Ivan Jacob Agaloos Pesigan

January 20, 2024

References

blx@hook@bibinit

M. W.-L. Cheung: Synthesizing indirect effects in mediation models with meta-analytic methods **Cheung-2021**

Mike W.-L. Cheung. "Synthesizing indirect effects in mediation models with meta-analytic methods". In: *Alcohol and Alcoholism* 57.1 (June 2021), pp. 5–15. DOI: 10.1093/alcalc/agab044.

Abstract: Aims A mediator is a variable that explains the underlying mechanism between an independent variable and a dependent variable. The indirect effect indicates the effect from the predictor to the outcome variable via the mediator. In contrast, the direct effect represents the predictor's effort on the outcome variable after controlling for the mediator. Methods A single study rarely provides enough evidence to answer research questions in a particular domain. Replications are generally recommended as the gold standard to conduct scientific research. When a sufficient number of studies have been conducted addressing similar research questions, a meta-analysis can be used to synthesize those studies' findings. Results The main objective of this paper is to introduce two frameworks to integrating studies using mediation analysis. The first framework involves calculating standardized indirect effects and direct effects and conducting a multivariate meta-analysis on those effect sizes. The second one uses meta-analytic structural equation modeling to synthesize correlation matrices and fit mediation models on the average correlation matrix. We illustrate these procedures on a real dataset using the R statistical platform. Conclusion This paper closes with some further directions for future studies.

S. F. Cheung et al.: FINDOUT: Using either SPSS commands or graphical user interface to identify influential cases in structural equation modeling in AMOS **Cheung-Pesigan-2023a**

Shu Fai Cheung and Ivan Jacob Agaloos Pesigan. "FINDOUT: Using either SPSS commands or graphical user interface to identify influential cases in structural equation modeling in AMOS". In: *Multivariate Behavioral Research* (Jan. 2023), pp. 1–5. DOI: 10.1080/00273171.2022.2148089.

Abstract: The results in a structural equation modeling (SEM) analysis can be influenced by just a few observations, called influential cases. Tools have been developed for users of R to identify them. However, similar tools are not available for AMOS, which is also a popular SEM software package. We introduce the FINDOUT toolset, a group of SPSS extension commands, and an AMOS plugin, to identify influential cases and examine how these cases influence the results. The SPSS commands can be used either as syntax commands or as custom dialogs from pull-down menus, and the AMOS plugin can be run from AMOS pull-down menu. We believe these tools can help researchers to examine the robustness of their findings to influential cases.

S. F. Cheung et al.: semlbci: An R package for forming likelihood-based confidence intervals for parameter estimates, correlations, indirect effects, and other derived parameters **Cheung-Pesigan-2023b**

Shu Fai Cheung and Ivan Jacob Agaloos Pesigan. "semlbci: An R package for forming likelihood-based confidence intervals for parameter estimates, correlations, indirect effects, and other derived parameters". In: *Structural Equation Modeling: A Multidisciplinary Journal* (May 2023), pp. 1–15. DOI: 10.1080/10705511.2023.2183860.

Abstract: There are three common types of confidence interval (CI) in structural equation modeling (SEM): Wald-type CI, bootstrapping CI, and likelihood-based CI (LBCI). LBCI has the following advantages: (1) it has better coverage probabilities and Type I error rate compared to Wald-type CI when the sample size is finite; (2) it correctly tests the null hypothesis of a parameter based on likelihood ratio chi-square difference test; (3) it is less computationally intensive than bootstrapping CI; and (4) it is invariant to transformations. However, LBCI is not available in many popular SEM software packages. We developed an R package, semlbci, for forming LBCI for parameters in models fitted by lavaan, a popular open-source SEM package, such that researchers have more options in forming CIs for parameters in SEM. The package supports both unstandardized and standardized estimates, derived parameters such as indirect effect, multisample models, and the robust LBCI proposed by Falk.

S. F. Cheung et al.: DIY bootstrapping: Getting the nonparametric bootstrap confidence interval in SPSS for any statistics or function of statistics (when this bootstrapping is appropriate) **Cheung-Pesigan-Vong-2022**

Shu Fai Cheung, Ivan Jacob Agaloos Pesigan, and Weng Ngai Vong. "DIY bootstrapping: Getting the nonparametric bootstrap confidence interval in SPSS for any statistics or function of statistics (when this bootstrapping is appropriate)". In: *Behavior Research Methods* 55.2 (Mar. 2022), pp. 474–490. DOI: 10.3758/s13428-022-01808-5.

Abstract: Researchers can generate bootstrap confidence intervals for some statistics in SPSS using the BOOTSTRAP command. However, this command can only be applied to selected procedures, and only to selected statistics in these procedures. We developed an extension command and prepared some sample syntax files based on existing approaches from the Internet to illustrate how researchers can (a) generate a large number of nonparametric bootstrap samples, (b) do desired analysis on all these samples, and (c) form the bootstrap confidence intervals for selected statistics using the OMS commands. We developed these tools to help researchers apply nonparametric bootstrapping to any statistics for which this method is appropriate, including statistics derived from other statistics, such as standardized effect size measures computed from the t test results. We also discussed how researchers can extend the tools for other statistics and scenarios they encounter.

Li et al.: Bayesian forecasting with a regime-switching zero-inflated multilevel poisson regression model: An application to adolescent alcohol use with spatial covariates

Li-Oravecz-Zhou-etal-2022

Yanling Li, Zita Oravecz, et al. "Bayesian forecasting with a regime-switching zero-inflated multilevel poisson regression model: An application to adolescent alcohol use with spatial covariates". In: *Psychometrika* 87.2 (Jan. 2022), pp. 376–402. DOI: 10.1007/s11336-021-09831-9.

Abstract: In this paper, we present and evaluate a novel Bayesian regime-switching zero-inflated multilevel Poisson (RS-ZIMLP) regression model for forecasting alcohol use dynamics. The model partitions individuals' data into two phases, known as regimes, with: (1) a zero-inflation regime that is used to accommodate high instances of zeros (non-drinking) and (2) a multilevel Poisson regression regime in which variations in individuals' log-transformed average rates of alcohol use are captured by means of an autoregressive process with exogenous predictors and a person-specific intercept. The times at which individuals are in each regime are unknown, but may be estimated from the data. We assume that the regime indicator follows a first-order Markov process as related to exogenous predictors of interest. The forecast performance of the proposed model was evaluated using a Monte Carlo simulation study and further demonstrated using substance use and spatial covariate data from the Colorado Online Twin Study (CoTwins). Results showed that the proposed model yielded better forecast performance compared to a baseline model which predicted all cases as non-drinking and a reduced ZIMLP model without the RS structure, as indicated by higher AUC (the area under the receiver operating characteristic (ROC) curve) scores, and lower mean absolute errors (MAEs) and root-mean-square errors (RMSEs). The improvements in forecast performance were even more pronounced when we limited the comparisons to participants who showed at least one instance of transition to drinking.

Li et al.: Fitting multilevel vector autoregressive models in Stan, JAGS, and Mplus Li-Wood-Ji-etal-2021

Yanling Li, Julie Wood, et al. “Fitting multilevel vector autoregressive models in Stan, JAGS, and Mplus”. In: *Structural Equation Modeling: A Multidisciplinary Journal* 29.3 (Sept. 2021), pp. 452–475. DOI: 10.1080/10705511.2021.1911657.

Abstract: The influx of intensive longitudinal data creates a pressing need for complex modeling tools that help enrich our understanding of how individuals change over time. Multilevel vector autoregressive (mlVAR) models allow for simultaneous evaluations of reciprocal linkages between dynamic processes and individual differences, and have gained increased recognition in recent years. High-dimensional and other complex variations of mlVAR models, though often computationally intractable in the frequentist framework, can be readily handled using Markov chain Monte Carlo techniques in a Bayesian framework. However, researchers in social science fields may be unfamiliar with ways to capitalize on recent developments in Bayesian software programs. In this paper, we provide step-by-step illustrations and comparisons of options to fit Bayesian mlVAR models using Stan, JAGS and Mplus, supplemented with a Monte Carlo simulation study. An empirical example is used to demonstrate the utility of mlVAR models in studying intra- and inter-individual variations in affective dynamics.

McNeish et al.: A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus McNeish-Hamaker-2020

Daniel McNeish and Ellen L. Hamaker. “A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus”. In: *Psychological Methods* 25.5 (Oct. 2020), pp. 610–635. DOI: 10.1037/met0000250.

Abstract: Technological advances have led to an increase in intensive longitudinal data and the statistical literature on modeling such data is rapidly expanding, as are software capabilities.

Common methods in this area are related to time-series analysis, a framework that historically has received little exposure in psychology. There is a scarcity of psychology-based resources introducing the basic ideas of time-series analysis, especially for data sets featuring multiple people. We begin with basics of N = 1 time-series analysis and build up to complex dynamic structural equation models available in the newest release of Mplus Version 8. The goal is to provide readers with a basic conceptual understanding of common models, template code, and result interpretation. We provide short descriptions of some advanced issues, but our main priority is to supply readers with a solid knowledge base so that the more advanced literature on the topic is more readily digestible to a larger group of researchers.

McNeish et al.: Intensive longitudinal mediation in Mplus McNeish-MacKinnon-2022

Daniel McNeish and David P. MacKinnon. "Intensive longitudinal mediation in Mplus". In: *Psychological Methods* (Dec. 2022). DOI: 10.1037/met0000536.

Abstract: Much of the existing longitudinal mediation literature focuses on panel data where relatively few repeated measures are collected over a relatively broad timespan. However, technological advances in data collection (e.g., smartphones, wearables) have led to a proliferation of short duration, densely collected longitudinal data in behavioral research. These intensive longitudinal data differ in structure and focus relative to traditionally collected panel data. As a result, existing methodological resources do not necessarily extend to nuances present in the recent influx of intensive longitudinal data and designs. In this tutorial, we first cover potential limitations of traditional longitudinal mediation models to accommodate unique characteristics of intensive longitudinal data. Then, we discuss how recently developed dynamic structural equation models (DSEMs) may be well-suited for mediation modeling with intensive longitudinal data and can overcome some of the limitations associated with traditional approaches. We describe four increasingly complex intensive longitudinal mediation models: (a) stationary models where the indirect effect is constant over time and people, (b) person-specific models where the indirect effect varies across people, (c) dynamic models where the indirect effect varies across time, and (d) cross-classified models where the indirect effect varies across both time and people. We apply each model to a running example featuring a mobile health intervention designed to improve health behavior of individuals with binge eating disorder. In each example, we provide annotated Mplus code and interpretation of the output to guide empirical researchers through mediation modeling with this increasingly popular type of longitudinal data.