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ABSTRACT

This paper provides theoretical and practical information about using structural equation modeling (SEM) techniques. The first section discusses the theory of SEM, including five general steps: (1) model specification; (2) model identification; (3) model estimation; (4) testing model-fit; and (5) model respecification. The second section applies these steps to an empirical example using data from a Federal Emergency Management Agency study of the effectiveness of stress debriefings. (Contains 4 figures and 40 references.) (Author/SLD)

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A BRIEF INTRODUCTION TO STRUCTURAL EQUATION MODELING TECHNIQUES: THEORY AND APPLICATION

by

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This paper provided theoretical and practical information in using structural equation modeling techniques. The first section discussed the theory of SEM including five general steps-- model specification, model identification, model estimation, testing model fit, and model respecification. The second section applied these steps to an empirical example.

Introduction

Scientists have developed statistical methods that help them investigate social and physical phenomena. First, descriptive statistics were developed to describe the phenomena. However, researchers were interested in more than a description. They also wanted to understand relationships among constructs. Inferential statistics were used to infer population characteristics from a sample(s). In the 1920s, Sewall Wright developed the path analysis method to analyze genetic theory in the field of biology. This method examined data fit to a theoretical model. Path analysis employed some of the existing statistical techniques (i.e., multiple regression analysis) but was considered as having distinct advantages over them because it could study direct and indirect effects of variables under investigation (Schumacker & Lomax, 1996). Path analysis is used to test theories about "hypothesized causal relationships"; however, it is not a methodology of discovering of causes (Olson, 1985; Schumacker & Lomax, 1996). This model, however, was not without limitations. The greatest limitations were the assumptions of unidirectional flow that precluded testing for non-directional relationships and the exclusion of error terms. Specifically, the path analysis method assumes no measurement or specification error in the specified model. It assumes that each measure is the exact manifestation of the construct (Maruyama, 1998; Pohlmann, 1991). These assumptions are not supported easily in social sciences. A newer technique, structural equation modeling, was developed to overcome these problems.

Structural Equation Modeling

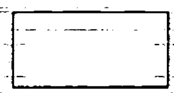
Structural Equation Modeling (SEM) is defined as "a comprehensive approach to testing hypothesis about relations among observed and latent variables" (Hoyle, 1995). Latent-variable analysis and linear structural analysis are other commonly used names for SEM (Duncan, 1975). The methodology of SEM are derived mostly from the work of Karl Jöreskog and his associates (King, 1997) and regarded as one of the most important and influential statistical revolutions (Cliff, 1983). SEM techniques are being employed in a variety of disciplines such as biology, business, education, and social sciences including sociology and psychology (Marcoulides and Schumacker, 1996). The essence of these models is that observed variables, variables that can be directly observed and measured such as heart-beat, are set to define a latent forming variable that cannot be observed directly (i.e., anxiety). In the process of structural models, univariate and multivariate regression models, confirmatory factor analysis, recursive and non-recursive models, covariance structure analysis, and path analysis models can be used (Jöreskog & Sörbom, 1986; Marcoulides & Schumacker, 1996). Thus, like the statistical techniques noted above, SEM is a linear model, which can evaluate statistically most research hypotheses in social sciences (Hoyle, 1995). Different from path analysis, SEM allows bi-dimensional flow among variables and takes measurement and specification errors into account.

Three general types of relationships can be defined in SEM. One is association that indicates a non-directional relation such as correlation. The second type is directional relationships, where a variable directly affects the outcome variable (i.e., multiple regression models). The last type is indirect effect, which describes the effect of an independent variable on a dependent variable through one or more intervening variables (Hoyle, 1995). For example, the effect of coping on anxiety might be through a construct like Negative Affectivity (see the sample model p.16). Indirect effect indicates an ability to treat a single variable as both a dependent and an independent variable. In this sense, structural equation models are described by the path models of latent variables (Jöreskog & Sörbom, 1986). However, structural equation models combine the measurement model(s) with the structural model. In these cases, the measurement model describes which measurable (observed) variables define a latent variable (construct); and, the structural model prescribes relationships between the latent variables (Pedhazur & Schmelkin, 1992). Several steps are suggested in the development of the measurement and the structural models that might employ one or all of the three types of relationships (i.e., association, direct, and indirect). Most structural equation models can be developed in either 5 (Bollen & Long, 1993) or 7 (Hair, Anderson, Tatham, & Black, 1995) steps. This paper will describe the 5-step model. These steps are: (a) model specification, (b) model identification, (c) model estimation, (d) testing model fit, and (e) respecification of the model. The following describes each of these 5 steps in detail.

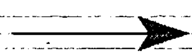
Structural equation models start with the specification of a model to be estimated. A model is "a statistical or visual representation about the relationships among latent and observed variables" (Wang, 1998, p.65). Models are specified based on a theory or as a result of an extensive literature of review of empirical findings. As mentioned before, there are two general models in SEM: the measurement model(s) and the structural model. In the measurement model(s), both dependent and independent latent variables are prescribed. Because latent variables cannot be directly measured, they are inferred from other directly measurable variables. The measurement models identify which measurable variables define a construct (latent variable). After the measurement models are specified, structural models are designed for the prediction of dependent variable(s). The structural models prescribe relations between latent and observed variables that are not indicators of latent variables (Schumacker & Lomax, 1996).

A second step in SEM is model identification. When identifying a model, a crucial decision concerns with "the correspondence between the information to be estimated and the information, from which it is to be estimated" (Hoyle, 1995). The structural equation models can be specified through confirmatory factor analysis, model generation, or model comparison strategies. Existing models can be investigated and tested on a specific sample through confirmatory factor analysis strategies; or, if there is not an existing model, in the lights of a specific theory, a model can be generated and tested for fit. Finally, more than one existing or generated models can be specified for comparison through model comparison strategies. In specifying a model, the structures of observed and latent variables and the relationships among them can be described in path diagrams. In the notation of the structural equation modeling diagrams, circles indicate latent variables and rectangles indicate manifest variables. The relationships among latent variables and/or manifest variables are shown by theory-driven directional or non-directional arrows. Single-headed arrows illustrate directional relationships between (a) latent variables and their manifest indicators, (b) structure coefficients that connects latent variables, (c) relationships between measurement errors, and (d) errors and their corresponding variables. Double-headed arrows indicate covariance or non-directional relationships among (a) the independent latent variables, (b) the equation prediction errors, and (c) the measurement errors. The following shows the most commonly used notations in a structural equation diagram.

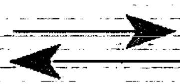
Latent Variable



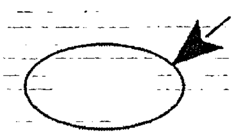
Observed Variable



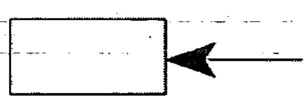
Recursive (unidirectional) relation



Nonrecursive (bidirectional) relation



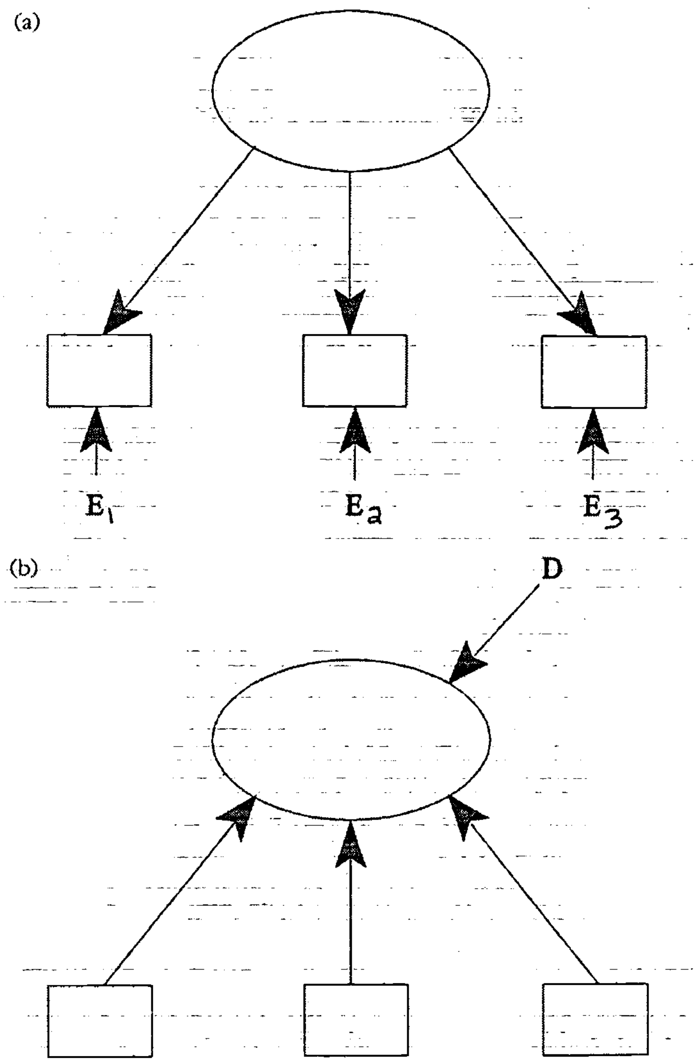
Disturbance or structual error in latent variable



Measurement error in observed variable

Correlational (symmetric) relation

In addition, there are two types of general models. Path diagrams can represent the common factor model (a) or the principles component model (b).



In either model, the numerical values associated with directional effects are values of regression coefficients. Numerical values associated with non-directional relationships are covariance or correlation values. These regression weights and covariances are called model parameters. A major objective in the SEM is to estimate the parameter values. Diagrams also include errors of the exogenous and the latent variables. Variables that receive a directional influence are called <u>endogenous variables</u>, while variables that do not receive a directional influence are called <u>exogenous variables</u>. Hoyle (1995) pointed out that directional arrows are sometimes incorrectly interpreted as indicating "causal" directionality, even though "...SEM cannot be used to test the hypothesis of directionality because directionality is a form of association distinguished from non-directional association either by logic, theory, or research design (i.e. experimental designs)" (Hoyle, 1995, pp. 10-11). Once a model is specified in terms of directional and non-directional relationships, the next step is to decide whether the parameters will be free, fixed, or constrained. A parameter is called free when it is unknown and to be estimated, whereas a fixed parameter is fixed at a constant value (i.e. 0 or 1). A constrained parameter is not known but set to equal other parameters. The ratio of the number of variables in the model to the number of unknown parameters is also important in model specification. In other words, model identification is the process of ratio determination. The number of independent variables must be less than or equal to the distinct values that describe relationships among variables and constructs. Schumacker and Lomax (1996) indicated three different identification types. If all the parameters are uniquely determined with just enough information, then the model is a "just-identified" one and has zero degrees of freedom. If there is more than enough information; therefore there is more than one way of estimating a parameter, then the model is "over-identified". If one or more parameters may not be uniquely determined because of the lack of information, then the model is "under-identified".

One way of checking whether the model is identified correctly is the Wald Test (See page 12). SEM computer software programs also check to determine whether the model is specified; if not, they do not produce a unique solution (Maruyama, 1998). Another way to check model identification is suggested by Jöreskoq and Sörbom as following:

"Analyze the sample covariance matrix, S, and save the estimated population matrix Σ. The second step is to analyze the estimated population matrix Σ. If the model is identified, then the estimates from both analyses should be identical" (Schumacker & Lomax, 1996, p.102).

After specifying and identifying a model, the third step is to estimate model parameters. As mentioned before, the parameters of SEM are regression coefficients and variance/covariances of independent variables. Again, model parameters are not known but have to be estimated after a model has been specified. There are three most commonly used estimation models: Maximum Likelihood (ML), Generalized Least Square (GLS), and Asymptotic Distribution Free (ADF). The first two methods require multivariate normality, while ADF does not require that data be normally distributed. Some researchers (i.e., Hoyle, 1995) suggested that the ML estimation technique can be employed, even though multivariate normality is not completely met because "ML estimates are quite robust to the violation of normality" (Hoyle, 1995, p. 38). In support of Hoyle (1995), Mueller (1997) suggested ML estimate as one of the best estimation techniques. Another important consideration with the model estimation is the sample size. Schumacker and Lomax (1996) indicated that ML and GLS estimation methods were scale-free. With the interpretation of parameters, Hoyle (1995), again, indicated that SEM results cannot be used for inferring causality because SEM only tests the relations among variables as they were assessed.

Once model parameters are obtained, the fourth step is to test the model fit. Model fit is tested by comparing the predicted model covariance with the sample covariance matrix. In other words, "the degree to which the structural equation model fits the sample data" is model fit (Schumacker & Lomax, 1996, p.124). A model is said fit to the extent that its covariance matrix is similar to that of a sample covariance matrix. When assessing model fit, there are two types of fit indices: the measures of incremental fit and the measures of absolute fit. Without getting into detail, a summary of these indices is provided below.

The incremental fit indices quantify accounted for variance. Some of the incremental fit indices are the Incremental Fit Index (IFI; Bollen, 1989), the Comparative Fit Index (CFI; Bentler, 1990), the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973), the Relative-Noncenterality Index (RNI), and the Normed Fit Index (NFI; Bentler & Bonett, 1980). Hoyle (1995) evaluated most incremental fit indices. He reported that

1. the NFI was not a good indicator for evaluating model fit when sample size is small,
2. under dependency condition, the mean values of the CFI and the Bentler Fit Index (BFI) based on ML and GLS methods were not associated with sample size. When latent variables were dependent the TLI behaved erratically across three estimation methods at sample size 5000 or less; and, the Adjusted Goodness-of-fit Index (AGFI) behaved relatively consistently across ML and GLS at n>500. Under independency condition, McDonald's Centrality Index (MCI) was not associated with sample size on ML and GLS, and
3. when latent variables were independent, the AGFI performed consistently across ML and GLS. At n>250, the AGFI behaved consistently across all three estimators.

Finally, Hoyle (1995) concluded that, in most cases, fit indexes obtained by ML would perform much better than other estimation methods such as GLS and ADF. When there is dependence, n>250, GLS based GFI and ML based BFI, CFI, BL89, and TLI perform relatively adequately.

The second types of fit indices are the absolute fit indices. The absolute fit indices assess the degree to which the hypothesized model covariances match with the observed covariences. Some of the absolute fit indices are χ^2 Goodness-of-Fit test, the Satorra-Bentler Scale Index, the Goodness-of-Fit Index (GFI; Jöreskog and Sörbom (1988), the Adjusted Goodness-of-Fit Index (AGFI), and the Root Mean Square Error Approximation (RMSEA). A χ^2 value indicates the degree to which observed and estimated matrices differ. A significant χ^2 would mean that there is a difference between the estimated and observed matrices. A non-significant χ^2 would indicate that the data fit the model. While an RMSEA $\leq .05$ is a standard cut-off score for model fit, RMSEA $\leq .08$ would still be an acceptable error approximation. RMSEA $\geq .10$ would suggest not using the model (Bentler & Bonnet, 1992).

Different models can be compared for the same sample group by specifying nested models. "Nested models contain the same parameters but the set of free parameters in one model is a subset of the free parameters in the other. A χ^2 statistic can be used to determine which model better accounts for the sample data" (Wang, 1998, p. 68).

The last step is model respecification. After the initial investigations, a model can be respecified to improve its fit. There are different measures of assessing whether the modified model improved the previous model. For example, when deciding whether the changes in a model improve or deteriorate model fit, the Wald Test can be used to determine the degree to which fit would deteriorate (or improve), if any selected parameters are dropped from the model (i.e. converted into fixed parameters with values of zero). Additionally, the Lagrange Multiplier Test can be used to determine the degree to which fit will improve, if additional parameters are included in the model (Hoyle, 1995). Other than employing these modification tests, another way to test whether the modified model will improve model fit is cross-validation. Independently drawn samples can be used to check model modification. While an hypothesized initial model can be improved by modifying the existing model, model modifications have to be done with caution because "the model modification processes appear to be sensitive to characteristics of the sample at hand and generalization beyond that sample is highly suspect unless sample size is extremely high" (Hoyle, 1995, p. 34). Above-mentioned 5 steps are general. They should be considered as guidelines.

Computer applications have made several of these steps easier, thus contributing to the wider use of SEM. Some of the computer software programs that are based on SEM techniques will be described briefly to give the reader a sense of what they do.

The most commonly used computer programs for structural equation modeling are AMOS/AMOSDraw (Arbuckle, 1997), Linear Structural Relations (LISREL8; Jöreskog & Sörbom, 1993), PRELIS2 (Jöreskog & Sörbom,1993b), Equations (EQS; Bentler, 1993), CALIS (SAS Institute), LISCOMP (Muthen), and Mx (Neal), and SEPATH (Steiger). AMOS is developed by James Arbuckle and currently being distributed by SPSS, Inc. Amos implements structural modeling by using the method estimates such as ML, Unweighted Least Squares, Generalized Least Squares, and Scale-Free Least Squares. One of the distinguishing features of Amos is that it can compute full information ML estimates even if data are missing. Like EQS, Amos can use path diagrams as model specification and displays parameter estimates graphically on a path diagram (Arbuckle, 1997). The EQS, another widely used SEM program, was developed by Peter Bentler and distributed by Multivariate Software, Inc. Tabachnick and Fidell (1996) evaluated the EQS as clear, well-organized, very user friendly. As a unique feature, EQS offers model modification procedures such as the Wald Test and the Lagrange Multiplier Tests. The decision to choose one of these software packages depends on preferences related to data characteristics.

This section provided a brief introduction to SEM techniques, including a short history of statistical techniques, description of the general steps of the structural equation modeling, and commonly used computer software applications. The next section provides an application of SEM techniques on a real data set. One of the most common SEM software packages, the EQS will be employed in this application.

An Application of SEM Techniques

The Federal Emergency Management Agency (FEMA) data set (Harris & Stacks, 1998) was chosen for this application. First, a brief description of the FEMA data set will be provided. Next, a complete SEM model will be developed and tested through the 5-step model (Bollen & Long, 1993) with the exception of model modification.

The FEMA study investigated the effectiveness of stress debriefings by integrating crisis theory and post-traumatic stress disorder models (Harris and Stacks, 1998). Briefly, crisis theory proposes that in stressful situations, certain balancing factors can help an individual regain his 'equilibrium' (Aguilera, 1994). These factors are the individual's beliefs about the world, available situational supports, and coping mechanisms. Additionally, post-traumatic stress disorder (PTSD) studies typically measure intrusion, avoidance, and arousal as the three effects of exposure to severe trauma (Horowitz, Wilner, & Alvarez, 1979). The FEMA study employed seven standardized instruments to assess the three 'balancing factors' of social support, beliefs, coping, post traumatic stress disorder symptoms of intrusion and avoidance, and the symptoms of anxiety and depression (Harris and Stacks, 1998). The following assessment instruments were used to assess the constructs: the Perceived Social Support Scale (Procidano & Heller, 1983), the World Assumptions Scale (Janof-Bulman, 1989), the Ways of Coping Questionnaire (Folkman & Lazarus, 1988), the Hospital Anxiety Scale (Zygmond and Snaith, 1983), the Impact of Events Scale (Horowitz, 1979), and the Evaluation of Debriefing Scale (Harris & Stacks, 1998).

For the purpose of this application, the FEMA study data file was transferred onto the EQS computer software. Before the analyses, two types of assumptions were tested. These assumptions included multivariate normality and independency. Schumacker and Lomax (1996) indicated that "if multivariate normality of the observed variables can be assumed, then moments beyond the second (i.e. skewness and kurtosis) is safely ignored; but, when normality assumption is violated, parameter estimates are at suspect" (p. 104). Even though Harris and Stacks (1998) reported problems with skewness and kurtosis in this data set, this did not seem to be a problem according to House (1996).

After checking the assumptions of SEM, several measurement models needed to be generated. To develop these measurement and the structural models, theoretical background information provided by the investigators was used. Four measurement models were developed. The first measurement model (Ways of Coping) described the ways of coping by two observed variables, namely problem solving and escape-avoidance. The original Ways of Coping Questionnaire has eight scales but recent research indicated that problem-solving and escape-avoidance were the most significant scales (Stacks, 1998). The second measurement model (Negative Affectivity) was predicted by three observed variables, depression, world assumptions, and social support. Finally, the third measurement model (PTSD) predicted PTSD from intrusion and avoidance. After the measurement models developed, a structural model was defined. This model assumed that PTSD was a separate construct from general negative affectivity. The model also assumed that anxiety was a manifestation of both PTSD and Negative Affectivity. Anxiety was used as the only endogenous variable in the structural model. It was hypothesized that world assumptions, social support and depression would be related to Negative Affectivity. Also, Ways of Coping would be a separate factor, which would affect Negative Affectivity. Intrusion and avoidance would be related to PTSD. Finally, both PTSD and Negative Affectivity would have some effect on anxiety. Figure 1 shows the initial measurement models and the structural model.

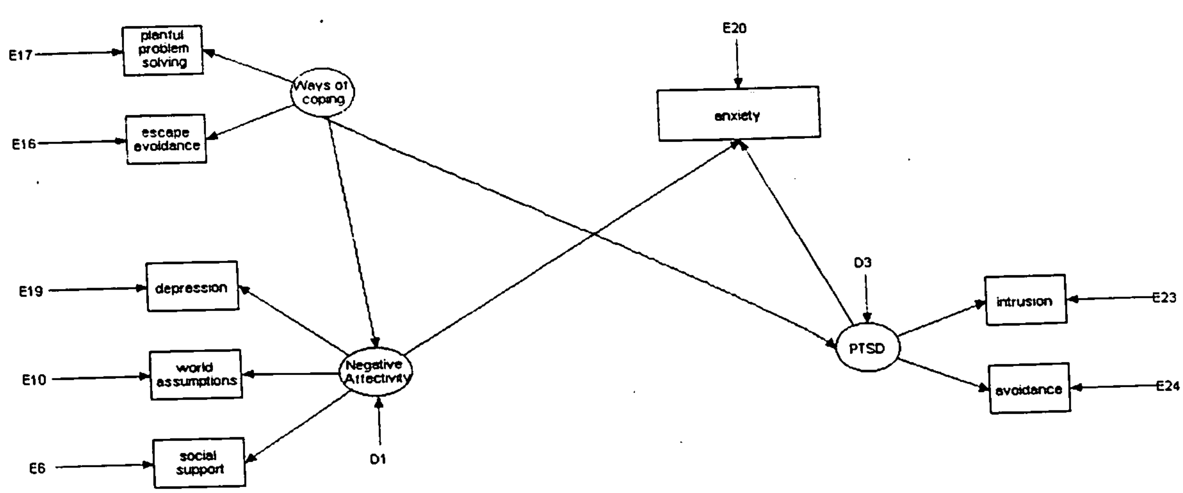


Figure 1. Model specification

In model identification step, all parameters were set unknown and to be estimated. The numbers of independent variables were less than the distinct values in the model. Thus, this model was a "just-identified" model. Figure 2 shows the specified model.

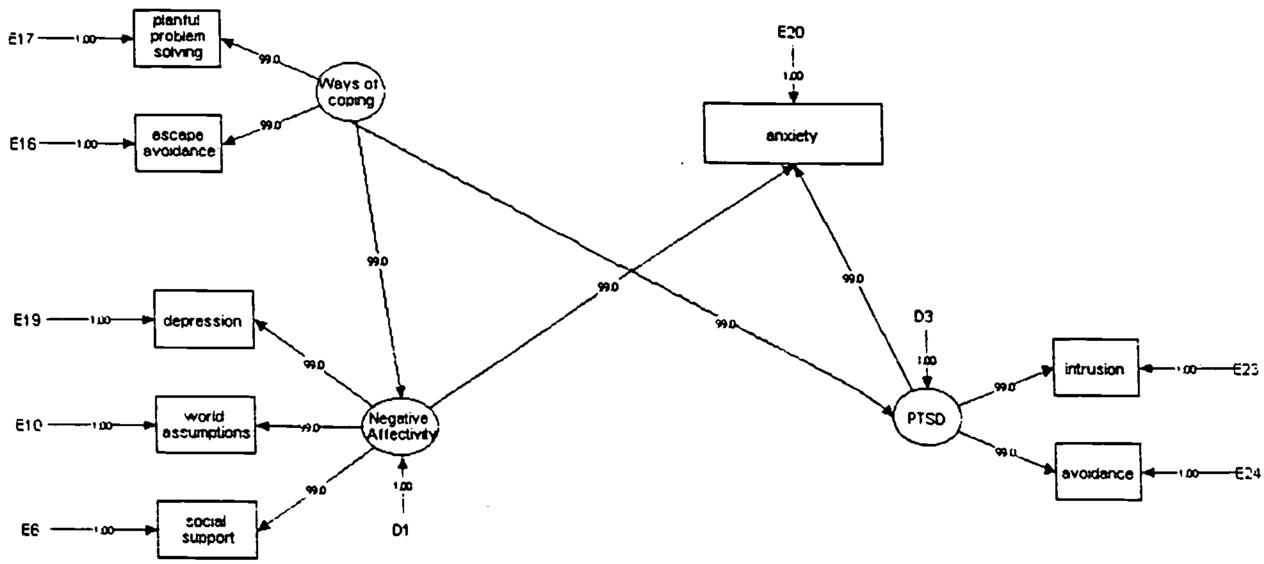


Figure 2. Model identification values

After preliminary data screening and dealing with missing data, the specified model was run on the EQS. The model included ten dependent variables (eight dependent variables–Planful Problem Solving, Escape-Avoidance, Depression, World Assumptions, Social Support, Anxiety, Intrusion, Avoidance -- and two dependent factors – Negative Affectivity and PTSD) and eleven independent variables (one independent factor – Ways of Coping--, two independent disturbances-errors of factors-, and eight independent errors). First, univariate and multivariate statistics such as means, standard deviations, skewness, and kurtosis were computed. Z-scores for kurtosis were significant for escape-avoidance, planful problem solving, and intrusion scales. Significant z-scores for skewness were for scales measuring social support, planful problem solving, anxiety, intrusion, and avoidance. The normalized estimate score for multivariate kurtosis was

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28.29, which suggested that the data were not normally distributed. Because of these reasons, the distribution-free fit indices might be more realistic in testing the model fit. Individual cases were investigated to reveal which case(s) contributed to the nonnormalized multivariate kurtosis. Case numbers 90, 124, 196, and 769 were the highest contributions to nonnormalized multivariate kurtosis. The case number 124 was the highest contributor (an estimate of 10755). Such a deviant case might be eliminated from the analyses. The determinant of the input matrix was found to be .4098E+13, which indicated that there was no singularity problem. After these preliminary investigations and modifications, the model was estimated.

In model estimation stage, even though preliminary analyses suggest deviations from multivariate normality, ML estimation method was used to predict the model parameters because the sample size was sufficiently large (n=770). With the large samples, the ML estimations are quite robust with the violation of normality (Hoyle, 1995). The EQS program was run; and, correlation coefficients, covariances, residual matrices, unstandardized parameter estimates, and standardized solutions were obtained along with the model fit indexes. Figure 3 shows unstandardized parameter estimates, where the parameters are regression coefficients. All but two parameter estimates were significant. Planful problem solving and escape-avoidance strategies contributed significantly to ways of coping (-4.01 and .404, respectively). While social support (-3.70) and depression (1.79) contributed significantly to negative affectivity, world assumptions was not a significant contributor. Avoidance was the only factor that was a significant contributor to PTSD (.70). Both negative affectivity (1.79) and PTSD (.09) significantly influenced anxiety. Ways of coping was a significant contributor to both negative affectivity (.82) and PTSD (3.23). Standardized solutions also showed these relationships.

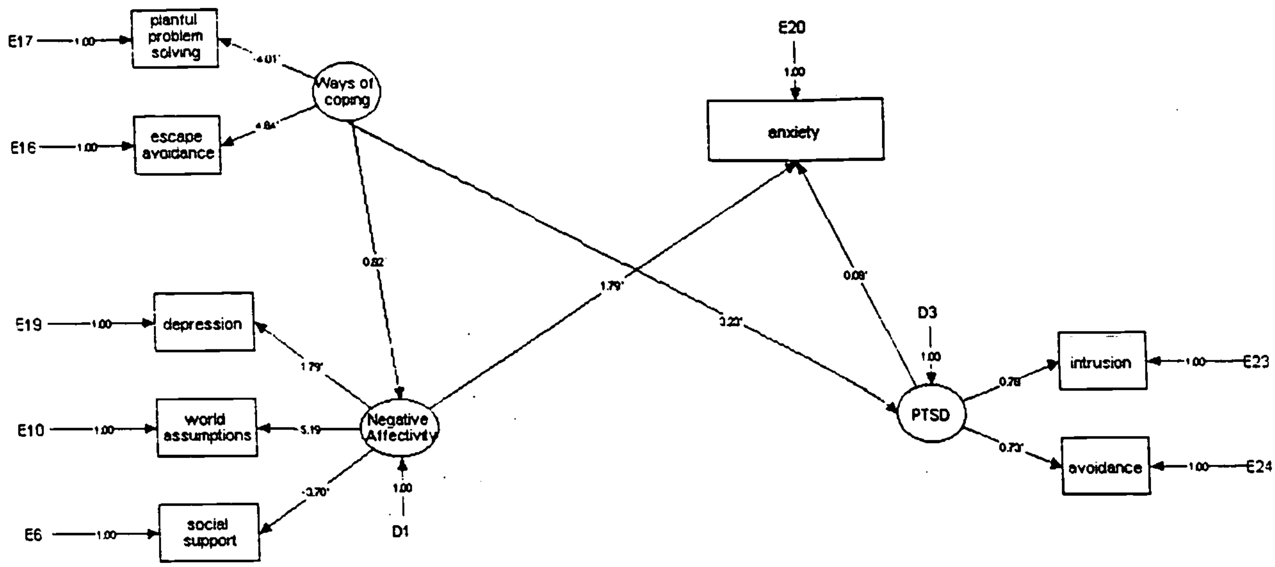

Figure 3. Unstandardized parameter estimates

Figure 4 shows the standardized solutions, where correlation coefficients are reported.

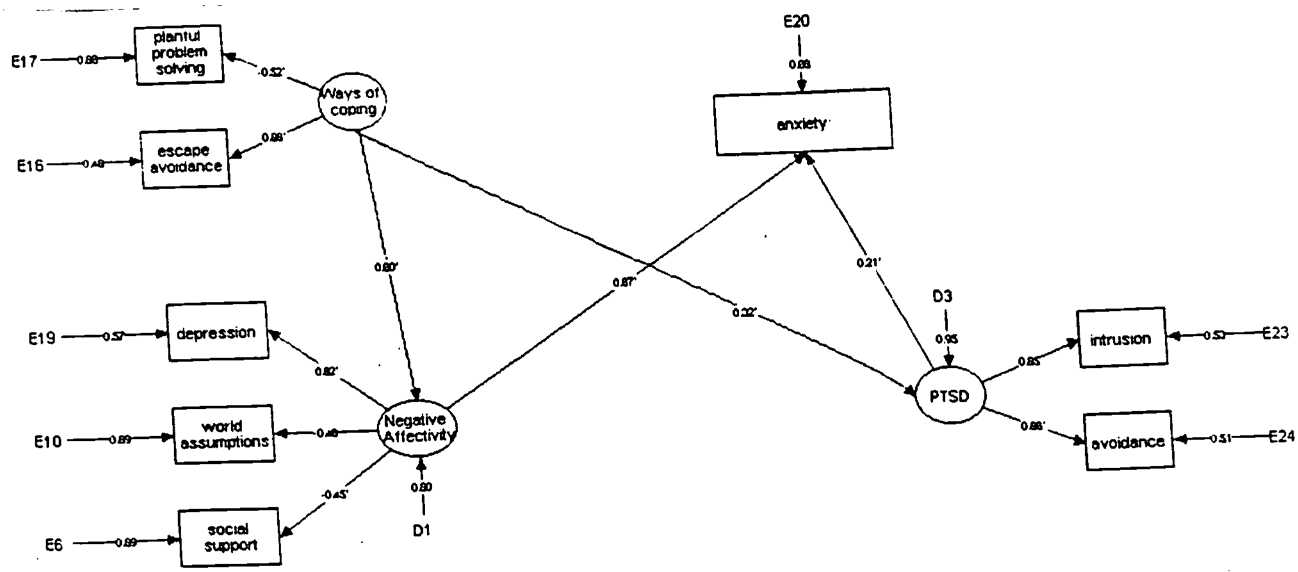

Figure 4. Standardized Solutions

Most correlations were significant in the model. After investigating initial parameters and standardized solutions through regression and correlation coefficients, it was necessary to test the overall structural model fit. Therefore, the model was tested by comparing its covariance matrix with the covariance matrix of observed data. Numerous fit indices (i.e., χ^2, GFI, MFI, AGFI) were used to assess the model fit. The independence model was significant ($\chi^2 = 1755$, p<.001), indicating that variables in the structural model were correlated. Therefore, this model was rejected. Akaike's information criterion (AIC) and Bozdogan's consistent version of statistics (CAIC) were computed for the model (69 and –16, respectively), indicating that the proposed model was much better than the independence model. Bentler (1993) suggests choosing the model that produces the minimum AIC or CAIC. In terms of model goodness-of-fit, the χ^2 value was found to be significant at .001(χ^2=98.92). Ideally, this χ^2 value is desired to be non-significant in order to conclude that the model adequately fits (Pedhazure, 1982). Even though the χ^2 test yielded a significant value in this case, it is less than the model degrees of freedom, indicating that the model may fit the data. Moreover, researchers advise not making decisions solely on the basis of the χ^2 goodness-of-fit because of its sensitivity to sample size (Bentler & Bonnet, 1980). Therefore, several incremental fit indices were obtained to further investigate the model fit. All of the fit indexes were greater then the acceptable .90 cut-off criteria (i.e., Bentler-Bonett Normed Fit Index = .94, Bentler-Bonett Nonnormed Fit Index = .91, CFI = .95, IFI = .95, MFI= .95, GFI= .97, and AGFI= .92) (Bentler, 1993). Therefore, the conclusion was that this model fit the data well by statistical criteria (i.e., regression and correlation coefficients) and fit indices.

Measurement equations, with standard errors and test statistics related to the dependent variable, were computed. The null hypotheses for each given parameter stated that a given parameter was zero in the population. In the model, all test statistics were much higher than ± 1.96; therefore, it is concluded that coefficients were not zero in the population. In the construct equations, the null hypotheses were rejected for each factor.

In sum, this model can be considered in the prediction of anxiety since a coefficient of .88 (.821*F1+212*F3) in the standardized solution would be associated with an $R^2 = .77$, corresponding 77 % of explained variance in the dependent variable (anxiety).

Summary

An application of SEM techniques was provided in this section. A model was generated and tested for fit. Each step that was discussed in the section of SEM theory was applied to the model with the exception of model respecification.

Using the EQS, relationships were examined for anxiety, a latent variable, and three indicators, ways of coping, negative affectivity, and PTSD. The model employed 770 cases and 21 variables. The ratio of cases to observed variables was about 90:1 and the ratio of cases to parameters was 35:1, which could be considered as excellent ratios (Tanacnick & Fidell, 1996). Even though some problems were encountered in terms of multivariate normality, parameter estimates were predominantly significant and the model fit indexes were sufficient. The model did not need respecification in this example. It could be concluded that this model was useful in predicting the dependent variable (anxiety).

References

Aguilera, D. C. (1994). Crisis Intervention: Theory and Methodology (7th ed.). St. Louis: Mosby-Year Book, Inc.

Asher, H. (1976). Causal modeling. Quantitative applications in social Sciences. V.3 CA: Sage Publication.

Arbuckle, J. (1997). Amos Users' Guide. Chicago: SmallWaters Corporation.

Bentler, P. M. (1993). EQS program manual. Los Angeles: BMDP Statistical Software.

Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological Bulletin, 107, 238-246.

Bentler, P. M. & Bonett, D. G. (1980). Significance tests and goodness-of-fit in the analysis of covariance structures. Psychological Bulletin, 88, 588-606.

Bollen, K. A. (1989). Structural equations with latent variables. New York: Wiley.

Bollen, K. A., & Long, J. S. (Eds.). (1993). Testing structural equation models. Newbury Park, CA: Sage Publications.

CALIS Software, SAS Institute INC.

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. Multivariate Behavioral Research, 18, 115-126.

Duncan, O. D. (1975). Introduction to structural equation models. New York: Academic Press.

Folkman, S. & Lazarus, R. S. (1988). Ways of Coping Questionnaire sampler set. CA: Mind Garden.

Hair, J. F. Anderson, R. E. Tatham, R. L. & Black, W. C. (1995). Multivariate analysis (4th Ed.). Englewood Cliffs, NJ: Prentice Hall.

Harris, M. C. & Stacks, J. R. (1998). A three year five state study on the relationships between Critical Incident Stress Debriefings, firefighters' disposition, and stress reaction. USFA-FEMA CISM Research Project. Commerce, TX: Texas A&M University-Commerce, Department of Counseling.

Horowitz, M. J. (1979). Stress response syndromes. New York: Jason Aronson.

Horowitz, M. J., Wilner, N., Kaltreider, N., & Alvarez, W. (1979). Signs and symptoms of post traumatic stress disorder. Archives of General Psychiatry, 37, 85-92.

House, G. W. (1996). Outcome comparison of linear and dynamical statistical models on the FEMA CISM project. Unpublished paper. TX.

Hoyle, R. H. (1995). Structural equation modeling: Concepts, issues, and applications. Thousand Oaks, CA: Sage Publications.

Janoff-Bulman, R. (1989). The benefits of illusions, the threat of disillusionment, and the limitations of inaccuracy. Journal of Social and Clinical Psychology, 8, 2, 158-175.

Jöreskog K. G. (1993). Testing structural equation models. In K. A. Bollen & J. S. Long (Eds.), Testing structural equation models (pp. 294-316). Newbury Park, CA: Sage Publications.

Jöreskog, K. G. & Sörbom, D. (1993a). LISREL8 user's reference guide. Chicago, IL: Scientific Software International, Inc.

Jöreskog, K. G. & Sörbom, D. (1993b). PRELIS2 user's reference guide. Chicago, IL: Scientific Software International, Inc.

Jöreskog, K. G. & Sörbom, D. (1988). LISREL 7: A guide to the program and applications. Chicago, IL: SPSS Inc.

Jöreskog, K. G. & Sörbom, D. (1986). LISREL VI user's guide: Analysis of linear structural relationships by maximum likelihood, instrumental variables, and least square methods. Mooresville, IN: Scientific Software, Inc.

King, W. D. (1997). A brief introduction to structural equation modeling. PTSD Research Quarterly, 8, 4, 1-4.

Marcoulides, G. A. & Schumacker, R. E. (Eds.). (1996). Advanced structural equation modeling. Mahwah, NJ: Lawrence Erlbaum Associates.

Maruyama, G. H. (1998). Basics of structural equation modeling. Thousand Oaks, CA: Sage Publications, Inc.

Mueller, R. O. (1997). Structural equation modeling: Back to basics. Structural Equation Modeling, 4, 4, 353-39.

Muthen, B. O. LISCOMP software. IL: Scientific Software International, Inc.

Neal, M. C. Mx software. Richmond, VA.

Pedhazur, E. J. & Schmelkin, L. P. (1992). Measurement, design, and analysis: an integrated approach. Hillsdale, NJ: Lawrence Erlbaum Associates.

Polhmann, J. T.(1991). Multiple regression in behavioral research: Explanation and prediction (2nd Ed.). New York: Holt, Rinehart & Winston.

Procidano & Heller, (1983). Social Support Scale.

Schumacker, R. E. & Lomax, R. G. (1996). A beginner's guide to structural equation modeling. Mahwah, NJ: Lawrence Erlbaum Associates.

Steiger, J. H. SEPATH software. OK: StatSoft.

Stacks, J. (1998). A test of unreplicated factors for two subscales in the Ways of Coping Questionnaire. Unpublished doctoral dissertation. Texas A&M University-Commerce, TX.

Tabachnick, B. G. & Fidell, L. S. (1996). Using Multivariate Statistics. Northridge: Harper Collins College Publishers.

Tucker, L. R. & Lewis, C. (1973). The reliability coefficient for maximum likelihood factor analysis. Psychometirica, 38, 1-10.

Wang, E. W. (1998). The use of structural equation modeling techniques to predict violence potential in mentally ill male prisoners. Unpublished doctoral dissertation, Texas A&M University-Commerce.

Zygmond, A. S. & Snaith, R. P. (1983). Hospital Anxiety and Depression Scale. Acta psychiatrica Scandinavia, 67, 361-370.

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