Ignoring Inter-Individual Differences in Autoregressive Effects Leads to Strongly Biased Average Effect Estimates

Alexander J. Jung[1)], Cora Parrisius[1,2)], Benjamin Nagengast[1)] & Kou Murayama[1)]

[1)] *Hector Research Institute of Education Sciences, University of Tübingen*
[2)] *University of Education Karlsruhe*

Autoregressive effects are frequently estimated in a plethora of models for the analysis of longitudinal data. For example, they are often estimated in longitudinal structure equation modelling (SEM) to account for stability in a construct that cannot be explained by other predictors in the model (e.g., Biesanz, 2012). However, in some cases, the stability of a construct differs between individuals depending on unobserved person-specific characteristics. For example, individuals with bipolar tendencies may exhibit more frequent mood changes and, therefore, show a lower stability in longitudinal measures of their mood than the average. In such cases, the multilevel SEM framework is usually employed to estimate random autoregressive effects with a mean and a standard deviation (e.g., Raudenbush & Bryk, 2002).

Using simulated data, we show that in such cases estimating random autoregressive effects leads to strongly biased average effect estimates if two or more consecutive autoregressive effects are estimated. This is because individuals who show lower (higher) stability in a construct between the first two measurement occasions also show lower (higher) stability between subsequent measurements – An information that is not modelled in traditional multilevel-SEM. Our results show that observed biases in autoregressive parameter estimates increase with higher means and higher variances of the true autoregressive-effect vectors, with higher correlations between the vectors of the true average effects, and with a higher number of modelled measurement occasions.

It is well known that misspecifications of one part of a model usually lead to problems in other parts of a model as well (e.g., Olsson et al., 2000). Thus, we assume that disregarding potential correlated effect vectors in SEM may be an issue that biases many effect estimates in current research practice.

References:

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