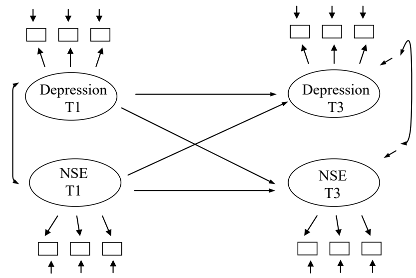
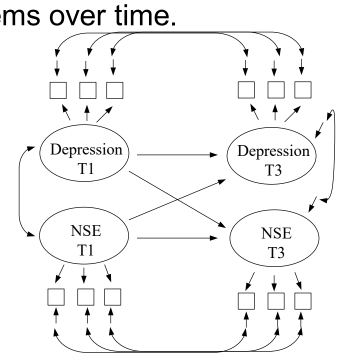
Latent Variable Cross-lagged Panel Models

The latent variable model version of the cross-lagged panel model has several advantages of the path model version. Multiple indicators of each construct are used to create a latent variable that removes measurement error.[1] Relations among these latent variables should provide better estimates of the true scores of each construct and therefore more accurate estimation of the causal relations over time.

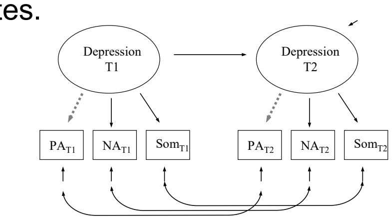


An important weakness of the cross-lagged path model is that all variables are assumed to be measured without measurement error. To the extent that measurement error is present, relations will tend to be attenuated (underestimated). The consequences of such attenuation can be complex in these models, but if the reliability is not equivalent for both variables, the causal paths may be inaccurate estimates of the true relationships. The latent variable model attempts to estimate measurement error and remove it from the estimates of relations among variables.

In addition to this concern, stability may be generally overestimated, because a portion of the autocorrelation for each variable may be due to a methodological artifact of asking the same questions more than once. For example, even though overall depression may be changing, one indicator of depression, sleep problems, may have consistency over time that is unrelated to the consistency in depression overall. Sleep disturbances may be related over time, over and above the extent to which depression is related over time. When the correlated measurement residuals (commonly "correlated errors") are not estimated, the unique correlation of sleep disturbance may be attributed to depression. This artifact can be accounted for by estimating correlations between measurement errors for same items over time.

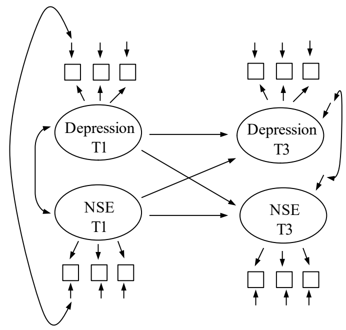


With the path model version of cross-lagged models, it is unknown whether there are any changes in the measurement properties of the variables over time. Reliability of a measure may change over time, leading to potentially erroneous conclusions. The latent variable version allows for tests of the measurement properties over time. Where measurement properties are equivalent over time (invariant), constraints can be imposed that increase precision of the model estimates.

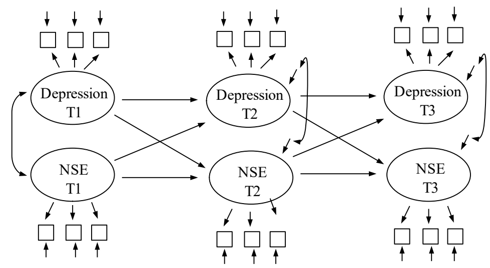


[1] Technically, this is not only measurement error but any other variance that is unique to an item and not shared among the indicators.

Correlated measurement residuals may also be necessary for individual indicators for the two constructs measured at the same time (synchronous correlated errors). Depending on the measures involved, this may or may not make theoretical sense, but if parallel wording construction is used, it may be an important artifactual source of covariance between the two constructs.



Three-wave cross-lagged panel models require some extra considerations. Equality constraints over time of autoregressive paths, cross-lagged paths, correlated disturbances, or correlated errors, may be appropriate to improve precision of the estimates. Nested tests can be used to investigate whether these constraints are reasonable. In addition, fit of the model may be compromised because autoregressive paths, cross-lagged paths, or correlated errors are needed over two waves (e.g., T1 to T3).



Cross-lagged panel models could be expanded to more waves or more variables. With three variables, one can examine meditational hypotheses by testing indirect effects (Cole & Maxwell, 2003; Roth & MacKinnon, 2012)

Nested tests of the differences in chi-square fit, comparing a model with equality constraints to a model without constraints, can be used in a variety of ways, to test the plausibility of longitudinal measurement invariance (equality of loadings, measurement errors), equivalence of correlated disturbances, equivalence of stability (auto regressive paths). Not all tests may make sense, however. Although tests of equivalence of cross-lagged paths (e.g, NSE to Depression vs. Depression to NSE in the above example), may be tempting, the unstandardized values for paths going in different directions are based on variances of the different predictor and outcome variables involved in each of the two regressions.

References and Recommended Further Reading

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