Covariates with Latent Growth Curve Models

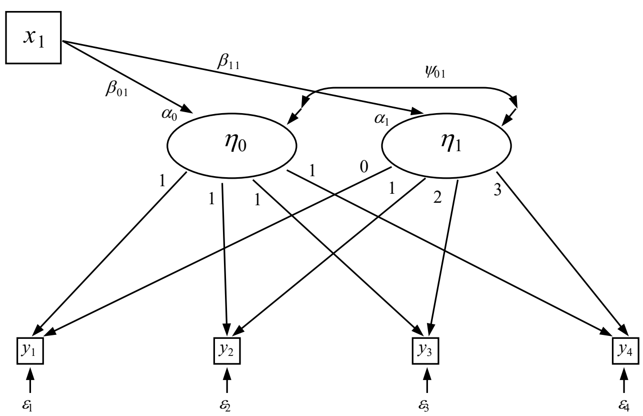
There are two ways that predictors might be included in latent growth curve models—time-invariant covariates and time-varying covariates. Despite the term "time invariant" a time-invariant predictor does not necessarily have to be a variable that is truly unchanging. It may be just a baseline measurement or just the single measurement that happens to be available for each person. Time-varying covariates, however, do need to be measured at individual time points. See the handout "Latent Growth Curve Models" for an introduction to the basics of latent growth curves.

Time Invariant Covariates

One or more predictors of the intercept and slope factors can be included in the model. In such models, the factor means, α_0 and α_1, are conditional on the predictor(s), and so they are referred to as "intercepts."

$$\eta_{0i} = \alpha_0 + \beta_{01}x_i + \zeta_{0i}$$
$$\eta_{1i} = \alpha_1 + \beta_{11}x_i + \zeta_{1i}$$

The intercept value for η_0 thus represents the average value of the outcome, usually at baseline, when the predictor, x_1, equals 0. The intercept value for η_1 is the average change in the outcome when x_1 equals 0. Because the 0 value for the predictor may not be meaningful (e.g., when age is equal to 0 or a 1-to-7 Likert scale is equal to 0), it is commonly recommended that the covariates be centered. Even with binary predictors, it may make sense to center the predictor, so that the intercept is the mean for both groups (e.g., unmarried, married), not just the 0 group.



The path coefficients, β_{01} and β_{11} above, represent the relationship to the baseline value and the change in the outcome, respectively. For example, if the model is of self-esteem predicting growth factors for elementary student prosocial behaviors, then β_{01} represents the effect of self-esteem on initial values of prosocial behavior, say at kindergarten. The β_{11} coefficient represents the relationship between self-esteem and increases in prosocial behavior over time.

When the β_{11} is significant, there is a cross-level interaction in which changes in the outcome (prosocial behavior) depend on the value of the predictor (self-esteem). We can see this if we expand the above equations.

$$y_{ti} = \lambda_{t0}\left(\alpha_0 + \beta_{01}x_i + \zeta_{0i}\right) + \lambda_{t1}\left(\alpha_1 + \beta_{11}x_i + \zeta_{1i}\right) + \varepsilon_{ti},$$

substituting t for λ_{t1} and dropping λ_{t0}, we have

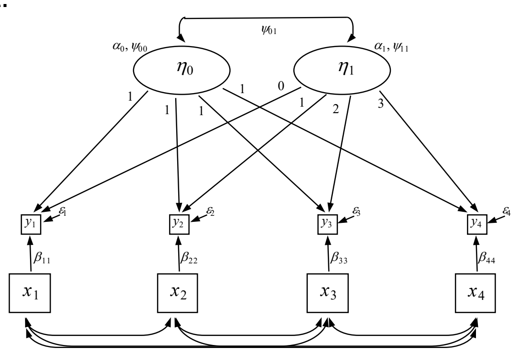
$$y_{ti} = \alpha_0 + \beta_{01}x_i + \alpha_1 t + \beta_{11}x_i t + \left(\zeta_{0i} + \zeta_{1i}t + \varepsilon_{ti}\right)$$

Because the intercept loadings equal 1 they can be dropped out. I replace the growth curve loadings λ_{ti} with t, the time variable (usually with values 0, 1, 2, 3…), to more easily see that the coefficient β_{11} is the coefficient for interaction effect between x_1 and t (β_{01} is the coefficient for the main effect for x_1 and α_1 is the coefficient main effect of time).

If the cross-level interaction is significant, simple slopes (or conditional effects), representing the effect of time (or changes in the outcome over time) for certain values of x_1 can be derived, tested for significance, and plotted, to probe the nature of the interaction (Curran, Bauer, Willoughby, 2004, 2006). The simple slope is then $\hat{y}_{ti} = \alpha_0 + \alpha_1 t$ for a particular value of x_1 representing the change in the outcome when x_1 is equal to that value. Although any chosen values of x_1 can be used, most commonly researchers use -1 SD below the mean, the mean, and +1 SD above the mean. Model constraints can be used to program the tests and plots just as with measured variable or latent variable interactions (see the "Simple Slopes for Continuous Measured and Latent Variable Interactions" handout from this class).

Time-Varying Covariates

Time-varying covariates are predictors of the outcome at each time point. I like to think of time-invariant predictors as variables used to explain variation in baseline values and variation in growth across individuals and time-varying predictors as control variables (or covariates) that give estimates of the growth parameters after removing the changes in the time-varying predictor. For example, if the growth model was of depression with health used as a time-varying covariate, then the slope would represent changes in depression after adjusting for the effects of health at each measurement time point. The default in SEM programs is for each time-specific effect of the covariate (β_{11}, β_{22}, β_{33}, and β_{44} below) are estimated separately. In multilevel regression models, these values would be equal across time (i.e., one effect for the time-varying covariate is estimated across all time points). Those constraints could be imposed in SEM and could be tested for equality using a likelihood ratio test but they are not typically estimated as equal by default.



Centering is also important for time-varying covariates, so that the intercept and slope factor means are not estimated for the value of x_t when equal to 0 (except in some case where that may be desired). There are several possible options for centering, however. Centering each time point according to the sample mean for that time point would remove changes across time in the covariate, so it may make more sense to center using the baseline mean ($\bar{x}_{1i}$) for each individual (centering within context or within person) or the baseline mean for the full sample ($\bar{x}_1$, grand mean centering). The decision between these two options is not always simple, however (see Enders & Tofighi, 2007 and Hoffman, 2015) for a detailed discussions).

References

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