

Dynamic Modeling with Intensive Longitudinal Data: One-Step and Two-Step DSEM Approaches

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ABSTRACT

This study evaluated and compared one-step and two-step dynamic structural equation modeling (DSEM) approaches for analyzing intensive longitudinal data. In one-step DSEM, the within-person dynamic model and the between-person model are estimated simultaneously. In two-step DSEM, dynamic component estimates are first extracted from the within-person model, followed by estimation of between-person relations in a second step. We further examined whether including person-level variables as auxiliary variables in the first step affects the performance of two-step DSEM. The modeling approaches were evaluated by a simulation study and illustrated with a real data example. Results showed that two-step DSEM without auxiliary variables exhibited estimation bias, low coverage rates, and deflated Type I error rates. In contrast, one-step DSEM and two-step DSEM with auxiliary variables yielded satisfactory results when sufficient data were available (e.g., ≥ 30 time points and ≥ 100 individuals). Implications, modeling recommendations, and future research directions were discussed.

KEYWORDS

DSEM; intensive longitudinal data; one-step; two-step; Bayesian

Intensive longitudinal data (ILD) consist of repeated measurements collected from many individuals over many time points. ILD is increasingly used in research fields such as psychology, behavioral science, and health research to study intraindividual dynamic processes in natural contexts (Bolger & Laurenceau, 2013). The widespread availability of smartphones, wearable devices, and user-friendly mobile apps has made it easier to collect frequent and real-time data, resulting in richer and more ecologically valid data. Common study designs for collecting ILD include the measurement-burst design (e.g., Nesselrode, 1991; Sliwinski, 2008), experience sampling (e.g., Carstensen et al., 2011), daily diary (e.g., Bolger et al., 2003; Ferrer et al., 2013), and ecological momentary assessments (e.g., Hedeker et al., 2008). ILD enables researchers to better understand how psychological states and behaviors change over time, offering insights into intraindividual variability and the temporal unfolding of processes such as mood fluctuations, stress responses, or health behaviors (Hamaker & Wichers, 2017).

An important feature of ILD is their multilevel or clustered structure, in which repeated measurements are nested within individuals. As a result, repeated measurements from the same individual are not independent but are correlated, violating the assumption of independent observations commonly required in traditional analyses such as regression. To account for this structure in ILD analysis, various modeling strategies have been proposed and applied. Among them, multilevel (or mixed-effects) modeling is widely used

because it was specifically developed to handle clustered or nested data structures. In multilevel modeling, time series data analyses are conducted simultaneously for all individuals using all ILD. Typically, a common form of dynamic process, for example, a first-order autoregressive (AR) process, is specified for all individuals in Level-1 modeling, while individuals are allowed to have different values in the modeled dynamic components (e.g., different first-order AR coefficient values). In Level-2 modeling, between-person relations among the dynamic components and other person-level variables are modeled. Examples of multilevel or mixed-effects modeling for ILD analysis include multilevel autoregressive modeling (e.g., Jongerling et al., 2015; Wang et al., 2012), mixed-effects location-scale modeling (e.g., Hedeker et al., 2009, 2012; Rast & Ferrer, 2018), and hierarchical continuous time dynamic modeling (e.g., Driver & Voelkle, 2018).

When multiple time-varying variables are involved, multilevel modeling is often integrated with structural equation modeling (SEM) to analyze ILD. This combination allows for the simultaneous modeling of complex dynamic relationships among multiple variables, while accounting for the nested data structure. Examples of such modeling strategies include multilevel dynamic factor analysis (e.g., Song & Zhang, 2014; Zhang et al., 2008), multilevel graphical modeling (e.g., Epskamp et al., 2018), multilevel vector autoregressive (VAR) modeling (e.g., Hamaker et al., 2015; Mulder & Hamaker, 2021; Schuurman et al., 2016; Zhang

et al., 2018). A more recently developed and flexible framework, dynamic structural equation modeling (DSEM), further extends these approaches by embedding time-series models within a multilevel SEM framework (e.g., Asparouhov et al., 2018; Hamaker et al., 2018; McNeish & Hamaker, 2020).

DSEM has become increasingly popular for ILD analysis, as it integrates time series analysis, multilevel modeling, and structural equation modeling and thus enjoys the advantages of all three modeling strategies. There are two types of models in DSEM: a within-person level model for modeling intraindividual dynamic processes and a between-person level model for modeling how the dynamic components are related among themselves and how they are associated with other person-level variables of interest. For example, the within-person level model may take the form of a first-order AR process with random effects in dynamic components including the intraindividual means, first-order AR coefficients, and residual or shock variances. These person-specific dynamic components can serve as predictors, mediators, moderators, or outcomes in the between-person level model. Additionally, measurement models using item-level data can be incorporated into DSEM to evaluate measurement invariance across time or individuals, and to more flexibly model item responses when the assumptions of using sum or average scores (equal loadings across items, time, and individuals) are not met (McNeish et al., 2021). Therefore, DSEM combines the strengths of (1) time series analysis for modeling temporal dependencies and dynamics, (2) multilevel modeling for handling clustered data with random effects, (3) SEM for multivariate analyses, and (4) measurement modeling for item-level analysis, enabling rich and flexible modeling of dynamic components in both within-person and between-person modeling. In the current study, we focused on evaluating and applying DSEM for ILD analysis.

The within-person and between-person level models of DSEM can be estimated simultaneously. We refer to this simultaneous estimation approach as the one-step DSEM approach. Different one-step estimation methods have been used and evaluated to estimate simple DSEM. For example, Hayakawa and Yin (2025) evaluated three methods: Bayesian estimation, restricted maximum likelihood (REML) estimation, and the mean-group (MG) estimator for estimating a multilevel time series model. In this model, the within-person part contained three random effects (intercept, autoregressive effect, and concurrent effect of a time-varying predictor), while the between-person part included person-level variables predicting the random effects. Using simulations with 100 individuals and 25 or 50 time points, they found that the REML and MG estimators were substantially faster than the Bayesian estimators. However, the REML and MG estimators exhibited estimation bias and coverage problems for some parameters, whereas Bayesian estimation showed superior performance in terms of both estimation accuracy and coverage rates.

Estimating complex DSEM can be more challenging, particularly when the within-person and/or between-person

level models involve many random effects, item-level data, mediation processes, or moderation processes (McNeish et al., 2021; McNeish & MacKinnon, 2025; Tseng, 2025). Fang and Wang (2024a) conducted a survey of DSEM applications in psychology published between 2018 and 2022 and found that all 80 identified studies implemented DSEM in Mplus using Bayesian estimation. Thus, in social science and behavioral research, Bayesian estimation has become the most widely used approach for statistical inference in DSEM. There are at least two reasons for this widespread use. First, Bayesian estimation excels at estimating complex multilevel models with many (e.g., six or eight) random effects via the use of Markov Chain Monte Carlo (MCMC) methods (Fang & Wang, 2024a; Hamaker et al., 2018; Wang & McArdle, 2008). Second, Bayesian estimation is available in SEM software Mplus (Asparouhov et al., 2018), which makes implementation relatively straightforward for both simple and complex DSEM. Given its strong performance (in estimation accuracy and coverage), ease of implementation, and broad adoption in social and behavioral research, we used Bayesian estimation (as implemented in Mplus) for one-step DSEM in this study.

Sometimes, the dynamic components extracted from DSEM are not aligned with the primary constructs of substantive interest. For example, researchers are often interested in studying individual differences in the variability of a process variable itself, commonly called intraindividual variability (Nesselroade, 1991; Ram & Gerstorf, 2009). Intraindividual variability can be computed based on a nonlinear transformation of the within-person residual (shock) variance and the AR(1) coefficient under the stationarity assumption (Wang et al., 2012). To enable complex intraindividual variability modeling within the DSEM framework, Fang and Wang (2024b, 2025) proposed two-step DSEM approaches. In the first step, a within-person multilevel dynamic model is fit with Bayesian estimation, in which dynamic parameters (e.g., first-order AR coefficients) and functions of dynamic parameters (e.g., intraindividual variance or intraindividual standard deviation) are quantified. In the second step, a between-person model (e.g., regression) is fit to assess how the dynamic component estimates predict outcomes of interest. Fang and Wang (2025) evaluated two variants of two-step DSEM: one using a single draw from the posterior distribution of each dynamic component and the other using multiple (50) draws for each individual. Through a simulation study, they compared the performance of the two-step DSEM approaches. Their results showed that the two-step approach with multiple draws performed well when sufficient data were available, whereas the single-draw approach performed poorly. The performance difference is due to how uncertainty is handled. That is, the single-draw approach ignores the uncertainty in dynamic component estimates, whereas the multiple-draw approach explicitly accounts for it.

Two-step DSEM is also useful for modeling complex change patterns for intensive longitudinal research. For example, Muthén et al. (2025) developed and demonstrated DSEM techniques with sine-cosine functions to capture

cyclical patterns in ILD. To examine how predictors influence the amplitude and phase shift of cyclical patterns, they employed a two-step DSEM approach, as both amplitude and phase shift are nonlinear functions of the dynamic model parameters. In the first step, multiple (200) datasets of plausible values of amplitude and phase shift were computed based on model parameter estimates. In the second step, the amplitude and phase shift estimates were regressed on between-person predictors. They stated that this two-step Bayesian analysis is preferable to a single-step Bayesian analysis, particularly when phase shifts are allowed to differ across individuals. In another study, Tseng (2025) argued that maximum likelihood estimation is not feasible for simultaneously estimating the multiple latent interaction effects in cross-lagged panel models (CLPMs), “due to the heavy computations involved” (p. 27). Therefore, they evaluated the performance of a two-step multiple imputation approach for estimating multiple latent interaction effects (within \times within and between \times within) in a CLPM, in which plausible values of the stable trait factors and the person-mean-centered scores are estimated in the first step and the fixed-effects interaction effects are estimated in the second step. Simulation results indicated that the two-step approach with 20 plausible values yielded satisfactory inference results, similar to the one-step Bayesian method. They also found that the two-step approach was substantially faster than the one-step Bayesian approach, and that the one-step approach encountered convergence issues whereas the two-step approach did not (see Table 7 in their article). In all three studies (Fang & Wang, 2025; Muthén et al., 2025; Tseng, 2025), the two-step approaches were implemented in Mplus with Bayesian estimation used for the Step 1 analysis and multiple plausible values of dynamic components of interest used for the Step 2 analysis. In the current study, we used this strategy for estimating two-step DSEM.

Two-step estimation strategies have also been developed for general SEM. For example, Rosseel and Loh (2024) developed the “structural after measurement” (SAM) strategy for estimating SEM, in which the measurement model is first estimated, followed by the structural model. SAM has two variants: local SAM and global SAM. In the first stage of local SAM, measurement models are fitted to yield estimates for the intercepts, factor loadings, and unique variances; these parameter estimates, together with the observed means and covariance matrix of the observed variables, are then used to obtain estimates of the means and the covariance matrix of latent variables. In the second stage of local SAM, the estimated summary statistics of the latent variables are used to obtain parameter estimates of the structural model. In global SAM, the first stage also produces measurement model parameter estimates; in the second stage, these estimates are used as fixed values in the measurement part of the SEM, while the parameters of the structural part are freely estimated. To account for uncertainty in the first-stage estimates, corrected standard error estimates are obtained using the closed-form correction methods of Bakk et al. (2014) and Gong and Samaniego (1981). Rosseel and Loh (2024) highlighted several advantages of SAM over one-

step (or simultaneous) estimation for SEM, such as more robust estimates against local model mis-specifications and fewer convergence issues in small samples. Two-step DSEM can be viewed as a SAM approach, in which within-person model estimation (dynamic component estimation; the measurement part) precedes between-person model estimation (e.g., regression or path analysis; the structural part). Accordingly, two-step DSEM can share the same advantages over one-step DSEM.

Despite the promising potential of two-step DSEM for ILD analysis, research on its performance remains limited. In one-step DSEM, time-varying variables are included in the within-person level model whereas person-level variables are included in the between-person level model, and the within-person and between-person models are estimated simultaneously. In two-step DSEM, if the same logic is followed, time-varying variables are included in the Step 1 within-person level model, and person-level variables are introduced in the Step 2 between-person level model. Unlike the integrated estimation in one-step DSEM, however, the two models in two-step DSEM are estimated separately. This leads to an important open question: Should person-level variables that are not part of the dynamic process model be included in Step 1 analysis as auxiliary variables? The present study aims to address this research question by evaluating two versions of two-step DSEM: one that includes and one that excludes person-level variables in the within-person modeling stage.

To this end, we compared the performance of the two versions of two-step DSEM to one-step DSEM using (1) a multilevel first-order AR for within-person dynamics and (2) a mediation model for between-person relationships. The multilevel first-order AR model was selected due to its wide use and discussion in the dynamic modeling literature. The mediation model was chosen for three reasons: (a) prior evaluations of one-step vs. two-step DSEM approaches have not addressed mediation contexts, (b) mediation effects are often of research interest in psychological and behavioral research, and (c) our designed mediation analysis involves dynamic components functioning both as dependent variables (of the input variable) and as independent variables (for the outcome). Bayesian estimation was used for one-step DSEM while Bayesian estimation was used for the Step 1 analysis and multiple plausible values were used for the Step 2 analysis of two-step DSEM, given the wide use of these estimation procedures in the DSEM literature. We hope that estimating this example model will offer meaningful insights into the performance of the different modeling approaches and assist researchers in choosing appropriate DSEM approaches.

The remainder of the article is organized as follows. First, we introduce the one-step and two-step DSEM approaches using the example model. Then, we conduct a simulation study to evaluate the performance of the modeling approaches. Next, we provide a real data example with shared online R and Mplus scripts to illustrate the applications of the approaches and compare the modeling results. Finally, we discuss the implications of our findings, offer

modeling recommendations, and outline directions for future research.

One-Step DSEM

In this section, we discuss the model specification and estimation of one-step DSEM using the example model. Specifically, the within-person level model is a multilevel univariate first-order autoregressive process. It can be written as:

$$m_{it} = \mu_i + \phi_i(m_{i,t-1} - \mu_i) + e_{it} \quad (1)$$

$$e_{it} \sim N(0, \sigma_{ei}^2).$$

In this model, m_{it} is the observed score in time-varying variable M from individual i ($i = 1, 2, \dots, N$) at time point t ($t = 1, 2, \dots, T_i$). Three dynamic parameters are modeled in this AR process for each individual. They are the mean level (μ_i), AR(1) coefficient (ϕ_i), and residual or shock variance (σ_{ei}^2) of variable M . The AR(1) coefficient, ϕ_i , tells us how the person-mean centered score of M at the previous occasion ($t - 1$) is related to the person-mean centered score of M at the current occasion (t), measuring the carrying-over effect (also called *inertia*) over time for individual i . If ϕ_i is equal to ± 1 or outside the range of $(-1, 1)$, then the time series is not stationary (Hamilton, 2020). In this study, we focused on studying stationary time series modeling and thus ϕ_i is assumed to be within the range of $(-1, 1)$, exclusive.

For a stationary process, the intraindividual mean is a constant over time and is quantified by μ_i in this model for individual i . Under stationarity, the shock variance σ_{ei}^2 is also a constant over time, measuring individual i 's within-person variability in variable M after accounting for the AR dynamic process. Shock variances have non-negative values and also often have a skewed distribution, making it challenging to model especially as a dependent variable. Following the standard procedure in DSEM, a log transformation is done to σ_{ei}^2 to obtain $\pi_i = \log(\sigma_{ei}^2)$, the log-transformed residual or shock variance of individual i . π_i can range from negative infinity to positive infinity and have a less skewed distribution than σ_{ei}^2 . In this within-person level model, all three dynamic components (μ_i , ϕ_i , and π_i) are modeled as random effects such that different individuals can have different values in the dynamic components.

For the between-person level model, a mediation model was specified with two types of equations: the a path equations and the b path equations. The a path equations can be written as:

$$\begin{aligned} \mu_i &= a_{01} + a_1x_i + \zeta_{a1i} \\ \phi_i &= a_{02} + a_2x_i + \zeta_{a2i} \\ \pi_i &= a_{03} + a_3x_i + \zeta_{a3i} \end{aligned} \quad (2)$$

The b path equations can be written as:

$$y_i = b_0 + c'x_i + b_1\mu_i + b_2\phi_i + b_3\pi_i + \zeta_{bi}. \quad (3)$$

In the a path equations, the dynamic components (μ_i , ϕ_i , and π_i) are modeled as the dependent variables of a person-

level input variable X . In contrast, in the b path equations, the dynamic components and input variable X are modeled as the independent variables of person-level outcome variable Y . Therefore, the dynamic components are modeled as multiple mediators in the between-person level model. In the one-step DSEM approach, dynamic components including μ_i , ϕ_i , and π_i are all modeled as latent variables in the a and b path equations, leveraging the strength of the multilevel SEM framework.

Specifically, in Eq. (2), the a coefficients quantify how input variable X predicts the mediators (the dynamic components). In Eq. (3), the b coefficients measure how a mediator (a dynamic component) predicts outcome Y after controlling for input variable X and the other dynamic components. Furthermore, c' is the direct effect of input variable X on outcome Y after controlling for the mediators. From estimating the model, researchers can make statistical inferences about whether and how the dynamic components mediate the relation between input variable X and outcome Y . The a , b , and c' coefficients and the indirect effects including a_1b_1 , a_2b_2 , and a_3b_3 are often the parameters or effects of interest. In the a path equations, the residuals (ζ_{a1i} , ζ_{a2i} , and ζ_{a3i}) are assumed to have a multivariate normal distribution with means of 0 and covariance matrix Σ_a . Thus, the dynamic components are allowed to covary, after controlling for input variable X . In the b path equation, the residuals (ζ_{bi}) are assumed to follow a univariate normal distribution with a mean of 0 and a residual variance σ_{eb}^2 .

The within-person level model is a multilevel time series model with random effects, addressing the temporal dependency and nested data structure of ILD. The between-person level model can be viewed as a standard SEM, modeling the relations of observed person-level variables and latent dynamic components simultaneously. Together, the within-person level model and the between-person level model integrate the strengths of time series analysis, multilevel modeling, and structural equation modeling for modeling ILD.

Figure 1 displays a path diagram illustration of one-step DSEM. It is important to note that cross-sectional mediation analysis is not recommended in the literature, as it ignores the temporal ordering in mediation mechanisms and can yield biased estimates and misleading inferences for both direct and indirect effects (e.g., Cole & Maxwell, 2003; Maxwell & Cole, 2007; Wang & Zhang, 2020). Thus, for the between-person mediation analysis in Eqs. (2) and (3), it is important to verify that the temporal ordering of the variables is appropriate (i.e., X occurs before M , and M occurs before Y). For example, the input variable X could be a baseline or antecedent variable, the outcome variable is a follow-up or future variable, and the mediators (the dynamic components) could be obtained from intensive longitudinal assessments (e.g., daily diary or experience sampling) conducted between baseline and follow-up surveys. Note that the mediation model examined in the current study differs from that in McNeish and MacKinnon (2025), in which the input, mediator, and outcome variables are all intensively measured and analyzed using the multilevel autoregressive mediation modeling framework. In our mediation model,

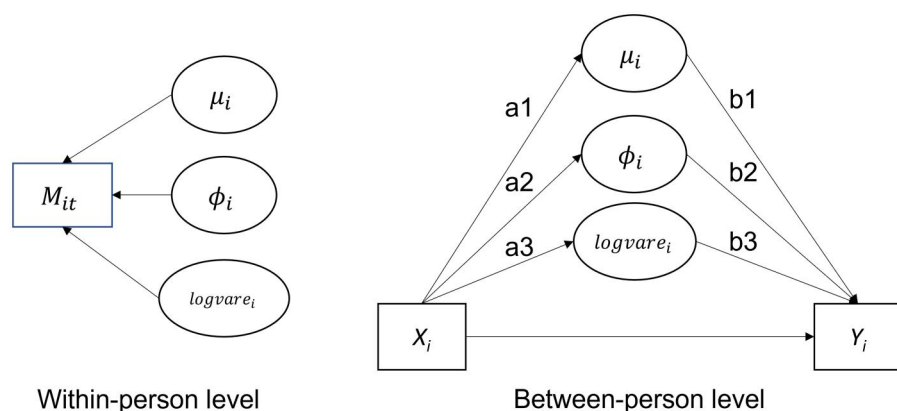


Figure 1. Path diagram illustration of one-step DSEM. The within-person level and between-person level models are simultaneously estimated.

the input and outcome variables are macro-time-level variables, whereas the mediators are from micro-time-level intensive measurements, making it suitable for addressing the research question of the current study.

In one-step DSEM, the within-person level model and the between-person level model are estimated simultaneously, often with Bayesian methods. SEM software programs such as Mplus or Bayesian software programs such as BUGS and JAGS can be used to implement the estimation. In this study, we used Mplus to estimate one-step DSEM with Bayesian methods because of its wide and easy use for DSEM (Fang & Wang, 2024a). When using Bayesian estimation, a prior distribution needs to be specified for each model parameter. Non-informative or weakly informative priors can be used when useful information about the model parameters is not available from pilot or prior research. For example, in Mplus, the default prior for means, intercepts, and path (or regression) coefficients is $N(0, 10^{10})$ and the default prior for univariate (residual) variances is $IG(0.001, 0.001)$ (Asparouhov & Muthén, 2023). In addition, the default prior for a covariance matrix in Mplus is $IW(0, -p - 1)$ where p is the dimension of the covariance matrix. This prior is numerically equivalent to the use of an improper prior which has constant density of 1 on the interval $(-\infty, \infty)$ for each element in the covariance matrix (Asparouhov & Muthén, 2023; Zhang, 2021). These default priors are all non-informative priors and used in this current study. Specifically, for the model in Eqs. (1)–(3), we used $N(0, 10^{10})$ for the priors of intercepts (a_{01} , a_{02} , a_{03} , and b_0) and path coefficients (as , bs , and c'), $IG(0.001, 0.001)$ for the prior of the b -path residual variance σ_{eb}^2 , and $IW(0, -4)$ for the prior of the a -path residual covariance matrix Σ_a .

Two-Step DSEM

In this section, we introduce two-step DSEM and describe two implementation approaches. In the first approach, only within-person level model variables (e.g., time-varying variables) are modeled in Step 1 analysis to estimate dynamic components; these estimates, along with person-level variables, are then used in Step 2 analysis to model between-person relations. In the second approach, in Step 1 analysis, within-person level variables are modeled while including

person-level variables as auxiliary variables to yield estimates of dynamic components; Step 2 analysis proceeds in the same way as in the first approach. The key distinction between the two approaches lies in whether person-level variables are incorporated as auxiliary variables during Step 1 analysis. We aim to examine whether the inclusion or not influences the estimation of between-person relations. In the rest of the article, we refer to the first and second two-step DSEM approaches as the two-step (no AUX) DSEM approach and the two-step (AUX) DSEM approach respectively. Below we provide details of these two-step DSEM approaches.

Two-Step (no AUX) DSEM

In Step 1 analysis of the two-step (no AUX) DSEM approach, dynamic processes are modeled to yield estimates of dynamic components, by including only variables in the within-person level model and not the person-level variables in the between-person level model of one-step DSEM. This modeling strategy is intuitive, as the goal of fitting the Step-1 model is to estimate dynamic components that appear to involve only the within-person level model variables.

For the model specified in the one-step DSEM section, the corresponding Step-1 model of two-step (no AUX) DSEM can be written as

$$m_{it} = \mu_i + \phi_i(m_{i,t-1} - \mu_i) + e_{it} \quad (4)$$

$$e_{it} \sim N(0, \sigma_{ei}^2)$$

$$\begin{pmatrix} \mu_i \\ \phi_i \\ \pi_i \end{pmatrix} \sim MVN \left(\begin{pmatrix} \gamma_\mu \\ \gamma_\phi \\ \gamma_\pi \end{pmatrix}, \Sigma_1 \right) \quad (5)$$

where $\pi_i = \log(\sigma_{ei}^2)$. This Step-1 model can be viewed as a standard multilevel univariate AR(1) model or a standard DSEM without person-level variables. The stationarity assumption is also made here for modeling the dynamic processes. Following standard specifications in DSEM, the dynamic parameters (μ_i , ϕ_i , and π_i) are modeled as random effects, allowing individual differences in the dynamic components and addressing the nested data feature of ILD. The random effects are assumed to have a multivariate normal distribution with γ s for the population means of the dynamic components and Σ_1 for the covariance matrix

quantifying the between-person variances of the dynamic components and how the dynamic components covary with one another.

Bayesian estimation, implemented using the same setup in one-step DSEM, is used to estimate the Step-1 model. Specifically, $N(0, 10^{10})$ is used as a non-informative prior for the means (γ s) and $IW(0, -4)$ is used as a non-informative prior for the covariance matrix Σ_1 . After obtaining the posterior distributions of the dynamic components including μ_i , ϕ_i , and π_i , random samples are drawn from the posterior distributions for each individual, resulting in D sets of dynamic component estimates ($\hat{\mu}_{id}$, $\hat{\phi}_{id}$, and $\hat{\pi}_{id}$, $d = 1, \dots, D$). If D is 1, a single draw would be obtained for each dynamic component and each individual. If D is greater than 1 (e.g., 50), multiple draws would be obtained for each dynamic component and each individual. Previous research (e.g., Fang & Wang, 2025) has shown that inference results with $D = 1$ are not satisfactory, as the uncertainty in the dynamic component estimates is improperly ignored. Therefore, in this study, we adopted the strategy of obtaining multiple draws for each dynamic component and each individual in the Step 1 analysis.

In the Step 2 analysis of two-step (no AUX) DSEM, the between-person level model is estimated, using each set of dynamic component estimates together with person-level variables. Specifically, for the a path equations in the between-person mediation analysis of one-step DSEM, the corresponding model equations in two-step (no AUX) DSEM are:

$$\begin{aligned}\hat{\mu}_{id} &= a_{01d} + a_{1d}x_i + \zeta_{a1id} \\ \hat{\phi}_{id} &= a_{02d} + a_{2d}x_i + \zeta_{a2id}, \\ \hat{\pi}_{id} &= a_{03d} + a_{3d}x_i + \zeta_{a3id}\end{aligned}\quad (6)$$

where the dynamic component estimates ($\hat{\mu}_{id}$, $\hat{\phi}_{id}$, and $\hat{\pi}_{id}$ under data set d , $d = 1, \dots, D$) are modeled as the dependent variables of person-level variable X . For the b path equations of one-step DSEM, the corresponding model equation in two-step (no AUX) DSEM is:

$$y_i = b_{0d} + c'_d x_i + b_{1d} \hat{\mu}_{id} + b_{2d} \hat{\phi}_{id} + b_{3d} \hat{\pi}_{id} + \zeta_{bid}. \quad (7)$$

Here, the dynamic component estimates ($\hat{\mu}_{id}$, $\hat{\phi}_{id}$, and $\hat{\pi}_{id}$ under data set d , $d = 1, \dots, D$) and person-level variable X are modeled as independent variables and the person-level variable Y is modeled as the outcome. Notably, dynamic component estimates are modeled in two-step DSEM (as shown in Eqs. (6) and (7)), whereas latent variables of dynamic components are modeled in one-step DSEM (see Eqs. (2) and (3)).

Various estimation methods can be used to estimate the between-person level model in the second step. In this study, we used maximum likelihood (ML) estimation to estimate the between-person level model. In this case, the overall estimation method is a hybrid-Bayesian estimation procedure with Bayesian estimation in the first step for estimating the within-person level model and ML estimation in the second step for estimating the between-person level

model. In contrast, full Bayesian is used for estimation in one-step DSEM in the current study.

Using each of the D sets of dynamic component estimates, between-person level parameter estimates (e.g., \hat{a}_{1d} and \hat{b}_{1d} , $d = 1, \dots, D$) are obtained with ML estimation. With D sets of path coefficient estimates, the standard pooling method in multiple imputation (Rubin, 1996, 2004) can be used to aggregate the results for each parameter or effect of interest. Let θ be a parameter of interest. The following formulas were used to obtain the aggregated results based on the estimates from the multiple draws ($\hat{\theta}_d$, $d = 1, \dots, D$).

$$\hat{\theta} = \sum_{d=1}^D (\hat{\theta}_d) / D \quad (8)$$

$$se(\hat{\theta}) = \sqrt{\sum_{d=1}^D \text{VAR}(\hat{\theta}_d) / D + \frac{D+1}{D} \sum_{d=1}^D (\hat{\theta}_d - \hat{\theta})^2 / (D-1)} \quad (9)$$

The aggregated quantities are the aggregated point estimate $\hat{\theta}$ and its standard error estimate, $se(\hat{\theta})$. In Eqs. (8) and (9), $\hat{\theta}_d$ is the parameter estimate from the d th draw of data set and $\text{VAR}(\hat{\theta}_d)$ is the variance estimate (or square of the standard error estimate) of the parameter estimate from the d th draw. Statistical inferences can be made, for example, using $\hat{\theta}$ as a point estimate and using $\hat{\theta}$ and $se(\hat{\theta})$ to form a 95% confidence interval for interval estimation and hypothesis testing. This pooling procedure is available in Mplus with ML estimation and we used Mplus to implement it.

Two-Step (AUX) DSEM

In Step 1 analysis of the two-step (AUX) DSEM approach, dynamic processes are modeled to yield estimates of dynamic components, by including variables in the within-person level model of one-step DSEM as primary analysis variables and also including person-level variables in the between-person level model of one-step DSEM, such as X and Y , as auxiliary variables. For the within-person level model specified in the one-step DSEM section, the Step-1 model of two-step (AUX) DSEM becomes:

$$m_{it} = \mu_i + \phi_i(m_{i,t-1} - \mu_i) + e_{it} \quad (10)$$

$$e_{it} \sim N(0, \sigma_{ei}^2)$$

$$\begin{pmatrix} \mu_i \\ \phi_i \\ \pi_i \\ x_i \\ y_i \end{pmatrix} \sim \text{MVN} \left(\begin{pmatrix} \gamma_\mu \\ \gamma_\phi \\ \gamma_\pi \\ \mu_x \\ \mu_y \end{pmatrix}, \Sigma_2 \right), \quad (11)$$

where $\pi_i = \log(\sigma_{ei}^2)$. This Step-1 model can be viewed as a multilevel AR(1) model or a DSEM, but with person-level variables as auxiliary variables. Consistent with the assumptions made in one-step DSEM and two-step (no AUX) DSEM, stationarity is assumed for modeling the time series. Following standard specifications in DSEM, the dynamic

parameters (μ_i , ϕ_i , and π_i) are modeled as random effects, allowing different individuals to have different dynamic component estimates and addressing the nested data feature of ILD. The random effects together with the person-level variables are assumed to have a multivariate normal distribution with γ s for the population means and Σ_2 for the covariance matrix quantifying the between-person variances of the dynamic components and the person-level variables, as well as how the dynamic components covary with one another and how they covary with the person-level variables. Thus, Σ_2 of two-step (AUX) DSEM has a greater dimension (5 in this example) than Σ_1 of two-step (no AUX) DSEM (3 in the example) and the increment in the dimension is the number of person-level variables in the between-person level model (i.e., $5 - 3 = 2$).

The person-level variables are only in the between-person level model of one-step DSEM. Thus, it may be counter-intuitive to include them for estimating dynamic components. Because the within-person level model and the between-person level model are estimated separately in two-step DSEM, we conducted a simulation study (shown in the next section) to evaluate the benefits and costs of adding the person-level variables as auxiliary variables in Step 1 analysis of two-step DSEM. Note that in this approach, X and Y are not included in the dynamic process equation (i.e., not in the first-order AR process; Eq. (10), but for modeling the covariance structure of the dynamic components and the person-level variables Eq. (11). Σ_2 specifically contains the covariances between the dynamic components and the person-level variables. Like the Step 1 analysis in two-step (no AUX) DSEM, Bayesian estimation can be used to obtain the posterior distributions of the dynamic components for each individual. In this study, $N(0, 10^{10})$ is used as a non-informative prior for the means (γ s, μ_x , and μ_y) and $IW(0, -6)$ is used as a non-informative prior for the covariance matrix Σ_2 . D (e.g., 50) random draws from the posterior distributions can be obtained for each individual, and D data sets of dynamic component estimates ($\hat{\mu}_{id}$, $\hat{\phi}_{id}$, and $\hat{\pi}_{id}$, $d = 1, \dots, D$) can be formed.

The Step 2 analysis of two-step (AUX) DSEM has the same procedure as that in two-step (no AUX) DSEM. Specifically, Eqs. (6) and (7) are estimated with ML using each set of the D random draws from the Step 1 analysis. Then, D sets of between-person path coefficient estimates are aggregated through the Rubin's rule using Eqs. (8) and (9). $\hat{\theta}$ in Eq. (8) is used as a point estimate and a 95% confidence interval can be constructed based on $\hat{\theta}$ and $se(\hat{\theta})$ in Eqs. (8) and (9) for statistical inference.

Two-Step DSEM and SAM

In both two-step DSEM approaches, the within-person model is first estimated using Bayesian estimation. In the second step, the between-person model is estimated using ML estimation, with multiple plausible values for each dynamic component of interest drawn from its posterior distribution in the first step. This idea aligns with the SAM

(“structural after measurement”) estimation strategy, particularly the global SAM approach (Rosseel & Loh, 2024). Specifically, the within-person model can be regarded as a measurement model in which dynamic parameters are modeled as latent constructs of interest, whereas the between-person model functions as a structural model that relates the dynamic components to other variables. Unlike Rosseel and Loh (2024), who employed a closed-form standard error correction to address uncertainty, we used the multiple imputation strategy (Fang & Wang, 2025; Muthén et al., 2025; Tseng, 2025) to account for the uncertainty in the dynamic component estimates from the first step. This strategy does not rely on distributional assumptions for handling the uncertainty, thereby allowing wide and flexible applications (e.g., small samples or nonnormal data).

A Simulation Study

We conducted a simulation study to evaluate the performance of the one-step DSEM, two-step (no AUX) DSEM, and two-step (AUX) DSEM approaches. Below we present the simulation study design and results.

Simulation Design

The data were generated based on the one-step DSEM in Eqs. (1) (2), and (3). Seven sets of values (see Table 1) were used to generate the a , b , and c' path coefficients, resulting in a mixed combination of null or approximately medium effect sizes ($f^2 = .15$; Cohen, 2013) for the a and b path coefficients. The effect size of c' was small. Input variable X was generated from the standard normal distribution $N(0, 1)$. Dynamic components were generated based on the summary statistics from Hamaker et al. (2018) and Eq. (2). Specifically, we have $\mu_i \sim N(\text{mean} = 1 + a_1x_i, \text{var} = 0.6)$, $\phi_i \sim N(\text{mean} = .4 + a_2x_i, \text{var} = 0.06)$, and $\pi_i \sim N(\text{mean} = -2 + a_3x_i, \text{var} = 1.9)$. With this data generation procedure, the correlations among the dynamic components were 0 or around 0.16. Then, the intensive longitudinal data of variable M were simulated by Eq. (1) using the generated dynamic component values. Outcome scores were generated by Eq. (3) and the residual variance σ_{eb}^2 was set in each condition to yield a variance of 1 for outcome variable Y .

The number of individuals N was set to be 50, 100, 200, 300, or 500. The number of time points, T , was set to be 10, 20, 30, 50, or 100. The combinations of N and T represent most intensive longitudinal study designs in psychology, behavioral, and health research fields. In total, there

Table 1. True values of the path coefficients considered in the simulation study.

Condition	a_1	a_2	a_3	b_1	b_2	b_3	c'
1	0.30	0.40	0.10	1.20	0.55	0.20	0.05
2	0	0.40	0.10	1.20	0.55	0.20	0.05
3	0.30	0	0.10	1.20	0.55	0.20	0.05
4	0.30	0.40	0	1.20	0.55	0.20	0.05
5	0.30	0.40	0.10	0	0.55	0.20	0.05
6	0.30	0.40	0.10	1.20	0	0.20	0.05
7	0.30	0.40	0.10	1.20	0.55	0	0.05

are $7 \times 5 \times 5 = 175$ simulation conditions. 500 replications were run for each simulation condition.

For the one-step DSEM approach and Step 1 analysis of the two-step DSEM approaches, Bayesian estimation was used and implemented in Mplus. MCMC based on the Gibbs sampler was used to obtain posterior distributions. In the simulation study, we used the following settings across all conditions. Two chains (the default in Mplus) each with 10,000 iterations were used, with the first half of the iterations (first 5,000 iterations) as burn-in. The second half (last 5,000 iterations) was used to form the posterior distributions and for convergence evaluation. Convergence was checked using the Gelman–Rubin potential scale reduce factor (PSRF; Gelman & Rubin, 1992). A model was considered as convergent if all parameters had PSRF values below 1.10. For a convergent model using the one-step DSEM approach, the posterior median (the default in Mplus) was used to form a point estimate for a parameter of interest and the 95% percentile credible interval was used to make inferences about the parameter. Different values have been used for the number of draws or imputed datasets (D) in the multiple imputation and two-step DSEM literature, ranging from as few as 5 to 10 (Rubin, 1996, 2004) to as many as 200 (Muthén et al., 2025). For the two-step DSEM approaches, we used $D = 50$ to ensure stable results, based on the satisfactory simulation findings from two-step DSEM studies with 20 or 50 draws reported in Tseng (2025) and Fang and Wang (2025). Specifically, $D = 50$ random draws were obtained for each dynamic component and for each individual in Step 1 analysis; ML estimation was used to estimate the between-person level model using each set of random draws in Step 2 analysis. The Rubin’s rule was used to obtain the aggregated point estimate and the 95% confidence interval for each parameter of interest. For model convergence, rates of 90% or higher were viewed as satisfactory.

Empirical bias or relative bias as well as empirical Type I error rates or coverage rates for path coefficients including a_1 to a_3 , b_1 to b_3 , and c' were evaluated to compare the performance of the three modeling approaches. Only converged replications were included in the performance evaluations. Let θ denote a parameter of interest and $\hat{\theta}_j$ denote the estimate from the j th converged replication. Let #Reps be the number of converged replications. Empirical bias is calculated by $EB = \sum_{j=1}^{\#Reps} \hat{\theta}_j / \#Reps$ when $\theta = 0$. The relative bias is calculated by $RB = \sum_{j=1}^{\#Reps} \#Reps \times (\hat{\theta}_j / \theta) - 1$ when $\theta \neq 0$. Relative biases within (–10%, 10%) are viewed as ignorable. Let \hat{l}_j and \hat{u}_j denote the lower and upper limits of an obtained 95% confidence or credible interval of θ in the j th replication. The coverage rate is calculated by $CP = \frac{\#(\hat{l}_j < \gamma < \hat{u}_j)}{\#Reps}$ where the numerator is the number of convergent replications with the confidence/credible intervals covering the true value. When the true parameter value is 0, $1 - CP$ is the empirical Type I error rate and a good-performing approach should yield close to 5% empirical Type I error rates (e.g., 2.5% to 7.5%; Bradley, 1978). When the true

parameter value is nonzero, we viewed coverage rates close to 95% (e.g., 0.91 to 0.98; Muthén & Muthén, 2002) as satisfactory.

Simulation Results

Convergence rates were satisfactory ($> 96\%$) across all studied conditions and for all three modeling approaches. Model comparison results were consistent across different effect size conditions. Thus, we focus on presenting results from two representative effect size conditions, Effect Size Conditions 1 and 6 in Table 1, in the main text. Results from the other effect size conditions are presented in the supplemental materials.

Figure 2 displays the relative bias results from Effect Size Condition 1, in which all path coefficients were nonzero. In general, we found that (1) one-step DSEM and two-step (AUX) DSEM had ignorable estimation biases when both T and N were sufficiently large, (2) one-step DSEM had relatively smaller estimation biases than two-step (AUX) DSEM in small-sample scenarios (e.g., $N = 50$ or $T = 10$), and (3) two-step (no AUX) DSEM demonstrated poorer estimation accuracy than one-step DSEM and two-step (AUX) DSEM and had nonignorable estimation bias even with $T = 100$ and $N = 500$. More specifically, one-step DSEM had nonignorable relative biases in estimates of path coefficients a_2 , b_2 , and c' when $T = 10$, but achieved ignorable relative biases in estimates of a_1 to a_3 and b_1 to b_3 when $T \geq 20$. For c' , relative biases were ignorable except under some small-sample conditions with $T \leq 20$ or $N \leq 100$. Two-step DSEM (AUX) had nonignorable relative biases for a_2 , b_1 to b_3 , and c' when $T = 10$, but the estimation biases in a_2 and b_1 to b_3 decreased to the ignorable relative bias level when $T \geq 20$. For c' , ignorable relative biases were reached when $T \geq 50$ and $N \geq 200$. In contrast, two-step (no AUX) DSEM had nonignorable relative biases in estimates of a_2 , b_2 , and c' across all the studied conditions in Figure 2. Even when $T = 100$ with $N = 500$, the relative biases remained nonignorable (–16% for a_2 , 82% for b_2 , and –17% for c').

Figure 3 displays the coverage rate results from Effect Size Condition 1 in which all path coefficients were nonzero. In general, both one-step DSEM and two-step (AUX) DSEM achieved satisfactory coverage rates for all path coefficients when $T \geq 20$, whereas two-step (no AUX) DSEM had severe undercoverage even with $T = 100$ and $N = 500$. Specifically, one-step DSEM had satisfactory coverage rates across the path coefficients and the studied conditions in Figure 3, except for undercoverage for path coefficient a_2 when $T = 10$ (coverage rates were 89%, 89%, and 83% with $N = 200$, 300, and 500 respectively). Two-step (AUX) DSEM also had satisfactory coverage rates across the path coefficients and the studied conditions in Figure 3, except for undercoverage for path coefficient b_3 when $T = 10$ (coverage rates were 90% and 73% with $N = 300$ and 500 respectively). In contrast, two-step (no AUX) DSEM had severe undercoverage problems. The coverage rates improved as T increases, but they became worse as N increases for a fixed T . For instance, the coverage rates

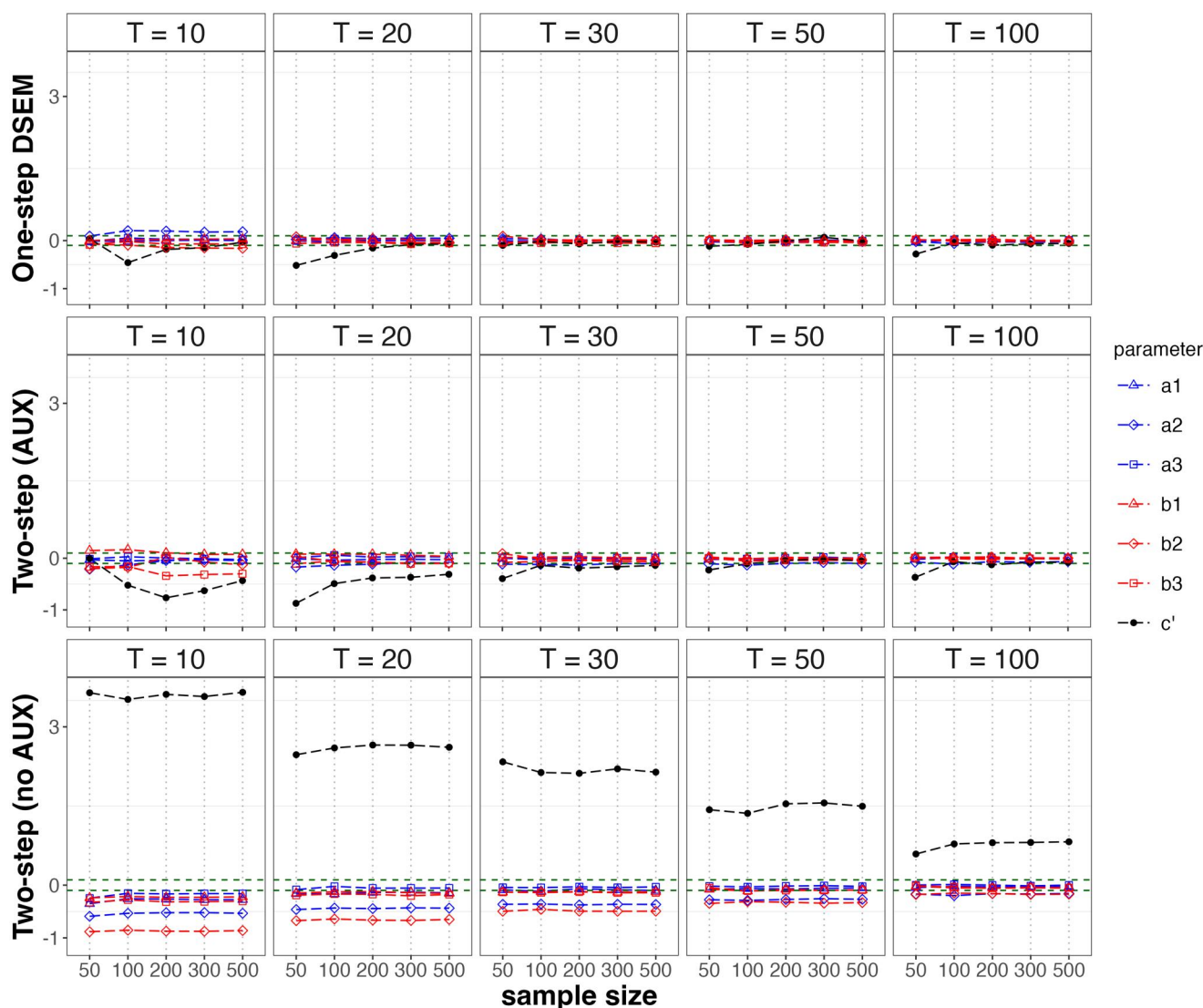


Figure 2. Relative bias results from effect size condition 1 with nonzero true values for all path coefficients.

ranged from 94% to 96% for a_2 , b_2 , and c' when $T = 100$ and $N = 50$, but the coverage rates dropped to the range of 69% to 87% for these path coefficients when $T = 100$ and $N = 500$. These findings underscore the limitations of two-step (no AUX) DSEM even under favorable data conditions (e.g., $T = 100$ and $N = 500$).

Figures 4 and 5 display respectively the empirical bias and Type I error rate results of b_2 from Effect Size Condition 6, in which the true value of b_2 is zero. All three methods generally had lower empirical biases in estimating b_2 as T or N increases (Figure 4). The empirical Type I error rates of testing b_2 from one-step DSEM were satisfactory across the studied conditions (Figure 5). Two-step (AUX) DSEM showed deflated Type I error rates (<2.5%) when $T = 10$ or 20, but the empirical Type I error rates improved to the nominal range (2.5% to 7.5%) with $T = 30$ and $N \geq 100$, or with $T \geq 50$ (Figure 5). In contrast, the empirical Type I error rates of b_2 from two-step (no AUX) DSEM were 0% or 1% when $T \leq 50$, but approached or were within the satisfactory range (2.5% – 7.5%) when $T = 100$ (Figure 5).

Figures 6 and 7 display respectively the relative bias and coverage rate results for the nonzero path coefficients (a_1 to a_3 , b_1 , b_3 , and c') from Effect Size Condition 6. The pattern of results was consistent with that observed under Effect Size Condition 1: one-step DSEM and two-step (AUX) DSEM had satisfactory results with sufficient T and N . The data requirements for achieving satisfactory results were generally lower for one-step DSEM than two-step (AUX) DSEM. In contrast, two-step (no AUX) DSEM again had nonignorable bias and undercoverage for some path coefficients (e.g., a_2 and c'), even when $T = 100$ and $N = 500$. Additionally, the performance of two-step (no AUX) DSEM became worse for some path coefficients (e.g., a_2) when N increases for a given T (Figure 7), further demonstrating the poorer performance of the two-step (no AUX) DSEM approach.

A Real Data Analysis Example

We used a subset of the data from the Notre Dame Study of Health & Well-Being (e.g., Bergeman et al., 2021; Blaxton

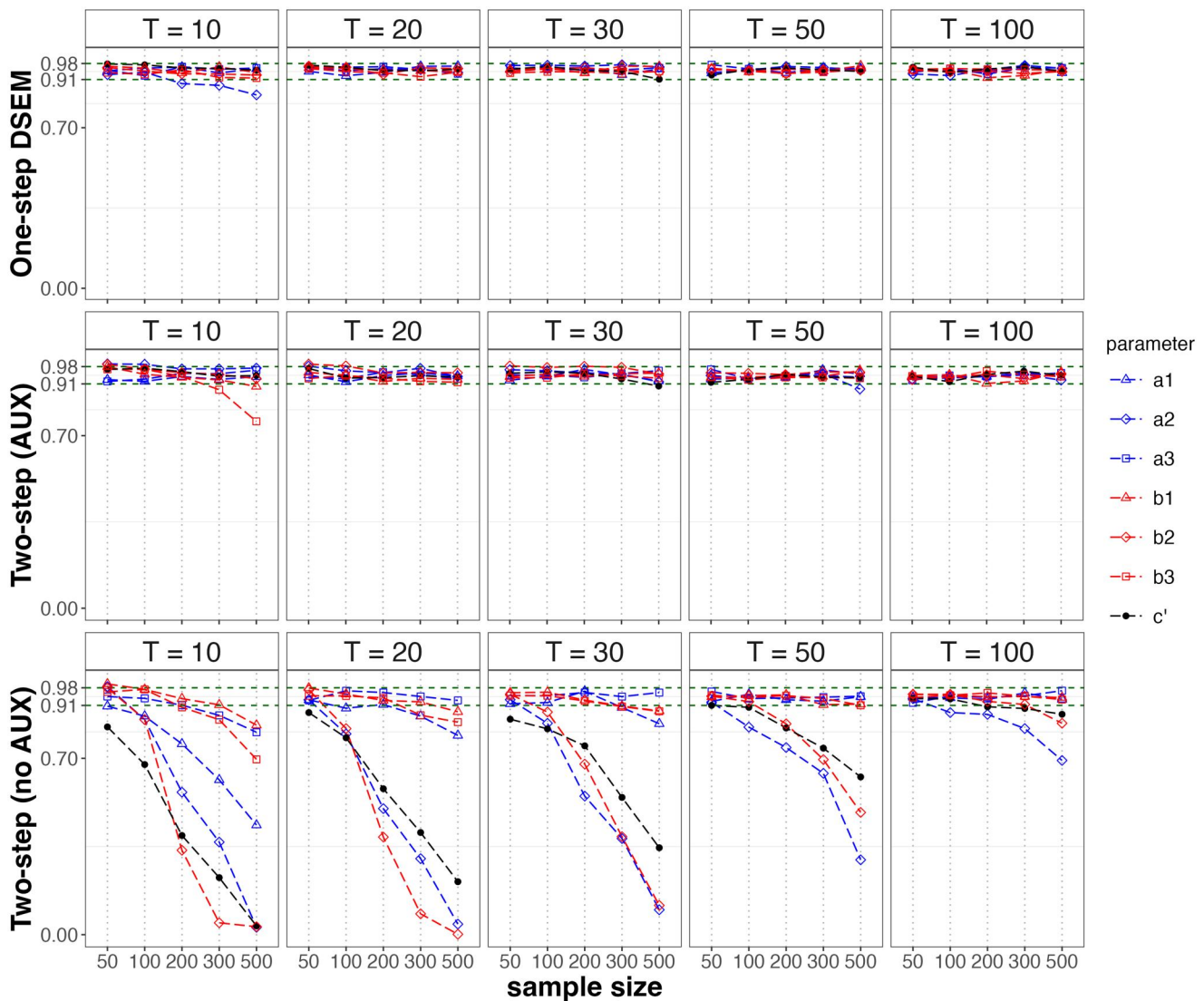


Figure 3. Coverage rate results from effect size condition 1 with nonzero true values for all path coefficients.

et al., 2020; Ong et al., 2025) to illustrate the applications of the modeling approaches. The sample contains data from 732 participants (41% male, 49% female) aged from 20 to 87. Daily negative affect (NA) was assessed over 56 consecutive days using the NA subscale of the Positive and Negative Affect Schedule (Watson et al., 1988), in which each of 10 negative emotions (e.g., “afraid”) was rated on a scale from 1 to 5 (“not at all”, “a little”, “moderately”, “quite a bit”, “extremely”). Depression symptom severity was measured on a yearly basis using the Center for Epidemiological Studies Depression Scale (Radloff, 1977). In this study, we used depression scores assessed during Wave 1 (right before the daily diary assessments; Depr1) and Wave 2 (one year later since wave 1; Depr2) surveys. Our primary goal was to examine whether and how daily dynamics in negative affect were related to depression over time.

We tested a mediation model in which Depr1 influenced the daily dynamic features of NA including the intraindividual mean, inertia or AR(1) coefficient, and log-transformed shock variance, which in turn predicted Depr2. Specifically, at the within-person level, the daily dynamics in NA were

modeled by a multilevel AR(1) process; at the between-person level, dynamic characteristics of NA were modeled as the multiple mediators, Depr1 was modeled as the input variable, and Depr2 was modeled as the outcome. The dynamic features of NA were extracted from the daily diary assessments conducted between Waves 1 and 2 surveys. Thus, the input variable occurred before the mediators and the mediators occurred before the outcome variable.

The one-step DSEM and two-step DSEM (both AUX and no AUX) approaches were applied to estimate and test the path coefficients. Consistent with the setup in the simulation study, for the one-step DSEM approach and the first step of two-step DSEM approaches, we used two MCMC chains, each with 10,000 total iterations, a burn-in period of 5,000 iterations, and a thinning number of 10; for Step 2 analysis of the two-step DSEM approaches, ML estimation with $D = 50$ was used. Model convergence was achieved from all three modeling approaches ($PSRF < 1.01$). To facilitate applications of the modeling approaches, the analysis code is shared at <https://github.com/peggywangnd/DSEM2025code>. Table 2 presents the results from the three modeling

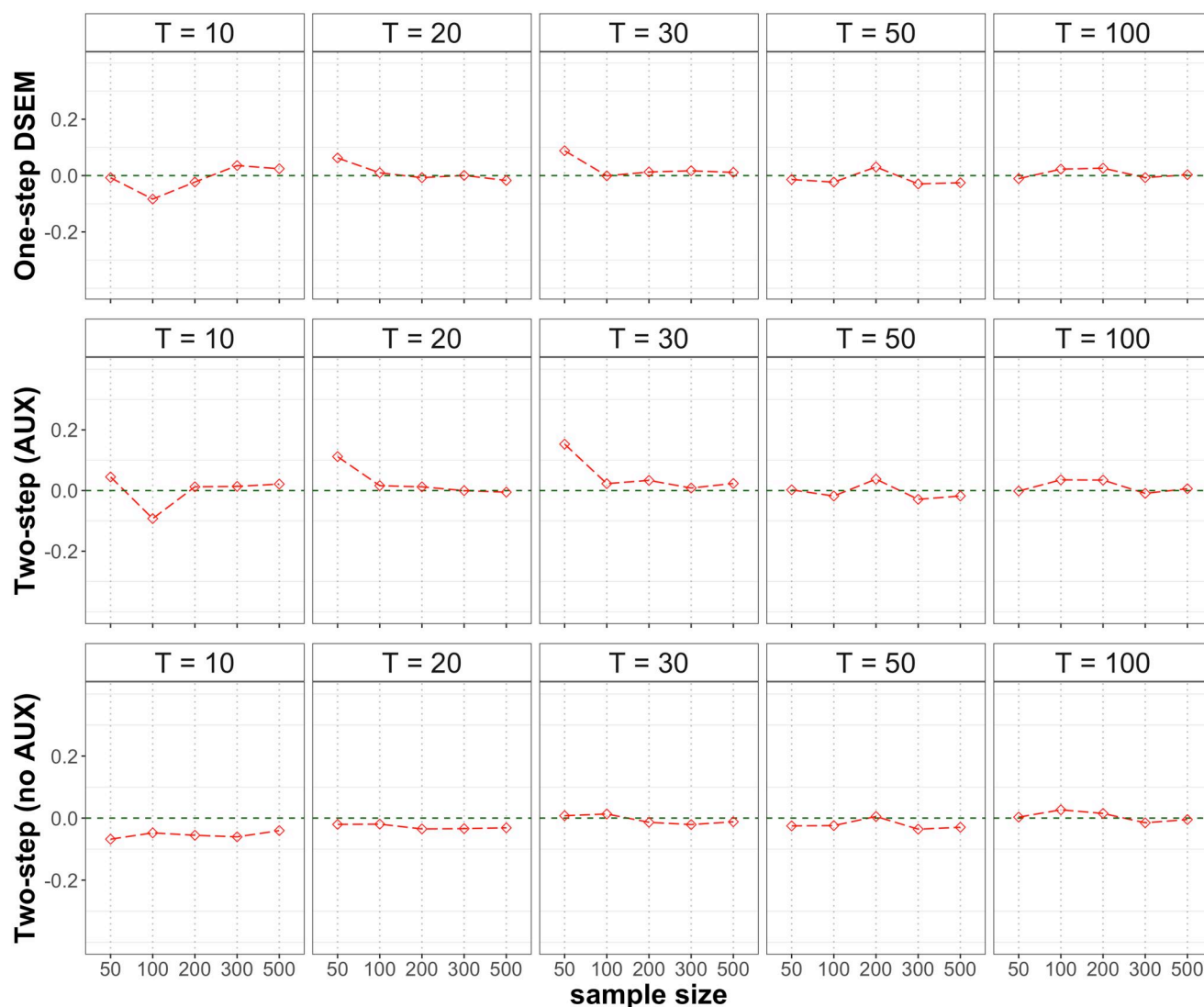


Figure 4. Empirical bias results of b_2 from effect size condition 6 with $b_2 = 0$.

approaches. Table 2 also displays the computation time for each modeling approach. The MCMC computation time of two-step (no AUX) DSEM was the shortest, followed by two-step (AUX) DSEM and one-step DSEM. The two-step approaches, however, used additional time for (1) outputting the 50 data sets containing estimated dynamic components in the Step 1 analysis and (2) estimating the direct and indirect effects in the Step 2 analysis. Together, the total computation time of one-step DSEM was the shortest, followed by two-step (no AUX) DSEM and two-step (AUX) DSEM.

Across all three approaches, the path coefficients a_1 to a_3 were significantly different from zero, with 95% credible/confidence intervals excluding zero. The point and interval estimates of these coefficients were also similar across modeling approaches. These results consistently indicated that higher depression scores at Wave 1 were associated with higher intraindividual means, greater inertia, and larger shock variances in daily NA.

For the b paths, all three approaches also led to the same statistical testing conclusions: the 95% credible or confidence interval estimates of b_1 excluded 0, but those of b_2

and b_3 included 0. These results consistently indicated higher levels of intraindividual means of daily negative affect were related to depression at Wave 2 after controlling for inertia, shock variability, and depression at Wave 1, whereas inertia and shock variability were not significantly related to Wave 2 depression after controlling for the other dynamic components and Wave 1 depression. Additionally, the point and interval estimates of b_1 to b_3 from one-step DSEM and two-step (AUX) DSEM were similar, whereas those from two-step (no AUX) DSEM were quite different. Specifically, the estimate of b_1 from two-step (no AUX) DSEM was 12.56 (95% CI: 6.37, 18.76) and substantially smaller than those from one-step DSEM (est = 20.84, 95% CI: 14.85, 27.21) and two-step (AUX) DSEM (est = 20.85, 95% CI: 14.70, 26.99). The estimates of b_2 and b_3 from two-step (no AUX) DSEM were positive (0.42 and 0.16, respectively), whereas those from one-step DSEM (−0.62 and −0.62 respectively) and two-step (AUX) DSEM (−0.73 and −0.62, respectively) were negative.

Results of the direct effect (c') and indirect effects (a_1b_1 , a_2b_2 , and a_3b_3) from all three approaches also led to the same testing conclusions: the 95% credible or confidence

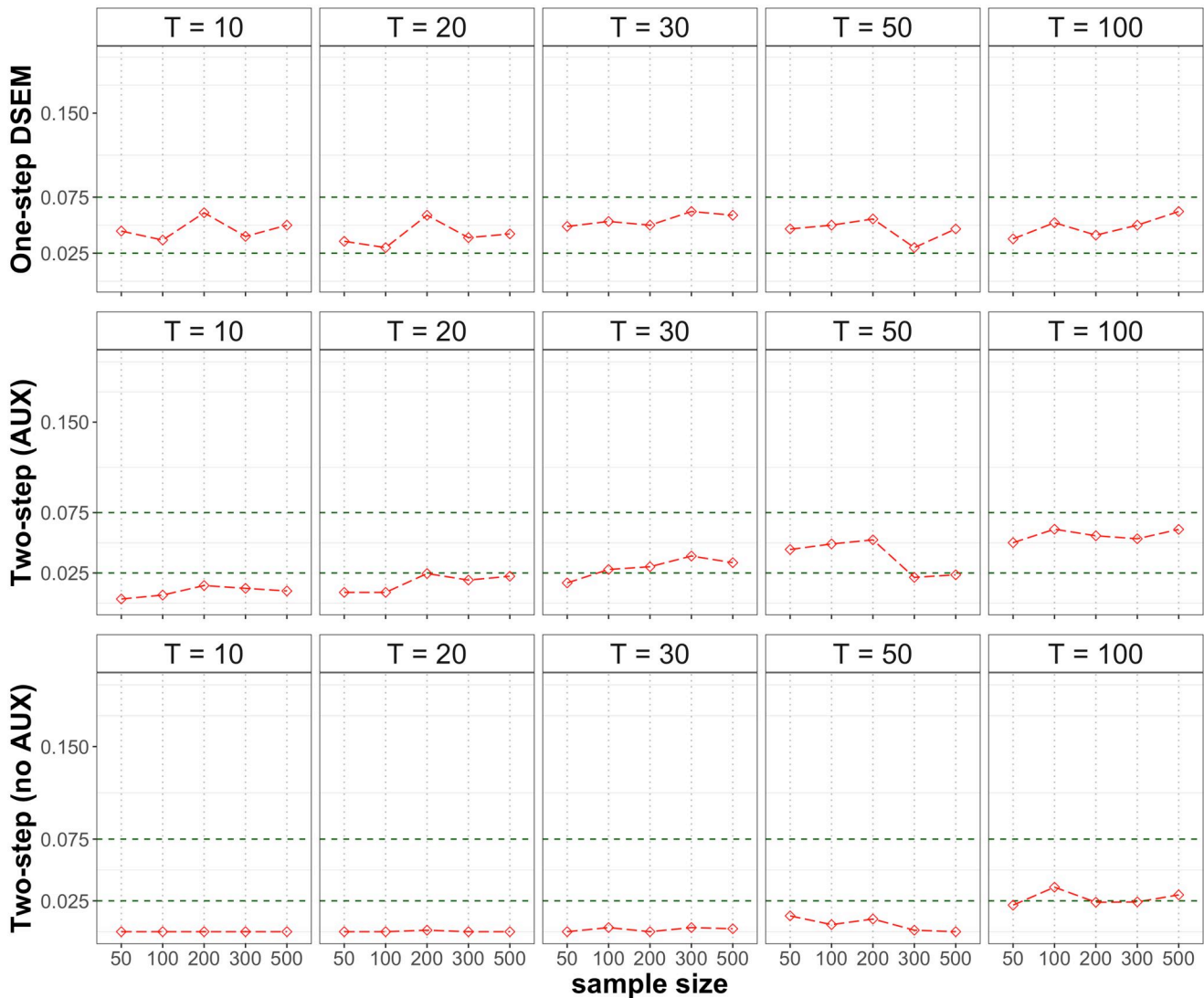


Figure 5. Empirical type I error rate results of b_2 from effect size condition 6 with $b_2 = 0$.

interval estimates of c' and a_1b_1 excluded 0 but those of a_2b_2 and a_3b_3 included 0. These results consistently indicated depression at Wave 1 was related to depression at Wave 2 through the intraindividual mean of daily negative affect, but not through inertia or shock variability. In other words, higher levels of Wave 1 depression was related to higher intraindividual means of daily negative affect, which in turn was related to higher levels of Wave 2 depression. The estimate of a_1b_1 from two-step (no AUX) DSEM was 0.14 (95% CI: 0.07, 0.20), only about half the sizes of those from one-step DSEM (est = 0.27, 95% CI: 0.19, 0.36) and two-step (AUX) DSEM (est = 0.27, 95% CI: 0.18, 0.35). In addition, the signs of the a_2b_2 and a_3b_3 estimates from two-step (no AUX) DSEM were opposite to those from one-step DSEM and two-step (AUX) DSEM.

In sum, one-step DSEM and two-step (AUX) DSEM yielded similar estimation and inference results, whereas two-step (no AUX) DSEM had different estimation results for some path coefficients (e.g., the b path coefficients). This pattern of results was consistent with what we observed in the simulation study. For this real data example, we have $T = 56$ and $N = 732$. Under a similar (or an even less

favorable) data condition ($T = 50$ and $N = 500$) in the simulation study, both one-step DSEM and two-step (AUX) DSEM yielded accurate estimation and inference results for all path coefficients, whereas two-step (no AUX) DSEM had nonignorable estimation bias and undercoverage for some path coefficients. Therefore, for this empirical example ($T = 56$, $N = 732$), we recommend using the results from either one-step DSEM or two-step (AUX) DSEM, and caution against relying on the two-step (no AUX) DSEM approach.

Discussion

In this study, we investigated three modeling approaches for intensive longitudinal data analysis: one-step DSEM, two-step (no AUX) DSEM, and two-step (AUX) DSEM. The within-person level model and between-person level model are estimated simultaneously in one-step DSEM, but separately in two-step DSEM. Within the two-step DSEM framework, person-level variables are included as auxiliary variables in Step-1 dynamic modeling of two-step (AUX) DSEM, but not included in Step 1 analysis of two-step (no

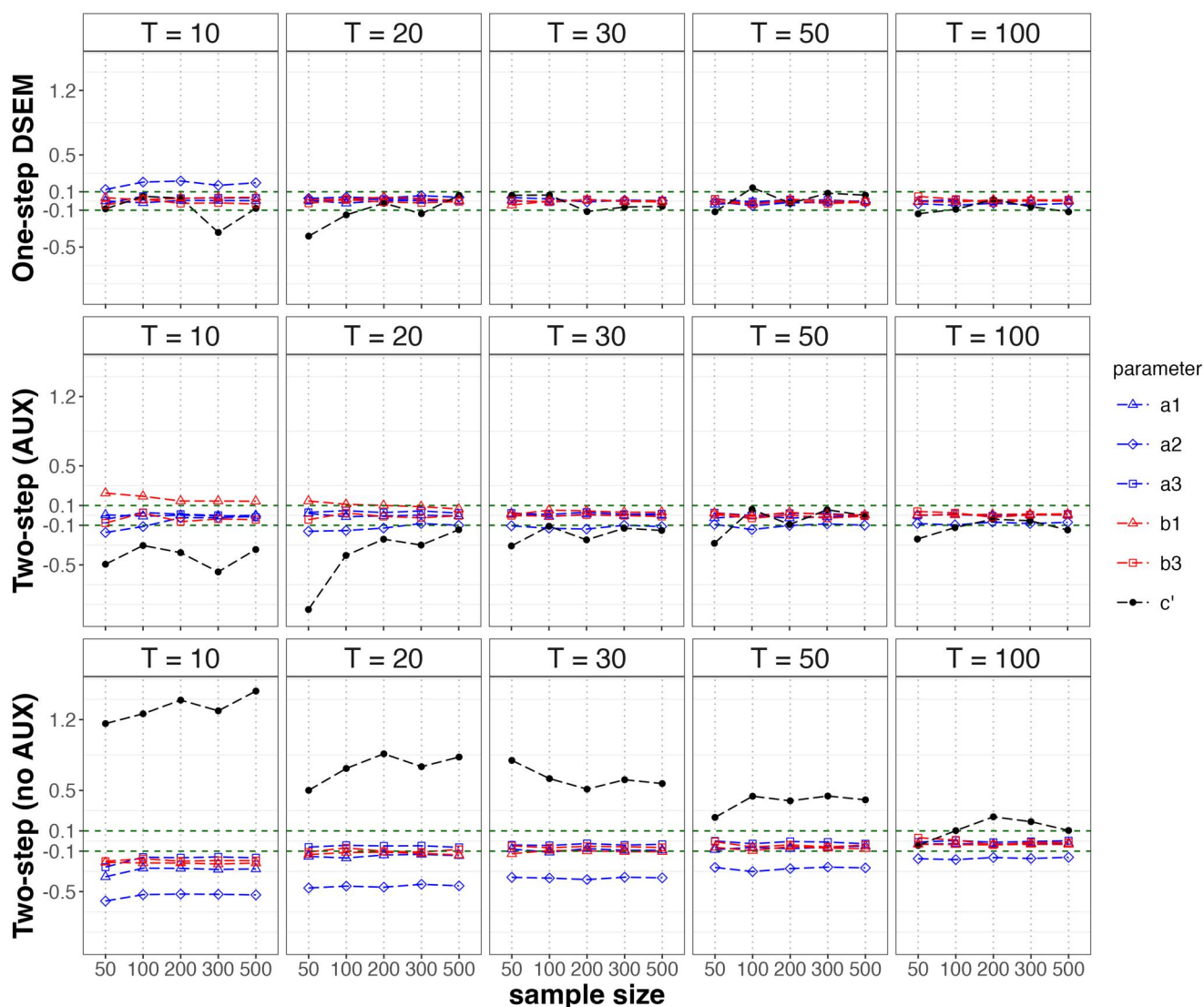


Figure 6. Relative bias results of a_1 - a_3 , b_1 , b_3 , and c' from effect size condition 6 with $b_2 = 0$.

AUX) DSEM. Full Bayesian was used for estimation in one-step DSEM, whereas a hybrid-Bayesian estimation method was used in the two-step DSEM approaches. A simulation study was conducted to compare the performance of the three modeling approaches and a real data example was used to illustrate the applications of the approaches. Below we discuss the simulation and real data example results, provide modeling recommendations, and outline future research directions.

Our simulation results demonstrated that both one-step DSEM and two-step (AUX) DSEM generally yielded satisfactory results for estimating and testing the path coefficients of interest when sufficient data are available (number of time points $T \geq 30$ and sample size $N \geq 100$). With more data (increasing T and/or N), both approaches performed better. One-step DSEM generally required fewer data to achieve satisfactory performance and showed better estimation accuracy under small-sample conditions compared to two-step (AUX) DSEM. In contrast, two-step (no AUX) DSEM consistently exhibited substantial bias, undercoverage, and deflated Type I error rates for certain parameters, even under favorable data conditions (e.g., $T = 100$,

$N = 500$). Additionally, two-step (no AUX) DSEM had worse inference performance (e.g., more severe undercoverage) when N increased while T was held constant. These patterns were observed across different effect size conditions in the simulation study, for both nonzero and zero path coefficients. These findings were also mirrored in the real data example: one-step DSEM and two-step (AUX) DSEM yielded similar point and interval estimates, whereas two-step (no AUX) DSEM produced more divergent results for several path coefficients. Note that the path estimates in the real data example differed from the effect size conditions used in the simulation, demonstrating the generalizability of our findings across a wider range of parameter settings. We also implemented the three modeling approaches using R packages 'rjags' and 'lavaan.' To illustrate the implementations, we used a simulated data set from Effect Size Condition 1 with $N = 300$ and $T = 50$. The results are presented in Table S1 of the online supplemental materials. We observed the same pattern of results as those from the simulation study and the real data example implemented in Mplus. We shared the data set with the R scripts to facilitate

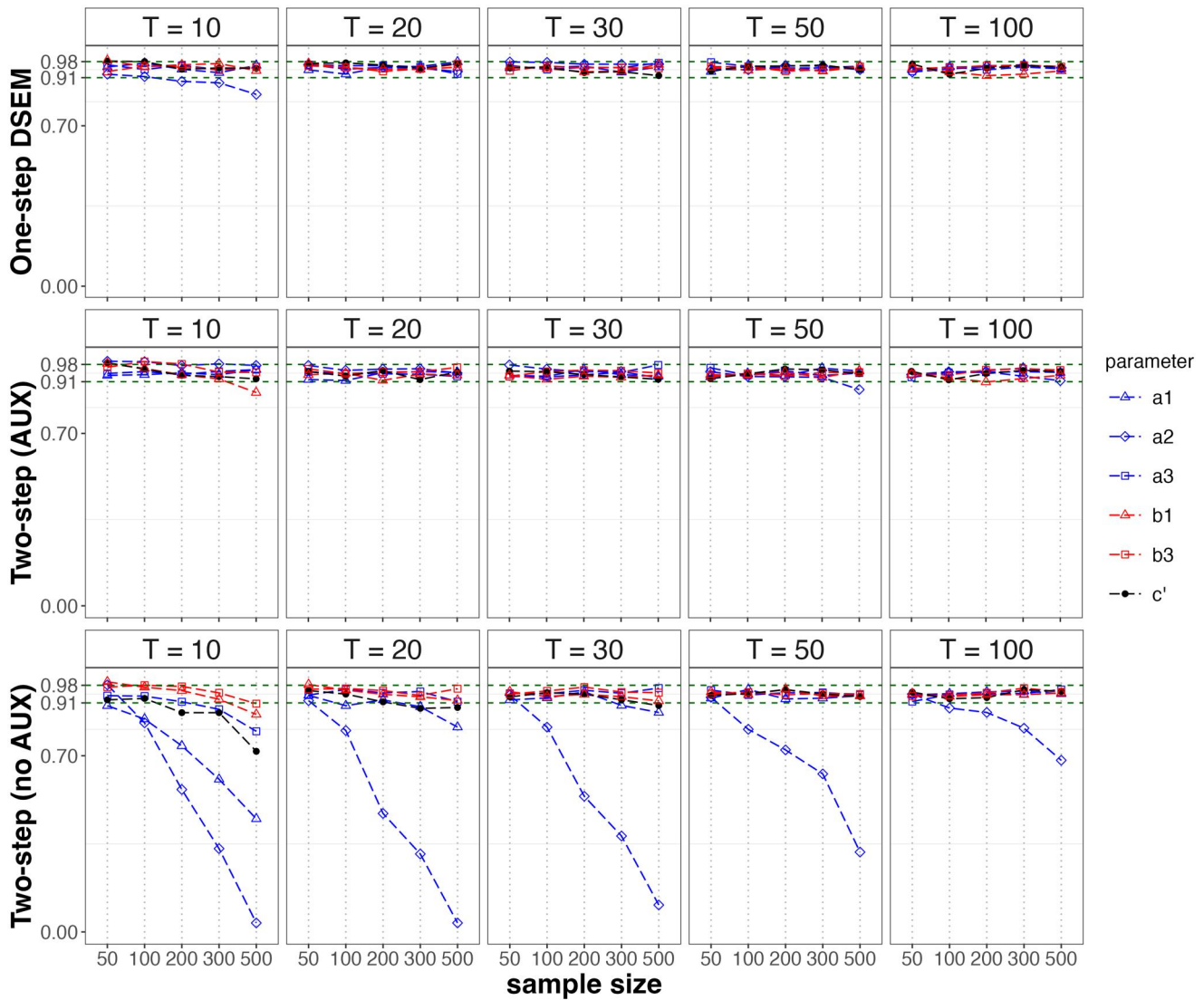


Figure 7. Coverage rate results of a_1 – a_3 , b_1 , b_3 , and c' from effect size condition 6 with $b_2 = 0$.

Table 2. Real data analysis example results.

Parameters	One-step DSEM	Two-step (AUX) DSEM	Two-step (no AUX) DSEM
a_1 (μ on Depr1)	0.013 (0.011, 0.015)	0.013 (0.011, 0.014)	0.011 (0.009, 0.012)
a_2 (ϕ on Depr1)	0.010 (0.008, 0.012)	0.009 (0.007, 0.011)	0.008 (0.006, 0.010)
a_3 (π on Depr1)	0.059 (0.050, 0.069)	0.059 (0.049, 0.069)	0.059 (0.049, 0.069)
b_1 (Depr2 on μ)	20.844 (14.845, 27.205)	20.847 (14.702, 26.992)	12.564 (6.366, 18.763)
b_2 (Depr2 on ϕ)	−0.622 (−3.964, 2.698)	−0.732 (−4.044, 2.580)	0.423 (−3.092, 3.938)
b_3 (Depr2 on π)	−0.619 (−1.298, 0.045)	−0.619 (−1.287, 0.049)	0.159 (−0.542, 0.860)
c' (Depr2 on Depr1)	0.491 (0.423, 0.559)	0.481 (0.412, 0.550)	0.565 (0.500, 0.631)
a_1b_1 (IndEff through μ)	0.272 (0.193, 0.356)	0.265 (0.184, 0.346)	0.135 (0.065, 0.204)
a_2b_2 (IndEff through ϕ)	−0.006 (−0.040, 0.027)	−0.006 (−0.036, 0.023)	0.004 (−0.026, 0.034)
a_3b_3 (IndEff through π)	−0.037 (−0.078, 0.003)	−0.037 (−0.077, 0.004)	0.009 (−0.032, 0.051)
Computation time			
Step 1—MCMC	37 min and 12 s	36 min and 7 s	29 min and 56 s
Step 1—produce 50 data sets	Na	19 min and 36 s	15 min and 58 s
Step 2	Na	1 second	2 s

Note. μ : intraindividual mean; ϕ : AR(1) coefficient or inertia; π : log-transformed shock variance. Depr1: wave-1 depression; Depr2: wave-2 depression. IndEff: indirect effect. NA: not applicable. Values outside the parentheses were point estimates and values inside the parentheses were 95% credible or confidence interval estimates. CIs that do not cover zero were bold. The analyses were run on a desktop with an i7 CPU and 32 GB of ram.

parallel implementations in R on <https://github.com/peggy-wangnd/DSEM2025code>.

Overall, the findings highlight the importance of including person-level variables as auxiliary variables in Step 1 analysis of two-step DSEM and support the use of either one-step

DSEM or two-step (AUX) DSEM, particularly in applications with adequate data, while cautioning against reliance on two-step (no AUX) DSEM due to its inferential limitations. Although person-level variables are not part of the dynamic model itself, their inclusion in Step 1 analysis theoretically

improves the estimation of the covariance matrix among dynamic components and person-level variables, which in turn enhances the estimation and inference of the between-person model in Step 2 analysis. Our finding is consistent with the plausible values methodology used to estimate population characteristics of proficiency in the item response theory (IRT) context (Mislevy et al., 1992, 1992) and for secondary analysis using plausible values of categorical latent class variables in the mixture modeling context (see Section 4.1 of Asparouhov & Muthén, 2010). Mislevy et al. (1992) discussed that, in the IRT context, the covariance matrix of trait score estimates and conditioning variables (e.g., demographics or attitude variables) “is not generally a defensible estimate of” the covariance matrix of true trait scores and conditioning variables (p. 150). There are two underlying reasons for this conclusion: (1) point estimates do not reflect the uncertainty in the trait score estimates and (2) the observed data in the conditioning variables are from only a sample rather than the population. To address these issues, Mislevy et al. (1992) proposed to use multiple plausible values to estimate an individual’s latent trait. In addition, they suggested that a predictive distribution or population-structure model (i.e., the conditional distribution of the latent trait variable given the conditioning variables) should be constructed to incorporate the conditioning variables when obtaining the multiple plausible values of an individual’s trait, in addition to specifying the primary measurement model (the conventional IRT model). Then, the relationship between the trait scores and the conditioning variables (i.e., population characteristics of proficiency) is estimated using the multiple plausible values of latent trait together with the observed data from the conditioning variables. This reasoning also applies to the two-step DSEM context and explains the performance difference between the two-step DSEM approaches. Specifically, two-step (no AUX) DSEM does not specify the predictive distribution or population-structure model, whereas two-step (AUX) DSEM does. In two-step (AUX) DSEM, person-level variables are included in Step 1 analysis as auxiliary variables and are modeled through a multivariate normal distribution (i.e., the predictive distribution), thus aiding the estimation of the relationship between the dynamic components and the person-level variables. Therefore, we recommend two-step (AUX) DSEM over two-step (no AUX) DSEM.

The overall model in one-step DSEM is bigger and more complex than the Step-1 or Step-2 models in the two-step DSEM approaches. Thus, the one-step approach technically requires more computational resources for MCMC implementation than the first step of the two-step approaches. Indeed, the MCMC computation time of one-step DSEM was longer than that of the first step of the two-step approaches in the real data example. Nevertheless, our simulation results showed that one-step DSEM could achieve acceptable inferential performance with relatively smaller data requirements and had convergence rates comparable to the two-step DSEM approaches. In this study, we employed a relatively simple modeling setup, a multilevel univariate AR(1) model at the within-person level and a mediation model at the between-person level. In this model specification, there is no need to do complex nonlinear transformations to obtain dynamic

components of interest, unlike in the more complex models of Fang and Wang (2025), Muthén et al. (2025), and Tseng (2025) with which advantages of two-step DSEM are better demonstrated. When the within-person model becomes more complex (e.g., bivariate or trivariate AR structures) or the within-person or between-person models include interaction effects (e.g., moderation), however, one-step DSEM becomes more challenging to estimate or sometimes cannot be estimated in standard SEM software. For instance, moderation models involving latent variable interactions (e.g., between latent intraindividual means and latent AR[1] coefficients) can pose challenges for one-step DSEM estimation. Tseng (2025) showed that one-step Bayesian estimation was slower and sometimes encountered convergence issues when estimating CLPMs with fixed-effects latent interactions, whereas the two-step multiple imputation approach was faster and did not experience convergence problems. This makes the two-step estimation strategy particularly appealing for modeling dynamic processes of greater complexity, especially when one-step DSEM faces estimation or convergence difficulties. For instance, the advantages of two-step (AUX) DSEM may be even more pronounced when estimating DSEM with random-effects latent interactions, as this type of DSEM is even more complex than the CLPMs examined in Tseng (2025). Future research should continue to evaluate the relative performance of these one-step and two-step approaches in more complex DSEM contexts, especially when interactions and other nonlinear effects are of interest.

One limitation of the current study is that we did not incorporate missing data into our simulation design, and our real data analysis assumed the missing at random (MAR) mechanism (Little & Rubin, 2019). Nevertheless, missingness is common in ILD studies. Prior research has shown that Bayesian estimation performs well in handling missing completely at random (MCAR) and MAR missingness in one-step DSEM (e.g., Asparouhov et al., 2018; Fang & Wang, 2024a; McNeish, 2025). Building on these findings, we expect that both one-step DSEM and two-step (AUX) DSEM would outperform two-step (no AUX) DSEM, when missingness in within-person variables (e.g., daily assessments of negative affect) depends on fully observed person-level variables (e.g., observed baseline depression). This is because these person-level variables are explicitly included in the full model for one-step DSEM or incorporated as auxiliary variables in the Step 1 analysis of two-step (AUX) DSEM. Thus, the missingness mechanism is MAR, as these two modeling approaches leverage observed information related to missingness. For two-step (no AUX) DSEM, however, the person-level variables are not included in the Step 1 analysis and the missingness in within-person variables is missing not at random (MNAR) in this case. Under MNAR, we expect that two-step (no AUX) DSEM would perform poorly without additional treatments for handling missingness, based on the recent findings in McNeish (2025). Furthermore, if missingness in within-person variables depends on unobserved person-level variables (e.g., unmeasured baseline depression), the missingness mechanism also becomes MNAR. In this case, we expect that none of the

three approaches would perform well without additional treatments for handling missingness. To address MNAR data in DSEM, McNeish (2025) embedded a Diggle-Kenward-type model into DSEM and estimated the joint model with Bayesian estimation. He also emphasized that no single approach is universally effective for MNAR data and advocated conducting sensitivity analyses and future research on DSEM with missing data. Therefore, future work should evaluate how missingness in time-varying and/or person-level variables affects estimation and inference in both one-step DSEM and two-step DSEM under different missingness mechanisms. Additionally, the examined modeling approaches assumed normality, consistent with the standard DSEM framework. Nonnormality is also frequently observed in social science data (e.g., Cain et al., 2017). Future research should also evaluate how nonnormality impacts statistical inference in both one-step DSEM and two-step DSEM. For instance, it would be valuable to investigate whether using a t distribution in one-step DSEM or applying robust ML in the Step 2 analysis of two-step DSEM improves estimation when person-level variables are nonnormally distributed.

Beyond the two-level DSEM context examined in this study, the two-step modeling strategy holds promise for a range of other complex modeling scenarios, including three-level DSEM for cross-time-scale analysis, multilevel structural equation modeling (SEM) with cross-sectional or longitudinal data, mixture modeling, latent profile analysis, and multilevel continuous time modeling. Evaluating the performance of two-step modeling approaches in these broader contexts represents an interesting direction for future work.

In sum, our study evaluated the performance of one-step DSEM and two versions of two-step DSEM. Our real data analysis results indicated that two-step (no AUX) DSEM had different estimation results, compared to those from one-step DSEM and two-step (AUX) DSEM. Our simulation results suggested that one-step DSEM and two-step (AUX) DSEM provide more accurate and consistent estimates than two-step (no AUX) DSEM. We therefore recommend one-step DSEM when computationally feasible. We also recommend the two-step DSEM approach with including person-level auxiliary variables in Step 1 analysis. We hope our findings, along with our modeling code shared online, will assist researchers in applying DSEM approaches more effectively to address complex research questions by intensive longitudinal data analyses.

Funding

Lijuan Wang is grateful for the support from IES grant R305D210023. The real data collection is supported by NIH grants (Grant # 1 R01 AG02357, UG3AG057039, UH3AG057039) to Cindy S. Bergeman.

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