Driving Fast In Reverse

The Relationship Between Software Development, Theory, and Education in Structural Equation Modeling

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Abstract

Structural Equation Modeling is one of the most widely used statistical techniques in the social sciences, especially psychology. Its popularity and complexity have spawned a large number of "user-friendly" computer programs, training seminars, introductory textbooks, edited volumes, and an internet discussion group (SEMNET). A review of several introductory textbooks and an edited volume raises disturbing questions about the interplay between commercial development, statistical theory, and "practical" statistical education in this field. keywords: Covariance structure modeling; Factor analysis; Path analysis; Statistics education; Structural equation modeling

1 Introduction

Covariance Structure Modeling (CSM) is a general statistical technique that includes a wide number of familiar multivariate analysis methods (exploratory factor analysis, confirmatory factor analysis, path analysis, multiple regression) as special cases. Consider a set of p observed random variables Y_i that have a covariance matrix $\mathbf{\Sigma}$. A *covariance structure model* is any model of the form

$$\mathbf{\Sigma} = \mathbf{M}(\boldsymbol{\theta}) \tag{1}$$

where $\boldsymbol{\theta}$ is a vector of k model parameters, and $\mathbf{M}$ is a matrix *model function.* If $\mathbf{M}$ is relatively simple and/or has an obvious substantive interpretation, and k is small relative to the number of non-redundant elements of $\mathbf{\Sigma}$, then the model may serve as a useful tool for understanding the processes under study, or for simple data reduction.

Structural Equation Modeling (SEM) is a special case of CSM that has achieved wide popularity in the social sciences. The appeal of SEM stems from the fact that it includes path analysis, multiple regression, and factor analysis as special cases. This popularity has

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increased to the point that the demand for qualified instruction in SEM far outstrips the supply. This has led to the publication of a large number of introductory texts.

Almost all books published in SEM fall into one of two major categories: (1) Low level introductory textbooks, which purport to convey adequate background without "intimidating" the reader with technicalities like matrix algebra, and (2) Edited volumes, in which approximately 10–15 chapters are written around a unified theme. This article began as a standard review of 4 books, three (Kelloway 1998, Kline 1998, and Maruyama 1998) in the former category, and one (Schumacker and Marcoulides 1998) in the latter. However, it soon became clear to me that the problems in the introductory books were general, and significant, and had implications that go beyond their subject matter — hence the extended nature of this review.

In what follows, I shall begin by reviewing the history of SEM's metamorphosis from an esoteric technique accessible to only a handful of experts and their disciples to a ubiquitous tool available to virtually anyone through the medium of "user-friendly" computer software.

Next, I shall delineate a number of significant practical and theoretical issues that users of SEM should probably be aware of to avoid being a danger to themselves or others. My list is of course a personal one, but it is not eccentric, and many of the issues can be understood by beginners with a modest technical background. I find that, although the edited volume by Schumacker and Marcoulides provides much useful information, but is probably accessible only to those with an intermediate (or higher) level of experience in SEM, the three introductory texts fail to mention many of my list of "key issues." A prospective use of SEM could purchase software, read these three books carefully, and be seriously uninformed about the proper way to perform SEM.

The natural question arises, "How could this happen?" I propose an answer, which revolves around my understanding of the way scientific and commercial interests are interacting at the start of a new millennium.

My comments here may strike some readers as excessively negative, perhaps even mean-spirited. Certainly it is easier to criticize a brief introductory text than it is to write a good one. However, my concerns are genuine— introductory students relying on these texts for their knowledge base risk huge amounts of wasted time, and possibly serious professional embarrassment.

2 User-Friendly Structural Equation Modeling—Some Recent History

The specification of CSM in Equation (1) was too general for efficient software implementation on the computers of 20 years ago, and so compromises were necessary to reduce the class of potential model functions $\mathbf{M}(\boldsymbol{\theta})$. The first (and still most popular) general-purpose CSM program, was LISREL (linear structural relations). Based on CSM pioneer Karl Jöreskog's model of the same name, LISREL provoked an exponential growth of interest in CSM by allowing a wide variety of models to be tested.

The original LISREL model (Jöreskog 1970) deals with regression relationships between *latent* variables and can be viewed as two factor analysis models (called "measurement models"), sandwiched around a multiple regression model (the "structural model"). The motivation behind this approach is that, in the social sciences, variables frequently are measured with substantial error, so linear relationships between observed variables may be misleading. Consequently, the "structure" of the independent and dependent variables is assessed by analyzing linear relationships between common factors. These factors, generally based on two or more observed variables (called "indicators") are thought to represent "purified" versions of the concepts under study.

Algebraically, the system is expressed as follows: The *structural model* is

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{2}$$

The *endogenous latent* variables in $\boldsymbol{\eta}$ and the *exogenous latent* variables in $\boldsymbol{\xi}$ each have a "measurement model," that is,

$$\mathbf{y} = \boldsymbol{\Lambda}_y\boldsymbol{\eta} + \boldsymbol{\epsilon}, \tag{3}$$

$$\mathbf{x} = \boldsymbol{\Lambda}_x\boldsymbol{\xi} + \boldsymbol{\delta}. \tag{4}$$

Side assumptions are the following:

1. all variables have zero means.
2. $\boldsymbol{\zeta}$ is uncorrelated with $\boldsymbol{\xi}$.
3. $\boldsymbol{\epsilon}$ is uncorrelated with $\boldsymbol{\eta}$.
4. $\boldsymbol{\delta}$ is uncorrelated with $\boldsymbol{\xi}$.
5. $\boldsymbol{\zeta}$, $\boldsymbol{\epsilon}$, and $\boldsymbol{\delta}$ are mutually uncorrelated.
6. $\boldsymbol{\epsilon}$ and $\boldsymbol{\xi}$ are uncorrelated.

Defining $\boldsymbol{\Phi}$, $\boldsymbol{\Psi}$, $\boldsymbol{\Theta}_\epsilon$, and $\boldsymbol{\Theta}_\delta$ as the covariance matrices for $\boldsymbol{\xi}$, $\boldsymbol{\zeta}$, $\boldsymbol{\epsilon}$, and $\boldsymbol{\delta}$, and partitioning the covariance matrix as

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{yy} & \boldsymbol{\Sigma}_{yx} \\ \boldsymbol{\Sigma}_{xy} & \boldsymbol{\Sigma}_{xx} \end{bmatrix}, \tag{5}$$

one may easily show that

$$\boldsymbol{\Sigma}_{yy} = \boldsymbol{\Lambda}_y(\mathbf{I} - \mathbf{B})^{-1}(\boldsymbol{\Gamma}\boldsymbol{\Phi}\boldsymbol{\Gamma'} + \boldsymbol{\Psi})(\mathbf{I} - \mathbf{B}')^{-1}\boldsymbol{\Lambda}_y' + \boldsymbol{\Theta}_\epsilon, \tag{6}$$

$$\boldsymbol{\Sigma}_{xx} = \boldsymbol{\Lambda}_x\boldsymbol{\Phi}\boldsymbol{\Lambda}_x' + \boldsymbol{\Theta}_\delta, \tag{7}$$

$$\boldsymbol{\Sigma}_{xy} = \boldsymbol{\Lambda}_x\boldsymbol{\Phi}\boldsymbol{\Gamma}'(\mathbf{I} - \mathbf{B}')^{-1}\boldsymbol{\Lambda}_y'. \tag{8}$$

Each matrix on the right side of Equations (6)–(8) contains elements that are either fixed numerical values, or free parameters, and thus these equations constitute the matrix model function referred to more generally in Equation (1). The emphasis in the LISREL model is on the structural equations in Equation 2, and hence CSM using the LISREL model (and, indeed, using other equivalent models) often has been called *Structural Equation Modeling*, or SEM.

Without some constraints on their elements, the LISREL model matrices would not be identified, in the sense that many different values of the model parameters would yield the same $\mathbf{\Sigma}$. For example, if all the elements of $\mathbf{\Lambda}_x$ and $\mathbf{\Phi}$ were free, there would be infinitely many $\mathbf{\Lambda}_x$ and $\mathbf{\Phi}$ matrices all yielding the same value of the expression $\mathbf{\Lambda}_x\mathbf{\Phi}\mathbf{\Lambda}_x'$ in Equation (7). (Simply post-multiply $\mathbf{\Lambda}_x$ with any nonsingular matrix $\mathbf{T}$, and simultaneously pre- and postmultiply $\mathbf{\Phi}$ by $\mathbf{T}^{-1}$ and $\mathbf{T}^{-1\prime}$, respectively.) This general lack of identification of $\mathbf{\Lambda}_x$ is, in the context of factor analysis, referred to as *rotational indeterminacy.* In many applications of SEM, most elements of the model matrices are fixed at zero and so multiplication by any non-singular matrix is not permissible. However, multiplication by a diagonal non-singular matrix preserves zeroes in place and so the scaling of the columns of $\mathbf{\Lambda}_x$ and the diagonal of $\mathbf{\Phi}$ is always arbitrary. In practice, this is resolved either by restricting the diagonal elements of $\mathbf{\Phi}$ to be equal to 1 or by fixing one non-zero element of each column of $\mathbf{\Lambda}_x$ at unity.

Despite much effort, attempts to establish general necessary and sufficient conditions for identification of model parameters in SEM have not been successful. If the model is simple, identification may be established either by hand computation, or with the aid of symbolic algebra programs like Mathematica or Maple. If the model is complex, certain numerical indices (i.e., rank of the information matrix, convergence to two different solutions from two different starting points) can help detect an identification problem.

Note that the LISREL model at the random variable level, Equations (2)–(4), implies a covariance structure model. Consequently, one may falsify the random variable model by falsifying the covariance structure model. (I have presented the simplified model with zero means here, because it is used in the vast majority of cases. The model can be extended easily to handle nonzero means.)

What makes the LISREL model (at the random variable level) especially popular among social scientists is that it has a convenient visual representation, often called a path diagram. In the path diagram, the latent variables, those not directly observed, are represented with circles or ovals, and the manifest variables in rectangles. Linear equations are represented with arrows from the independent to the dependent variables. It is easy to show that such a diagram implies a covariance structure model.

It is extremely tempting to view the path diagram, with its directional arrows, as a model that represents causal flow between variables (hence the term "causal model"). Although the phrase "correlation is not causation" is still recited in virtually every introductory course in social science statistics, an entire generation of psychologists has vague notions that this principle is somehow suspended in SEM.

Social scientists usually began their SEM efforts by sketching a substantive model with a path diagram. The next step in the early "post-LISREL" days of SEM was a tedious, error-prone one—converting the diagram to the matrices.

1. All the variables in the diagram are classified as an element of $\mathbf{x}, \mathbf{y}, \boldsymbol{\eta}$, and so forth.

2. Each directed path between two variables has a coefficient that is either a fixed or free parameter. The coefficient from variable j in one list to variable i in another list appears as element i, j in the appropriate matrix. For example, whereas $\mathbf{\Gamma}$ contains regression weights relating variables in $\boldsymbol{\xi}$ to those in $\boldsymbol{\eta}$, a path from the first variable in $\boldsymbol{\xi}$ to the second in $\boldsymbol{\eta}$ would have a coefficient $\gamma_{2,1}$ in $\mathbf{\Gamma}$.

3. A similar procedure was followed for variances and covariances.

This tedious exercise often proved too difficult for the beginner, because the slightest error, involving misplacement of a single element in a model matrix, could cause completely unanticipated behavior, including lengthy failures to converge, costing expensive mainframe computer time. Individuals (sometimes referred to as LISRELites) who were adept in the required skills were much in demand. What made the process especially frustrating was that small changes in a path diagram (i.e., reversal of the direction of a single arrow) might lead to significant changes in the model matrices.

Time-consuming organizational exercises are perfect fodder for computer programs. Within a decade, the necessity for hand translation had been eliminated for a broad class of models. J. Jack McArdle and Peter Bentler each produced simplified algebraic approaches to structural modeling, which came to be known as the RAM model and Bentler-Weeks model. Their approaches were much simpler than the LISREL model and lent themselves to very simple algorithms for converting a path diagram directly into an algebraic model. These advantages were translated rather quickly into a first wave of "user- friendly" microcomputer programs, EQS, EzPATH, and CALIS, which allowed the user to express the path diagram rather directly in a command language. The program then converted these commands into an algebraic model, tested it, and output the results. In 1992, James Arbuckle, with his program AMOS Draw, introduced a system that allowed the user to construct a path diagram with a graphical interface, enabling the user to draw a path diagram directly on the screen, complete with arrows, rectangles, and ovals. This was an important landmark in the history of the field. Although the software (and that of its subsequent competitors) had some limitations, its availability enhanced the general view that structural equation modeling is a "natural mode of thought" that is available to anyone with a computer. This view was reinforced when several general-purpose statistical packages (SAS, STATISTICA, and SYSTAT) included structural equation modeling software modules that are more than adequate to meet the needs of many users. Indeed, a freeware CSM package, Mx, is now available over the internet.

By the end of the millennium, covariance structure modeling software was available (in a sense) to virtually everyone in the social sciences community.

3 Some Key Problems

Proper analysis of a structural model is many levels more complex than an analysis of variance, yet the speed, simplicity, and flexibility of SEM software might give a different impression. There are several topics that anyone attempting SEM (or, more generally, CSM) should know about, but that are given short shrift in most introductory texts. Some are problems that, if not handled properly within a SEM analysis, could seriously compromise the interpretation and value of the SEM enterprise. Others are techniques that can save work and prevent suboptimal analyses. None of the books has anything approaching adequate coverage of this list of topics.

3.1 Equivalent Models and Path Reversibility

Causal modeling, rightly or wrongly, attaches a causal interpretation to the direction of an arrow in a path diagram. If the direction of an arrow can be reversed without affecting the fit of the model to *any* data set, then the model may be uninterpretable. Only in recent years have the issues of equivalent models and possible reversal of paths attracted attention. For example, Lee and Hershberger (1990) gave a particularly clear and simple set of rules for examining a path diagram and determining whether arrows could be reversed without altering model fit. Somewhat to the embarrassment of the psychology community, it turned out that numerous models with reversable arrows already had been published (MacCallum, Wegener, Uchino, and Fabrigar 1993). My view is that *any* textbook on SEM, no matter how rudimentary, should present the work of Lee and Hershberger, along with some examples of their rules.

3.2 Non-Convergence and Local Minima

Estimation techniques employed in SEM require, except in a handful of special cases, iterative solution of a nonlinear optimization problem, often in 25 or more unknowns. In such cases, it is not uncommon for the minimization algorithm to fail to converge.

The vast majority of textbooks in SEM create the impression that this phenomenon does not exist, because it is seldom even mentioned. The books reviewed here concentrate on a few simple examples for which convergence occurs in a second or two. As a result, readers are deprived in two distinct ways:

1. They have no idea that there are important differences between the various SEM programs in the variety of iterative techniques available, and the ease with which the iterative routines may be adjusted to overcome convergence problems,

2. They have little or no idea why convergence problems occur, how to prevent them (if they are preventable through proper experimental planning), and how to cure them (if they can be cured by adjusting the iterative algorithm).

3.3 Power and Sample Size Analysis

Choice of an appropriate sample size is critical in any multivariate analysis. Proactive Monte Carlo analysis can help assess the sample size necessary to achieve accurate Type I error control and reasonable precision of estimation in a particular SEM effort.

Recently, MacCallum, Browne, and Sugawara (1996) recommended a general technique for assessing sample size in terms of the power of the overall chi-square test to assess the quality of population fit. However, none of the three introductory book authors discussed power or sample size estimation in any detail, although one (Maruyama) mentioned it in passing and provided important references.

3.4 Proper Reporting Techniques

In many published papers, the models are small, the data are compact, and it is relatively easy to report SEM results so that any competent practitioner could replicate them. However, reporting of covariance structure models is, in general, outrageously sloppy in many social science journals. Only a modest fraction of the papers that are published contain enough information for anyone to replicate the reported analysis easily, and in many cases the actual model tested by the authors is not represented properly. Any introductory textbook on SEM is setting the tone for future work in the field. In my opinion, such books should include a chapter with examples of what to do and what not to do when reporting the results of SEM.

3.5 Violation of Statistical Assumptions

Social science textbooks in statistics handle the question of robustness very unevenly. For example, most intermediate texts discuss robustness of parametric tests on means against violations of normality, while hardly any discuss nonrobustness of standard tests on correlations. Virtually all texts that cover the simple "paired sample t-test" fail to describe correctly its underlying assumption of *bivariate* normality.

In a similar vein, basic introductory texts in SEM pay lip service to the issue of robustness against violations of multivariate normality, but provide virtually no useful practical information. It is well known (e.g., Browne, 1982, 1984; Steiger and Hakstian 1982) that the asymptotic χ^2 commonly employed in SEM and the analysis of correlation structures is strongly affected by kurtosis. So in any practical application, this problem needs to be dealt with. Several questions come to mind. What is a quantitatively accceptable level of nonnormality? How should one assess the impact of nonnormality? What should one do to compensate for it? Of the three introductory texts reviewed here, only one (Klein) mentions the problem of nonrobustness.

3.6 Standardized Models—Problems and Paradoxes

There are many arguments for and against using standardized coefficients. In many situations in the social sciences, however, the variances of the variables are essentially arbitrary, and so it makes sense to use standardized coefficients. Many versions of the most popular software (e.g., LISREL through version 8) did not provide estimated standard errors with standardized coefficients. Moreover, statistical tests on coefficients that proved significant in the unstandardized case might not achieve significance in the standardized case. Particularly ironic, in retrospect, is that some software programs using constrained estimation methods obtain standardized solutions with standard errors and allow statistical tests on standardized coefficients. Most books on SEM never mention this.

3.7 The Analysis of Correlations

Just as there are many arguments for and against using standardized coefficients, there are similar arguments for analyzing correlations and covariances. Needless to say, there are many situations in which the metric of a variable conveys important information that standardization can obscure, and there are other cases where the metric is essentially arbitrary information that can obscure important relationships if it is not eliminated.

Unfortunately, traditional estimation methods employed by such programs as LISREL, AMOS, and EQS were designed for the analysis of covariance matrices. One can, of course, pretend that the sample correlation matrix is a sample covariance matrix and submit it to the software for analysis. However, although the parameter estimates resulting from such sleight-of-hand may be correct, the estimated standard errors will often be incorrect, sometimes by an order of magnitude. (Lawley and Maxwell 1971;, Cudeck 1989).

The approach to this problem taken by the more popular software packages was to acknowledge it, then gloss over it. A typical approach would be (a) to begin by reciting arguments in favor of analysis of covariances, (b) mention that the program presupposes analysis of the covariance matrix, then (c) provide several example analyses that ignore the problem, using the correlation matrix, and proceeding as if the resulting estimates were valid. For example, the LISREL VII manual (Jöreskog and Sörbom, 1989, p. 46–49) gave a detailed treatment of "Problems with Analysis of Correlation Matrices," then, albeit with a brief caution, analyzed a correlation matrix as though it is a covariance matrix on pages 145–150.

Constrained estimation methods (Browne and DuToit 1992) offer a simple solution to this problem, and several programs have already implemented it. Most textbooks fail to mention these developments.

4 Three Introductory Tests – Some Specific Comments

The three introductory books under review here omit, or barely mention, the majority of 7 topics that would seem useful or even crucial to the intelligent application of SEM. Self-directed study with with only a computer program, its associated manual, and one (or indeed all) of these books would leave the student badly underequipped to purse SEM.

However, one of the three (Kline) books is clearly superior to the others, and should be credited on that basis. Some specific comments follow.

4.1 *Principles and Practice of Structural Equation Modeling* by Rex B. Kline

This book is clearly written, well edited, and generally accurate. Moreover, each chapter contains a useful list of recommended followup readings. Despite its failure to cover a number of key areas, the book would be useful as a "starter text" in a 12 week course on SEM, and has the potential, with some significant revisions, to become outstanding.

4.1.1 Part I—Fundamental Concepts.

After a brief introduction in Chapter 1, the book discusses introductory statistical concepts in Chapter 2. The time is not well spent, because the topics are clear prerequisites for anyone planning to study SEM, and Kline's treatment is not particularly insightful. In Chapters 3 and 4, the author seems to hit his stride. Chapter 3, on the "SEM Family Tree," works smoothly through several major types of models, and introduces the standard notation for path diagrams. Chapter 4 discusses data screening, a topic fundamental to all data analysis, with special attention to issues of particular relevance to SEM.

4.1.2 Part II—Core SEM Techniques.

Chapters 5 and 6 discuss recursive and nonrecursive path models for observed variables. Here, again, time is wasted on topics that are ultimately of little interest to the modern SEM practitioner. Any would-be practitioner of SEM who would want to learn how to hand-calculate path coefficients would be better served by a full multivariate treatment of the topic, complete with a substantial module on matrix algebra.

Chapter 7 discusses measurement models and confirmatory factor analysis. Having worked through the preliminaries with a fair amount of attention to detail, the reader is ready for the payoff, that is, the full LISREL model (which Klein calls the "hybrid model"). Unfortunately, it is at just this point where the book fizzles out with an all-too-brief 25 page chapter, a perfunctory run through two simple examples. The author should expand the coverage to several types of models (including models with manifest exogenous variables), including at least one example that produces convergence problems for at least one of the programs.

4.1.3 Part III—Avoiding Mistakes; Advanced Techniques; Software.

The book concludes with 3 chapters that vary substantially in quality. Chapter 9, on avoiding mistakes, has a list of 35 points worth emphasizing to any newcomer to SEM. It is, in my opinion, one of the highlights of the book. Chapter 10 attempts to cover advanced techniques, but Klein does not deal with the topics in any critical way. For example, he discusses full information maximum likelihood methods for analysis of missing data without discussing the statistical assumptions or robustness properties of the method. Simply because the proponents of these methods ignore these topics is no reason for Klein to follow suit. He discusses interaction models while missing many of the key issues. The chapter on Software has brief, perfunctory comments which ignore many relevant points of comparison.

4.2 *Using LISREL for Structural Equation Modeling* by E. Kevin Kelloway

Less ambitious and much shorter than the other books reviewed here, this 147 page monograph is designed specifically as a very brief introduction to SEM using LISREL, the most popular SEM program. Kelloway has a very accessible writing style, one senses that he is an excellent teacher, and the book is very good in places. Kelloway bravely chooses to dispense with the user-friendly path diagramming advances in LISREL VIII, and presents the modeling procedure in terms of the matrix model specification language that LISREL users of versions I–VII were forced to contend with. This is, in principle, a wise decision. Given the limitations of the more recent advances in LISREL, the user may need to revert to the matrix language and program an unusual model from the ground up. However, some unfortunate pedagogical choices ultimately undermine the effort.

After a very brief introduction in Chapter 1, the book attempts a casual introduction to SEM in Chapter 2, with brief treatments of such topics as model specification, identification, estimation, testing fit, and model modification. This chapter is marred by some serious confusion in concept and terminology. Most authors talk of *solutions* to the model equation

(1) as a set of parameters that satisfy the equation. If there are more equations than unknowns, it may well be that no solution exists, and the model is therefore falsifiable. Kelloway botches this badly, informing the reader on page 15 that

> When models are overidentified, there are a number of unique solutions, and the task in most applications of structural equation modeling techniques is to find a solution that provides the best fit to the data. Thus, the identification of a structural equation model is purely a matter of the number of estimated parameters ...

Not only is the first sentence obviously wrong, but so is the second, as Anderson and Rubin (1956) demonstrated in their classic Berkeley Symposium paper. One cannot determine identification simply by counting equations and unknowns. Kelloway repeats the error at the beginning of the next section, in which he discusses estimation and fit.

His discussion of sample size estimation ignores the recent work of MacCallum, Browne, and Sugawara (1996).

Chapter 3 discusses methods for assessing model fit, and does a good job given the space limitations.

Chapter 4 is the key chapter for beginners, because it discusses the LISREL model, matrix terminology, and some input constants used to control output options. Here is where the author should have concentrated his effort. Unfortunately, the chapter is far too brief and makes a near-fatal pedagogical decision. Kelloway tries to explain the LISREL model with an example model that has only 2 latent variables, each with one "indicator." This sharply reduces the usefulness of the example to beginners who might want to use it as a template for their own analyses. With only one variable of each type, many of the myriad LISREL model matrices become 1×1. It is difficult to imagine why this choice was made, given the plethora of simple models discussed in other textbooks.

There are other surprising errors as well. For example, the reader is told on page 42 that

> 2. A fixed element in a LISREL path is the same as a hypothesis of no path between the variables represented by the column and the row.

This is simply wrong. A fixed element is just that, a parameter fixed to a specific numerical value. True, the default for fixed values may be zero, in which case the quoted statement is true, but this is hardly a requirement.

The remaining three chapters cover simple examples of confirmatory factor analysis, path analysis with observed variables, and path analysis with latent variables. Much of the chapter content is printed LISREL output, and the author offers only a few cursory comments.

Given the availability of stronger books aimed at the low level textbook market (for example, Kline's text), this book appears to be most useful as an extremely quick (say, 1 day) introduction to LISREL, as supporting material in an introductory seminar. In that context, its brevity and relatively low cost may be significant advantages.

4.3 *Basics of Structural Equation Modeling* by Geoffrey M. Maruyama

This 310 page introductory text attempts to approach the subject matter at a slightly higher level than Kline's book: it includes a brief module on matrix algebra and adds an occasional derivation in matrix notation. However, the approach is still relatively nontechnical, in an attempt to appeal to a broad range of readers. The book has a number of strong points: the author writes with a clear narrative style, and explains a number of key points with some interesting pedagogical approaches.

Unfortunately, in addition to its failure to come to grips with several of the key issues I identified earlier, the book is marred by two flaws that seem to signify a lack of statistical sophistication. First, the author presents several derivations that are simply incorrect, that is, he consistently confuses the product of two random vectors with the expected value of the product. For example, on page 180, after defining $\mathbf{y}$ as in Equation (2), he concludes that

$$\mathbf{\Sigma}_{yy} = \mathbf{\Lambda}_y \boldsymbol{\eta}\boldsymbol{\eta}' \mathbf{\Lambda}_y' + \mathbf{\Theta}_\epsilon \tag{9}$$

rather than

$$\mathbf{\Sigma}_{yy} = \mathcal{E}(\mathbf{y}\mathbf{y}') = \mathbf{\Lambda}_y \mathcal{E}(\boldsymbol{\eta}\boldsymbol{\eta}') \mathbf{\Lambda}_y' + \mathbf{\Theta}_\epsilon \tag{10}$$

with $\mathcal{E}(\ )$ denoting matrix expected value.

Second, the mathematical typesetting is awful—the publisher (Sage) seems unable to surround matrices with brackets, vertically center multiline formulas, or provide many other notational nuances normally taken for granted in a statistics text. For example, $\mathbf{\Theta}_\epsilon$ is typeset as $\mathbf{\Theta}\boldsymbol{\epsilon}$, and several similar errors can be found on pages 180–181. In an era in which such typesetting can be performed routinely in the Microsoft Windows environment with programs like MathType, and flawlessly with TeX or LaTeX, there is simply no excuse for such a lapse.

Maruyama's general approach mirrors that seen in numerous other SEM books. He begins with multiple regression and partial correlation, works through path analysis with single observed indicators, introduces factor analysis, and then combines the material in a coverage of SEM with latent variables. Unfortunately, at almost every stage there are obvious errors, omissions, or bad pedagogical choices.

For example, on pages 71–73, the author discusses confidence intervals for correlations. This is a topic covered at an elementary level in hundreds of textbooks, yet the author adds nothing to these elementary discussions and manages to say things that are not true. For example, he states that "Calculating confidence intervals requires converting correlations to Fisher's z," yet this method is simply a convenient approximation, and exact confidence intervals can be calculated using other methods.

On pages 181–184, Maruyama discusses the topic of "reference indicators." This is an interesting and potentially important topic that is given short shrift in most texts, and Maruyama's attempt to provide deeper coverage is laudable. Unfortunately, it misses the mark, because he says several things that are not true, and misses key points. For example:

1. He states (p. 181) that "without reference indicators, it is not possible to attain identification of latent variable models." In fact, several available programs offer just such a capability.

2. Maruyama provides an extensive illustration in which path coefficients from the endogenous latent variable to an indicator retain the same *relative* sizes regardless of which indicator is selected. He fails to mention that this (desirable) behavior does not occur in all covariance structure models or that the user, as a diagnostic device, should check to see whether it does occur to uncover possible problems. As a consequence, the SEM beginner would be misled into thinking that the behavior always occurs.

On page 200, Maruyama states that "Chi-square is distributed with a mean equal to its degrees of freedom, so dividing chi-square by its degrees of freedom should provide an index of some value as well . . ." This is true only if the null hypothesis is true, in which case fit is perfect, and there is, of course, no need to be estimating model fit. As a general statement, it is very misleading, and the ratio of the chi-square to its degrees of freedom is a very poor measure of structural model fit (e.g., Steiger, 2000).

The key examples in the book are confusing and poorly presented. I will analyze just one in detail. As I mentioned at the outset, a useful skill for LISREL users is understanding how to translate path diagrams into LISREL model matrices and, particularly, how to place path coefficients into the proper place in the LISREL matrices. Transmitting this skill efficiently without substantial frustration involves careful selection of examples that are complicated enough to be representative, but that avoid, in the early stages, introducing distracting "side issues." A good rule of thumb for authors is to avoid using examples from their own work, as they frequently fail to see aspects of their own models that might be confusing to a beginner.

Maruyama uses, as his initial example ("Example 1: A Longitudinal Path Model" on pages 204–209 and 222–226) a model that is a very poor choice as a teaching device:

1. The LISREL model has a problem with exogenous manifest variables. Notice that they are not represented in Equations (2)–(4), because the manifest variables (in $\mathbf{x}$ and $\mathbf{y}$) do not appear on the right side of any of the equations. To compensate for this deficiency, an entire generation of LISREL users were taught the "trick" of creating a "dummy" latent variable with a loading of 1 on the single manifest variable, with no residual. This, in effect, creates a latent variable "stand-in" for the observed variable. This deficiency of the LISREL model is not shared by competing systems, and leads to path diagrams that are needlessly complex and conceptually confusing. The diagram on page 206 is simpler if the unnecessary dummy latent variables "SES," "School % White," and "Popularity with Whites" are eliminated, and paths are drawn directly between the manifest variables. Rather than discuss the etiology of this awkward reparameterization, Maruyama sidesteps the issue entirely, possibly leaving the beginner with a range of misconceptions.

2. Maruyama analyzes the correlation matrix incorrectly as if it were a covariance matrix, without mentioning that this is formally incorrect.

3. The variable names in the path diagram do not match those in the correlation matrix on page 205. A translation table at the bottom of Table 9.1 would have been useful.

4. The notation in the path diagram does not match that used in the text, which in turn does not match LISREL model notation. So, for example, the coefficient labeled y_2 in the diagram is λ_2 in the text and is LISREL coefficient $\Lambda_{y_{1,1}}$.

5. The author does not take the time to establish, carefully, the connection between what appears in the diagram and what appears in the LISREL model specification on pages 222 and 223. Elements of matrices are not properly aligned, fixed values of 1.0 are represented in two different ways, and, after laying out model equations on page 222, Maruyama doesn't bother to connect them with the specification on the following page. For example, just *how* does the model statement "FR LY 2 1 BE 2 1" relate to what appears on the preceding page? Perhaps this is obvious to Maruyama, but it is not likely to be obvious to a beginner.

6. Perhaps the most stunning omission in this introductory example is that it offers an opportunity to apply the *replacement rules* discussed by Lee and Hershberger (1990). Specifically, anyone aware of the replacement rules can examine the path diagram on page 206 and see immediately that the model fit will be exactly the same if the path from "Past Academic Achievement" to "Popularity with Whites" is reversed. In this case, the time sequencing may make the second version of the model nonsensical, but the technical point should be made just the same. All covariance structure models should be checked for possible equivalent models and application of the replacement rules as a routine step in model development.

5 *Interaction and Nonlinear Effects in Structural Equation Modeling* by Randall E. Schmumacker and George A. Marcoulides (Eds.)

The edited volume by Schumacker and Marcoulides (1998) is an excellent example of the strengths and weaknesses of such volumes in the field of SEM. In this case, the strengths far outnumber the weaknesses, and the book is a worthwhile acquisition for anyone with a serious interest in the topic.

The topic of how to model interaction effects between latent variables in SEM is complex, and a number of alternative procedures have been proposed. This book presents a prior comparative review, followed by nine chapters presenting a variety of techniques, some of which were new at the time of printing. A final chapter by Karl Jöreskog provides an impressively succinct and clear overview and comparison of the techniques, both old and new, discussed in the previous chapters.

Producing an edited volume like this is often a thankless task involving a substantial amount of coordination, inability to exert much control over the content, and only moderate levels of technical support from the publisher. Schumacker and Marcoulides have a substantial amount of editorial experience with the journal *Structural Equation Modeling*, and, as such volumes go, this one is typographically consistent, well indexed, and well edited.

The book is definitely not for beginners, and many of the finer technical points in the various chapters will elude even those with intermediate levels of experience. Consequently, the availability of examples to serve as templates is especially important. Several examples are, by necessity, software-specific, and most are performed with LISREL, although Mx and

Amos also appear in places.

The reader is best advised to start with the prior review by Rigdon, Schumacker, and Wothke, then flip to the back of the book and carefully read the retrospective review with recommendations by Jöreskog. His comments place many of the other articles in proper perspective, and may allow the user to perform a reasonable analysis with a minimal waste of time. It turns out that a substantial number of the techniques that are presented in the earlier chapters are of limited usefulness, either because they make unrealistic assumptions unlikely to be met in practice, are too complicated to be implemented on available software, require unrealistic sample sizes, or have been supplanted by superior techniques. This chapter alone make the book worth its asking price. The book suffers from some problems that are all too typical of books of this type. The following issues should be mentioned:

1. There is no mention of a web site where input and data files can be downloaded. Several of the articles do not print the raw data used in the examples. Consequently, not all the examples can be performed even if the input files are typed in accurately. This simple oversight probably cost each purchaser of the book many hours of wasted time. In my opinion, editors and publishers should feel obligated to demand from the authors of each chapter input, data, and output files for long-term placement on a web site.

2. Some of the examples could profit from more details. Sometimes this is difficult for advanced authors to realize. Often, a careful review of examples by student volunteers will uncover aspects of the examples that might be essential for implementing the method in practice, but which the authors forgot to mention. An example is the appearance of starting values in an example on page 42. There is a cryptic comment that LISREL cannot compute starting values for this problem, so they must be provided by the user. However, no advice on how to calculate the values is provided.

This volume demonstrates well the way the difficulties the typical user faces in evaluating procedures in a software-driven field like SEM. Working through the chapters in the book, including executing the examples, would require weeks of effort. Given the complexities of the procedures, it would be extremely difficult for the typical user to make a meaningful evaluation of their relative strengths and weaknesses.

6 Conclusions

The books reviewed here are not atypical of the state of the art—there are many others like them. In this section, I review some of the factors that have led to this state of affairs.

At the start of a new millennium, statistical practice is, in many areas, software-driven. Techniques are becoming increasingly complicated and capable custom programming increasingly difficult to find. Consequently, unless a software implementation of a statistical procedure is available on a popular platform, the procedure is unlikely to be used.

Not only is statistical practice substantially software-driven, so is the field of textbook publishing. Publishing houses are sales-driven, and owners of a particular statistical software package constitute a "natural constituency" for a textbook writer. As a result, an author with mediocre knowledge and/or writing skill, with a prospective book built around a widely used software package, may be a much more attractive prospect to a publisher than a writer who wishes to approach the same subject matter at a higher level, with only occasional references to software.

As a field becomes increasingly software-driven, it can, ultimately, become theoretically fragmented. Rather than flowing from a central core of expertise (i.e., downward from contributors to top journals with highly qualified reviewers), ideas now appear piecemeal, either in the software, in "applied journals" (whose ratio of noise to signal is often appallingly high), or in "edited volumes," which apply varying levels of quality control.

Authors with the skill and experience to write high quality, introductory-level texts often are busy writing journal articles or software. The end result is a depressing lack of criticality and depth in many introductory texts. In many cases, the authors are simply not aware of important technical issues. In others, not wishing to alienate the authors of software packages who might provide important impetus for sales, they confuse blandness for neutrality, thereby failing to alert users about important strengths and weaknesses in competing software packages. Meanwhile, the publishing houses, operating on ever-decreasing profit margins and facing major adjustment problems with the rapid technological changes, lack the resources to properly edit such books.

SEM is an excellent example of a reasonably esoteric software-driven field, and the books reviewed here represent a natural consequence of the factors I have described. Superficially, the newcomer is led to believe that there is this impressive, but easy-to-use technique that allows modeling of causality in a kind of flow diagram. All one need do is sketch the model using a path diagrammer or simple programming language, input the data, and the model is fitted automatically, complete with statistical tests of fit, standard errors on the model parameters, and even hints ("modification indices") on how to improve the model. In practice, however, there are serious challenges for newcomers, especially those with limited education in statistics. Many things can go wrong, and often do. A common experience is for a newcomer, impressed by the advertising for a user-friendly program, to acquire the software and try to use it, only to find that the effort ends either in a computer system crash or in a barrage of error messages and uninterpretable output.

Looking around for help, such a user frequently finds that none is available. Whereas the largest and most powerful social science departments might have a few "quantitatively trained" people on staff, many departments decided long ago that such people were an unnecessary luxury.

These developments led to an interesting state of affairs. People needed to learn something about SEM, but often there was no expert available to teach a local course. A special course in SEM does not fit well into the mathematical statistics curriculum, and so the best many universities could manage would be a course taught by someone with "practical experience" using SEM, rather than deep understanding of the theory behind it. A first step in mounting such a course would be the choice of a textbook. Kenneth Bollen (1989) had written a well-balanced, intermediate level textbook that, in a previous generation, might have become a standard, but that might now seem too "high level" for those now being pressed into service as teachers of SEM.

The result, over the last decade, has been a virtual blizzard of "small introductory texts" in SEM. These texts have much in common. Unfazed by the fact that the actual problems users encounter are highly technical, all aim to fill a niche for a "nontechnical introduction" to the subject. Most of the books have been written by people who have published few if any technical articles in the field. Not surprisingly, all ignore topics that most statisticians would consider essential preliminaries to any attempt to apply SEM in practice. The reality is that anyone who finds Bollen's (1989) text too "high level" simply should not be teaching the subject. Anyone teaching from *any* of the currently available texts would have to supplement them substantially.

Unfortunately, entry into the practice of structural equation modeling is like trying to merge onto a busy superhighway filled with large trucks and buses. There are many obstacles and dangers. Some social scientists might believe the comments on the covers of these books, and infer that they can learn an advanced multivariate technique like SEM without any direct guidance from someone with advanced statistical training and extensive experience in the area. They may well try to do this by purchasing user-friendly software, and reading one or more simple nontechnical books like the three introductory books reviewed here. Metaphorically speaking, this would be like trying to merge onto the highway driving fast in reverse.

7 References

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