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BOOK REVIEW

Structural Equation Modeling: Foundations and Extensions. David Kaplan.
 Thousand Oaks, CA: Sage Publications, 2000, 215 pages, \$49.95 (cloth).

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As indicated in recent reviews (Glaser, 2000, 2001) up to a few years ago, outside of Schumacker and Lomax (1996) or Loehlin (1992), there were few texts to select from that provided an introduction to structural equation modeling (SEM). Even though Hayduk (1987) and Bollen (1989) set the standards for SEM texts, for an introductory graduate course, especially if SEM was a subcomponent of a multivariate statistics class, time constraints precluded use of such books. However, in the last few years a spate of SEM texts have been published (e.g., Byrne, 1998, 2001; Kelloway, 1998; Kline, 1998; Maruyama, 1997; Raykov & Marcoulides, 2000), each with its own perspective on modeling as well as emphasis on specific software (e.g., EQS, LISREL, etc.). This recent outpouring of texts gives readers a vantage point to select a text that best suits their needs. If the instructor or researcher prefers a text that is more agnostic in its software preference, then Kline (1998) or the most recent edition of Loehlin (1998) may be an opportune choice. For the researcher or student who is interested in a text that is software-specific, then the series of books by Byrne (1994, 1998, 2001) may be apt. And for a treatise on recent developments such as latent change modeling, then Raykov and Marcoulides (2000) may be suitable.

As part of the Sage Publications series in Advanced Quantitative Techniques in the Social Sciences, David Kaplan has added to the cornucopia of SEM texts with *Structural Equation Modeling: Foundations and Extensions*. In the preface, Kaplan acknowledges the recent flourish of SEM texts, those being primarily geared to the novice. However, with this text, and as the title suggests, Kaplan has in mind a more sophisticated audience, given the statistical underpinnings that are detailed as well as "recent extensions of structural equation modeling" (p. xiv). Given his affiliation with the School of Education, Kaplan also introduces SEM in the context of addressing substantive problems in the aforementioned field. This emphasis is well justified. As Kaplan alludes to in the preface, even though SEM

has earned its slot as a valuable research tool, if policymakers or decision makers view SEM as nothing but a research tool, "there is no reason to believe that structural modeling will last in perpetuity simply because the software is easy to use or because structural modeling generates purely methodological studies" (p. xiv). The text also diverts from the other more social science grounded books by incorporating econometric methodology.

Chapter 1 presents an overview of the history and current practice of SEM. Those versed in the historical antecedents of SEM, as well as the oft-cited contributions of such luminaries as Spearman, Wright, and Jöreskog, may find the brief treatment of the factor and path analytic origins to be a bit redundant, but the subsequent discussion regarding the interweaving contribution of fields as diverse as biometrics and econometrics is nicely summarized. A brief discourse on modern developments in SEM (e.g., multilevel modeling) segues into the "conventional" (author's quotes) practice of SEM, diagramming the approach generally employed in model testing. Although discussed in more detail later in the text, Kaplan discusses that the conventional mode of testing, that is, from (a) theory to (b) model specification to (c) sample selection and measurement to (d) estimation to (e) fit assessment to (f) model modification, and then to Step d again if warranted, rarely involves into "prediction studies wherein policy-clinically relevant variables are manipulated and their effects on outcome variables observed" (p. 8). This shortcoming (i.e., post hoc fitting) also culminates in a gap between the hitherto ignored process that generates the observed data, referred to as data generating process, and the structural model. Thus, besides Kaplan's contention that SEM rarely is used to validate theoretical predictions, a particular deficiency with the conventional approach "is that theory, theoretical models, and structure models are viewed as one and the same thing apart from the error term—with the actual data playing little to no role at all" (p. 9). This perceived pitfall prompts Kaplan to reference the econometric work of Spanos and an alternative approach to modeling that is discussed in fuller detail in the final chapter. Throughout the text, Kaplan uses an input-process-output model of the U.S. Educational System as the foundation for analysis and pedagogical explication of the various SEM techniques (e.g., multilevel modeling).

Chapter 2 provides a comprehensive coverage of path analysis. The various elements and notation that make up the structural equation are discussed. Those who are versed in LISREL (see Jöreskog & Sörbom, 1996) will find much that is familiar in this text, because the notation follows the matrix language employed in LISREL. However, Kaplan's analysis of the education models is conducted via plus and AMOS. The nomenclature associated with path models is detailed as well as the variations of modeling, that is, recursive versus nonrecursive. As the discussion follows into reduced form versus structural form specifications, a cursory familiarity with matrix algebra and vectors will be imperative to fully comprehend the equations. Even though a minor point, there are a couple of instances

in the text where the notation is not defined (e.g., the identity matrix $[I]$ from Equation 2.2 or $\log L_0$ from Equation 2.21). Although, in all likelihood the reading audience will have sufficient grounding in matrix algebra or model testing, clear explanation of all notation would be helpful for the novice reader. As opposed to other SEM texts, Kaplan emphasizes the utility of the reduced form and its "priority in the sequence of methodological steps leading to the specification of a structural model" (p. 18). An extended treatment of identification and a review of the rank and order condition are included. Examples of each condition, and the necessary conditions needed to satisfy these, are fully detailed.

Moreover, the following section on estimation of model parameters provides a relatively technical derivation of the maximum likelihood (ML) and generalized least squares (GLS) estimators. The assumptions, such as multivariate normality, associated with the use of such estimators are discussed briefly, as well as a series of equations that culminate in the proper discrepancy function. Those who are familiar with Bollen (1989) will find Kaplan's derivation to be similar to the derivation of F_{ML} in Bollen (pp. 131–134); thus, as a basis for comparison, many sections in this chapter and the attendant derivations are at about the level of technicality of Bollen. The next section on model and parameter test covers the chi-square distribution, the likelihood ratio test, and the role of freeing-fixing parameters in the context of more or less restrictive models. The role of the modification index and the Wald test is given a preliminary introduction. Throughout, an education model is tested with interpretation of the AMOS parameters provided, including such standard topics as path decompositions and standardization.

Chapter 3 covers factor analysis. Kaplan uses slightly different nomenclature, in that he uses the term *unrestricted factor analysis* to describe exploratory factor analysis (EFA) and *restricted factor analysis* to describe what is commonly referred to as confirmatory factor analysis (CFA). The factor structure of student perceptions of school climate is the focus of analysis for the chapter. A brief discussion about the various vectors and matrixes that compose the linear factor analytic model, as well as the nature of unique variables (couched within the context of classical true score theory), precedes a more extended and technical discussion about identification and rotation in the unrestricted factor model. The circumstances that may culminate in a not identified and indeterminate solution are detailed, with a discussion following how factor rotation may ameliorate indeterminacies. The various methods of rotation are delineated, although it is clear that Kaplan does not intend to delve into EFA. For the reader seeking further knowledge in this area (especially because Kaplan's notation slightly deviates from the standard EFA notation), chapters in various multivariate texts will suffice as an introduction (Johnson & Wichern, 1998; Marcoulides & Hershberger, 1997; Stevens, 1996; Tabachnick & Fidell, 1996) or, for more detail, texts devoted to this topic in full (e.g., Gorusch, 1983). Discussion regarding factor extraction is confined to ML and GLS, with a comparison of factor load-

ings derived from both modes of extraction. In the context of Kaplan's discussion of how sample size and nonnormality may have impacted the test solution, the interested reader may want to peruse a recent article by Olsson, Foss, Troye, and Howell (2000) that specifically focuses on this issue. The restricted factor model (i.e., CFA) is then the subject matter at hand. The various assumptions associated with the use of this method are detailed, including the necessity of setting the metric as well as preconditions needed to result in an identified solution. The restricted factor model is given rather sparse coverage, at least when contrasted with other introductory SEM texts. Part of this may be due to the coverage of other areas germane to CFA that are detailed in ancillary chapters, or the econometric (as opposed to psychometric) orientation of the author.

Structural equation models in single and multiple groups form Chapter 4, which is characterized as a linking of path analysis and factor analysis, or as Kaplan describes, "adding a measurement model to a path model" (p. 54). Much of the section on specification will be familiar to those versed in LISREL notation and the seminal contributions of Jöreskog. As with prior chapters, Kaplan discusses the conditions leading to identified models, with the two-step process (measurement then structural model) proposed as a "simple rule for establishing the identification of structural equation models" (p. 57). Even though this is not the proper forum to discuss the pros and cons of the two-step process, for further elaboration (which tied up SEMNET traffic for a nontrivial amount of time) see the special issue of *Structural Equation Modeling* (Volume 7, Number 1, 2000), which discusses this issue in detail. An example of testing a full model of science achievement, and the rationale for the postulated paths, is presented. The only complexity this model contains, which may prove challenging to those new to SEM, is that this model employs causal (i.e., formative) indicators. Even though Kaplan doesn't characterize this model as a multiple indicator and multiple cause (MIMIC) model, methods of fitting MIMIC models are detailed toward the end of the chapter. Both the standardized and unstandardized solution is provided, with the only incongruity being the inclusion of a parameter estimate for the INVOLVE→SCIGRA10 path (in Table 4.1) even though that path is not graphed per Figure 4.1.

The next section covers multiple group modeling using a two-group scenario. The progression of testing stacked models, from the equality of covariance structures up to complete invariance of all parameters across all groups, will be familiar to those acquainted with Jöreskog's (1971) contribution to multiple group modeling. Kaplan describes each step in testing invariance and applies this to assessing the factorial structure, across groups, for a school climate instrument. This segues into a brief discussion of mean structure modeling, with again the notation adopted from Jöreskog and Sörbom (1996). For those interested in a recent review of the measurement invariance literature, a very comprehensive article by Vandenberg and Lance (2000) details the various strategies that have been used to assess invariance. The next section covers group difference modeling via the MIMIC model, with the group

variable modeled as a dummy-coded vector. Kaplan discusses the flexibility of the MIMIC model and its ability to incorporate various metrics for the exogenous variable (i.e., categorical or continuous). This, of course, is aligned with Cohen's (1968) oft-cited article, which brought to the fore the flexibility of the general linear model and its ability to subsume fixed factor models as well as continuous vectors. An intriguing discussion regarding causal inference and random selection or assignment follows. It is not atypical that many SEM efforts are a product of survey research or nonrandom selection or assignment, with the research pursuit generally concentrating on arriving at a suitable sample size. What generally is neglected is the need to ensure that the sample is generalizable to the target population. Thus, I was pleased to see the abbreviated discussion about nonrandom selection within the context of causal effect of treatments. The chapter concludes with two possible approaches to model selection: analysis of covariance and propensity scores and their potential use in multiple group modeling.

Chapter 5, "Statistical Assumptions Underlying Structural Equation Modeling," encompasses topics that will be known to most seasoned SEM users, such as multivariate normality, sample size issues, missing data, and model specification. However, the chapter begins with a brief discourse on sampling assumptions; this dovetails nicely with the discussion of nonrandom selection or assignment from the prior chapter. As echoed in my prior observation, sampling issues rarely are discussed in the context of SEM, even though the general (if not implicit) assumption is that simple random sampling has occurred. The effects of nonnormality for continuous nonnormal distributions are summarized, with a generous treatment of Browne's seminal work with weighted least squares (WLS) and the asymptotic distribution free estimator. Muthén's body of work with estimators for categorical variables is then discussed, with a review of threshold parameters. As Kaplan asserts, many social science studies involve variables measured at the ordinal or nominal level, thus violating the multivariate normality associated with ML-GLS estimators. It is in this context that Muthén's work has proved to be influential. The various types of correlation matrixes, given the variable metric, are detailed. However, and as many SEM users are aware, there may be some limitations to the types of matrixes (e.g., polychoric-polyserial correlation) or types of estimates or estimators (e.g., robust standard errors, mean adjusted WLS estimator) that can be derived or used contingent on the software of choice. With the reader keeping this in mind, Kaplan discusses recent developments in estimators given nonnormality, such as mean-adjusted WLS estimator and mean- and variance-adjusted WLS estimator, which to date may be available only in *Mplus*. Very promising work is being done in this area; thus, it is hoped that the aforementioned estimators become a staple in alternative software applications.

Even though missing data have been the bane of many a researcher's existence, the text by Little and Rubin (1987) proved to be especially groundbreaking. In the last few years it seems that this topic has seen an increased interest not only in the

statistical discipline (e.g., D'Agostino & Rubin, 2000) but also in applied research (e.g., McDonald, Thurston, & Nelson, 2000). Notwithstanding that there have been various DOS-based and/or freeware missing data programs for a while, the release of user-friendly missing data programs (e.g., SPSS Missing Value Analysis™ 7.5) makes it much easier for the applied researcher to employ such missing data techniques as regression or expectation-maximization that hitherto may have seemed intractable. Kaplan reviews the nomenclature unique to the examination of missing data as well as the various approaches that can be used. Given the burgeoning interest in likelihood approaches to missing data, in conjunction with the well-known deficiencies associated with listwise and pairwise deletion, model-based approaches to missing data are given an extended, relatively technical, treatment in this chapter. Particularly, Muthén's work with the full quasi-likelihood is detailed. Missing-at-random approaches for modeling missing data are discussed with focus on the full-information ML approach. Given that the various likelihood approaches are provided contingent on the researcher's software, the interested reader will want to peruse a recent article that provides a primer on likelihood approaches (Enders, 2001). Specification error and the ramifications (e.g., biased estimates) of misspecification are then delineated. The text then deviates from most discussions about assumptions, introducing, in extended fashion, the topic of exogeneity. Kaplan prefaces this section by maintaining that "simply designating a variable as 'exogenous' does not render it as such. Nor is the standard requirement of orthogonality of a variable and a disturbance term sufficient for a variable to be exogenous" (p. 99). An explication of exogeneity and weak exogeneity via classic linear regression is detailed. Much of this discussion may be familiar to those versed on econometrics but is novel for many of us who have a social science background. The implications of violating this assumption culminate with the author recommending that "software programs should be expanded to allow for the characterization of alternative distributional forms of the joint distribution of the data" (p. 104).

The topic of evaluating and modifying structural equation models follows. As many software users know, a plethora of fit indexes are available across the various applications; thus, the onus is on the researcher to select among the indexes that best reflect the nature of the research pursuit. Thus, it is not imprudent to present a variety of indexes (Boomsma, 2000; Hoyle & Panter, 1995) that best inform the reader. Also, a recent line of research provides evidence for combinations of fit indexes that may be most informative of model fit (Hu & Bentler, 1998, 1999). The discussion begins with an examination of alternative fit indexes, most of which have been covered in other texts (e.g., Normed Fit Index, Tucker-Lewis Index, etc.). Of interest to many readers will be the controversy about the use of a baseline model that may, for all intents and purposes, be practically untenable (i.e., completely uncorrelated observed variables). An intriguing alternative to the independence model is the equal correlation baseline model as proposed by Rigdon (1998). A comprehensive discussion fol-

lows regarding measures based on errors of approximation, such as the root mean square error of approximation, with guidelines offered to assess model fit. Again, the interested reader may want to consult the recent research by Hu and Bentler that specifically addresses this domain. Measures that assess cross-validation adequacy form the next discussion, including the Akaike Information Criterion (AIC) and the Expected Cross-Validation Index (ECVI). The utility of these information-theoretic indexes in comparing nested and nonnested models has been duly noted, although there was some discussion on SEMNET regarding the biased nature of these indexes as the model approaches saturation. Of general interest, Burnham and Anderson (1998), both coming from a biological background, have authored a text primarily focusing on the information-theoretic approach with various extensions of the AIC reviewed. The confluence of sample size and power and the role of modification indexes are discussed. The chapter concludes with Kaplan questioning the emphasis on model fit in the social and behavioral sciences, which generally is subordinated to the focus, as is the case within economics, "on proportion of variance in the endogenous variables accounted for by each equation as well as evaluation of the predictive utility of the model" (p. 127).

The two following chapters (7 and 8) encompass techniques that have seen widespread use and interest of late: multilevel SEM and latent growth curve modeling. Part of this interest may be due to the ongoing development of software that has made these techniques a bit more accessible (e.g., compare DOS-based language from an older version of hierarchical linear modeling [HLM]). Kaplan introduces multilevel modeling adopting the notation of Bryk and Raudenbush (1992), describing the intercepts- and slopes-as-outcomes model. Acknowledging that using either HLM or SEM alone in these hierarchical structures may "result in different but perhaps equally serious specification errors" (p. 134), the merging of both methodologies, based prominently on the body of work by Muthén and cohorts, is outlined. Along these lines, a recent article by Rovine and Molenaar (2000) further elaborates on employing an SEM approach to multilevel random coefficients models. Examples of both multilevel factor analysis and multilevel path analysis provide further evidence of the advantages afforded by merging SEM and HLM.

The interest in latent growth curve modeling has accelerated sufficiently that a recent text focuses solely on this type of analyses (Duncan, Duncan, Strycker, Li, & Alpert, 1999) with introductory texts including full chapters devoted to this methodology (e.g., Raykov & Marcoulides, 2000). Examining change over time is an area that has captivated researchers for decades, and with the development of increasingly more sophisticated methodologies, the ability to capture the intricacies of change has accelerated markedly (Collins & Horn, 1991; Gottman, 1995). Kaplan presents growth models within the context of multilevel linear models, using again the notation of Bryk and Raudenbush (1992). After considering a univariate growth curve model from a study examining science achievement and attitudes toward science, a more complex multivariate model is explored. Exten-