ASSESSING MEASUREMENT INVARIANCE FOR APPLIED RESEARCH

Assessing Measurement Invariance for Applied Research will provide psychometricians and researchers across diverse disciplines in the social sciences with the necessary knowledge and skills to select and apply appropriate methods to assess measurement invariance. It is a user-friendly guide that describes a variety of statistical methods using a pedagogical framework emphasizing conceptual understanding, with extensive illustrations that demonstrate how to use software to analyze real data. A companion website (people.umass.edu/cswells) provides downloadable computer syntax and the data sets demonstrated in this book so readers can use them to become familiar with the analyses and understand how to apply the methods with proficiency to their own work. Evidence-supported methods that can be readily applied to real-world data are described and illustrated, providing researchers with many options from which to select given the characteristics of their data. The approaches include observed-score methods and those that use item response theory models and confirmatory factor analysis.

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ASSESSING MEASUREMENT INVARIANCE FOR APPLIED RESEARCH

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> This book is dedicated to my loving family: Amanda, Madeline, and Elianna.

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You can download the data files and computer syntax described in this book at the companion website: people.umass.edu/cswells

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Preface

Why write a book about assessing measurement invariance? This question is not about justifying the importance of examining measurement invariance (I address that issue in Chapter 1) but instead about why a book on measurement invariance is useful for social science researchers. In the past 30 years, there have been several excellent texts that have described statistical methods for detecting a lack of measurement invariance (often referred to as differential item functioning), such as Holland and Wainer (1993), Camilli and Shepard (1994), Zumbo (1999), Osterlind and Everson (2009), Engelhard (2012), and Millsap's comprehensive Statistical Approaches to Measurement Invariance (2011) in which he provided a unifying theory of measurement invariance. Each of these books provided a valuable contribution to the literature, and we are indebted to the authors and the many other researchers who have added to the theory and practice of assessing measurement invariance. What sets this book apart from those excellent resources on this topic is that, as the title implies, this book focuses on the practical application of assessing measurement invariance, with less emphasis on theoretical development or exposition. As such, a primary emphasis of the book is to describe the methods using a pedagogical framework, followed by extensive illustrations that demonstrate how to use software to analyze real data. My intention is that you will use this book to learn about practical methods to assess measurement invariance and how to apply them to your own data. This book is intended to be a user-friendly guide for anyone who wants to assess measurement invariance in their own work. To support this goal, the computer syntax and data sets used in this book are available for download at the following website: www.people.umass.edu/cswells.

As someone who has taught statistics and psychometrics for many years, I have learned that students learn better when they are actively engaged in the learning process. Therefore, I invite you to download the example data files and syntax and perform the analyses while you read along in this

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Preface

book. My goal is to provide you with enough instruction and practice in the most useful methods so that you can apply what you have learned to novel problems and data sets in your own work.

The audience I envisioned while writing this book is applied researchers, both graduate students and professionals, from the social sciences in which educational tests, psychological inventories, questionnaires, and surveys are administered. This includes researchers from diverse fields, such as education, psychology, public policy, higher education, marketing, sports management, sociology, and public health, to name a few. The purpose of this book is to provide researchers and psychometricians from these diverse fields with the necessary knowledge and skills to select and apply an appropriate method to assess measurement invariance for the problems they are trying to solve and the research questions they are trying to answer. Regardless of your field, I wrote this book assuming you understand basic statistics taught in an introductory statistics course (e.g., mean, standard deviation, correlation, regression, effect size, hypothesis testing, confidence intervals), as well as the concepts of reliability and validity.

This book includes chapters that describe the big ideas and the theoretical concepts of measurement invariance and various statistical procedures, while other chapters include a pedagogical framework for you to learn a new method, including guided practice opportunities. In Chapter 1 I describe the basic ideas of measurement invariance, including why it is important to assess, and I address important issues to consider when applying the methods described in this book. Chapters 2, 4, and 6 are written to teach you specific methods for assessing measurement invariance. The basic structure of each of these chapters is a description of the method, followed by detailed illustrations on how to examine measurement invariance using computer software. Chapter 2 describes observedscore methods where the groups are matched using raw scores. Chapter 4 describes detection methods that use item response theory (IRT) models. Chapter 6 describes methods that rely on confirmatory factor analysis (CFA). For those who are unfamiliar with IRT, Chapter 3 provides a description of the basic concepts of and models used in IRT. I also provide an illustration of how to use the computer program flexMIRT (Cai, 2017) to estimate the parameters for several IRT models. Chapter 5 provides a description of the underlying concepts of CFA that are needed to understand the CFA-based methods described in Chapter 6. Several CFA models are fit to data using the computer program Mplus (Muthén & Muthén, 2008–2017). Finally, Appendix A provides a brief tutorial on the

Preface

computer program R, because many of the techniques described in this book rely on packages in R.

There are many statistical methods available that I could have included in this book. Given that I was writing for practitioners and not writing a methodological tome that addresses all methods that have been created, I had to strategically select the methods I wanted to address. To accomplish this goal, I decided to include methods that met four criteria. The methods must (1) have been studied empirically and shown to provide reasonably accurate assessment of measurement invariance; (2) be able to incorporate an effect size or some type of information for determining whether the lack of invariance was nontrivial; (3) be relatively simple to use, especially for practitioners who are non-psychometricians; and (4) have software readily available to implement them. Indeed, there are methods that meet these criteria that I may not have included, but there will always be more to learn and write.

One of the challenges in writing a book that encompasses methods from different areas (i.e., observed-score and IRT- and CFA-based detection methods) is that the same symbols can take on different meanings depending on the context. I have attempted to use the symbols in their original meaning, which may cause confusion. For example, the Greek letter α is often used to represent the nominal Type I error rate, common odds ratio, or item discrimination parameter in an IRT model. It is important for the reader to discern the appropriate meaning of a symbol based on the context. To help prevent possible confusion, I have tried to define the symbols when they are first introduced in a chapter.

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