

- Marcoulides, G. A. (2001, October). *A genetic algorithm for conducting specification searches in structural equation modeling*. Paper presented at the Annual Meeting of the Society of Multivariate Experimental Psychology, Monterey, CA.
- Marcoulides, G. A., Drezner, Z., & Schumacker, R. E. (1998). Model specification searches in structural equation modeling using Tabu search. *Structural Equation Modeling, 5*, 365-376.
- Marcoulides, G., & Drezner, Z. (1999). Using simulated annealing for model selection in multiple regression analysis. *Multiple Linear Regression Viewpoints, 25*, 1-4.
- Marcoulides, G. A., & Drezner, Z. (2001). Specification searches in structural equation modeling with a genetic algorithm. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: New developments and techniques*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Spires, P., Scheines, R., & Glymour, C. (1990). Simulation studies of the reliability of computer-aided model specification using the TETRAD II, EQS, and LISREL programs. *Sociological Methods and Research, 19*(1), 3-66.
- Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research, 25*, 173-180.

STRUCTURAL EQUATION MODELING, 10(1), 165-174  
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## BOOK REVIEW

**Latent Variable and Latent Structure Models.** George A. Marcoulides and Irfi Moustaki (Eds.). Mahwah, NJ: Lawrence Erlbaum Associates, Inc., 2002, 288 pages, \$69.95 (cloth).

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As pointed out in prior structural equation modeling (SEM) text reviews (Glaser, 2000, 2001, 2002), up to 1995, there was a paucity of SEM texts that were readily accessible to the fledgling SEM user. Many of us used Bollen (1989), Loehlin (1992), and Hayduk (1987) as our primary reference points, and they still stand a seminal readings in this domain. However, a flurry of introductory texts have been released since Schumacker and Lomax's (1996) user-friendly text. With the surmounting increase in interest in SEM, has come an attendant rise in the level of sophisticated of modeling efforts (concomitant with software capability), with various edited texts addressing either an array of topical areas (e.g., Hoyle, 1995; Bollen & Long, 1993) or focused areas such as interaction and nonlinear modeling (Schumacker & Marcoulides, 1998), latent growth curve modeling (Duncan, Duncan, Strycker, Li, & Alpert, 1999), multilevel applications (Moskowitz & Hershberger, 2002) or change analysis (e.g., Collins & Horn, 1991; Collins & Sayer, 2001). The reviewed text herein by Marcoulides and Moustaki (2002), titled *Latent Variable and Latent Structure Models*, further supplements the library of relatively advanced texts dedicated to the umbrella topic of latent variable analysis. As will become clear in the review, those who have accessed the two volumes on advanced topics in SEM (i.e., Marcoulides & Schumacker, 1996, 2001) will find that this text is a suitable literary companion.

As detailed in the preface, the genesis of this edited text is "material presented at the 22nd biennial conference of the Society for Multivariate Analysis in the Behavioral Sciences (SMABS) held by the Department of Statistics at the London School of Economics and Political Science in July 2000" (Marcoulides & Moustaki, 2002, p. III). The overall theme was theoretical developments in latent variable modeling and SEM; thus, though each of the papers address modeling

topics, the topics cover a broad swath of subject material, most of which is not necessarily overlapping (e.g., semiparametric estimation, confidence regions, etc.).

The first chapter, titled "Old and New Approaches to Latent Variable Modeling," by David J. Bartholomew, starts off with a review of the well-known history of factor analysis, latent class analysis, covariance structure analysis, and so on. However, Bartholomew asserts that the new approach "derives from the observation that all of the [prior] models ... are, from a statistical point of view, mixtures" (p. 3). The author then proceeds to discuss an intermediate approach between the Bayesian versus frequentist inferential method in the context of latent variable analysis. After a discussion on the indeterminacy problem and the sufficiency principle, the theory behind the general linear latent variable model is introduced. Even though, as with most of the text, the explanations become reduced to relatively technical equations (and hence a fundamental understanding of matrix algebra and linear modeling will serve the reader well), the gist of this section is that the general linear latent variable model, based in part on the sufficiency property, has the capacity to subsume a wide range of standard models. Evidence of this is provided with examples for both the binary and normal case. Contrasts between the "old and new approaches" (p. 7) are offered, focusing on areas such as types of variables and probability modeling.

In survey research, an oft-cited concern is the appropriateness of including a middle point such as "neutral" or "neither disagree or agree" or differentiating between "don't know" (DK) versus "not applicable/no answer" (NA) options. Addressing this conundrum is the second chapter, titled "Locating 'Don't Know,' 'No Answer' and Middle Alternatives on an Attitude Scale: A Latent Variable Approach," by Irini Moustaki and Colm O'Muircheartaigh. The authors correctly assert that "the common practice is to treat all DKs and NAs as missing cases without distinguishing them. However, it might be that for some questionnaire items respondents choose the DK category when they really have no knowledge of the subject, but in other cases they might use the DK category to avoid expressing an opinion. The same might be true for NA responses" (p. 15). Thus, treating DK and NA responses as the same (or as missing) ignores the fundamentally different perceptions that are associated with each of those anchors. There are also varying opinions about including middle points, such as *neutral* or *neither agree nor disagree* for scaling purposes, insofar as it may be used all too readily as a default category. In exploring these topics, Moustaki and O'Muircheartaigh explored the "idea of using polytomous response propensity variables (rather than binary) to distinguish between different type of nonresponse in a latent variable framework" (p. 15). Regarding the DK/refusal and nonresponse case, the authors provide the derivations for the propensity variables for the following types of measurement: binary, polytomous nominal, ordinal, and metric. Assessing goodness of fit via chi-square testing is then reviewed. The authors then discuss the use of pseudo binary items when examining Likert scales with middle categories. For those who have experi-

ence with ordinal regression and threshold parameters, the derivations in this section will be familiar. The rest of the chapter provides examples of the various latent approaches to the DK/NA and middle-category cases.

Given that many times our analyses is not circumscribed to continuous-level and multivariate normal distributions, there has been a burgeoning interest in categorical and nonparametric modeling. Thus, L. Andries Van der Ark, Bas Hemker, and Klaas Sijma add to this increasing literature, specifically with reference to the Item Response Theory (IRT) domain in their chapter titled "Hierarchically Related Nonparametric IRT Models, and Practical Data Analysis Methods." The focus of this chapter is contrasting various nonparametric IRT models (NIRT) for polytomous test scores, with the models being (a) nonparametric partial credit model, (b) nonparametric sequential model, and (c) nonparametric graded response model. Each of the models is reviewed, as well as the attendant assumptions (i.e., unidimensionality, local independence, etc.). Each of those models is then associated with the following classes of models: cumulative probability models, continuation ratio models, and adjacent category models. Given the relative sophistication of this chapter, a cursory review, if warranted, of an IRT text, such as Hambleton, Swaminathan, and Rogers (1991) may be helpful. The relationships between the three models are then detailed and the hierarchical nature of their relationship; that is, "the partial credit model implies the sequential model and the sequential model implies the graded response model" (p. 45). Evidence for the posulated hierarchical nature of these models is then provided, illustrating the conditions when one of the models is a special case of another (i.e., sequential model is a special case of the graded response models). A fairly extended discussion follows on the ordering properties of the three NIRT models, insofar as "NIRT models are solely defined by order restrictions, and only ordinal estimates of  $\theta$  are available" (p. 48). Note that  $\theta$  is the latent trait value for the respondent. The various strategies (and attendant software) for analyzing each of these NIRT models are reviewed, entailing investigation of observable consequences, ordered latent class analysis, and kernel smoothing. The chapter concludes with a detailed overview of the software and modes of assessing goodness of fit that is unique to each of these tested models.

IRT models are further discussed in Panagiota Tzamourani and Martin Knott's chapter, titled "Fully Semiparametric Estimation of the Two-Parameter Latent Trait Model for Binary Data." The authors' focus is on the binary case with two parameters: a difficulty parameter and a discrimination parameter, with a specific focus on presenting "an EM [Expectation Maximization] algorithm, which carries out fully semiparametric estimation for the two-parameter latent trait model" (p. 62). A brief review of the derivation for the binary case using parametric maximum likelihood (ML) estimation is detailed. This segues into semiparametric ML estimation. In differentiating semiparametric versus nonparametric estimation, the authors point out "if the latent trait model is estimated semiparametrically, then the

prior is estimated together with the item parameters. It is *semiparametric* [italics in original] rather than *nonparametric*, because a parametric form is still assumed for the response function, though one could say that the prior is estimated nonparametrically" (p. 66). The adjustment to the EM algorithm to estimate the weights is reviewed and applied to datasets consisting of scores for primary school boys on the NEFER test 1, an intercultural scale (items that regard future outlook), and an artificial dataset. The authors also varied the number of starting points, "varying in number from 2 to 16, equally and differently spaced, and with equal and unequal probabilities" (p. 67). Results are also provided, when varying the number of points, when employing fully semiparametric estimation. After optimality criteria are discussed, meaning "conditions for the estimated mixing distribution to be optimal" (p. 75), scoring of the latent variable is detailed. The authors conclude that the simple and fully semiparametric estimation methods essentially generate the same results, though more points are needed for the simple semiparametric case to obtain optimal adjustment of the weights.

Many advances have been made in SEM in the last decade, the most prominent being latent growth curve modeling, nonlinear modeling, and mixture modeling. Moreover, multigroup modeling has also piqued many a researcher's interest, especially when assessing the invariance of factorial structures across groups. This form of modeling is the focus in Pilar Rivera and Albert Sarra's chapter, "Analyzing Group Differences: A Comparison of SEM Approaches." In this chapter, the focus is on comparing various countries' attitudes and behavior regarding environmental issues. Particularly of interest is comparing various approaches such as multiple-group, single group multiple indicator multiple causes model (MIMIC) in the event of nonnormality.

The author's commence the chapter with a discussion on statistical issues of nonnormal data, briefly reviewing the research concerning the various estimators such as ML, generalized least squares (GLS), and asymptotic distribution-free (ADF) approaches. The robustness of the various methods is discussed, especially regarding the conditions requisite for asymptotic robustness. The issue of sample size and its impact on the chi-square goodness-of-fit test is discussed in the context of the frequently stated opinion that "for a very large sample size, the chi-square goodness-of-fit test should be abandoned in favor of goodness-of-fit indices" (p. 88). However, the authors counter this rejection of the chi-square test in light of their empirical analyses and attendant large sample size.

The data and model for the empirical analyses, involving 22 countries, and primarily ordinal data, is introduced. A multiple group versus single group MIMIC approach (also incorporating mean structures) with the attendant constraints are contrasted. Also compared was continuous versus ordinal methods and normal theory versus asymptotic robust methods. In summary, the authors found that "major substantive conclusions are fairly robust to the choice of alternative model strategies and estimation methods" (p. 101). Also of interest (especially given the

ongoing debate on exact fit versus approximate fit indexes on SEMNET) was the usefulness of the chi-square goodness-of-fit index in light of the large sample size used in this empirical analysis.

For many a researcher, the bane of the data collection process is missing data. Even though, to some extent, this may be more controlled in experimental research, for many of us who conduct applied survey research, missing data is inevitable. Whereas many software default to listwise deletion, missing data is inevitably indeed be formidable. The other option readily accessible to the casual software user, pairwise deletion, also carries with it its own problems of inconsistency (Roth, 1994). Moreover, there are certain complexities associated with the missing data technique that the researcher awaits of themselves given the pattern of missingness (i.e., missing completely at random, missing at random, missing not at random). However, given the availability of software, either in packaged statistical software (e.g., Missing Values Analysis in SPSS) or SEM software (AMOS; Arbuckle & Wothke, 1999), the applied researcher has more options at their disposal to treat missing data. Especially of note is the use of likelihood approaches to missing data, with an excellent review of these methods in Enders (2001). In light of the burgeoning interest in missing data techniques, the chapter by Richard Wiggins and Amanda Sacker, "Strategies for Handling Data in SEM: A User's Perspective," comparing "eight alternative strategies for handling item non-response in the context of structural equation modeling" (p. 105) proves to be most timely.

The authors compartmentalize the missing data solutions under review into three major categories: (a) ad hoc-based solutions include well-known default solutions such as listwise and pairwise deletion; (b) simple model based solutions include expectation maximization (EM) algorithm, and regression methods; and (c) rated in AMOS or multiple imputation (MI), or what the author refers to as data augmentation (DA). The motivation for this chapter is to compare missing data techniques from each of those categories, across three levels of missingness for each variable (5%, 15%, and 25%), patterns of missingness (MCAR versus MAR) and varying levels of normality. A large sample from a cohort study served as the focus of analysis. Not surprisingly, the authors found that pairwise deletion and mean substitution are to be avoided (though, the interested reader may want to pursue Roth, Switzer, & Switzer, [1999] in regard to some promising findings associated with mean substitution for the person). And in parallel with other recent studies examining missing data techniques, FIML and DA approaches were ascertained to be the most encouraging.

The next chapter, by Tenko Raykov and Spirin Penev, titled "Exploring Structural Equation Model Misspecifications via Latent Individual Residuals," expands on the subject of assessing goodness of fit by way of subject level residuals. After a brief review of the notation (it behooves the reader to have more than a cursory knowledge of the various SEM matrices, for instance those incor-

porated in the LISREL model), the authors detail the derivation of the latent individual residuals ( $\hat{\zeta}$ ). The authors use the latent individual residuals (LIR) as a mode to evaluate "fit of structural equation models, particularly with respect to model misspecifications at the unobservable variable level" (p. 123). In the context of causality, the author's provide a rebuttal to the notion that lack of a latent relationship implies "a lack of causality between its unobservable constructs" (p. 124); this argument is supported by examining the LIR in a polynomial model. Whereas a linear model would demonstrate problematic fit, examination of the LIR provides evidence of a nonlinear relationship. Another example is provided that shows the utility of latent individual residuals in delineating model misspecification, specifically for a piece-wise linear model.

The following chapter, by Jian-Qing Shi, Sik-Yum Lee, and Bo-Cheng Wei, titled "On Confidence Regions of SEM Models," specifically explores the use of the generalized least squares (GLS) theory in developing confidence regions. The authors point out the advantages of using confidence intervals in assessing not only bandwidth of error but also practical significance, thus complementing (or, in the more extreme, replacing) null hypothesis significance testing (NHST). Their argument corresponds closely to the recommendations of the American Psychological Association, as well as the flurry of activity since Cohen's 1994 paper, which, even though not advocating eliminating NHST, advises the researcher to supplement *p*-value reporting with effect sizes and confidence intervals. This is a relatively technical chapter and the derivations via matrix algebra are of some complexity. The basic theory of GLS confidence region is elucidated with a description of the geometric framework of the SEM model, an elaboration on the GLS confidence region, and the attendant quadratic approximation. A very technical detailing of the theorems and proofs associated with regions for subsets of parameters follows. Moreover, numerical examples using the geometric approach, with nonlinear constraints, are provided.

The following chapter, by Peter Filzmoser, is titled "Robust Factor Analysis: Methods and Applications." The chapter commences with a definition of robustness, in this context it having to do with the impact of outliers or unusual observations. The primary objective of this chapter is to illustrate the use of robust statistics in factor analysis (FA). The author differentiates between just deleting anomalous values as opposed to using a robust procedure, which entails downweighting the values in the analysis of interest. Initially, the fundamentals of robust statistics are reviewed, such as the influence function, outlier identification, and so on. Some of the details will be familiar to those with a background in regression diagnostics (e.g., Mahalanobis distance measures), whereas some may be a bit arcane (e.g., minimum volume ellipsoid estimator). After a brief review of the FA model, the application of the robust method to FA is delineated. Even though a few robust approaches are offered, most promising is the use of the minimum covariance determinant (MCD) estimator used "for robustly estimating location

and covariance" (p. 156). Examples of using the influence functions (EIFs) for both principal factor analysis (PFA) and ML methods are provided. An alternative method "to robustify FA" (p. 164) is called factor analysis by interlocking regression (FAIR), which employs a series of regression analyses until convergence is obtained. Where this method deviates is that it "does not use the correlation matrix for the parameter estimation but takes directly the data matrix for estimating loadings and scores" (p. 167). Using a robust procedure such as median absolute deviation (MAD), interlocking regression yields some intriguing features, one especially being that "the number of variables can exceed the number of observations" (p. 166). A relatively technical treatment of the principles and features of the FAIR technique are detailed. Given that PCA "is very sensitive to outlying observations" (p. 183), the application of the robust method to principal components analysis (PCA) follows. To accomplish the objectives of PCA (i.e., reduce dimensionality and maximize variance), projection pursuit (PP) is used in this context, the method entailing "finding interesting structures in a *p*-dimensional data set . . . in subspace of low dimension . . . found by maximizing a projection index" (p. 184). The algorithm associated with this method is also detailed. Overall, this chapter offers an array of robust methods to factor analytic studies that serves in minimizing the deleterious influence of anomalous values.

The next chapter by Marcel Croon is titled "Using Predicted Latent Scores in General Latent Structure Models." After a brief review of general latent structure models, the various estimation methods employed in latent structure modeling are discussed. Given the prominence of ML estimation in estimating structural equation models, the advantages and disadvantages are detailed. One critique revolves around the estimation of the model in a single simultaneous estimation procedure and how "misspecification in some part of the model may have negative consequences for the accuracy of the parameter estimates in other parts of the model" (p. 198). Thus, to ameliorate the effects of misspecification, the option of using a search strategy, "which splits up the global model in different autonomous parts" (p. 198), is offered (not unlike search programs such as TETRAD). Limited information methods are then discussed, with the author turning his attention to the use of "predicted latent scores to test the causal hypotheses formulated in the structural submodel" (p. 199). The steps outlined are as follows: (a) start with separate estimation of the parameters of the measurement submodels; (b) proceed to estimation or prediction of subjects' scores on the latent variables; and (c) treat these scores as observed scores, and enter the next analyses based on the structural submodel (p. 199). It is maintained that the analysis of predicted latent scores can be used with such traditional techniques as logistic or linear regression, with the ensuing discussion revolving around the use of latent scores in latent class and factor analytic models (the latter including a review of the well-known factor indeterminacy problem). A fairly technical description of the "naive use of predicted latent scores" (p. 202) follows, using integration theory to "demonstrate that substituting predicted

latent scores for the true latent scores and treating the predicted scores as observed variables in the analysis for the structural part of the model will generally lead to inconsistent estimation of the joint distribution of the latent variable with the observed exogenous variable" (p. 205). Numerical examples using this method for latent class and factor analysis are presented.

Harvey Goldstein and William Browne's chapter, "Multilevel Factor Analysis Modeling Using Markov Chain Monte Carlo Estimation," extends the impressive research efforts that have been expended in the last half-decade in multilevel modeling. In this chapter the authors illustrated how a Markov Chain Monte Carlo (MCMC) algorithm can be used to fit multilevel models, with it providing "a chain sampled from the full posterior distribution of the parameters from which one can calculate uncertainty intervals based upon quantiles" (p. 225). Since the chapter goes straight into a model with a 2-level model, without an elaboration on defining the various levels, it would behoove the reader to have more than a cursory familiarity with multilevel modeling. The authors provide an example with a simple model, illustrating that "MCMC works by simulating new values for each unknown parameter in turn from their respective conditional posterior distribution assuming the other parameters are known" (pp. 226-227). Using this Bayesian approach, the authors assert this method allows the researcher to provide estimates for complex techniques such as multilevel factor analysis. Using a three-step Gibbs sampling algorithm, an implementation of this computation is provided. An extension of this algorithm to general multilevel Bayesian factor models follows with a relatively technical rendering of the steps necessitated to arrive at the prior distributions. The use of this algorithm is also presented in the case of unconstrained factor variance matrices, that is, when "variance are constrained to be 1 but the covariances can be freely estimated" (p. 235). The chapter concludes offering extensions of this method to other models besides factor analysis, such as nonlinear and generalized linear models.

The final chapter, by Jean-Paul Fox and Cees A. W. Glas and titled "Modelling Measurement Errors in Structural Multilevel Models," starts off with the well-known problem of aggregation and, hence, the need for multilevel modeling. A brief discourse on measurement error and its impact on the estimation process follows. It is pointed out that the bulk of the attention on measurement error has "focused on linear measurement error models" (p. 247); thus, the objective of this chapter is to address measurement error in both the dependent and independent variables in a structural multilevel model, given that "measurement error in both dependent and independent variables leads to attenuated parameter estimates of the structural multilevel model" (p. 248). After a description of the use of multilevel modeling in the school context, models for measurement error are detailed (e.g., item response theory [IRT]). This segues into a section on multilevel IRT, which entails "the combination of a multilevel model with one or more latent variables modeled by an item response model" (p. 251). An argument is made for the

use of IRT in a multilevel context, to handle response error in both the dependent and independent variables. Following this is a detailed discussion of the use of Markov chain monte carlo (MCMC), which "is a simulation based technique for sampling from high dimensional joint distributions" (p. 253). Evidence is then furnished for the non-ignorability of measurement errors in both the dependent and independent variables in multilevel models. After an illustrative example, the authors conclude that the Bayesian approach "accommodates both covariate and response measurement error, and provides more reliable estimates of the variability of the model parameters" (p. 264). However, they do concede that this procedure is not only computer intensive but still unfamiliar to many researchers.

Overall, this text is a fairly expansive and technical text that will be of interest to those who have a more than cursory background in latent variable modeling. Whenever an edited text encompasses a wide array of topics, a sense of coherence across chapters may be compromised. This is not the case with this edited volume by Marcoulides and Moustaki. Though the topics are wide-ranging, their relevance to latent structure models is maintained. However, the chapters do vary in levels of difficulty. Some are readily accessible (e.g., the chapter on robust factor analysis) whereas others may be technically challenging for some readers (e.g., the chapter on confidence regions). Thus, this book will be of interest to those curious about recent advances in latent structure modeling, and who expect a modicum of technical detail. This text is not dedicated to any particular software, and is not in any way close to being a step-by-step primer.

## REFERENCES

- Arbuckle, J. L., & Wothke, W. (1999). *Amos User's Guide Version 4.0*. Chicago: SmallWaters.
- 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.
- Cohen, J. (1994). The earth is round ( $p < .05$ ). *American Psychologist*, 49, 997-1003.
- Collins, L. M., & Horn, J. L. (Eds.). (1991). *Best methods for the analysis of change*. Washington, DC: American Psychological Association.
- Collins, L. M., & Sayer, A. (Eds.). (2001). *New methods for the analysis of change*. Washington, DC: American Psychological Association.
- Duncan, T., Duncan, S. C., Strycker, L. A., Li, F., & Alpert, A. (1999). *An introduction to latent variable growth curve modeling*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Eiders, C. K. (2001). A primer on maximum likelihood algorithms available for use with missing data. *Structural Equation Modeling*, 8, 128-141.
- Glaser, D. N. (2000). Book review of principles and practice of structural equation modeling (R. B. Kline). *Structural Equation Modeling*, 7, 489-495.
- Glaser, D. N. (2001). Book review of a first course in structural equation modeling (T. Raykov & G. A. Marcoulides). *Structural Equation Modeling*, 8, 316-323.
- Glaser, D. N. (2002). Book review of structural equation modeling: Foundations and extensions (D. Kaplan). *Structural Equation Modeling*, 9, 141-150.

- Hambleton, R. K., Swaminathan, H., & Rogers, H. J. (1991). *Fundamentals of item response theory*. Newbury Park, CA: Sage.
- Jayduk (1987). *Structural equation modeling with LISREL: Essentials and advances*. Baltimore: Johns Hopkins University Press.
- Hill, M. (1997). *SPSS missing value analysis 7.5*. Chicago: SPSS Inc.
- Hoyte, R. H. (Ed.). (1995). *Structural equation modeling: Concepts, issues, and applications*. Thousand Oaks, CA: Sage.
- Loehlin, J. C. (1992). *Latent variable models* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.
- Marcoulides, G. A., & Schumacker, R. E. (Eds.). (1996). *Advanced structural equation modeling: Issues and techniques*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Marcoulides, G. A., & Schumacker, R. E. (Eds.). (2001). *New developments and techniques in structural equation modeling*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Moskowitz, D. S., & Hershberger, S. L. (Eds.). (2002). *Modeling intraindividual variability with repeated measures data*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Roth, P. L. (1994). Missing data: A conceptual review for applied psychologists. *Personnel Psychology*, 47, 537-559.
- Roth, P. L., Switzer, F. S., & Switzer, D. M. (1999). Missing data in multiple item scales: A Monte Carlo analysis of missing data techniques. *Organizational Research Methods*, 2, 211-232.
- Schumacker, R. E., & Lomax, R. G. (1996). *A beginner's guide to structural equation modeling*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Schumacker, R. E., & Marcoulides, G. A. (Eds.). (1998). *Interaction and nonlinear effects in structural equation modeling*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- SPSS Inc. (1997). *Missing values analysis 7.5*. Chicago.

## CONTRIBUTOR INFORMATION

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