Available online at www.sciencedirect.com
ScienceDirect
Research in Social and Administrative Pharmacy 13 (2017) 634–643
RESEARCH IN SOCIAL & ADMINISTRATIVE PHARMACY

Update to core reporting practices in structural equation modeling

James B. Schreiber, Ph.D.
Duquesne University, School of Nursing, 600 Forbes Ave., Pittsburgh, PA 15282, USA

Summary

This paper is a technical update to "Core Reporting Practices in Structural Equation Modeling."[1] As such, the content covered in this paper includes, sample size, missing data, specification and identification of models, estimation method choices, fit and residual concerns, nested, alternative, and equivalent models, and unique issues within the SEM family of techniques.

Keywords: Structural equation modeling; Reporting; Research methods

Introduction

SEM and the SEM family of analysis techniques are a way of attempting to understand the complex and nuanced world in which we live. They are not truth finders – your model will one day be superseded by another model or shown to be misspecified with a variable that was not important in your research epoch. Because of the complexity and the number of people working in this area, researchers will need to continually be scholars of their methods and analytical decisions along with the rich knowledge of their theoretical and applied areas.[1]

As in Schreiber (2008),[2] a general checklist is useful and can be found in Table 1. The checklist is in the spirit of Gawand's[3] "checklist manifesto" but with quite lower stakes involved (Table 1).

Sample size-power

SEM remains a large sample analytic technique. More recent work has demonstrated that the sample size needed is not as large as previously argued.[4] But there are some important caveats. Sample size needed to research a certain level of power can be thought of as a function of the degrees of freedom, the RMSEA fit value (see section on fit values) under the null hypothesis, the RMSEA fit value under the research hypothesis, and a critical chi-square value aligned to a given alpha level.[5] As your degrees of freedom decrease, all else equal, the larger your sample size must be to reach the desired power level.[4,6] Because of the number of issues involved, sample size needs should be developed during the design phase, and not post-analysis which is "observed power."[6]

Recently simulation work has demonstrated similar interactions along with confidence interval and expected widths.[4] For example, if you have a

* Corresponding author.
E-mail address: schreiberj@duq.edu

1551-7411/$ - see front matter © 2016 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.sapharm.2016.06.006

belief that the population value of RMSEA value is .04, and your model has 60 df, and you desire a 95% CI and narrow width of .05, you will need a sample size of 544. This approach is more about not focusing on a strict cutoff level of RMSEA but a tight width around the RMSEA value so that researchers and future readers can evaluate the model tested and not a universal cutoff.

As the field has expanded and researchers have taken on the challenge of sample size estimation with more complex models, some software options have become more available. There is the AIPE approach in the open source R package with the ss.aipe.rmsea() function from the MBESS package.[4] There is also Kris Preacher's website at http://www.quantpsy.org/rmsea/rmsea.htm which will generate R code for sample size, power, and nested models. The important point to remember is to plan the sample size needed for the model being tested before data collection or in the case of existing data sets, significantly before analysis. This is a growing and evolving area and more options continually arrive.

Missing data

Missing data are still the scourge of studies utilizing long surveys or longitudinal designs and even those with planned missing.[7–11] The traditional understanding of the missing data are still the key, that is, missing completely at random (MCAR), missing at random (MAR), and not missing at random (NMAR). MCAR is rare, and MAR is more common and the reason for the missingness is predictable[12,13] but sometimes you do not know if it is or what the missing mechanism is such as gender or income level. If the data are NMAR and you do not know why, traditionally this has put the breaks on our analyses. But more recent work has shown that you can deal with some of the NMAR bias before you decide

Table 1
Checklist for non-analytic reporting

Well developed theoretical framework
Theorized model display
Operational definitions
Checklist for analytic reporting
Sample size
Original and final
Missing data
How handled (listwise deletion, imputed means …)
Justification of missing data resolution present
Specification/identification
Normality
Outliers
Linearity/multicollinearity
Software and estimation method stated: justified and aligned with data types, normality, etc.
Power discussion
Assessment of fit
Model chi-square
Multiple fit indices with justification provided
Parameters estimated and significant tests
Squared multiple correlation (CFA) variance accounted for (SEM)
Standardized and unstandardized estimates
Residual analysis—predicted and actual covariance matrix and standardized residual discussion
Examination
Correlation and means tables
Modifications
Rationale for modification
Lagrange test for adding paths
Wald test for dropping paths
Correlation between estimated parameters (hypothesized & final models)
Equivalent model
Diagram of final model