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Evaluating the use of the automated unified structural equation model for daily diary data

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While there is a wealth of resources delineating both why and how researchers should collect time series data, fewer resources speak to the analysis of time series data within psychological science (Hamaker, Cuelemans, Grasman, & Tuerlinckx, 2015). Researchers may concatenate time series across individuals to arrive at one model, or researchers may analyze each individual separately, utilizing no information common to the sample. Recent research suggests that a superior approach may be to arrive at individual-level models, but utilize information shared across the sample (Gates & Molenaar, 2012).

The group iterative multiple model estimation (GIMME) framework presents an automated procedure for estimating individual-level structural equation models composed of both lagged and contemporaneous effects (see Figure 1) using the unified SEM (Kim et al., 2007). In the GIMME framework, each individual model is composed of group-, (potentially) subgroup-, and individual-level paths.

The performance of GIMME has been well documented in the context of resting-state fMRI data (Mumford & Ramsey, 2014), which is characterized by sizable autoregressive (AR) effects. In contrast, daily diary data is often characterized by much smaller, potentially nonsignificant AR effects, particularly if the construct under study occurs faster than the time scale of observation. It is unknown whether the inclusion of small autoregressive effects will allow for the reliable recovery of the lagged and contemporaneous relationships.

A simulation study was conducted to investigate the performance of GIMME under conditions encountered in daily diary research. A variety of simulation factors were manipulated: number of variables (5, 10); number of time points (30, 60, 90, 120); number of individuals (25, 75, 150); and the presence of the lagged relationships at the start of model estimation. Contemporaneous relationships were set to $\beta = 0.5$, and the AR effects were set to be small, $\beta = 0.2$. GIMME's performance was evaluated using recall and precision, measures of sensitivity and specificity. Additionally, given the iterative nature of the algorithm, we also evaluated the percentage of properly converged models across conditions.

Conflict of Interest Disclosures: Each author signed a form for disclosure of potential conflicts of interest. No authors reported any financial or other conflicts of interest in relation to the work described.

Ethical Principles: The authors affirm having followed professional ethical guidelines in preparing this work. These guidelines include obtaining informed consent from human participants, maintaining ethical treatment and respect for the rights of human or animal participants, and ensuring the privacy of participants and their data, such as ensuring that individual participants cannot be identified in reported results or from publicly available original or archival data.

We found that the most important determinants of path recovery were the number of time points and beginning estimation with autoregressive effects freely estimated. We conclude that the autoregressive effects are particularly important when attempting to correctly identify not only the presence, but also the direction of effects within intensive longitudinal data in psychological research.

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Figure 1.
Simplified depiction of unified SEM among three variables of interest. Dashed lines represent directed lag-1 effects, and solid lines represent directed lag-0 effects.