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Exploratory Structural Equation Modeling

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Exploratory structural equation modeling (ESEM) is a data analytic framework developed in 2009 by Tihomir Asparouhov and Bengt Muthén and implemented in the Mplus statistical software. ESEM extends the structural equation modeling (SEM) framework to incorporate latent factors defined according to exploratory factor analysis (EFA) specifications. The ESEM framework can thus incorporate different sets of EFA factors (a set corresponding to a series of indicators related to a series of factors with all cross-loadings freely estimated within this set, but not between sets), confirmatory factor analysis (CFA) factors (where factor indicators are used to define their a priori factors without the incorporation of all possible cross-loadings), and observed variables measured using any combination of continuous and categorical measurement scales. These factors and observed variables can be correlated with one another and/or related via regressions and incorporate a variety of methodological controls (e.g., method factors, correlated uniquenesses) in a way that can be extended to multiple-group analyses, longitudinal analyses, or a combination of both.

ESEM makes available for EFA factors all of the statistical advances traditionally associated with CFA/SEM: (a) multiple-group or longitudinal tests of measurement invariance, (b) goodness-of-fit, (c) predictions among latent factors corrected for measurement error, (d) bifactor models, (e) a priori specification (i.e., confirmatory) using target rotation, (f) methodological controls, and (g) longitudinal analyses. This entry provides a review of how EFA and ESEM have been revived and answers questions about why it remains useful compared to CFA. Construct-relevant psychometric multidimensionality is then considered, followed by a concluding section on limitations of ESEM.

Reviving EFA

EFA, then referred to as factor analysis, was developed at the start of the 20th century by the pioneering work of psychologists, such as Charles Spearman, interested in understanding the structure of intelligence. EFA quickly became the approach of choice to study the underlying structure of the unobservable entities, referred to as psychological constructs, that form the core of psychological research. Many years later, in the 1970s, Karl Jöreskog developed an alternative approach to factor analyses, CFA, which allowed researchers to explicitly rely on a priori expectations to define factors and to obtain goodness-of-fit information regarding the ability of this representation to appropriately reflect the underlying structure of the data.

By merging path analytic methods with CFA, Jöreskog created a way to estimate predictive relations between CFA factors corrected for measurement errors, which came to be known as SEM. This new analytic framework rapidly superseded EFA, relegating its use to preliminary analyses of new measures for which a priori expectations were unclear, always with the caveat that these analyses should be replicated using CFA. ESEM revives EFA by making all of the advances traditionally reserved to CFA available to researchers interested in adopting an EFA approach. However, the apparent superiority of CFA is so well established that some questions regarding the true usefulness of EFA, and thus ESEM, remain.

Cross-Loadings and Parsimony

In CFA, all indicators are typically related to one, and only one, factor. However, research evidence has been accumulating for years that some well-established measures with a well-replicated EFA structure systematically fail to be supported using CFA. Statistical research has also demonstrated that whenever cross-loadings exist, CFA tends to produce inflated estimates of factor correlations, whereas the unnecessary incorporation of cross-loadings does not result in biased estimates. These inflated factor correlations carry the risk of creating unnecessary multicollinearity, leading to biased estimates of relations among constructs and to an underestimation of their construct validity. It remains true that adding all possible cross-loadings to a model reduces parsimony, which is why best-practice recommendations still favor CFA when both models have a comparable level of fit (particularly considering parsimony-adjusted indices) and factor correlations remain unchanged.

Reflective Models

Since the revival of EFA via ESEM, some have expressed concerns that cross-loadings might change the meaning of the factors. However, this concern is unfounded, at least as long as cross-loadings remain smaller than the main loadings and aligned with theory, given the reflective nature of factor analyses. In a reflective model, causality flows downward: Factors are assumed to cause scores on the indicators. It logically follows that cross-loadings allow factors to be linked to all of the information available at the indicator level. For cross-loadings to change the meaning of the factors, causality would need to flow backward.

Methods Versus Objectives

A final misunderstanding stems from the labels confirmatory and exploratory. Statistically, these labels only describe the methods, not their application, and refer to the idea that CFA assigns indicators to a single factor whereas EFA (and ESEM) freely estimates all factors-indicators associations. However, nothing precludes the use of any of these methods to address exploratory or confirmatory research objectives. Moreover, nonmechanical rotations procedures (i.e., target rotation) make it possible to estimate EFA (and ESEM) solutions using a priori specifications where loadings and cross-loadings can be given a target value (typically, loadings are freely estimated and cross-loadings are given a target value of 0, but alternatives are possible). In modern applications, ESEM is typically considered a viable approach for confirmatory and exploratory purposes and has been more frequently used for confirmatory purposes.

Psychometric Multidimensionality

Classical test theory proposes that any measure reflects three components: (1) random measurement error, which is absorbed into indicators' uniquenesses in a factor analytic model, resulting in perfectly reliable factors; (2) construct-relevant variance, reflecting the extent to which each indicator is related to the construct it is assumed to represent and which is reflected by the main factor loadings in factor analyses; and (3) construct-irrelevant variance, reflecting the extent to which each indicator is related to constructs other than the one they were designed to measure. This last source of variation can take two forms. On the one hand, it could reflect something that is completely irrelevant to all of the latent constructs included in a model. This form of construct-irrelevant psychometric multidimensionality can be modeled using method factors (e.g., to control for informant effects, negative wording) or correlated uniquenesses (with two items sharing something over and above the various constructs included in the model). On the other hand, although irrelevant to the construct the indicator was designed to assess, this last source of variation could still be relevant to the other constructs included in the model. This form of construct-relevant psychometric multidimensionality can itself take two forms:

When Constructs Are Related Conceptually

When working with latent variables (e.g., EFA, CFA, SEM), many indicators are imperfect in that they often share associations with more than one latent construct. For example, a questionnaire item referring to insomnia might share valid relations with factors reflecting anxiety, depression, substance abuse, workaholism, and sleep difficulties. Observing cross-construct associations is frequent in questionnaires designed to assess multiple facets taken from the same domain (e.g., motivation, personality). Cross-construct associations are independent from the clarity of the definition of the constructs themselves and do not need to be expected a priori. They simply reflect the fact that indicators naturally tend to share associations with more than one conceptually related construct. This type of construct-relevant psychometric multidimensionality is ignored in CFA, and best reflected via the incorporation of cross-loadings (EFA/ESEM), which allows all constructs to be estimated using all information present in the indicators.

When Constructs Are Related Hierarchically

Another source of construct-relevant psychometric multidimensionality comes from the fact that many measures include items designed to measure distinct subscales (e.g., satisfaction of one's need for autonomy, relatedness, and competence; or vocabulary, mathematical reasoning, and memory) from a hierarchically ordered global construct (e.g., global need satisfaction, global intelligence). Hierarchically ordered constructs have often been modeled using hierarchical factor models, where indicators are used to define first-order factors, themselves used to define a higher-order factor. Unfortunately, these models rely on a very strict assumption, which seldom holds in real life, according to which the ratio of global to specific variance is forced to be the same for all indicators linked with the same first-order factor. Bifactor models are more flexible and allow each indicator to simultaneously define their specific factor and the global factor, resulting in a direct partitioning of the variance into these two components. For both approaches (higher-order and bifactor), all factors are specified as orthogonal (i.e., uncorrelated with one another).

For many psychological measures, both sources of construct-relevant psychometric multidimensionality are likely to be present and can be accounted for by simply including a bifactor component (or a higher order factor) to an ESEM measurement model.

Limitations and Solutions

Relative to SEM, ESEM still presents some limitations linked to the need to rely on factor rotation procedures to estimate a set of EFA factors. Thus, all EFA factors from the same set need to share the same relations with other constructs. Likewise, any constraints (e.g., measurement invariance) imposed on the factor loadings matrix, or on the latent variance-covariance matrix, have to be applied to the whole matrix, making tests of partial invariance of factor loadings and factor variances–covariances impossible. Furthermore, higher order ESEM models cannot be directly estimated. More broadly, whereas the SEM framework has been connected with multilevel analyses (allowing one to disaggregate relations occurring at different levels, such as individual, classroom, and school) and mixture modeling (allowing one to incorporate latent categorical variables, such as in latent profile analyses) as part of the generalized SEM framework, these connections are not yet available for ESEM. Many of the aforementioned limitations can, however, be circumvented using a variety of approaches. The two most common involve ESEM-within-CFA and factor scores. ESEM-within-CFA involves the reexpression of an optimal ESEM solution in CFA using the parameter estimates from that final solution as start values (using * in Mplus). To achieve identification, one referent indicator has to be selected per factor (including the global factor in bifactor models), and all cross-loadings of this indicator have to be fixed to this start value (using @, rather than *, in Mplus). Factor variances also have to be fixed to 1, and factor covariances have to be fixed to 0 for bifactor ESEM models. For the estimation of higher order ESEM models, the main loading of the referent indicator also has to be fixed to its exact value, and factor variances have to be freely estimated. Alternatively, one could export factor scores from the ESEM or bifactor ESEM model for use in other analyses. Factor scores are not as robust to measurement error but provide a partial control for unreliability and preserve the measurement structure of the model. Although ESEM-within-CFA is more accurate, it is also far less parsimonious and thus will not typically work in complex models (e.g., complex predictive models, mixture models, multilevel models) for which factor scores appear more appropriate.

See also Classical Test Theory; Confirmatory Factor Analysis; Exploratory Factor Analysis; Measurement Invariance; Mplus (Software); Multiple Group Structural Equation Modeling; Psychometrics; Structural Equation Modeling

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