Advanced Topics and Further Reading

Longitudinal Structural Equation Models-General


Latent Growth Curve Models


Latent Variable Interactions

There are two general approaches to testing moderator (i.e., interaction) hypotheses in SEM. The most common and simplest approach is by using multigroup SEM. In this approach, the moderator must be a categorical variable that moderates the relationships tested in the model. In regression analysis, moderation is tested by computing a product variable where the two predictors hypothesized to interact are multiplied together. The two predictors and the product variable are used to predict the dependent variable.

If the two interacting predictors are measured variables, the exact same procedure as that used in regression can be used to test for moderation. An analogous procedure can also be used for latent variables, but latent variable interactions have faced a number of issues, including dealing with multiple product indicators and standard error accurate estimate in the face of nonnormality of interaction terms. Mplus (Version 3 and above) will automatically handle latent variable interactions using a modified version of the Klein and Moosbrugger latent moderated structural equations (2000; LMS) approach (using the XWITH keyword). The chapter by Marsh and colleagues (2012) is a good overview and introduction to some of the issues.


### Multilevel SEM

Hierarchical linear modeling (multilevel regression) can be extended to latent variable models as well. When data are hierarchically structured, as is the case with students nested within schools or patients within hospitals, assumptions about the independence of observations are violated in regression and SEM. An older approach used a multigroup analysis to model between-group variance (level-2 variance) and within group variance (level-1 variance; Muthen & Satorra, 1994). Multilevel SEM is not available in most SEM packages. Mplus is perhaps the most widely used, with special features that facilitate analysis of multilevel models with two levels (see Heck & Thomas, 2015), but xxM package in R (Mehta, 2013) and OpenMx (Boker et al., 2020) also estimate multilevel SEMs. Advantages of this approach over HLM include the use of latent variables, the ability to test multilevel measurement hypotheses, and the ability to estimate correlated errors and test various measurement error assumptions. Good introductions are found in Heck and Thomas (2015) and Hox (2017).


### Latent Class Analysis and Growth Mixture Models

Latent class analysis tests categorical latent variables. Used when the latent variables are assumed to be categorical (2 or more classes). Akin to a latent variable approach to discriminant analysis in which
individuals are classified according to probability of membership in classes. Mplus, Lisrel, EQS, and Amos all have features for latent class analysis and “mixture modeling,” the term used to refer to combining continuous and categorical latent variables in a single model. Use of latent classes to categorize trajectories from growth models is referred to as “growth mixture models”.


Causal Indicators

One can specify “latent” variables so that the indicators predict the latent variable (arrows go in the opposite direction from usual). Such indicators are sometimes called “causal indicators” or “formative indicators”. The resulting aggregate variables are not really latent variables, because they do not estimate measurement error. They are more related to linear composites such as that found in principal components analysis. The Edwards and Bagozzi article provides an excellent overview and link to the literature.


See also the special section on formative indicators in the 2007 *Psychological Methods, Issue 2,* Howe et al. Reconsidering formative measurement; Bollen, Interpretational confounding is due to misspecification, not to type of indicator: Comment on Howell, Breivik, and Wilcox (2007); Bagozzi, On the meaning of formative measurement and how it differs from reflective measurement: Comment on Howell, Breivik, and Wilcox (2007); Howell, Is formative measurement really measurement? Reply to Bollen (2007) and Bagozzi (2007)

Multitrait-Multimethod Matrix (MTMM) Models

MTMM models use structural equation modeling to expand upon an approach to testing construct validity by Campbell & Fiske (1959). The object is to separate out variation in the latent variables that is due to method variance. Method variance is variance that is due to the method of measurement rather than the substantive content of the measure. For instance, latent variables based on self-reported volunteerism items reflect true volunteerism and self-report method bias. Using multiple methods to measure a construct (e.g., observation, self-report, archival data) and multiple indicators for each method, one can separate out method and “trait” (the substantive construct being measured) variance. These models often run into problems with empirical underidentification unless there are at least three traits measured and three methods of measurement (see Eid, 2000, a practical approach that seems to work well).
Latent State-Trait Models

Another longitudinal data approach involves an attempt to use SEM to partition variance that remains stable over time and variance that fluctuates from wave to wave. For instance, some cities have a chronically low or high crime rate over time, but there are yearly fluctuations that may depend on migration or economic factors. The latent trait-state models attempt to separate out the stable aspect of a variable from the fluctuating aspect, and each can be used as a predictor or a predicted variable in a larger model. There are several major approaches that have been proposed (see Newsom, 2015, for a summary).

Further Reading


Power Issues and Power Analysis in SEM

There are several important issues regarding statistical power in SEM. One of the primary concerns is how to conduct power analyses to determine sample size and effect sizes in SEM. Greg Hancock’s chapter is a nice recent overview of the topic. Online calculators and macros for SAS and R are available (see https://timo.gnambs.at/research/power-for-sem and http://www.datavis.ca/sasmac/csmppower.html and http://quantpsy.org/rmsea/rmsea.htm). See the handout “Power Analysis for SEM: A Few Basics” for this class for some more detail.


Assumptions and Diagnostics

In addition to assumptions of multivariate normality, there are several other assumptions in SEM that follow the assumptions from regression analysis, including constant distribution of residuals, linearity, and outliers. In addition, we have not discussed multicollinearity issues in much detail. Although these assumptions can be tested, few researchers do enough to screen their data and evaluate various assumptions about the data. One barrier is the fact that most SEM packages do not have features that make testing various assumptions easy.


Sample Weighting and Complex Sampling Designs

Large, population-based studies that use stratified random sampling or cluster sampling can be adjusted for sampling selection biases. Such adjustments provide better estimates of the population parameters and standard errors than the assumption of random sampling used in traditional SEM (i.e., an assumption of all traditional statistical testing). Presently, only Mplus provides capabilities for making such adjustments automatically.


Keeping Abreast of Developments

(There are several journals that often feature articles on developments in SEM.)

Structural Equation Modeling: An Interdisciplinary Journal (published by Lawrence Erlbaum)
Psychological Methods (published by the American Psychological Association)
Psychometrika (published by the Psychometric Society)
Sociological Methods and Research (published by Sage)
Sociological Methodology (an annual volume published by Blackwell)
Multivariate Behavioral Research (published by Society of Multivariate Experimental Psychology)
Organizational Research Methods (Sage)