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BOOK REVIEW OF LONGITUDINAL STRUCTURAL EQUATION MODELING WITH MPLUS: A LATENT STATE-TRAIT PERSPECTIVE BY GEISER

REVIEW OF LONGITUDINAL STRUCTURAL EQUATION MODELING WITH MPLUS: A LATENT STATE-TRAIT PERSPECTIVE

The importance of longitudinal research to the social and behavioral sciences is difficult to overstate. A large body of research implements longitudinal designs and analyzes dynamic, repeated measures data to answer a broad range of research questions surrounding growth or change over time. A key decision involved in longitudinal research is the choice of appropriate statistical models. Christian Geiser's new book—*Longitudinal Structural Equation Modeling with Mplus: A Latent State-Trait Perspective*—focuses on the implementation of longitudinal statistical models with latent variables and their application in M*plus*. The book specifically introduces and discusses longitudinal structural equation models in the context of latent state-trait (LST) theory.[1] By couching LST theory into a longitudinal structural equation modeling framework, this book describes how researchers can reflect the change of individual states or traits under situational influences. Such a feature makes the book a distinctive resource that stands out in comparison with other longitudinal modeling books.

1. Summary and Impression

Longitudinal Structural Equation Modeling with Mplus: A Latent State-Trait Perspective is comprised of 8 chapters, which focus on an extensive array of topics, including the following: notion and logic underlying LST theory, a variety of longitudinal models, as well as methodological issues and guidelines for implementation and dissemination of research using these statistical and estimation tools. The sequence of chapters mirrors the full process of longitudinal modeling. The book begins with a gentle introduction to LST theory. This introduction serves as a precursor to the subsequent chapters covering various longitudinal models. Each of the models covered is introduced in an order of increasing complexity, and comparisons among these models are provided in easy-to-comprehend formats. The pedagogical features of this book are conducive to aiding even a novice reader in understanding the material. Indeed, Geiser is sure to explain the modeling methodology in a way that will prevent readers from being confused about the statistical models presented. What follows next are methodological issues on missing data, as well as guidelines on model selection and transparency of reporting results. Geiser's treatment of these topics reflects an intentional plan to expose readers to the full story of longitudinal structural equation modeling: underlying theory, model details, software implementations, methodological issues, and setting clear reporting standards. Another salient aspect of the book is its didactic nature; for instance, chapters on longitudinal models consist of the definition of a model using formulas and path diagrams, links to LST theory, variance decomposition, and M*plus* tutorials. The M*plus* tutorials contain step-by-step interpretations of outputs and syntax, making this book

[1] The original LST theory assumed a rigid trait concept in which trait variables strictly depend on person characteristics, and previous experiences or situations were not allowed to cause changes in traits (Steyer et al. 1992, 1999). Steyer et al. (2015) revised the theory by allowing the influence of situations or individual experiences on traits over time. Still, many features of the original LST theory remain unchanged, and Geiser formulates and explains longitudinal models based on perspectives from the original and revised LST theories. In light of this, we use the term LST theory without differentiating between its classical or modified versions.

a terrific guide for graduate students and researchers working with M*plus*. For advanced modeling issues that are relevant but of the upper level, the information is provided as separate boxes to enhance readers' understanding. This structuring of the separate boxes makes the information easy to access for a reader of any level. In the next section, we expand on this topic of audience and scope of the book.

2. Primary Audience and Expected Usage

This book can be a great resource for students or researchers whose interests lie in modeling individual changes based on LST theory. The book includes statistical symbols to represent structural equation models. If readers are familiar with this statistical notation, then the book is beneficial for them for grasping the underlying process beyond basic themes. However, the author includes a section of guidelines on statistical symbols before the first chapter, making the text accessible to readers who are unfamiliar with the common notation used in this field of statistics. The existence of statistical representation, therefore, does not discourage readers who are not comfortable with equation-based representations. Because of the broad way in which modeling and statistical complexity have been handled, the book is suitable as a textbook for a graduate course on longitudinal data analysis. If students have taken an introductory course on structural equation modeling, studying this book can be a useful extension of their learning or research. The book is also suitable as a handbook for researchers who plan to analyze their data using longitudinal structural equation models. The M*plus* code provided in this book can be easily adapted by researchers for their purposes.[2] In either usage, we feel that it is preferable for readers to possess basic knowledge in structural equation modeling or have experience in programming M*plus* before reading the book. For readers who need basic skills in M*plus*, we refer to Geiser (2012) as a companion book.

3. Chapter Overviews

Chapter 1 begins with a discussion of why considering a measurement theoretical framework is important in longitudinal statistical modeling with latent variables. Next, the chapter provides the fundamentals of LST theory by illustrating key latent variables (i.e., latent state variable, latent trait variable, latent state residual variable, and random measurement error). This first chapter thus lays the foundations to understand other longitudinal models discussed in subsequent chapters.

Chapter 2 introduces the three simplest longitudinal measurement models, including the random intercept model, the random and fixed intercept model, and the ξ-congeneric model. In the three models, a single repeatedly measured indicator loads on to a single factor, and basic hypotheses about change processes are tested by imposing/relaxing different types of constraints. These models are usually considered too restrictive. Their limitations can be addressed by models discussed in the following chapters.

Chapter 3 extends the single-indicator design to incorporate multiple latent factors. This chapter contains model extensions that can act as springboards into more complex models, including the following: the simplex model, the latent change score model, the trait-state-error model, and the latent growth curve model, which includes a discussion of specified and unspecified growth patterns. Within the context of these models, problems with estimation and bias are discussed, bringing knowledge from the simulation literature into the presentation of these model forms.

Chapter 4 brings the reader to the issue of measurement equivalence and how to address it. Starting with this chapter, longitudinal models with multiple indicators are explained; particularly,

[2] Online materials for M*plus* code are available at https://www.guilford.com/geiser2-materials/.

the latent state model and the latent state model with indicator-specific factors are introduced. Addressing measurement equivalence across four hierarchical levels of measurement (i.e., configural, weak, strong, and strict invariance) is delineated using the latent state model.

Chapter 5 continues introducing longitudinal models with multiple indicators. The chapter presents the latent state change model, the latent autoregressive/cross-lagged model (e.g., the latent autoregressive states model and the latent autoregressive/cross-lagged states model), the latent state-trait model (e.g., the singletrait-multistate model, the singletrait-multistate model with indicator-specific factors, and the multitrait-multistate model), the latent trait-change model (e.g., the latent state-trait trait-change model), and the multiple-indicator latent growth curve model (e.g., the linear indicator-specific growth model). With a summary of many models discussed, the advantages and limitations of multiple-indicator models finalize this chapter.

Chapter 6 focuses on the analysis of intensive longitudinal data and discusses two approaches—the multilevel modeling approach and the dynamic structural equation modeling approach. The multilevel modeling approach is explained by introducing the random intercept model, the linear latent growth model, the multitrait-multistate model, and the indicator-specific growth model. The dynamic structural equation modeling approach is illustrated by presenting the single-indicator latent autoregressive (simplex) model. Moreover, this chapter offers an introduction to Bayesian analysis, on which dynamic structural equation modeling is based.

Chapter 7 centers on a ubiquitous issue in longitudinal studies: missing data. When improperly handled, the presence of missing values can lead to biased estimates of model parameters and a reduction in statistical power. This chapter provides readers with an adequate background of missing data theory, and hands-on applications of two state-of-the-art missing data handling techniques, i.e., full information maximum likelihood and multiple imputation. It also discusses a promising data collection strategy in longitudinal research known as planned missing data designs, which can make use of missingness to help reduce the fatigue effect due to repeated measurement, and increase budget efficiency.

Chapter 8 covers an important topic that is too often overlooked in the literature: reporting standards. Often researchers employing new statistical methods can use step-by-step guides for implementation, but then they are left on their own to figure out how to report findings or problems that arose during the estimation process. This chapter offers a unique guide for reporting results for longitudinal structural equation models. Thorough examples for writing up different elements of design, modeling details, and results are provided. In addition to an exemplary tutorial for how to write up findings, there is a strong emphasis on the importance of transparency within statistical modeling. This chapter is sure to be a valuable resource for students and other researchers looking to implement these techniques in their own work.

4. Extending Knowledge Beyond This Book

The ability for Geiser to demonstrate key concepts and longitudinal models in plain terms throughout the chapters is a true asset for readers. Given the guidance of the book to theory and issues that arise within the longitudinal modeling context, we believe that the book can be a more valuable learning tool if readers are looking to expand their knowledge base on some of the topics covered.

In particular, Bayesian data analysis and missing data analysis are two themes that are closely intertwined with the content presented throughout the book. For instance, the Bayesian approach has the advantage of estimating complex longitudinal models (e.g., Depaoli, 2013; Smid et al., 2020), and the presence of missing data can lead to misleading conclusions in longitudinal studies (e.g., Graham, 2017; Nicholson et al., 2009). Thus, these two topics hold important positions in longitudinal modeling. While Geiser provides a concise introduction to these topics, we provide an additional list of resources that readers may find helpful after reading through Geiser's book.

The following resources are practical books or tutorial-style papers with the purpose of providing a gentle introduction to applied users. For more information about Bayesian data analysis, we recommend Kaplan (2014) for a general treatment of Bayesian statistics, and van de Schoot et al. (2021) for a primer that details the stages of Bayesian inference. For a treatment of Bayesian structural equation models, including longitudinal variants, readers can consult Depaoli (2021). For more information about missing data analysis, we refer readers to Enders (2022) and van Buuren (2018) for a thorough treatment of issues surrounding missing data. To learn more about planned missing data designs, we recommend Wu and Jia (2021).

5. Conclusion

Overall, this book provides a well-written treatment of longitudinal modeling topics, and it does an excellent job of presenting an expansive overview of longitudinal structural equation modeling based on LST theory. Geiser is a leading figure in the field, and this recent contribution to the literature provides an extensive discussion of LST-based longitudinal structural equation models—a topic where resources had been previously lacking. Each chapter is organized in a way to help readers accomplish their goal of analyzing longitudinal data by selecting models that accurately reflect substantive research questions. In addition to the structure, the book flows well, with the main text presented in a didactic tone that is aimed toward methodologists and practitioners. Another true asset of this book is the inclusion of M*plus* code for every model, which will no doubt act as an important learning tool for readers looking to implement these models in their own research. It is not easy to write a book that is balanced between methodological rigor and applicability, but Geiser has done just that. This book will remain a great standard for graduate students and researchers interested in learning about LST-based longitudinal structural equation modeling. We look forward to seeing many future works that will be benefited by this book.

UNIVERSITY OF CALIFORNIA, MERCED *Ihnwhi Heo, Fan Jia and Sarah Depaoli*

Declarations

Conflict of interest We have no conflicts of interest to disclose.

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