of-fit statistics, the most recent version of EQS computes several different internal consistency reliability coefficients, which are automatically printed out by default.

As might be expected, each program varies in the manner by which model-fit information is reported. The summary of goodness-of-fit indexes related to the hypothesized model of MBI structure portrayed in Figures 2, 3, and 4, is presented in

TABLE 4
AMOS Goodness-of-Fit Statistics for a Hypothesized Model
of MBI Structure

Summary of Models					
Model	NPAR	CMIN	DF	P	
Your model	47	1010.908	206	0.000	
Saturated model	253	0.000	0		
Independence model	22	5598.461	231	0.000	
Model	RMR	GFI	AGFI	PGFI	
Your model	0.146	0.858	0.825	0.698	
Saturated model	0.000	1.000			
Independence model	0.723	0.313	0.247	0.286	
Model	DELTA1 NFI	RHOI RFI	DELTA2 IFI	RHO2 TLI	CFI
Your model	0.819	0.798	0.851	0.832	0.850
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000
Model	PRATIO	PNFI	PCFI		
Your model	0.892	0.731	0.758		
Saturated model	0.000	0.000	0.000		
Independence model	1.000	0.000	0.000		
Model	RMSEA	LO 90	HI 90	PCLOSE	
Your model	0.082	0.077	0.087	0.000	
Independence model	0.200	0.196	0.205	0.000	
Model	ECVI	LO 90	HI 90	MECVI	
Your model	1.908	1.744	2.086	1.915	
Saturated model	0.874	0.874	0.874	0.910	
Independence model	9.745	9.330	10.171	9.748	

Note. MBI = Maslach Burnout Inventory.

Tables 4, 5, and 6, for the AMOS, EQS, and LISREL programs, respectively. (For detailed explanation and discussion regarding these statistics, as they relate to the model, readers are referred to Byrne, 1994, 1998, 2001.) As can be determined from a review of the key fit indexes reported in the output files (CFI, GFI, RMSEA, and the robust variant of the CFI and RMSEA, in the case of EQS), the hypothesized model exhibits a very poor fit to the sample data, thereby indicating a substantial degree of misspecification.

Parameter Estimates

In assessing the fit of individual parameters in the model, there are three aspects of concern: (a) the feasibility of the parameter estimates, (b) the appropriateness of the standard errors, and (c) the statistical significance of the parameter estimates. Given that details are presented elsewhere with respect to these topics in general (e.g., Bollen, 1989), and pertinent to the hypothesized model in particular (Byrne, 1994, 1998, 2001), these topics are not addressed here. Rather, in keeping with the purpose of this article, I wish only to illustrate the manner by which this information is reported in the output file. In the interest of space, only factor loading and error variance estimates related to Factor 1 (EE), along with the factor variances and covariances, are displayed.

AMOS. Factor loading estimates in the AMOS output are reported as regression weights. As shown in Table 7, parameter estimation is very clearly and succinctly presented. Listed to the right of each parameter is its estimated value (column 1), standard error (column 2), and critical ratio (column 3). The latter value represents the parameter estimate divided by its standard error and is distributed as a *z*-statistic, thereby indicating the statistical significance of the parameter.

EQS. Factor loading estimates in the EQS output are reported as measurement equations; these parameters, along with the variances and covariances, are listed together with their standard errors and *z*-values. In the event that the Satorra-Bentler ² statistic was requested (as was the case here), the corrected standard error and the resulting *z*-statistic are reported in parentheses.⁴ Turning to information reported for the first estimated parameter in Table 8 (Item 2), we see five lines of numbers. The value presented on the first line (.921) represents the maximum likelihood estimate, on the second line, its standard error (.048), and on the third line, the resulting *z*-statistic (19.161). The parenthesized value on the fourth line represents the corrected standard error after multivariate kurtosis has been taken into account (.032), followed by its related *z*-statistic (28.731). Finally,

⁴Due to the manner by which parameter estimates are reported in the EQS output, and in the interest of space, only three of the factor loading and error variance estimates are reported in Table 8.

TABLE 5
EQS Goodness-of-Fit Statistics for a Hypothesized Model of MBI Structure

GOODNESS OF FIT SUMMARY FOR METHOD = ML	
INDEPENDENCE MODEL CHI-SQUARE = 5598.461 ON 231 DEGREES OF FREEDOM	
INDEPENDENCE AIC = 5136.46094 INDEPENDENCE CAIC = 3897.60145	
MODEL AIC = 598.90939 MODEL CAIC = -505.87440	
CHI-SQUARE = 1010.909 BASED ON 206 DEGREES OF FREEDOM	
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS .00000	
THE NORMAL THEORY RLS CHI-SQUARE FOR THIS ML SOLUTION IS 1057.856.	
BENTLER-BONETT NORMED FIT INDEX = .819	
BENTLER-BONETT NONNORMED FIT INDEX = .832	
COMPARATIVE FIT INDEX (CFI) = .850	
BOLLEN (IFI) FIT INDEX = .851	
McDonald (MFI) FIT INDEX = .500	
LISREL GFI FIT INDEX = .858	
LISREL AGFI FIT INDEX = .825	
ROOT MEAN SQUARED RESIDUAL (RMR) = .146	
STANDARDIZED RMR = .071	
ROOT MEAN SQ. ERROR OF APP.(RMSEA) = .082	
90% CONFIDENCE INTERVAL OF RMSEA (.077, .087)	
GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST	
INDEPENDENCE MODEL CHI-SQUARE = 4362.364 ON 231 DEGREES OF FREEDOM	
INDEPENDENCE AIC = 3900.36360 INDEPENDENCE CAIC = 2661.50411	
MODEL AIC = 392.08453 MODEL CAIC = -712.69925	
SATORRA-BENTLER SCALED CHI-SQUARE = 804.0845 ON 206 DEGREES OF FREEDOM	
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS .00000	
BENTLER-BONETT NORMED FIT INDEX = .816	
BENTLER-BONETT NONNORMED FIT INDEX = .838	
COMPARATIVE FIT INDEX (CFI) = .855	
BOLLEN (IFI) FIT INDEX = .856	
McDonald (MFI) FIT INDEX = .597	
ROOT MEAN SQ. ERROR OF APP.(RMSEA) = .071	
90% CONFIDENCE INTERVAL OF RMSEA (.066, .076)	

Note. MBI = Maslach Burnout Inventory.

because the first parameter (Item 1) was fixed to a value of 1.00 for purposes of scaling and model identification, no estimated values are reported.

LISREL. All parameter estimates in the standard LISREL output file are reported within the context of their related matrices. In a vast improvement over earlier versions of the program, however, information bearing on the parameter estimate, its

TABLE 6
LISREL Goodness-of-Fit Statistics for a Hypothesized Model of MBI Structure

GOODNESS OF FIT STATISTICS	
CHI-SQUARE WITH 206 DEGREES OF FREEDOM = 1010.89 (P = 0.0)	
ESTIMATED NON-CENTRALITY PARAMETER (NCP) = 804.89	
MINIMUM FIT FUNCTION VALUE = 1.75	
POPULATION DISCREPANCY FUNCTION VALUE (F0) = 1.39	
ROOT MEAN SQUARE ERROR OF APPROXIMATION (RMSEA) = 0.082	
P-VALUE FOR TEST OF CLOSE FIT (RMSEA < 0.05) = 0.000036	
EXPECTED CROSS-VALIDATION INDEX (ECVI) = 1.91	
ECVI FOR SATURATED MODEL = 0.87	
ECVI FOR INDEPENDENCE MODEL = 9.75	
CHI-SQUARE FOR INDEPENDENCE MODEL WITH 231 DEGREES OF FREEDOM = 5598.44	
INDEPENDENCE AIC = 5642.44	
MODEL AIC = 1104.89	
SATURATED AIC = 506.00	
INDEPENDENCE CAIC = 5760.42	
MODEL CAIC = 1356.95	
SATURATED CAIC = 1862.85	
ROOT MEAN SQUARE RESIDUAL (RMR) = 0.15	
STANDARDIZED RMR = 0.071	
GOODNESS OF FIT INDEX (GFI) = 0.86	
ADJUSTED GOODNESS OF FIT INDEX (AGFI) = 0.83	
PARSIMONY GOODNESS OF FIT INDEX (PGFI) = 0.70	
NORMED FIT INDEX (NFI) = 0.82	
NON-NORMED FIT INDEX (NNFI) = 0.83	
PARSIMONY NORMED FIT INDEX (PNFI) = 0.73	
COMPARATIVE FIT INDEX (CFI) = 0.85	
INCREMENTAL FIT INDEX (IFI) = 0.85	
RELATIVE FIT INDEX (RFI) = 0.80	
CRITICAL N (CN) = 147.71	

Note. MBI = Maslach Burnout Inventory.

standard error, and related z -statistic is reported as a unit for each parameter; as with the EQS program, the estimate appears on the first line, followed on the second line by the standard error, and finally, by the z -statistic on the third line. The reduced output related to the hypothesized model is presented in Table 9.

Model Misspecification

As noted earlier, our test of the hypothesized model yielded findings that suggested substantial misspecification. Presented with such evidence of inadequate fit be-

TABLE 7
 AMOS: Selected Parameter Estimates for a Hypothesized Model
 of MBI Structure

Regression Weights:	Estimate	S.E.	C.R.
ITEM20 <----- EMOTIONAL_EXHAUSTION	0.820	0.044	18.561
ITEM16 <----- EMOTIONAL_EXHAUSTION	0.755	0.048	15.817
ITEM14 <----- EMOTIONAL_EXHAUSTION	0.927	0.057	16.240
ITEM13 <----- EMOTIONAL_EXHAUSTION	1.009	0.053	19.168
ITEM8 <----- EMOTIONAL_EXHAUSTION	1.204	0.054	22.338
ITEM6 <----- EMOTIONAL_EXHAUSTION	0.812	0.052	15.554
ITEM3 <----- EMOTIONAL_EXHAUSTION	0.983	0.052	18.750
ITEM2 <----- EMOTIONAL_EXHAUSTION	0.921	0.048	19.162
ITEM1 <----- EMOTIONAL_EXHAUSTION	1.000		
.			
.			
.			
Covariances:			
EMOTIONAL_EXHAUS <> PERSONAL_ACCOMPL	-0.254	0.037	-6.842
EMOTIONAL_EXHAUS <> DEPERSONAL-_IZAT	0.688	0.077	8.912
DEPERSONAL-_IZAT <> PERSONAL_ACCOMPL	-0.184	0.028	-6.514
Variances:			
EMOTIONAL_EXHAUSTION	1.657	0.153	10.848
DEPERSONAL-_IZATION	0.723	0.104	6.955
PERSONAL_ACCOMPLISHMENT	0.174	0.034	5.149
err20	0.954	0.062	15.333
err16	1.363	0.085	16.020
err14	1.897	0.119	15.937
err13	1.281	0.085	15.115
err8	0.886	0.068	13.095
err6	1.655	0.103	16.068
err3	1.322	0.087	15.269
err2	1.067	0.071	15.118
err1	1.095	0.074	14.832
.			
.			
.			

Note. MBI = Maslach Burnout Inventory.

TABLE 8
EQS: Selected Parameter Estimates for a Hypothesized Model of MBI Structure

MEASUREMENT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS STATISTICS SIGNIFICANT AT THE 95% LEVEL ARE MARKED WITH @. (ROBUST STATISTICS IN PARENTHESES)			
V1	=V1	= 1.000 F1 + 1.000 E1	
V2	=V2	= .921*F1 + 1.000 E2	
		.048	
		19.161@	
		(.032)	
		(28.731@	
.			
.			
V20	=V20	= .820*F1 + 1.000 E20	
		.044	
		18.560@	
		(.048)	
		(16.974@	
VARIANCES OF INDEPENDENT VARIABLES		COVARIANCES AMONG INDEPENDENT VARIABLES	
F			
F1-F1	1.660*	F2-F2	.690*
	.153	F1-F1	.077
	10.848@		8.919@
	(.113)		(.084)
	(14.748@		8.206@
F2-F2	.725*	F3-F3	-.254*
	.104	F1-F1	.037
	6.963@		-6.842@
	(.129)		(.038)
	(5.620@		-6.702@
F3-F3	.174*	F3-F3	-.184*
	.034	F2-F2	.028
	5.150@		-6.519@
	(.047)		(.037)
	(3.690@		-4.951@
E			
E1-V1	1.097*		
	.074		
	14.832@		
	(.072)		
	15.328@		
E2-V2	1.069*		
	.071		
	15.118@		
	(.068)		
	(15.726@		
.			
.			
.			
E20-V20	.955*		
	.062		
	15.333@		
	(.096)		
	(9.931@		

Note. MBI = Maslach Burnout Inventory.

TABLE 9
LISREL: Selected Parameter Estimates for a Hypothesized Model of MBI Structure

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)

LAMBDA-X

	EE	DP	PA
ITEM 1	1.00	—	—
ITEM 2	0.92 (0.05)	—	—
ITEM 3	19.16 0.98 (0.05)	—	—
ITEM 6	18.75 0.81 (0.05)	—	—
ITEM 8	15.55 1.20 (0.05)	—	—
ITEM 13	22.34 1.01 (0.05)	—	—
ITEM 14	19.17 0.93 (0.06)	—	—
ITEM 16	16.24 0.76 (0.05)	—	—
ITEM 20	15.82 0.82 (0.04)	—	—
	18.56		

PHI

	EE	DP	PA
EE	1.66 (0.15)		
	10.85		
DP	0.69 (0.08)	0.72 (0.10)	
	8.91	6.95	
PA	-0.25 (0.04)	-0.18 (0.03)	0.17 (0.03)
	-6.84	-6.51	5.15

THETA-DELTA

ITEM 1	ITEM 2	ITEM 3	ITEM 6	ITEM 8	ITEM 13	ITEM 14	ITEM 16	ITEM 20
1.10 (0.07)	1.07 (0.07)	1.32 (0.09)	1.66 (0.10)	0.89 (0.07)	1.28 (0.08)	1.90 (0.12)	1.36 (0.09)	0.96 (0.06)
14.83	15.12	15.27	16.07	13.10	15.12	15.94	16.02	15.33

Note. MBI = Maslach Burnout Inventory; EE = emotional exhaustion; DP = depersonalization; PA = reduced personal accomplishment.

tween the sample and the restricted variance and covariance matrices, the next logical step is to identify the source of misfit in the model. Assessment of model adequacy focuses on two types of information—the residuals and the modification indexes. Although each of the three programs is consistent in providing both types of information, they differ substantially in (a) the amount of default information provided, (b) the manner by which the information is provided, and (c) the methods used in assessing the adequacy of fit.

Residuals

Residual values represent the discrepancy between elements in the sample and those in the restricted variance and covariance matrices; one residual represents each pair of observed variables. Given a well-fitting model, these values will be close to zero and evenly distributed among all observed variables; large residuals associated with particular parameters indicate their misspecification in the model, thereby affecting overall model fit.

AMOS. When working with AMOS, information bearing on the residuals must be specifically requested. However, this task is easily accomplished, once again, by first accessing the “Analysis Properties” dialogue box (as illustrated earlier), and then, selecting the “Output” tab and checking off “Residual Moments.” Residual values are displayed in matrix form in the output file.

EQS. By default, EQS automatically provides the user with abundant information bearing on the residuals. More specifically, the program produces both the unstandardized and standardized residual matrices. For both of these matrices, EQS computes two averages—one based on all elements of the lower triangular matrix, and one that ignores the diagonal elements. Based on an ordering from large to small, the program then lists the 20 largest standardized residuals and designates which pairs of variables are involved. Finally, a frequency distribution of the standardized residuals is presented. Ideally, this distribution should be symmetric and centered around zero.

LISREL. The LISREL program, by default, provides summary statistics, only, related to both unstandardized and standardized residuals. Specifically, the information provided for both unstandardized and standardized residuals is as follows: identification of the smallest, median, and largest residual values; a stem-leaf plot showing their distribution; and both the largest negative and largest positive residuals, complete with variable labels. The program, however, does not automatically provide information on residuals at the matrix level. Nonetheless, this addition can be requested including the keyword *RS* on the Output line.

Modification Indexes

The second type of information related to misspecification serves to pinpoint areas of possible misfit in the model. Although both AMOS and LISREL use a univariate approach in testing for these malfitting parameters, EQS uses a multivariate approach. The impact of this discrepancy bears on the manner by which a researcher respecifies a subsequent model. Because modification index values associated with targeted malfitting parameters can vary substantially with each respecified model, the addition of freely estimated parameters to the model must necessarily occur one at a time. In contrast, the multivariate approach embraced by EQS allows for the concomitant incorporation of several new parameters considered to be theoretically justified in the respecification process.

AMOS. Evidence of misfit, as captured by the modification indexes (MIs) in the AMOS program, can be conceptualized as a χ^2 statistic with one degree of freedom (Jöreskog & Sörbom, 1996b). Specifically, for each fixed parameter specified, AMOS provides a MI, the value of which represents the expected drop in overall χ^2 value if the parameter were to be freely estimated in a subsequent run; all freely estimated parameters automatically have MI values equal to zero. Although this decrease in χ^2 is expected to approximate the MI value, the actual differential can be larger. Associated with each MI is an Expected Parameter Change (EPC) value (Saris, Satorra, & Sörbom, 1987). The EPC represents the predicted estimated change, in either a positive or negative direction, for each fixed parameter in the model and yields important information regarding the sensitivity of the evaluation of fit to any reparameterization of the model.

Extrapolated from the AMOS output file related to the hypothesized MBI model, and shown in Table 10 (AMOS), is a list of suggested misspecified covariances which, in this case, represent error covariances. Accompanying each of these MI values, in column 2, is the expected value of each parameter should it be estimated in a subsequent run. In reviewing these MIs, we see clear evidence of misspecification associated with the pairing of Items 1 and 2 (MI = 93.373) and Items 6 and 16 (MI = 175.606). Details related both to the rationale and justification for the free estimation of these parameters, and to the interpretation of this portion of the output file, can be found in Byrne (2001).

EQS. Determination of malfitting parameters in EQS is accomplished through use of the LMTest. With the inclusion of an “/LMTest” paragraph (as shown in Table 1), the program will yield both univariate and multivariate Lagrange Multiplier (LM) χ^2 statistics related to suggested malfitting parameters; these statistics are analogous to the MIs reported by the AMOS and LISREL programs. Under the univariate LMTest, restrictions in the model are tested independently, and correlations among particular variables are not taken into account. As a

TABLE 10
Selected Modification Indexes From the AMOS, EQS, and LISREL Output Files

(a) AMOS

Covariances	M.I.	Par Change
err7 <-----> err4	40.818	0.175
err12 <-----> PERSONAL_ACCOMPLISHMENT	13.141	-0.065
err12 <-----> EMOTIONAL_EXHAUSTION	73.017	-0.419
err19 <-----> err18	36.140	0.231
err11 <-----> err10	19.088	0.194
err15 <-----> err5	24.104	0.255
err2 <-----> err1	93.373	0.484
err3 <-----> err12	28.113	-0.287
err6 <-----> err5	23.690	0.337
err13 <-----> err12	12.413	0.189
err14 <-----> PERSONAL_ACCOMPLISHMENT	17.587	0.101
err16 <-----> err5	18.385	0.269
err16 <-----> err6	175.606	0.871
err20 <-----> err1	13.813	-0.175

(b) EQS

CUMULATIVE MULTIVARIATE STATISTICS

UNIVARIATE INCREMENT

STEP	PARAMETER	CHI-SQUARE	D.F.	PROBABILITY	CHI-SQUARE	PROBABILITY
1	E16,E6	180.006	1	.000	180.006	.000
2	E2,E1	277.423	2	.000	97.416	.000
3	V12,F1	358.585	3	.000	81.163	.000
4	E11,E10	426.201	4	.000	67.616	.000
5	E7,E4	466.869	5	.000	40.668	.000
6	E19,E18	501.328	6	.000	34.459	.000
7	V16,F2	533.006	7	.000	31.678	.000
8	V14,F3	556.432	8	.000	23.426	.000
9	E6,E5	579.047	9	.000	22.615	.000
10	E13,E12	600.474	10	.000	21.427	.000

(c) LISREL

MODIFICATION INDEXES FOR THETA-DELTA

	ITEM1	ITEM2	ITEM3	ITEM6	ITEM8	ITEM13
ITEM1	—					
ITEM2	102.98	—				
ITEM3	3.44	1.07	—			
ITEM6	8.64	7.98	0.22	—		
ITEM8	0.08	0.20	1.34	4.74	—	
ITEM13	1.93	6.96	3.74	0.91	2.03	—
ITEM14	1.14	13.97	0.04	7.09	4.22	13.64
ITEM16	16.02	17.60	7.11	179.98	0.54	0.49
ITEM20	15.07	17.74	1.83	1.98	14.22	16.04
ITEM5	1.96	4.17	5.03	23.72	5.54	0.03
ITEM10	0.43	0.85	6.48	0.32	2.75	1.90
ITEM11	0.80	0.77	0.14	3.22	3.75	1.71

result, there are typically more statistically significant LM χ^2 s under this test than under the multivariate test. Thus, it is considered more judicious to base model respecifications on the multivariate LMTest.

In evaluating the multivariate LM statistics reported in the output, it is important to note that these statistics are two or three, and so forth, degrees of freedom χ^2 tests and, as such, predict the expected drop in χ^2 due to freeing up two or three fixed parameters, respectively. However, often their absolute magnitude is not as important as their relative size, which can then serve as a means to measuring the relative importance of one against the others in pinpointing possible malfitting parameters. Typically, one looks for a substantial drop in the reported univariate incremental LM statistic values and uses this point as the cutoff for determining which parameters should be freely estimated in a subsequently respecified model. In reviewing the related portion of the output shown in Table 10 (EQS), it is easy to see that the first two parameters (E16, E6; E2, E1) are substantially larger than those that follow. These findings are consistent with those of AMOS in pinpointing error covariances between Items 6 and 16, and between Items 1 and 2. Although the third parameter (V12, F1) appears, also, to be a possible candidate for free estimation, this fixed parameter was not released, in the interest of parsimony.

LISREL. As noted earlier, the LISREL program uses the same univariate approach to targeting malfitting parameters as AMOS. In contrast to the manner by which these results are reported in the AMOS output, however, LISREL presents the MI values in matrix form. Shown in Table 10 (LISREL) is the portion of the error variance/covariance matrix (THETA-DELTA) in which the MI values related to the two previously noted error covariances have been highlighted.

OTHER IMPORTANT ISSUES

Treatment of Missing Data

Increasingly recognized as a critical issue in SEM is the presence of missing scores, and the capability of software packages to deal with such incomplete data. Because incomplete data can seriously bias conclusions drawn from an empirical study, they should be addressed, regardless of the reason for their missingness. The extent to which such conclusions can be biased depends on both the amount and the pattern of missing values. Unfortunately, to the best of my knowledge, there are currently no clear guidelines regarding what constitutes a “large” amount of incomplete data. On the other hand, guidelines related to the pattern of incomplete data are now widely cited and derive from the seminal works of Rubin (1976), Allison (1987), and Little and Rubin (1987). Each of the three computer programs reviewed here varies, both in the manner by which it approaches the task, and in the

number of methods made available to the user. (For a review of the literature related to the topic of missing data, and an extensive discussion of the advantages and disadvantages of each method, readers are referred to Byrne, 2001; for illustrated example applications, as they pertain to AMOS and LISREL, see Byrne, 2001, 1998, respectively.)

AMOS. The single method used in dealing with missing data in AMOS represents a direct approach based on full-information maximum likelihood estimation. It is direct in the sense that analyses are undertaken with no attempt to restore the data matrix to rectangular form, as is the case with methods involving imputation and weighting (Gold & Bentler, 2000); the latter are termed indirect methods. In contrast to the more commonly-used indirect methods, the maximum likelihood approach is considered to be theoretically-based, and has been shown to offer several advantages over the other methods (Arbuckle, 1996; Arbuckle & Wothke, 1999).

EQS. In addition to allowing for listwise (i.e., casewise) deletion, EQS offers several approaches to the handling of missing data; these include mean-based and regression-based imputation (indirect methods), as well as the direct method of maximum likelihood estimation. More specifically, estimation of missing values is based on the expectation maximization method which has recently been shown to outperform other missing data procedures, regardless of sample size, proportion of missing data, and distributional characteristics of the data (Gold & Bentler, 2000). An important feature of EQS is that, based on the results reported by Yuan and Bentler (in press), the program now also computes robust statistics for this method. If there are no missing data, the statistics are the same as those provided for the Satorra-Bentler methods.

An invaluable additional feature of the EQS program is its extensive diagnostic capabilities for mapping both the amount and pattern of incomplete data. Each of these tasks is easily accomplished, interactively, via the "Missing Data" dialogue box and the "Analysis" pull-down menu.

LISREL. The task of dealing with incomplete data in LISREL must actually be performed using the PRELIS program (Jöreskog & Sörbom, 1996b). As such, it provides for both listwise and pairwise deletion of missing data, as well as for the imputation of missing values based on a system that matches cases. With pattern-matching imputation, a missing value is replaced with an observed score from another case in the data for which the response pattern is similar across all variables. The primary limitation of this procedure is that, in the event that no matching case is determined, then no imputation is performed. As a consequence, the researcher is still left with a proportion of the data that is incomplete. A second limitation in the PRELIS approach arises when the set of variables on which the pro-

cess of matching is based, overlaps with the set of variables for which one wishes to impute values. Because an existing imputed value can be used as a matching variable in the imputation of another variable, the ordering of the variables can lead to differential results (Gold & Bentler, 2000; Jöreskog & Sörbom, 1996a). Indeed, these limitations of the pattern-matching procedure associated with LISREL severely restrict its usefulness in practice.

Treatment of Nonnormal Data

One critically important assumption associated with the SEM methodology is the requirement that the data have a multivariate normal distribution. Violation of this assumption can seriously invalidate statistical hypothesis-testing such that the normal theory test statistic may not reflect an adequate evaluation of the model under study (Hu, Bentler, & Kano, 1992; West, Finch, & Curran, 1995). In this regard, once again, the three programs vary in their approach to addressing the non-normality issue. (For a summary of consequences related to the use of nonnormal data in SEM, readers are referred to Byrne, 2001; West et al., 1995. For illustrated example applications using AMOS and LISREL, see Byrne, 2001, 1998, respectively; illustration of the EQS approach was presented earlier.)

AMOS. One approach to handling the presence of multivariate nonnormal data is to use a procedure known as “the bootstrap” (see West et al., 1995; Yung & Bentler, 1996); this is the approach taken by the AMOS program. Bootstrapping serves as a resampling procedure by which the original sample (“parent sample”) is considered to represent the population. Multiple subsamples of the same size as the parent sample are then drawn randomly, with replacement, from this population. These subsamples then provide the data for empirical investigation of the variability of parameter estimates and indexes of fit. The considered advantage of this approach is that it allows the researcher to assess the stability of parameter estimates and thereby report their values with a greater degree of accuracy.

EQS. As illustrated and discussed earlier, EQS focuses on the presence of multivariate kurtosis and allows for the computation of the Satorra-Bentler ² (Satorra & Bentler, 1988), a scaled statistic that takes this nonnormality into account. Correction is made to both the original ² statistic and the standard errors associated with each estimated parameter, thereby allowing for a more appropriate interpretation of findings. These corrected statistics have recently been extended to incomplete data (Yuan & Bentler, in press) and are now available in the most recent version of the EQS program. In addition, bootstrap statistics are available with use of the “/SIMULATION” option.

LISREL. A third approach to dealing with multivariate nonnormal data is the use of asymptotic (i.e., large-sample) distribution-free (ADF) methods for which normality assumptions are not required (Browne, 1984); this is the approach taken by LISREL. This strategy, however, involves a two-step process. First, using PRELis, the researcher recasts the data into asymptotic matrix form. LISREL analyses are then based on this matrix using weighted least squares estimation. Unfortunately, the major limitation associated with the ADF method is its excessively demanding sample size requirement which severely restricts its usefulness, thereby rendering the approach as quite impractical for most researchers.

Treatment of Categorical Data

A second important assumption associated with SEM is the requirement that all variables be of a continuous scale. However, given that psychological data in general, and assessment data in particular, are typically of ordinal scale, this issue has long been the topic of arduous debate in the literature. Although use of the distribution-free method is widely recognized as an appropriate estimation procedure in this regard, its very stringent and impractical sample size requirements (as noted earlier) have precluded its widespread use. Indeed, findings from numerous Monte Carlo studies have led Bentler and Chou (1987; see also, West et al., 1995) to conclude that, given normally distributed categorical variables having more than four categories, continuous methods can be used with little need for concern. (For an expanded discussion of issues related to the treatment of categorical data in SEM, and for an illustrated example application using LISREL, see Byrne, 1998.)

AMOS. As yet, the AMOS program is unable to recognize the categorical scaling of variables.

EQS. The EQS program allows for the analysis of models that have categorical, as well as continuous, measured variables (Bentler, 2000). Based on the estimation of polychoric and polyserial correlation matrices, and modified statistics drawn from the work of Lee, Poon, and Bentler (1994), the most recent version of the program can now handle 200 categorical variables. Other than needing to identify the variables that are of categorical scale, model specification remains basically the same as when the variables are either truly continuous, or are treated as if they were continuous. Once the program knows that the analysis involves categorical variables, it automatically determines the number of categories for each related variable, and then computes the correct correlation coefficient (polychoric or polyserial) on which the analyses will be based. These determined categories, along with their coefficients, are reported in the output file. Furthermore, EQS now allows for estimation with normal theory maximum likelihood, and then provides

the robust ² and standard errors for correct statistical inference. This approach is recommended for all but the largest sample sizes.

LISREL. The approach taken by the LISREL program to the analysis of categorical variables is based on the distribution-free estimation procedure, as outlined earlier. As such, the excessively restrictive requirements associated with this strategy, as previously cited, represent its major weakness.

CONCLUSION

The purpose of this article was to provide a comparative review of three of the most widely-used SEM computer programs: AMOS, EQS, and LISREL. For illustrative purposes, an application based on a study of the MBI (Maslach & Jackson, 1986), with particular reference to elementary school teachers (Byrne, 1993), was used to facilitate the comparison of various program features. Finally, the review examined the approach taken by each program in dealing with the presence of missing, nonnormal, and categorical data. Undoubtedly, limitations of space associated with an article of this kind necessarily preclude a comprehensive review of each program. For greater detail pertinent to each of the features targeted here in particular, as well as to other aspects of each program in general, readers are referred both to their related technical manuals, and to the books specifically designed to illustrate aspects of each program, as cited in this article. Overall, however, it is hoped that this comparative review has provided the reader with a more informed insight, albeit modest, into key elements of the AMOS, EQS, and LISREL programs that are linked to applications of SEM within the framework of a CFA model.

REFERENCES

- Allison, P. D. (1987). Estimation of linear models with incomplete data. In C. Clogg (Ed.), *Sociological methodology 1987* (pp. 71–103). San Francisco: Jossey-Bass.
- Arbuckle, J. L. (1996). Full information estimation in the presence of incomplete data. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: Issues and techniques* (pp. 243–277). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Arbuckle, J. L. (1999). *Amos 4.0* [Computer software]. Chicago: Smallwaters.
- Arbuckle, J. L., & Wothke, W. (1999). *AMOS 4.0 user's guide*. Chicago: Smallwaters.
- Bentler, P. M. (1980). Multivariate analysis with latent variables: Causal modeling. *Annual Review of Psychology*, 31, 419–456.
- Bentler, P. M. (2000). *EQS 6 structural equations program manual*. Encino, CA: Multivariate Software Inc.
- Bentler, P. M., & Chou, C.-P. (1987). Practical issues in structural modeling. *Sociological Methods & Research*, 16, 78–117.
- Bentler, P. M., & Wu, E. J. C. (2000). *EQS 6 for Windows user's guide*. Encino, CA: Multivariate Software Inc.

- Bollen, K. A. (1989). *Structural equations with latent variables*. New York: Wiley.
- Browne, M. W. (1984). Asymptotically distribution-free methods for the analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology*, 37, 62–83.
- Browne, M. W., & Mels, G. (1999). *Path analysis: RAMONA. SYSTAT 9.0 for Windows: Statistics II* (pp. 161–219). Chicago: SPSS Inc.
- Byrne, B. M. (1993). The Maslach Burnout Inventory: Testing for factorial validity and invariance across elementary, intermediate, and secondary teachers. *Journal of Occupational and Organizational Psychology*, 66, 197–212.
- Byrne, B. M. (1994). *Structural equation modeling with EQS and EQS/Windows: Basic concepts, applications, and programming*. Thousand Oaks, CA: Sage.
- Byrne, B. M. (1998). *Structural equation modeling with LISREL, PRELIS, and SIMPLIS: Basic concepts, applications, and programming*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Byrne, B. M. (2001). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Gold, M. S., & Bentler, P. M. (2000). Treatments of missing data: A Monte Carlo comparison of RBHDI, iterative stochastic regression imputation, and expectation-maximization. *Structural Equation Modeling*, 7, 319–355.
- Hu, L.-T., Bentler, P. M., & Kano, Y. (1992). Can test statistics in covariance structure analysis be trusted? *Psychological Bulletin*, 112, 351–362.
- Jöreskog, K. G., & Sörbom, D. (1993). *LISREL 8: Structural equation modeling with the SIMPLIS command language*. Chicago: Scientific Software International.
- Jöreskog, K. G., & Sörbom, D. (1996a). *PRELIS 2: User's reference guide*. Chicago: Scientific Software International.
- Jöreskog, K. G., & Sörbom, D. (1996b). *LISREL 8: User's reference guide*. Chicago: Scientific Software International.
- Lee, S.-Y., Poon, W.-Y., & Bentler, P. M. (1994). Covariance and correlation structure analyses with continuous and polytomous variables. In T. W. Anderson, K.-T. Fang, & I. Olkin (Eds.), *Multivariate analysis and its applications: Vol. 24* (pp. 347–358). Hayward, CA: Institute of Mathematical Statistics.
- Little, T. D. (1997). Mean and covariance structures (MACS) analyses of cross-cultural data: Practical and theoretical issues. *Multivariate Behavioral Research*, 32, 53–76.
- Little, R. J. A., & Rubin, D. B. (1987). *Statistical analysis with missing data*. New York: Wiley.
- Maslach, C., & Jackson, S. E. (1981). *Maslach Burnout Inventory manual*. Palo Alto, CA: Consulting Psychologists Press.
- Maslach, C., & Jackson, S. E. (1986). *Maslach Burnout Inventory manual* (2nd ed.). Palo Alto, CA: Consulting Psychologists Press.
- Muthén, L. K., & Muthén, B. O. (1998). *Mplus users' guide*. Los Angeles: Authors.
- Neale, M. C., Boker, S. M., Xie, G., & Maes, H. H. (1999). *Mx: Statistical modeling* (5th ed.). Richmond, VA: Virginia Commonwealth University, Department of Psychiatry.
- Rubin, D. B. (1976). Inference and missing data. *Biometrika*, 63, 581–592.
- Saris, W. E., Satorra, A., & Sörbom, D. (1987). The detection and correction of specification errors in structural equation models. In C. Clogg (Ed.), *Sociological methodology 1987* (pp. 105–130). San Francisco: Jossey-Bass.
- SAS Institute Inc. (1992). *The CALIS procedure extended user's guide*. Cary, NC: Author.
- Satorra, A., & Bentler, P. M. (1988). Scaling corrections for chi-square statistics in covariance structure analysis. *American Statistical Association 1988 Proceedings of the Business and Economics Section* (pp. 308–313). Alexandria, VA: American Statistical Association.
- West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables: Problems and remedies. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 56–75). Thousand Oaks, CA: Sage.

- Yuan, K.-H., & Bentler, P. M. (in press). Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology* 2000.
- Yung, Y.-F., & Bentler, P. M. (1996). Bootstrapping techniques in analysis of mean and covariance structures. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: Issues and techniques* (pp. 195–226). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.