First Steps in Structural Equation Modeling: Confirmatory Factor Analysis

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Confirmatory factor analysis (CFA) is the fundamental first step in running most types of SEM models. You want to do this first to verify the measurement quality of any and all latent constructs you’re using in your structural equation model.

The term “regression” is an umbrella for numerous statistical methods. These methods explore the relationship between an outcome variable and predictor variables. Examples of statistical analyses found under the regression umbrella are linear, logistic, Cox, and multilevel regression.

Structural equation modeling (SEM) is an umbrella, too. It contains numerous techniques for analyzing data. Examples of statistical analyses found under the SEM umbrella are confirmatory factor analysis (CFA), multi-group CFA, regression with [latent variable](https://www.theanalysisfactor.com/what-is-a-latent-variable/) outcomes and/or latent predictors, as well as [latent growth models](https://www.theanalysisfactor.com/october-2018-latent-growth-curve-models/) for longitudinal analysis.

**The Measurement Model**

As I said, CFA is the fundamental first step in running most types of SEM models, and you want to do this first to verify the measurement quality of any and all latent constructs you’re using in your structural equation model.

A latent construct (also known as a factor or scale) is a variable that cannot directly be measured. It is measured by a set of observable variables (indicators) that are weighted based on their variance/covariance structure.

It is a misconception that you can simply measure a latent construct by averaging its indicators. Conceptually, that implies every indicator influences the strength of the latent construct equally.

Another misconception is that a latent construct that has been verified by previous research need not be tested again. We need to remind ourselves that samples from the same population are seldom identical. You can’t assume that all samples taken from the population are equivalent.

As a result, your first step is to verify the viability of any latent constructs (known as the measurement model) before using them as independent and/or dependent variables in a structural equation model.

How do we verify the viability of the latent construct? There are a series of steps to take.

**Steps in a Confirmatory Factor Analysis**

The first step is to [calculate the factor loadings](https://www.theanalysisfactor.com/confirmatory-and-exploratory-factor-analysis/) of the indicators (observed variables) that make up the latent construct. The standardized factor loading squared is the estimate of the amount of the variance of the indicator that is accounted for by the latent construct.

Many fields of study are comfortable with loadings of 0.4 or higher. Beware that reviewers might require loadings of 0.5 or higher.

The variance that is not explained by the latent construct is known as the unique variance (a.k.a. error variance or indicator unreliability). If justifiable, the error variances of indicators within the construct can be correlated. (This is also called correlated uniquenesses, error covariances, and correlated residuals.)

Creating this CFA measurement model lets you check convergent validity of your construct. Convergent validity is indicated by high indicator loadings, which shows the strength of how well the indicators are theoretically similar.

Most SEM models contain more than one factor. If that’s your situation, run a CFA for all of the model’s latent constructs within one measurement model. This allows you to check discriminant validity. Discriminant validity exists when no two constructs are highly correlated. If two constructs are highly correlated (greater than 0.85), explore combining the constructs.

One of the final steps for reviewing the measurement model is to run goodness of fit statistics. Goodness of fit statistics test for absolute, parsimonious, and incremental goodness of fit.

Absolute fit statistics (model chi-square, SRMR) examine the data’s observed variance/covariance matrix versus the model implied variance/covariance matrix. Parsimonious fit statistics (RMSEA, AGFI) penalize for overly complex structures. Incremental fit statistics (CFI, NFI) examine the target versus the baseline models.

[Confirmatory factor analysis](https://www.theanalysisfactor.com/confirmatory-factor-analysis-measure-something-we-cannot-observe/) for all constructs is an important first step before developing a structural equation model.