Mair, P. (2018). *Modern psychometrics with R*. Springer. https://doi.org/10.1007/978-3-319-93177-7\_1

Chapter 1 – Classical Test Theory

- the true score model of classical test theory (CTT):

- *X* is the observed score in a test, *T* is the true score (unknown), and *E* is the error (unknown). This equation implies that *X* can deviate from *T*, that is, our measurement *X* is associated with an error *E*;

- problems with the measurement task: (1) precision of a test: we have to deal with some degree of *measurement error*; (2) instability over time: if we were to perform repeated measurements on a single person over time, we cannot expect that the results will be identical;

- CTT attempts to formalize a statistical theory of (psychological) measurement and, eventually, allows us to make statements about the quality of a scale;

- the above equation is the most general population (of participants) and universe (of items) model, whereas the next equation “zooms in” on a particular item:

- in another formulation (), if we were to present the same item to an individual many times, the true score is the average of the observed scores. At a population level, this means that the expected value . It follows that the expected value , that is, in the long run the error is 0 on average. This error is normally distributed and uncorrelated with the true score;

- in CTT, the smaller the error variance is, the more accurately the true score is reflected by our observed scores (across multiple individuals). The corresponding *SD* of the errors has its own name: the *standard error of measurement*, denoted by ;

- quality, within the context of CTT, means that we are able to replicate the results if the individuals were tested multiple times. In other words, *reliability* represents the accuracy with which a test can measure true scores;

- if the reliability is large, is small: *X* has little measurement error and will be close to *T*. On the other hand, if reliability is small, is large: *X* has large measurement errors and will deviate from *T*. Formally, reliability is defined as:

- reliability is the proportion of variance in observed scores that is attributable to variance in true scores. If variance of measurement (error) is zero, then reliability equals 1. This is the same as the squared correlation between *X* and *T*. This, if the (squared) correlation between the observed scores and the true scores is high, the test has high reliability;

- however, the problem is that we cannot directly compute since we do not know ;

- a parallel test ( is a second version of the original test () with the same true score and the same error variance. Let denote the covariance between these two tests which can be transformed into s squared correlation (i.e., a reliability measure). The previous equation becomes:

- from this equation we can derive an expression for the standard error of measurement:

- in Cronbach’s alpha, the basic idea is that the total score is made up of the *k* individual item scores. Thus, each item is considered as a single test, and we have, at least conceptually, constructed *k* parallel tests. This allows us to compute a lower bound—since we cannot assume that the composites are strictly parallel—for the reliability:

- the value of alpha might be replaced in the standard error of measurement formula. In practice, we aim for an alpha in the area of 0.8–0.9. Values of alpha greater than 0.9 may reflect a scale burdened by question redundancy and will generally have a lower correlation with external variables (which is an indication of low *validity*);

- Cronbach’s alpha is a reasonable lower bound for reliability if the items in a test are *essentially tau-equivalent*—if this assumption is violated, alpha underestimates the reliability, whereas the *greatest lower bound* (GLB) provides a better reliability approximation;

- Cronbach extended the reliability concept by combining the true score model with ANOVA techniques in order to account for multiple sources of measurement errors, a framework known as *generalizabity theory* (G-theory). Examples of error sources (i.e., *facets*) are items, raters, measurement occasions, etc.;

Chapter 2 – Factor Analysis

- if our multivariate dataset has *m* manifest variables, let **X** denote the *n* × *m* data matrix, with *n* being the sample size. EFA tries to find *p* latent variables on the basis of the correlation structure of the *m* manifest variables. Mathematically, the EFA problem can be formulated as follows:

- using matrix notation, this becomes:

Chapter 3 – Path Analysis and Structural Equation Models

- multivariate regression:

- em um modelo usando dois itens de agradabilidade e dois itens de abertura a experiências predizendo preconceito étnico e preconceito contra pessoas com deficiência poderia ser descrito da seguinte maneira:

- statistically speaking, moderation is expressed as interaction: in order to account for the moderation effect of *Z* in a regression model, we need to allow for an interaction between the predictors *X* and *Z*;

- centering for multicollinearity purposes has been debunked as myth and is therefore not necessary;

- however, centering *Z* and/or *X* can be helpful since parameters can be interpreted relative to the mean levels of the other variables; but this does not affect the model fit;

- a simple mediator model consists of the following set of regression equations:

- where *c*′, *a*, and *b* correspond, respectively, to the effects of *X* on *Y*, of *X* on *M*, and of *M* on *Y*. The indirect effect of *X* on *Y* (through *M*) is simply *ab*;

- em uma mediação moderada no primeiro estágio da mediação, as equações podem ser expressa por:

- where the conditional indirect effect is , implying that the indirect effect needs to be evaluated for different values of *Z*;

- SEM integrate CFA into a larger path analytic framework;

- where is the random vector containing the *m* observed variables, is the *m* × 1 intercept vector, is the *p* × 1 latent variable vector, is the *m* × *p* matrix containing the loadings, and is the *m* × 1 vector of errors associated with the latent variables; is the *p* × 1 latent variable intercept vector, is the *p* × *p* matrix of directed path coefficients, and is the *p* × 1 vector of errors associated with the latent variables. The conventional assumptions for the errors are and ;

- a *latent growth model* (LGM), in its basic form, does not involve any latent variables that are based on a measurement model. In the simplest form of an LGM, we specify two growth factors: (a) latent intercept: allows us to describe individual starting points of the trajectories (as opposed to each individual starting at the same consumption level); and (b) latent shape: allows us to specify various shapes or trend patterns for the growth trajectories;