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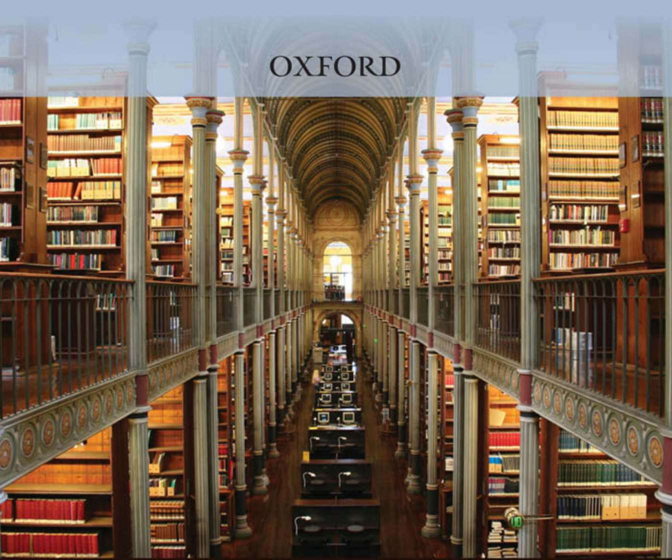

Structural Equation Modeling

Natasha K. Bowen
Shenyang Guo

Structural Equation Modeling

POCKET GUIDES TO
SOCIAL WORK RESEARCH METHODS

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Contents

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1

Introduction

RATIONALE AND HIGHLIGHTS OF THE BOOK

Social work practitioners and researchers commonly measure complex patterns of cognition, affect, and behavior. Attitudes (e.g., racism), cognitions (e.g., self-perceptions), behavior patterns (e.g., aggression), social experiences (e.g., social support), and emotions (e.g., depression) are complex phenomena that can neither be observed directly nor measured accurately with only one questionnaire item. Measuring such phenomena with multiple items is necessary, therefore, in most social work contexts. Often, scores from the multiple items used to measure a construct are combined into one composite score by summing or averaging. The new composite score is then used to guide practice decisions, to evaluate change in social work clients, or in research contexts, is entered as a variable in statistical analyses. Structural equation modeling (SEM) offers a highly desirable alternative to this approach; it is arguably a mandatory tool for researchers developing new measures. In sum, SEM is highly recommended for social work researchers who use or develop multiple-item measures. Using SEM will improve the quality and rigor of research involving such measures, thereby increasing the credibility of results and strengthening the contribution of studies to the social work literature.

One barrier to the use of SEM in social work has been the complexity of the literature and the software for the method. SEM software programs vary considerably, the literature is statistically intimidating to many researchers, sources disagree on procedures and evaluation criteria, and existing books often provide more statistical information than many social workers want and too little practical information on how to conduct analyses. This book is designed to overcome these barriers. The book will provide the reader with a strong conceptual understanding of SEM, a general understanding of its basic statistical underpinnings, a clear understanding of when it should be used by social work researchers, and step-by-step guidelines for carrying out analyses. After reading the book, committed readers will be able to conduct an SEM analysis with at least one of two common software programs, interpret output, problem-solve undesirable output, and report results with confidence in peer-reviewed journal articles or conference presentations.

The book is meant to be a concise practical guide for the informed and responsible use of SEM. It is designed for social work faculty, researchers, and doctoral students who view themselves more as substantive experts than statistical experts, but who need to use SEM in their research. It is designed for social workers who desire a degree of analytical skill but have neither the time for coursework nor the patience to glean from the immense SEM literature the specifics needed to carry out an SEM analysis. Although the book focuses on what the typical social work researcher needs to know to conduct his or her own SEM analyses competently, it also provides numerous references to more in-depth treatments of the topics covered. Because of this feature, readers with multiple levels of skill and statistical fortitude can be accommodated in their search for greater understanding of SEM. At a minimum, however, the book assumes that readers are familiar with basic statistical concepts, such as mean, variance, explained and unexplained variance, basic statistical distributions (e.g., normal distributions), sum of squares, standard deviation, covariance and correlation, linear regression, statistical significance, and standard error. Knowledge of exploratory factor analysis, matrix algebra, and other more advanced topics will be useful to the reader but are not required.

Highlights of the book include: (a) a focus on the most common applications of SEM in research by social workers, (b) examples of SEM research from the social work literature, (c) information on "best practices" in SEM, (d) how to report SEM findings and critique SEM articles, (e) a chronological presentation of SEM steps, (f) strategies for addressing common social work data issues (e.g., ordinal and nonnormal data), (g) information on interpreting output and problem solving undesirable output, (h) references to sources of more in-depth statistical information and information on advanced SEM topics, (i) online data and syntax for conducting SEM in Amos and Mplus, and (j) a glossary of terms. In keeping with the goals of the *Pocket Guides to Social Work Research Methods* series, we synthesize a vast literature into what we believe to be a concise presentation of solid, defensible practices for social work researchers.

WHAT IS STRUCTURAL EQUATION MODELING?

SEM may be viewed as a general model of many commonly employed statistical models, such as analysis of variance, analysis of covariance, multiple regression, factor analysis, path analysis, econometric models of simultaneous equation and nonrecursive modeling, multilevel modeling, and latent growth curve modeling. Readers are referred to Tabachnick & Fidell (2007) for an overview of many of these methods. Through appropriate algebraic manipulations, any one of these models can be expressed as a structural equation model. Hence, SEM can be viewed as an "umbrella" encompassing a set of multivariate statistical approaches to empirical data, both conventional and recently developed approaches.

Other names of structural equation modeling include covariance structural analysis, equation system analysis, and analysis of moment structures. Developers of popular software packages for SEM often refer to these terms in the naming of the programs, such as Amos, which stands for analysis of moment structures; LISREL, which stands for linear structural relations; and EQS, which stands for equation systems. A number of software programs can be used for SEM analyses. See Box 1.1 for citations and links for Amos, EQS, LISREL, and Mplus, four SEM programs commonly used by social workers. This book provides instructions and online resources for using Amos and Mplus, each of which has distinct advantages for the social work researcher. The general principles covered, however, apply to all SEM software.

For social work researchers, SEM may most often be used as an approach to data analysis that combines simultaneous regression equations and factor analysis (Ecob & Cuttance, 1987). Factor analysis models test hypotheses about how well sets of *observed* variables in an existing dataset measure *latent* constructs (i.e., factors). Latent constructs represent

Box 1-1 Examples of SEM Software Programs Used by Social Work Researchers

The following four programs are widely used for SEM analyses:
Amos (Arbuckle, 1983–2007, 1995–2007).
Website: http://www.spss.com/amos/
EQS (Bentler & Wu, 1995; Bentler & Wu, 2001).
Website: http://www.mvsoft.com/index.htm
LISREL (Jöreskog & Sörbom, 1999; Sörbom & Jöreskog, 2006).
Website: http://www.ssicentral.com/lisrel/
Mplus (Muthén & Muthén, 1998–2007; Muthén & Muthén, 2010).
Website: http://www.statmodel.com/index.shtml

theoretical, abstract concepts or phenomena such as attitudes, behavior patterns, cognitions, social experiences, and emotions that cannot be observed or measured directly or with single items. Factor models are also called *measurement models* because they focus on how one or more latent constructs are *measured*, or represented, by a set of observed variables. Confirmatory factor analysis (CFA) in the SEM framework permits sophisticated tests of the *factor structure* and quality of social work measures. (Shortly we will provide examples and much more detail about the terms being introduced here.) Latent variables with adequate statistical properties can then be used in cross-sectional and longitudinal regression analyses.

Regression models test hypotheses about the strength and direction of relationships between predictor variables and an outcome variable. Unlike standard regression models, SEM accommodates regression relationships among latent variables and between observed and latent variables. Unlike conventional regression models, SEM can estimate in a single analysis procedure models in which one or more variables are simultaneously *predicted* and *predictor* variables. Structural equation models with directional relationships among latent variables are often called *general structural equation models* (general SEMs).

In sum, SEM is a general statistical approach with many applications. Over the past two decades, statistical theories and computing software packages for SEM have developed at an accelerated pace. Newer SEM approaches include methods for analyzing latent classes cross-sectionally and over time (mixture modeling), and latent growth curve modeling (Bollen & Curran, 2006). Consistent with the goals of the pocket guides, this book focuses on a manageable subset of SEM topics that are relevant to social work research. Specifically, we focus on SEM's most common social work applications—*confirmatory factor analysis* and *cross-sectional* structural models with latent variables. In addition, we focus on proper methods for addressing common data concerns in social work research, ordinal-level data, nonnormal data, and missing data.

THE ROLE OF THEORY IN STRUCTURAL EQUATION MODELING

The primary goal of an SEM analysis is to confirm research hypotheses about the observed means, variances, and covariances of a set of variables. The hypotheses are represented by a number of structural parameters (e.g., factor loadings, regression paths) that is smaller than the number of observed parameters. As a confirmatory approach, it is crucial for researchers using SEM to test models that have strong theoretical or empirical foundations. Nugent and Glisson (1999), for example, operationalized two ways children's service systems might respond to children: either as responsive or reactive systems. "Responsive systems," the ideal, were defined as "[quick] to respond appropriately or sympathetically" to each child's specific mental health needs (p. 43). "Reactive systems" were operationalized as those that refuse to provide services, provide disruptive services, or otherwise fail to provide children with needed mental health treatments. With well-defined hypotheses based on previous research, the authors tested the nature of services provided in 28 counties in one state and the relationship between reactivity and responsiveness of the systems. Similarly, confirmatory factor analyses should be based on theory and/or the results of exploratory factor analyses and other psychometric tests.

SEM models are commonly presented in path diagrams. The path diagram is a summary of theoretically suggested relationships among latent variables and indicator variables, and directional (regression) and nondirectional (i.e., correlational) relationships among latent variables. Importantly, correlated errors of measurement and prediction can also be modeled in SEM analyses. We emphasize throughout the book that having a theoretical model and/or theory-derived constructs prior to any empirical modeling is mandated for both CFA and structural modeling with latent variables.

Path diagrams are graphics with geometric figures and arrows suggesting causal influences. SEM, however, has no better ability to identify causal relationships than any other regression or factor analytic procedure. Cross-sectional SEMs reveal associations among variables (one criterion for causality), and repeated measures in SEM can model time order of variables (another criterion for causality), but SEM in and of itself cannot definitively rule out other potential explanations for relationships among variables (the third criterion for establishing causality). The arrows in SEM illustrations reflect hypothesized relationships based on theory and previous research. SEM results may or may not provide support for the theory being tested, but they cannot *prove* or *disprove* theory or causality. Reversing the direction of arrows in any SEM may yield equally significant parameter estimates and statistics on model quality. For another brief treatment of this subject, see Fabrigar, Porter, and Norris (2010). These authors point out that although SEM cannot compensate for a nonexperimental design, it can be a useful analysis technique for experimental data and can be superior to other techniques with quasi-experimental data for ruling out competing causes of intervention outcomes.

Because models proposing opposite effects can yield similar statistics, it is a common and desirable practice to test alternative models in SEM. Good model statistics for an SEM model support its validity; model statistics that are superior to those obtained for a competing model provide valuable additional credibility. But neither establishes causality nor proves theory. Using experimental or quasi-experimental designs or statistical models specially developed for observational data in research studies remains the best way to identify causal effects.

WHAT KINDS OF DATA CAN OR SHOULD BE ANALYZED WITH SEM?

Ideally, SEM is conducted with large sample sizes and continuous variables with multivariate normality. The number of cases needed varies substantially based on the strength of the measurement and structural relationships being modeled, and the complexity of the model being tested. CFA models and general SEM with strong relationships among variables (e.g., standardized values of 0.80), for example, with all else being equal, can be tested with smaller samples than models with weak relationships (e.g., standardized values of 0.20) among variables. Sample size and statistical power are discussed further in Chapters 3 and 7.

Social workers often work with variables that are *ordinal* and/or nonnormally distributed, and datasets containing missing values. SEM software provides a number of satisfactory options for handling data with these statistically undesirable characteristics. In addition to its advantages over traditional regression approaches, therefore, SEM software provides solutions to common social work methodological issues that, if ignored, reduce the quality of social work studies, and consequently, the literature used to guide social work practice.

WHAT RESEARCH QUESTIONS ARE BEST ANSWERED WITH SEM? EXAMPLES FROM SOCIAL WORK STUDIES

Measurement Questions Answered with SEM

Measurement questions relate to the reliability and validity of data collected with questionnaires, checklists, rating sheets, interview schedules, and so on. SEM's ability to model sets of questions as indicators of hypothesized latent constructs (such as depression, social support, attitudes toward health care, organizational climate) provides a number of major statistical advantages, which will become evident later. Questions about the quality of multiple items as indicators of one or more dimensions of a construct are factor analysis questions.

The questions answered by CFA differ from those answered by exploratory factor analysis (EFA) procedures. As implied in the title, *confirmatory* factor analysis is used to test the adequacy of a well-defined model. The specified model is predetermined by theory or past research. The questions asked are closed ended: Do these indicators measure the phenomenon well? Do the data support the existence of multiple dimensions of the phenomenon, each measured by prespecified items? EFA is used earlier in the scale development process to answer more open-ended questions—for example, how many dimensions of the phenomenon are represented by these items? Which items are associated with each dimension? More about the distinction between EFA and CFA and their roles in the scale development process will be presented in Chapter 4.

CFA provides answers to questions about the structure of latent phenomena (e.g., the nature and number of dimensions), and the individual and collective performance of indicators. For example, researchers in one study (Bride, Robinson, Yegidis, & Figley, 2004) used data from 287 social workers who completed the Secondary Traumatic Stress Scale (STSS) to validate the scale as a measure of indirect trauma. Items on the STSS assess dimensions of traumatic stress as defined in the diagnostic criteria for posttraumatic stress disorder in the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 1994). Therefore, the hypothesized factor structure was derived from a strong foundation in theory and previous research. The results of the researchers' CFA provided answers to the following measurement questions:

1. **Did the items measure the three hypothesized dimensions of trauma symptomatology?** Yes, each of the 17 items on the scale was associated with the one dimension of trauma it was hypothesized to measure and not strongly associated with the other two dimensions it was not hypothesized to measure.
2. **How well did each indicator perform?** Factor loadings were moderate to high (0.58 to 0.79) and statistically significant. The size of the factor loadings indicates which items are most strongly related to each dimension.
3. **How good was the model overall?** The model explained 33% to 63% of the variance of each indicator, which is "reasonable" according to Bride et al. (2004). Other measures of the quality of the model met or exceeded standard criteria.
4. **How highly correlated were the three dimensions of trauma symptomatology?** Intercorrelations of the three dimensions ranged from 0.74 to 0.83 and were statistically significant. These correlations are consistent with theory and previous research about the components of trauma, according to the authors.

Bride et al. (2004) did not report the *variances* of the latent variables associated with the three dimensions of trauma symptoms in their model, but CFA results do indicate the magnitude of variances and whether they are statistically significantly different from zero. Subscales with little variance are not useful in practice, so it is important to examine these variance estimates in SEM output.

Like Bride et al. (2004), social workers may use CFA as a final test in a process of developing a new scale. Another important measurement question for social workers that can be answered with CFA is "whether measures . . . have the same meaning for different groups and over time" (Maitland, Dixon, Hultsch, & Hertzog, 2001, p. 74). If scores on a measure are compared for individuals from different populations (e.g., of different ages, gender, cultural backgrounds) or for the same individuals over time, it is critical to establish that the scores obtained from different groups or at different times have the same meaning. Maitland et al. (2001) used CFA to study the *measurement equivalence* or *invariance* of the Bradburn Affect Balance Scale (Bradburn ABS) across gender and age groups and over time. The researchers found that a small number of items from the two-dimension scale performed differently across groups and time, leading them to conclude that comparisons of scores across groups and time from past and future studies needed to be interpreted cautiously. Observed group and longitudinal differences in positive and negative affect could be partly attributed to variations in item performance rather than differences in the true scores for affect.

Structural Questions Answered with SEM

Relationships among latent variables (or factors) and other variables in an SEM model are *structural* relationships. Structural questions relate to the regression and correlational relationships among latent variables and among latent and observed variables. SEM structural models can include any combination of latent variables and observed variables. Observed demographic variables can be included as *covariate* or *control* variables, for example, in a model with latent independent and dependent variables. As with CFA models, all variables and relationships in structural models should be justifiable with theory and/or previous research.

SEM permits *simultaneous regression equations,* that is, equations in which one variable can serve as both an independent and a dependent variable. It is therefore a valuable tool for testing mediation models, that is, models in which the relationship between an independent variable and a dependent variable is hypothesized to be partially or completely explained by a third, intervening variable. It also permits tests of models in which there are multiple dependent variables. In Nugent and Glisson's (1999) model of predictors of child service system characteristics, for example, "system reactivity" and "system responsivity" were simultaneously predicted by all other variables in the model (either directly, indirectly, or both).

SEM is also a useful framework for testing moderation (interaction) models, or models in which the effects of one variable on another vary by the values or levels of a third variable. It provides more detailed output about moderation effects than typical regression procedures. In multiple regression, for example, moderation effects are obtained by creating product terms of the variables that are expected to interact (e.g., gender × stress). The results indicate the magnitude, direction, and statistical significance of interaction terms. In an SEM analysis, in contrast, the estimate and statistical significance of each parameter for each group (e.g., boys and girls) can be obtained, and differences across groups can be tested for statistical significance. Every parameter or any subset of parameters can be allowed to vary across groups, while others are constrained to be equal. The quality of models with and without equality constraints can be compared to determine which is best. Such information is useful for determining the validity of measures across demographic or developmental groups.

A study by Bowen, Bowen, and Ware (2002) provides examples of the flexibility of SEM to answer structural questions. The study examined the direct and indirect effects of neighborhood social disorganization on educational behavior using self-report data from 1,757 adolescents. Supportive parenting and parent educational support were hypothesized mediators of the relationship between neighborhood characteristics and educational behavior. Race/ethnicity and family poverty were observed control variables in the model. The rest of the variables in the structural model were latent. The authors hypothesized that the magnitude of the direct and indirect effects in the model would be different for middle and high school students—a moderation hypothesis—based on past research. Results of the analysis answered the following structural questions:

1. **Did neighborhood disorganization have a direct effect on educational behavior?** Yes, negative neighborhood characteristics had a statistically significant moderate and negative direct effect on adolescents' educational behavior.
2. **Was the effect of neighborhood disorganization on educational behavior mediated by parental behaviors (supportive parenting and parent educational behavior)?** Yes, the effect was partially

mediated by a three-part path with statistically significant coefficients between neighborhood disorganization and supportive parenting (negative), between supportive parenting and parent educational support (positive), and between parent educational support and educational behavior (positive).

3. **Were race/ethnicity and family poverty predictive of educational behavior?** No. Race/ethnicity and family poverty were significantly correlated with each other and with neighborhood disorganization, but the regression path between each observed variable and the dependent variable was not statistically significant.
4. **Did the structural paths differ for middle and high school students as hypothesized?** No. The moderation hypothesis was not supported. The relationships among the constructs were statistically equivalent for adolescents at both school levels.
5. **How good was the model overall?** Multiple measures of the quality of the final model met or exceeded standard criteria. As with traditional regression analyses, SEM results indicate the percent of variance of dependent variables explained by predictor variables. In this study: 14% to 33% of the variance of the mediators was explained, and 34% to 44% of educational behavior was explained.

It bears repeating that even when SEM models are grounded in theory and previous research, support for models in the form of statistically significant regression paths, factor loadings, and correlations, and good overall model fit does not "prove" that the model or the theory from which it is derived is correct. Nor does such support indicate causality. Such support, as we will discuss in more detail later, can only be interpreted as consistency with the observed data used to test the model.

SEM AS A USEFUL AND EFFICIENT TOOL IN SOCIAL WORK RESEARCH

Many challenging questions confronted by social work researchers can be answered efficiently, effectively, and succinctly by SEM. SEM is often the best choice for social work analyses given the nature of their measures and data. The topics and characteristics of SEM articles in a sampling of social work journals were examined by Guo and Lee (2007). The authors reviewed all articles published during the period of January 1, 1999 to December 31, 2004 in the following eight social work or social-work-related journals: *Child Abuse & Neglect*, *Journal of Gerontology Series B: Psychological Sciences and Social Sciences*, *Journal of Social Service Research*, *Journal of Studies on Alcohol*, *Research on Social Work Practice*, *Social Work Research*, *Social Work*, and *Social Service Review*. During the 6-year period, *Social Work* and *Social Service Review* published no studies that employed SEM. A total of 139 articles using SEM were published by the seven remaining journals that were examined.

Table 1.1 summarizes the 139 SEM publications by substantive areas and types of SEM. As the table shows, the majority of SEM applications in the targeted social work journals were general structural models (54.7%). The finding is not surprising because many social work research questions concern theoretically derived relationships among concepts that are best measured with latent variables. The second most common type of SEM was CFA (33.1%). Again, this finding is reasonable because developing measures of unobservable constructs is a primary task of

Table 1.1 SEM Applications by Social Work Research Area and SEM Type

Substantive area	*CFA*	*General structural models*	*Path analysis*	*Total*
Aging	9	29	7	45
	20.0%	64.4%	15.6%	100%
Child welfare	2	11	1	14
	14.3%	78.6%	7.1%	100%
Health/Mental health	20	5	2	27
	74.1%	18.5%	7.4%	100%
School social work	2	2	2	6
	33.3%	33.3%	33.3%	100%
Substance abuse	13	29	5	47
	27.7%	61.7%	10.6%	100%
Total	46	76	17	139
Total %	33.1%	54.7%	12.2%	100%

social work research. The remaining SEM articles reported on studies using path analysis (12.2%). Path analysis is useful for examining simultaneous regression equations among observed variables but does not exploit fully the advantages of SEM. In addition, it is possible (albeit more difficult) to obtain many of the results of a path analysis with more conventional analyses and software. Therefore, it makes sense that fewer social work articles used path analysis than the two SEM procedures with latent variables.

Across substantive areas, the proportion of studies using different types of SEM varied, with general structural models more common in the fields of child welfare, aging, and substance abuse. CFA was the most common type of analysis used in SEM studies of health and mental health. The Guo and Lee (2007) study indicated that SEM was being used by researchers in many major topical areas of social work research. It is hoped that by the end of this book, readers will agree that SEM is the most appropriate analysis tool for much of the research done by social researchers.

2

Structural Equation Modeling Concepts

In this chapter we discuss in detail a number of theoretical and statistical concepts and principles that are central to SEM. SEM notation and equations are introduced in the context of more familiar graphics and terminology. The role of matrices in SEM analyses is explained. The material in this chapter is essential to understanding the more detailed treatment of topics in later chapters, but later chapters also reinforce and help illustrate concepts introduced here. Iacobucci (2009) also provides a complementary and instructive summary of SEM notation and its relationship to the matrices. For more in-depth information on basic statistical concepts, refer to a social science statistics text (e.g., Cohen & Cohen, 1983; Pagano, 1994; Rosenthal, 2001). More advanced treatment of the statistical foundations of SEM can be found in Bollen (1989), Long (1983), and Kaplan (2009), and among other SEM texts in the reference list.

LATENT VERSUS OBSERVED VARIABLES

Latent variable is a central concept in SEM. Latent variables are measures of hidden or unobserved phenomena and theoretical constructs. In social