Abstract

Lorem Ipsum is simply dummy text of the printing and typesetting industry. Lorem Ipsum has been the industry's standard dummy text ever since the 1500s, when an unknown printer took a galley of type and scrambled it to make a type specimen book. It has survived not only five centuries, but also the leap into electronic typesetting, remaining essentially unchanged. It was popularised in the 1960s with the release of Letraset sheets containing Lorem Ipsum passages, and more recently with desktop publishing software like Aldus PageMaker including versions of Lorem Ipsum.

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Introduction

Work in progress, just a placeholder for now: Karl Popper once described science as the art of "systematic over-simplification." This term ironically yet accurately describes the very basic cycle of empirical research, where we lay out general claims about the world as hypotheses, translate them into measurable constructs, and choose how to gather data from certain populations, which finally, in turn, updates our beliefs about general verbal claims about the world. One core challenge in every research endeavor is mapping the general to the specific when designing and conducting a study, or from the specific and empirical to the verbal and general when interpreting the results. This mapping appears to be the crux of most research and is where most, if not all, of a researcher's degrees of freedom lie.Divergences in these mappings can be the source of ambiguity and verbal disputes. When differences in mappings from the verbal plane are not recognized or lack transparency, persistent and seemingly unresolvable disagreements in the general and verbal domains can occur. This challenge transfers to Monte Carlo simulation studies. These are commonly used tools to test statistical methods in simulated data to evaluate any method against a known ground truth. As it is impossible to simulate and test every possible data and analysis model combination, researchers are confronted with a multitude of degrees of freedom and decisions about what "prototypical" models to test in which "prototypical" data and settings. Especially the comparison of different methods in their "general" applicability and performance for various research settings is prone to conflicting verbal claims based on diverging simulation decisions. Biases for a specific method developed by one researcher might additionally amplify these divergences, not only at the step of interpreting results but importantly also when designing a simulation. To address these challenges of entrenched disagreements, the practice of adversarial collaboration has been proposed to unveil discrepancies in underlying methodological decisions and assumptions. It was famously pioneered by Ralph Hertwig and Daniel Kahneman, who tried to settle a persistent scientific disagreement about frequency representation and consulted Barbara Mellers as a neutral arbiter. Today, it is recognized as a potent tool in the social empirical research community. The basic idea is for two researchers in disagreement to first identify a general verbal dispute and agree on a research question to settle the debate. Based on this, they collaboratively work on operationalizing, testing, and interpreting this verbal claim. This process aims to unveil and concretize underlying disagreements and thus reduce ambiguity and increase generalizability. In this project, we aimed to transfer the concept of adversarial collaboration from the empirical domain to Monte Carlo simulation studies and assess its feasibility and viability in a case study in this context. To conduct such an exemplary adversarial collaboration, we first need a framework that structures the collaborative process tailored to the outline of simulation studies. Traditional SEM methods, like maximum likelihood estimation, optimize all parameters of a model simultaneously under the assumption of multivariate normality. While powerful and although robust estimation techniques relax the normality assumption, all system wide estimators suffer from several shortcomings, they often face issues such as non-convergence, improper solutions (with parameters out of definitional range), and biases from local measurement misspecifications that affect the entire model. They also typically require large sample sizes for adequate performance, especially in complex models.

Methods

A Framework for Adversarial Collaboration

We developed a specific adversarial simulation framework and structured the collaboration into two rounds. In the first round, each collaborator independently conducts a separate simulation study. In the second round, they come together to work on a joint study, building on the findings from the first round. This two-step approach is designed to highlight differences in a systematic way and to establish a virtual foundation for collaboration before engaging in a joint effort in our case study.

Individual Simulation Studies

Studies by Collaborator A (Kriegmair)

The methodological setup of my individual simulation studies follows the structure we established for our *adversarial simulation* framework to facilitate stepwise collaboration. It is based on a preregistered protocol but includes some deviations from the preregistration (See Appendix A for the full protocol and all deviations from the preregistration). In the initial phase of our case study, I independently conducted two separate simulation studies without my collaborator's involvement with the goal to conceptually replicate the findings regarding SAM compared to standard SEM estimation of Rosseel & Loh (2022) and Dhaene & Rosseel (2023). However, there are several differences in the design and setup of the studies compared to the original studies as outlined below.

Aims, objectives and research questions Both studies aimed to evaluate the performance of traditional SEM (with maximum likelihood) compared to global SAM (gSAM), local SAM with maximum likelihood (lSAM-ML), and local SAM with unweighted least squares (lSAM-ULS) under various conditions. The two research questions we jointly established prior to conducting the studies served as general basis for both studies:

1. How do SAM and traditional SEM methods (including ML and ULS) compare in terms ofbias, Mean Squared Error (MSE), and convergence rates in small to moderate samples?
2. What is the impact of model misspecifications, such as residual correlations and cross-loadings, on the performance of SAM compared to traditional SEM methods?

Population Models and Data Generation Mechanisms

Study 1 Data were generated based on a 5-factor population structural model with 3 indicators for each factor. Four different models were simulated (see Figure 1). In line with Rosseel & Loh (2022) this model design was chosen to represent a realistic model with sufficient complexity to pose a challange for the estimation methods, especially in the presence of misspecifications:

- Model 1.1: Correctly specified model.
- Model 1.2: Misspecified with cross-loadings in the population model that are ignored in the estimation model (model 1.1)
- Model 1.3: Misspecified with correlated residuals and a reversed structural path between the third and fourth latent factors in the population model that are ignored in the estimation model (model 1.1)
- Model 1.4: Misspecified with a bidirectional structural relation between factors 3 and 4 specified as only one directional

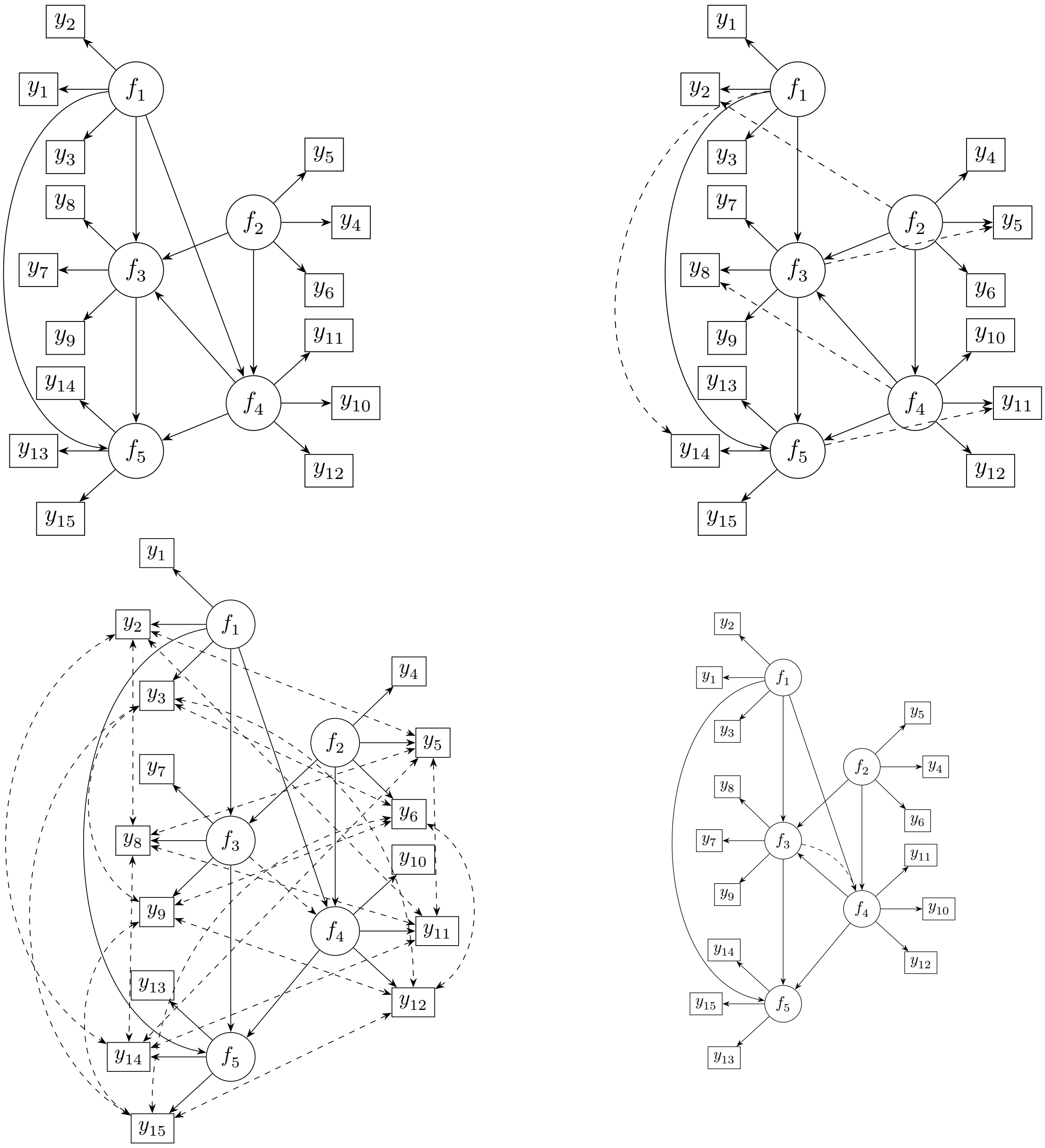
Factor loadings were fixed across all reliability conditions, with the first indicator of each factor serving as the scaling indicator ($\lambda = 1.0$), and the other two indicators having loadings of 0.7. Indicator reliability levels were manipulated by adjusting the measurement error variances in the Θ matrix. Specifically, the a reliability value was set at different levels (low = 0.3, moderate = 0.5 or high = 0.7) to compute the respective error variances on the diagonal of Θ: $\Theta^* = \mathrm{Var}(\eta)\Lambda^T \times \frac{1}{r-1}$.

To investigate additioanl possible and realisitic scenarios beyond the ones studied by Rosseel & Loh (2022) model 1.3 included a combination of measuremnt and structural misspecifications as opposed to only measurement misspecifications to introduce an even more severly misspecified model under which SAM methods might perform even better than traditional SEM. Further, model 1.4 included a (not estimated) bidirectional structural relation between factors 3 and 4 as opposed to the unidirectional reversed one. For all models, the population-level values of the structural parameters were set to 0.1.

Study 2 Data were generated based on a 5-factor population structural model with three indicators for each factor with loadings set to 1, 0.9 and 0.8 for each factor and reliability modulated like in study 1. Regression weights were set to either 0.183 and 0.224 (low) or 0.365 and 0.447 (medium). This should represent varying variance explained (R^2) by the endogenous factors set at

Figure 1

Population Model Variations of Study 1

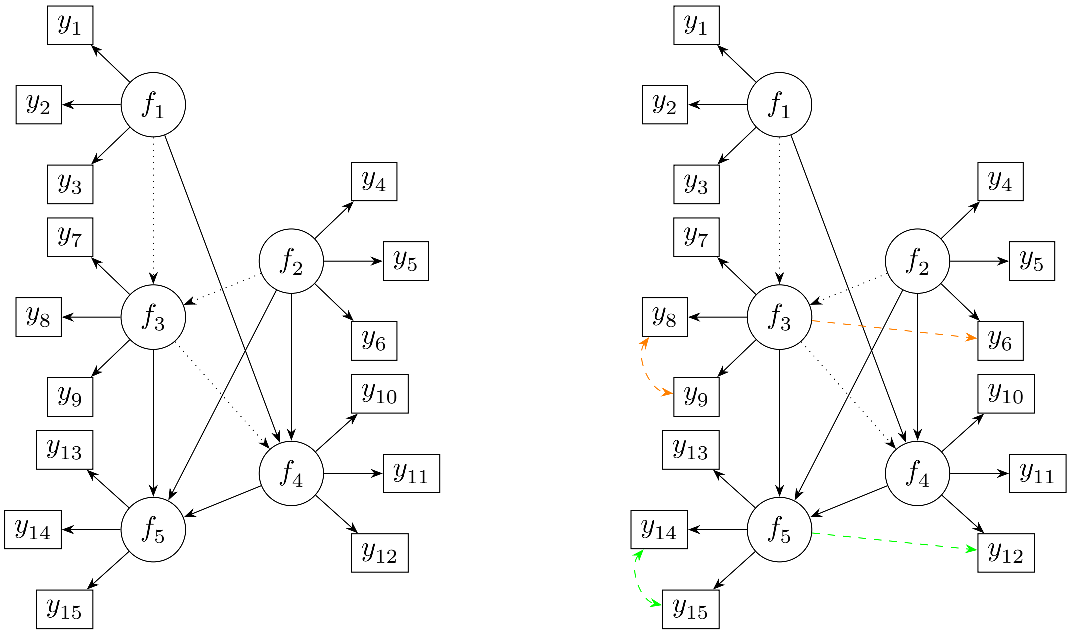


Note. Error terms are not explicitly shown in the figure. Dashed lines represent relations omitted in the estimation model present in the population model."

low ($R^2 = 0.1$) or medium ($R^2 = 0.4$). Note however that the computation of this was a simplification and does not accurately result in said R^2 values. The aim here was only to generally modulate between lower and higher regression weights. The population models resulted in the following model types with varying misspecification in the estimation model: (1) Structural misspecifcation with falsely specified paths in the estimation model absent in the population model (See Figure 2). (2) correlated residuals and a factor cross-loading in either the exogenous, endogenous part of the model or both with falsely specified paths in the estimation model absent in the population model (see Figure 2). To enable the analysis of the impact of falsely specified paths in the estiamtion model that are not present in the population model and how well the different methods recover these non-existing relations both population models included several such misspecifications in addtion to the measurement misspecifications evaluated by Dhaene & Rosseel (2023).

Figure 2

Population Model Variations of Study 2



Note. Error terms are not explicitly shown in the figure. Dotted paths represent relations specified in the estimation model not present in the population model. For the model on the right, orange lines represent misspecifications in the exogenous part of the model, and green lines represent misspecifications in the endogenous part. These types of misspecifications result in different realizations of the model when they are modulated as factors of misspecification (endogenous, exogenous or endo- and exogenous) in study 2 but are subsumed under one model here.

Experimental Design of simulation procedures

Study 1 Study 1 varied three main conditions: (1) sample sizes of small ($N = 100$), moderate ($N = 400$), and large ($N = 6400$); (2) Indicator reliability of low ($= 0.3$), moderate (0.5), high

(= 0.7); (3) Model specifications: correctly specified model and misspecified with not specified cross loadings in the population model (see figure 2), misspecified with not-specified correlated residuals and a reversed structural path between the the third and the fourth latent factor in the population model (see figure 3) and a recursive structural relation between factor 3 and 4 in the population specified as only one directional (see figure 4).

Study 2 Study 2 varied five conditions: (1) sample sizes: small ($N = 100$), medium ($N = 400$), and large ($N = 6400$). (2) Variance explained by endogenous factors: low ($R^2 = 0.1$) and medium ($R^2 = 0.4$). (3) Indicator reliability: low (0.3), moderate (0.5), and high (0.7). (4) Model misspecifications: varying the population model by omitting a residual covariance and a factor cross-loading in different parts of the model. (5) Number of measurement blocks: separate measurement model per latent variable ($b = 5$) and joint measurement model for all exogenous variables ($b = 3$) for the local SAM condition (lSAM-ML).

Method Selection Both studies compared the performance of four estimation methods: Traditional SEM with maximum likelihood (ML), Global SAM with maximum likelihood (gSAM), Local SAM with maximum likelihood (lSAM-ML), Local SAM with unweighted least squares (lSAM-ULS).

Performance Measures For both studies convergence rates were tracked via lavaan's built-in function that indicates convergence. Further, improper solutions, converged models that showed negative variances (as the only type of improper solution present), were tracked via lavaan warning messages. Next of all converged and propper solutions bias ($\bar{T}-\theta$), and RMSE ($\sqrt{\frac{1}{K}\sum_{k=1}^{K}(T_k-\theta)^2}$) where T_k is the estimated parameter, $\bar{T}$ the mean of the estimated parameters and θ the true parameter value, and K is the number of replications computed. For comparability across varying regression weights for study 2, relative bias ($\frac{\bar{T}-\theta}{\theta}$) and relative RMSE ($\sqrt{\frac{(\bar{T}-\theta)^2+S_T^2}{\theta^2}}$) were computed. Monte Carlo standard errors (MCSE) were computed for bias and RMSE as well as relative bias and relative RMSE: $\sqrt{\frac{S_T^2}{K}}$ and $\sqrt{\frac{S_T^2}{K\theta^2}}$ for bias and relative bias, and $\sqrt{\frac{K-1}{K}\sum_{j=1}^{K}\left(\text{RMSE}_{(j)}-\text{RMSE}\right)^2}$ and $\sqrt{\frac{K-1}{K}\sum_{j=1}^{K}\left(rRMSE_{(j)}-rRMSE\right)^2}$ for RMSE and relative RMSE.

Software All analyses were conducted in R Core Team (2023). Simulation and estimation was done using Rosseel (2012). To ensure reproducability and avoid synchronization in parallelized a pre-generated list of seeds was used for all replications. For further details and a complete list of libraries and dependencies, visit https://github.com/valentinkm/AdversarialSimulation.

Analysis and Interpretation plan Similar to the studies by Rosseel & Loh (2022) and Dhaene & Rosseel (2023) results were interpreted by descriptively comparing the performance measures of the different estimation methods under varying sample sizes, indicator reliability levels, and model misspecifications without predetermined cut-off values or critical distances. Performance metric values were aggregated across all parameters excluding the misspecified parameters (present in the population but not in the estimation model).

Studies by Collaborator B (Kosanke)

Quoted verbatim from Kosanke's report (Git commit SHA 4d0e95e):

The structure of this section closely aligns to our agreed upon structure of simulation studies in Table 1.

In a first step, I published a simulation protocol containing all the planned analysis to be replicated from the original paper by Robitzsch (2022). This protocol can be accessed here: https://github.com/lkosanke/AdversarialSimulation/blob/main/LK/simulation_protocol.pdf.

Aims, objectives and research questions

For my individual study, I replicated parts of Robitzsch (2022) that were relevant to our two substantive research questions. Overall, I conducted 6 simulation studies.

Population Models and Data Generation Mechanisms

The most important details with regards to the population models and data-generating mechanisms are visible in Table 7. With regards to the population models, all factors in all studies loaded onto 3 indicators each. I chose the population values to align with the original paper by Robitzsch (2022). The multivariate normally distributed data was generated parametrically, based on a specified population model. All simulations were conducted using seeds to allow for the reproducibility of results.

For more details on the exact values of each study, see the simulation scripts in the Github repository.

Figure 3

Overview of Simulation Studies Conducted by Kosanke

Study	Model	Correct model included?	Unmodelled RC	Unmodelled CL	N Sizes	φ/ β	λ
Study 1	2-factor-CFA	Yes	1 and 2, both pos. and neg.	x	7	φ = 0.6	Fixed
Study 1b	2-factor-CFA	Yes	x	x	2	φ = 0,2 - 0.8	Varied
Study 2	2-factor-CFA	x	x	1 and 2, both pos. and neg.	7	φ = 0.6	Fixed
Study 3	2-factor-CFA	x	1, pos.	1, pos.	7	φ = 0.6	Fixed
Study 4	5-factors	Yes	20, all pos.	5, all pos.	7	β = 0.1	Fixed
Study 4a	5-factors	x	20, all pos.	5, all pos.	7	β = 0.1 - 0.4	Fixed

Note. Φ: factor correlation, N: sample size, λ: factor loading, σ: residual variance, τ: factor variance, RC: residual correlations, CL: cross-loadings, CFA: confirmatory factor analysis, β: regression coefficient between factors.

Experimental Design of simulation procedures

Overall, 3 different types of factors were varied that can be deduced from Table 7 and are detailed again in the simulation scripts provided.

Firstly, I varied the sample size in all studies, ranging from N = 50 to 100.000. I included a smaller sample size N=50 for all studies, to be able to answer our substantive research questions in more detail. Study 1b explicitly investigated the small sample bias of LSAM estimation in low sample sizes. Thus, only N=50 and N=100 were present in this study.

Additionally, I varied the amount of misspecification in all studies, either via different numbers of unmodelled residual correlations, cross-loadings, or both.

Thirdly, in Studies 1b and 4a, I varied the population values for three model parameters (phi, beta and/ or lambda).

Besides studies 1 and 2, I implemented full factorial designs. In Studies 1 and 2 I omitted conditions were both one positive and one negative value would be present. I hypothesize that this was done in Robitzsch (2022) to avoid cancellation of biases, but the authors did not give reasoning for this decision themselves.

In Studies 4 and 4a I investigated the differential performance of the estimators in a model that included a non-saturated structural model (i.e. regressions between some of the factors). These studies were replications not only of the paper by Robitzsch (2022), but of the first paper on the SAM approach by Rosseel & Loh (2022). In contrast to the other studies, studies 4 and 4a differed in the way the misspecification variation was labelled in Robitzsch (2022). Instead of varying a factor misspecification as in the previous study, they varied 3 different data-generating mechanisms (DGM's) as a whole. Thus the conditions are labelled differently: DGM 1 contained no misspecification. DGM 2 contained 5 cross-loadings in the data-generating model, that were not modelled in the estimated models. DGM 3 contained 20 residual correlations that were not modelled in the models. I extended them to investigate the interaction of beta and N for the 5-factor regression model, as this again was of interest four our substantial research questions. Additionally, I omitted the inclusion of DGM 1 in Study 4a, as it neither contained misspecification (which is central to our research question), nor did it lead to interesting results in the original study.

Method Selection

In terms of estimation methods, I used constrained SEM maximum-likelihood (SEM-ML) and unweighted-least-squares estimation (SEM-ULS), so that loadings and variance parameters were given the constraints that they had to be positive and larger than 0.01. Additionally, I implemented local-SAM (LSAM) and global-SAM (GSAM) estimation, in both maximum-likelihood (LSAM-ML/ GSAM-ML), and unweighted-least-squares estimation (GSAM-ML/ GSAM-ULS) contexts. Exceptions were studies 1b, 4 and 4a, where only LSAM was investigated, as results did not really differ between the two different SAM-methods (Robitzsch, 2022).

Performance Measures

I calculated the bias and RMSE of the estimated factor correlations in all studies, as well as the standard deviation of the one factor correlation present in Studies 1,2 and 3. For the type of bias calculated, I oriented on Robitzsch (2022), besides in Study 1b. Thus, I calculated average relative bias in Studies 1, 2 and 3, and average absolute bias in Studies 1b, 4 and 4a. In Study 1b, I took the absolute value to see if negative and positive biases canceled each other out in the original study for conditions with lower phi values. In addition to what was done in Robitzsch (2022), I calculated confidence intervals for the bias estimates, but omitted them in the results tables for presentation purposes. The exact computation of the performance measures is detailed in the simulation scripts and results.pdf file in my sub-folder of the Github repository.

I did not include a detailed mechanism to capture model convergence as detailed in the first substantive research question. As Robitzsch (2022) argued in their paper, and was shown already in other simulations, using constrained maximum likelihood estimation should resolve convergence issues of classical maximum likelihood estimation in smaller samples (Lüdtke et al., 2021; Ulitzsch et al., 2023). I did include, however, a mechanism to track the total number of warnings for each estimation and compare it to the total number of estimations as a sanity check.

Software

All analyses were conducted in R (R Core Team, 2023). I used the packages lavaan, purrr, tidyverse, furrr to conduct the simulations, as well as knitr and kableExtra for presenting the results (Rosseel, 2012; Vaughan & Dancho, 2022; Wickham et al., 2019; Wickham & Henry, 2023; Xie, 2024; Zhu et al., 2024) .

Analysis and Interpretation plan

For the interpretation of results, I oriented on cut-offs that were used in the original paper by Robitzsch (2022). For bias, I interpreted differences of 0.05 or higher as substantial. For SD, I explicitly mentioned percentage reductions of more or equal to 5%. For RMSE, the same interpretation was used for differences of 0.03 or higher. The simulation was repeated 1500 times for each Study.

Joint Simulation Study

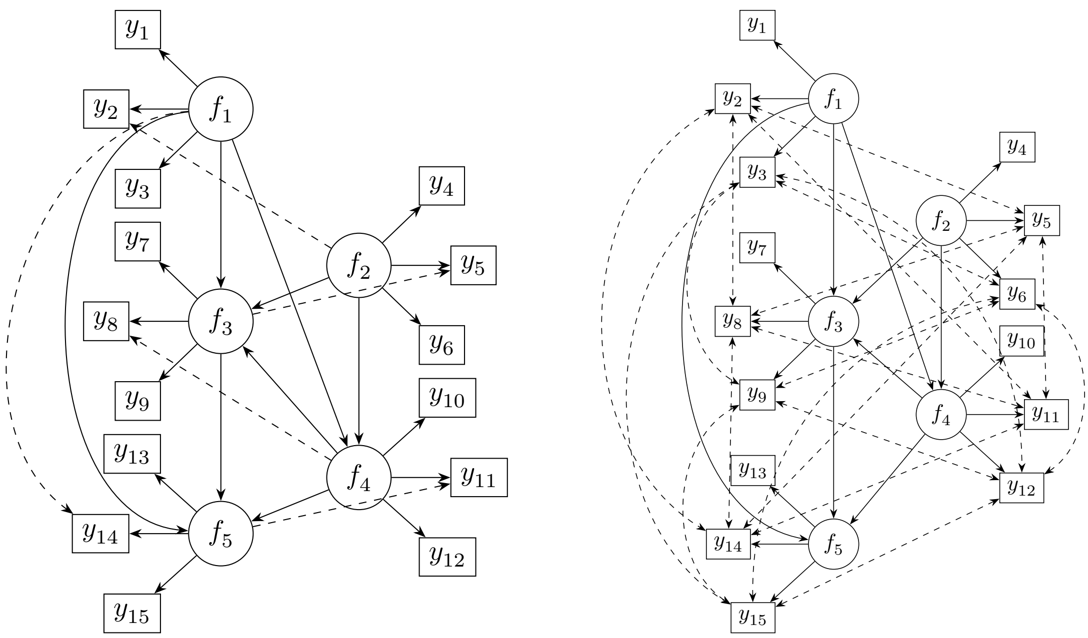
After collaborating based on the individually conducted studies and the respective results, we did not jointly arrive at the conclusion that conducting a collaborative simulation study as planned was warrented.
However I identified several reasons for setting up another simulation. Firstly, to test and evaluate the viability and technical fesability of AC for simulation studies, setting up a study based on the individual studies, their results and with Kosanke can provide valuable…

Aims, objectives and research questions Following our framework for collaboration the research questions for the joint study remains the same as specified prior to the individual studies.

Population Models and Data Generation Mechanisms As in study 1 and 2 data for study 3 was generated based on a 5-factor population structural model with 3 indicators for each factor. Factor loadings and indicator reliability was computed in the same way as in study 1. Two different population models were simulated that resulted in misspecifications of either omitted crossloadings (model 3.1) or omitted correlated residuals (model 3.2). The population-level values of the structural parameters were set to 0.1. Reliability levels were manipulated as in Study 1. The omitted crossloadings (see figure 7) could either be all positive or negative and were set to be 10% lower in absolute values than the factor loadings. Correlated residuals were also either all positive or all negative and were set to not exceed a factor of 0.6 of the residual variances of the indicators.

Figure 4

Population Model Variations for Study 3



Note. Note. Error terms are not explicitly shown in the figure. Dashed lines represent relations omitted in the estimation model present in the population model. Unspecified crossloadings and correlated residuals could be either positive or negative resulting in 2 modulations of model 3.1 and 3.2 in the study.

Experimental Design of simulation procedures** The joint study varied three conditions: (1) sample sizes of very small ($N = 50$), small ($N = 100$) or moderate ($N = 400$). (2) Indicator reliability of low ($= 0.3$), moderate (0.5) or high ($= 0.7$); (3) Model misspecifications with not-specified cross loadings in the population model that were positive or negative (see figure) or not-specified correlated residuals in the population model that were postive or negative (see figure 8).

Method Selection To address the question …

Performance Measures

Software To fully evaluate the effect of bound SEM on convergence convergence rate and rate of proper solutions were tracked condition wise (Kriegmair's individual studies).

Analysis and Interpretation plan The analysis was conducted largely in the same way as in the individual studies

Results

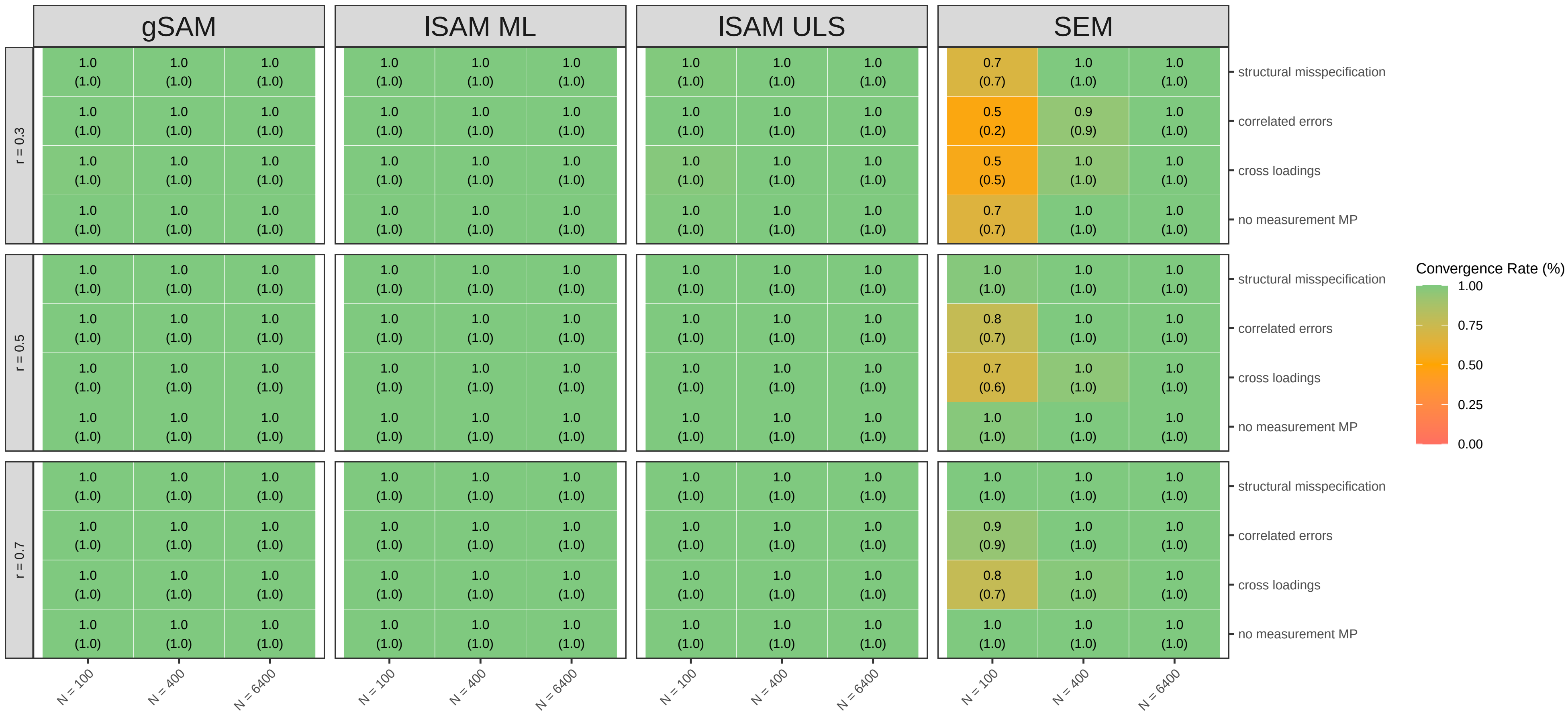
Individual Simulation Studies

Results of Collaborator A (Kriegmair)

As shown in Figure 5 there were no convergence issues for all SAM methods (gSAM, lSAM ML and ULS) with a convergence rate of 100% and no improper solutions across all conditions even in small samples with low reliability. Standard SEM however showed severe convergence issues in small samples with low to moderate reliability with a convergence rate of as low as 50% and 50% improper solutions in the cross loading misspecification condition as the most challenging condition.

Figure 5

Convergence Rate and Rate of Proper Solutions in Study 1



Note. Convergence and proper solutions (in parentheses) rates across sample sizes (N), reliability (r), and model misspecifications for global SAM (gSAM), local SAM with Maximum Likelihood (lSAM-ML), Unweighted Least Squares (lSAM-ULS), and SEM.

Convergence rates in study 2 were consistent with this with 100% convergence rates for all SAM methods and as low as 60% for standard SEM with exogenous measurement misspecifications posing more challenges than endogenous misspecifications (see Figure B1 in Appendix B).
Next the bias of the path coeffecient estimates averaged across each model in absolute values showed that all SAM methods were more accurate than standard SEM especially under omitted cross loadings in the analysis model (See Figure 6).

Figure 6

Mean Average Bias of Regression Parameters in Study 1

		gSAM			lSAM ML			lSAM ULS			SEM		
		100	400	6400	100	400	6400	100	400	6400	100	400	6400
r = 0.3	no MP	0.007 (±0.003)	0.001 (±0.001)	0.000 (±0.000)	0.007 (±0.002)	0.001 (±0.001)	0.000 (±0.000)	0.003 (±0.003)	0.001 (±0.001)	0.000 (±0.000)	0.019 (±0.004)	0.003 (±0.001)	0.000 (±0.000)
r = 0.3	cross loadings	0.068 (±0.004)	0.076 (±0.001)	0.078 (±0.000)	0.069 (±0.003)	0.075 (±0.001)	0.077 (±0.000)	0.080 (±0.004)	0.078 (±0.001)	0.080 (±0.000)	0.182 (±0.010)	0.140 (±0.002)	0.126 (±0.000)
r = 0.3	correlated errors	0.056 (±0.001)	0.054 (±0.001)	0.052 (±0.000)	0.056 (±0.001)	0.054 (±0.001)	0.052 (±0.000)	0.055 (±0.001)	0.053 (±0.001)	0.052 (±0.000)	0.040 (±0.004)	0.051 (±0.001)	0.052 (±0.000)
r = 0.3	structural MP	0.007 (±0.004)	0.007 (±0.001)	0.006 (±0.000)	0.007 (±0.002)	0.007 (±0.001)	0.006 (±0.000)	0.006 (±0.004)	0.006 (±0.001)	0.006 (±0.000)	0.018 (±0.005)	0.008 (±0.001)	0.006 (±0.000)
r = 0.5	no MP	0.002 (±0.001)	0.001 (±0.001)	0.000 (±0.000)	0.002 (±0.001)	0.001 (±0.001)	0.000 (±0.000)	0.001 (±0.002)	0.001 (±0.001)	0.000 (±0.000)	0.002 (±0.002)	0.001 (±0.001)	0.000 (±0.000)
r = 0.5	cross loadings	0.064 (±0.002)	0.067 (±0.001)	0.067 (±0.000)	0.063 (±0.002)	0.067 (±0.001)	0.067 (±0.000)	0.067 (±0.002)	0.069 (±0.001)	0.069 (±0.000)	0.123 (±0.003)	0.114 (±0.001)	0.097 (±0.000)
r = 0.5	correlated errors	0.033 (±0.001)	0.031 (±0.001)	0.031 (±0.000)	0.033 (±0.001)	0.031 (±0.001)	0.031 (±0.000)	0.030 (±0.003)	0.031 (±0.001)	0.031 (±0.000)	0.028 (±0.001)	0.030 (±0.001)	0.031 (±0.000)
r = 0.5	structural MP	0.007 (±0.001)	0.007 (±0.001)	0.006 (±0.000)	0.007 (±0.001)	0.007 (±0.001)	0.006 (±0.000)	0.007 (±0.002)	0.007 (±0.001)	0.006 (±0.000)	0.008 (±0.002)	0.007 (±0.001)	0.006 (±0.000)
r = 0.7	no MP	0.001 (±0.001)	0.001 (±0.001)	0.000 (±0.000)	0.001 (±0.001)	0.001 (±0.001)	0.000 (±0.000)	0.001 (±0.001)	0.001 (±0.001)	0.000 (±0.000)	0.001 (±0.001)	0.001 (±0.001)	0.000 (±0.000)
r = 0.7	cross loadings	0.049 (±0.001)	0.051 (±0.001)	0.051 (±0.000)	0.049 (±0.001)	0.051 (±0.001)	0.051 (±0.000)	0.051 (±0.001)	0.052 (±0.001)	0.052 (±0.000)	0.064 (±0.002)	0.064 (±0.001)	0.062 (±0.000)
r = 0.7	correlated errors	0.017 (±0.001)	0.016 (±0.001)	0.016 (±0.000)	0.017 (±0.001)	0.016 (±0.001)	0.016 (±0.000)	0.016 (±0.001)	0.016 (±0.001)	0.016 (±0.000)	0.015 (±0.001)	0.016 (±0.001)	0.016 (±0.000)
r = 0.7	structural MP	0.006 (±0.001)	0.007 (±0.001)	0.006 (±0.000)	0.006 (±0.001)	0.007 (±0.001)	0.006 (±0.000)	0.006 (±0.001)	0.007 (±0.001)	0.006 (±0.000)	0.006 (±0.001)	0.007 (±0.001)	0.006 (±0.000)

Note. Mean absolute bias averaged (in absolute values) over all parameters with true value of 0.1 in one model for sample sizes (N), reliability (r), and misspecifications for global SAM (gSAM), local SAM with Maximum Likelihood (lSAM-ML), Unweighted Least Squares (lSAM-ULS) and SEM. Monte Carlos Standard Errors (MCSE) are shown in parentheses for each value.

Results of Collaborator B (Kosanke)

Results of the "Joint" Simulation Study

Results of the Adversarial Collaboration

Discussion

Discussing the substantial results

Disucssing the Adversarial Collaboration

Idea: living simulations

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Appendix

Appendix A: Simulation Protocol

Here the full simulation protocol of my simulation studies conducted individually prior to collaboration as well as the follow up study I conducted in light of the collaboration with Kosanke after the first round of conducting and evaluating our individual studies is presented. It is based on the preregistration of my individual studies (Kriegmair (2024)) and outlines all deviations from it.

Preregistration template designed by: Björn S. Siepe, František Bartoš, Tim P. Morris, Anne-Laure Boulesteix, Daniel W. Heck, and Samuel Pawel

1. General Information

1.1 What is the title of the project?

Comparing a Structural After Measurement (SAM) Approach to Standard Structural Equation Model (SEM) Estimation

1.2 Who are the current and future project contributors?

Valentin Kriegmair

1.3 Provide a description of the project.

The studies registered were part of an adversarial collaboration project. The aim was to conceptually (only in part) replicate the results obtained by Dhaene & Rosseel (2023) and Rosseel & Loh (2022). I set out to evaluate the performance of a Structural After Measurement (SAM) approach for estimating structural equation models (SEM) in comparison to standard SEM estimation methods. This served as the basis for the adversarial collaboration with another researcher who evaluated the same research question from the perspective of a conceptual replication of the (in part contradicting) results obtained by Robitzsch (2022). However, the following only describes the first (conceptual) replication.

1.4 Did any of the contributors already conduct related simulation studies on this specific question?

No prior related simulation studies have been conducted by the contributors.

2. Aims

Structural After Measurement (SAM) is an estimation method for structural equation models that consists of a stepwise estimation of the measurement and structural parts of a model. The research questions of the current simulation were:

1. How do SAM and traditional SEM methods (including ML and ULS) compare in terms of bias, Mean Squared Error (MSE), and convergence rates in small to moderate samples?
2. What is the impact of model misspecifications, such as residual correlations and cross-loadings, on the performance of SAM compared to traditional SEM methods?

3. Data-Generating Mechanism

3.1 Study 1

In study 1 (conceptually replicating Rosseel & Loh (2022)) data was generated parametrically. Four different population structural equation models (SEM) with five latent variables and three continuous indicators per facotr based on the following matrices were simulated:

- B as $M \times M$ matrix representing latent regression coefficients with all $b = 0.1$.
  - Model 1.1 and 1.2:

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.1 & 0.1 & 0 & 0.1 & 0 \\ 0.1 & 0.1 & 0 & 0 & 0 \\ 0.1 & 0 & 0.1 & 0.1 & 0 \end{bmatrix}$$

  - Model 1.3 in deviation from the preregistration with a reversed effect between latent factors f3 and f4 to introduce another realistic and more severe misspecification to show the potential of SAM in most challenging conditions:

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.1 & 0.1 & 0 & 0 & 0 \\ 0.1 & 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0.1 & 0.1 & 0 \end{bmatrix}$$

  - Model 1.4 in deviation from the preregistration with a bidirectional structural relation between f3 and f4 specified as only one directional instead of just reversing the effect to investigate a different type of misspecification:

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.1 & 0.1 & 0 & 0.1 & 0 \\ 0.1 & 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0.1 & 0.1 & 0 \end{bmatrix}$$

- Ψ as $M \times M$ as diagonal matrix representing the residual variances in deviation from the preregistration not adjusted for the varying structural relations. This was only updated in the joint study (study 3) to adjust residual variances of all endogenous factors to accurately reflect the number of regressors

- Model 1.1, 1.2, 1.3, and 1.4:

$$\Psi = \begin{bmatrix} 1.0 & 0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 0 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \\ 0 & 0 & 0 & 0 & 1.0 \end{bmatrix}$$

- Λ as $P \times M$ matrix representing factor loadings.
  - Model 1.1, 1.3 and 1.4:

$$\Lambda = \begin{bmatrix} 1.0 & 0 & 0 & 0 & 0 \\ 0.7 & 0 & 0 & 0 & 0 \\ 0.7 & 0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 0.7 & 0 & 0 & 0 \\ 0 & 0.7 & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 0 & 0 \\ 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \\ 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0 & 0 & 1.0 \\ 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0.7 \end{bmatrix}$$

  - Model 1.2: cross loadings will be set to be 10% lower than the factor loadings: $\Lambda_{ik,jk} = 0.63 = 0.9 \times 0.7$. They will be generated by the following elements in Λ: (2, 2), (5, 3), (8, 4), (11, 5), (14, 1).

- Θ as a $P \times P$ matrix representing the residual variances and covariances of the indicators.
  - Model 1.1, 1.2 and 1.4: The diagonal generated as:

$$\Theta^* = \ \mathrm{Var}(\eta)\Lambda^T \times \frac{1}{r-1}$$

    (where r is the reliability of the indicators) and 0 on all off-diagonal elements
  - Model 1.3:

* Θ^* on the diagonal.
* Correlated residuals generated between specific indicator pairs: for $i = (2, 5, 8, 11, 14)$ and $i' = (3, 6, 9, 12, 15)$, and for each $k = 1, \ldots, 4$ and $l = k + 1, \ldots, 5$, the entries (i_k, i'_l) and (i'_l, i_k) in Θ are set to $0.6 \times \min \Theta^*$, ensuring correlated errors among selected indicator pairs without exceeding a 0.6 correlation coefficient.

3.1.2 Study 2

For study 2, again, different five-factor population models with three continious indicators per facotr were generated parametrically . Further, the different models of study 2 were used for different simulation settings resulting in two sub-studies 2.1 and 2.2 (see simulation settings).

* B as $M \times M$ matrix representing latent regression coefficients with varying parameter size defined by two conditions of endogenous factor variance explained by the exogenous factors (low: $R^2 = 0.1$ or medium: $R^2 = 0.4$ see below under factor):
  - Model 2.1 and 2.2:

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ \beta_{\eta_4,\eta_1} & \beta_{\eta_4,\eta_2} & 0 & 0 & 0 \\ 0 & \beta_{\eta_5,\eta_2} & \beta_{\eta_5,\eta_3} & \beta_{\eta_5,\eta_4} & 0 \end{bmatrix}$$

* Λ as $P \times M$ matrix representing factor loadings of indicators on the latent factors.

– Model 2.1:

$$\Lambda = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.9 & 0 & 0 & 0 & 0 \\ 0.8 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0.9 & 0 & 0 & 0 \\ 0 & 0.8 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0.9 & 0 & 0 \\ 0 & 0 & 0.8 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.8 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0.9 \\ 0 & 0 & 0 & 0 & 0.8 \end{bmatrix}$$

– Model 2.2 with cross-loadings either in the exogenous ($\lambda_{6,3}$), endogenous ($\lambda_{12,5}$) or both parts of the model. Which cross loading was present depended on the misspecification simulation factor. The specific magnitude of the endogenous ($\lambda_{12,5}$) loading depended on R^2 (see under 3.2.2):

$$\Lambda = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.9 & 0 & 0 & 0 & 0 \\ 0.8 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0.9 & 0 & 0 & 0 \\ 0 & 0.8 & \lambda_{6,3} & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0.9 & 0 & 0 \\ 0 & 0 & 0.8 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.8 & \lambda_{12,5} \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0.9 \\ 0 & 0 & 0 & 0 & 0.8 \end{bmatrix}$$

- Θ as a $P \times P$ matrix representing the residual variances and covariances of the indicators. This was computed as the portion of the indicator's total variance that is not explained by the latent factors, after accounting for the strength and reliability of its relationship to these factors (factor loadings), as well as the effects of regressions between the latent factors themselves.
  - Model 2.1: The diagonal of Θ generated as:

$$\Theta^* = \ \mathrm{Var}(\eta)\Lambda^T \times \frac{1}{r-1}$$

    (where r is the reliability of the indicators) and 0 on all off-diagonal elements
  - Model 2.2:
    * Θ^* on the diagonal.
    * Correlated residuals generated between specific indicator pairs in either the endogenous, exogenous or both parts of the model.

    Thus depending on the simulation setting either:
    * $\Theta_{8,9}$, $\Theta_{9,8}$ (exogenous part)
    * $\Theta_{14,15}$ and $\Theta_{15,14}$ (endogenous part)
    * $\Theta_{8,9}$, $\Theta_{9,8}$, $\Theta_{14,15}$ and $\Theta_{15,14}$ (both parts)

    were set $0.6 \times \min \Theta^*$, ensuring correlated errors among selected indicator pairs without exceeding a 0.6 correlation coefficient:

3.1.3 Study 3

For study 3, again, four different five-factor population models with three indicators per factor were generated parametrically with B as $M \times M$ matrix representing latent regression coefficients with all $b = 0.1$ for all models in study 3:

$$\Psi = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.1 & 0.1 & 0 & 0.1 & 0 \\ 0.1 & 0.1 & 0 & 0 & 0 \\ 0.1 & 0 & 0.1 & 0.1 & 0 \end{bmatrix}$$

and Ψ as $M \times M$ as diagonal matrix (0 on the off diagonal) representing variances of the factors with $1 - kb^2$ on the diagonal where k is the number of latent regressor per factor and b the regression coefficients (0.1) for all models in study 3. Each model in study 3 included either cross loadings or correlated residual errors in the measurement model based on Λ and Θ (constructed as in study 1) but these modifications in the measurement models could be either positive or negative.

3.2 Factors of the Data-Generating Mechanism

3.2.1 Study 1 The first study modulated the following factors:

- Different misspecifications of the population model where the population model varies between the different models (1.1, 1.2, 1.3, 1.4) as described above, while the analysis model remains specified as model 1.1.
- Sample sizes of small (N = 100), medium (N = 400), or large (N = 6400)
- Indicator reliability of low (.3), moderate (.5), or high (.7)

3.2.2 Study 2 The second study modulated the following factors of the data generating process across both studies:

- Sample sizes of small (N = 100), medium (N = 400), or large (N = 6400)
- Variance explained (R^2) of the endogenous factor variance explained by the exogenous factors: low ($R^2 = 0.1$) or medium ($R^2 = 0.4$)
- Indicator reliability of three indicators per factor: *all high* (.8), *all low* (.5), *average low* (.5) varying between .7 to .3 with the highest reliability for the scaling indicator.
- Sample sizes of small (N = 100), medium (N = 400), or large (N = 6400)
- Deviating from the preregistration distribution (normal vs. non-normal) was not considered in the simulation settings to limit the scope of the study.
- Measurement misspecifications of a residual covariance and a factor loading either in the exogenous, endogoneous or both parts of the model (in deviation from the preregistration without additional structural misspecifications and only three modulations to limit the scope of the study):
- Number of measurement blocks (how many separate measurement models are fitted in the first step of SAM) of either a separate measurement model per latent variable (b = k = 5) or one joint measurement model for all exogenous variables (b = 3)

In deviation from the preregistration, additionally all models in study 2 were estimated including stuructral specifications that were not present in the population model to investigate the performance of the methods on recovering falsely specified absent structural relations.

3.2.3 Study 3 The third study modulated the following factors of the data generating process:

- Sample sizes of N = 50, N = 100, N = 250 and N = 400.
- Indicator reliability of low (.3), moderate (.5), or high (.7)

3.3 Simulation Conditions

- Study 1: in deviation from the preregistration only one estimattion model was considered to limit the scope of the study resulting in 36 conditions (4 population models x 3 sample sizes x 3 reliabilities)
- Study 2.1 (4 population models x 3 sample sizes x 2 R^2 x 3 reliabilities x 2 measurement blocks = 144 conditions) (in dviation from the preregistration the misspecifications were reduced and counted here as differnet population odels as well)

4. Estimands and Targets

Estimated structural model parameters (path coefficients) represented the estimands of interest.

5. Methods

Both studies will compare four different estimation methods for SEMs:

- Traditional SEM: (structural and measurement model estimated simultaneously) (rationale: the current standard approach in SEM estimation serving as a baseline with maximum likelihood (ML)):
- SAM: (separating the estimation of the measurement and structural model to alleviate the potential for propagation of bias from (e.g. misspecified) measurement part to the structural part of the model)
  - Local SAM (Uses summary statistics from the measurement model to derive the model-implied mean vector and variance-covariance matrix of latent variables. These statistics are then utilized to estimate the structural parameters. A mapping matrix (M) is used to transform the observed data into the latent variable space. It can be estimated using different methods.)
    - With ML mapping matrix (Akin to a factor score approach (Bartlett (1937), Bartlett (1938)))
    - With ULS mapping matrix (Uses the Moore-Penrose pseudoinverse, suitable for scenarios with complex or underdetermined systems, where the K matrix is rank-deficient but requires adjustments for structural constraints.)

- Global SAM (rationale: Fixing the parameters obtained from the measurement model in the first step, and then using them as constants in the full SEM during the second step. Suitable for models where local SAM is impractical due to higher-order latent variables or rank deficiencies in λ.)

Traditional SEM as well as both steps in the SAM approach will be estimated using Maximum Likelihood (ML) using the `lavaan` (Rosseel (2012)) package in R (R Core Team (2023)).

6. Performance Measures

Across both studies the following performance measures were captured:

- Convergence rates: Proportions of observed data sets that successfully converged for each estimation method detected using `lavaan`.
- In deviation from the preregistration also impropper solutions of converged models showing negative variances as the only type of improper solution present were computed.
- Rrelative biases: Average difference between an estimate and its true value, normalized by the true value, assessed across all path coefficients: $\frac{\bar{T}-\theta}{\theta}$
- Absolute biases: (in deviation from the preregistration this measure as it might be more intuitive and applicable for study 1 and 3 with invariant regression weights): $(\bar{T}-\theta)$
- Root Mean Squared Errors (RMSE): Calculated as the square root of the average squared difference between an estimate and its true value, evaluated under conditions of model misspecification: $(\sqrt{\frac{1}{K}\sum_{k=1}^{K}(T_k-\theta)^2})$ where T_k is the estimated parameter, $\bar{T}$ the mean of the estimated parameters and θ the true parameter value, and K is the number of replications computed.
- Relative Root Mean Squared Errors (RRMSE) in deviation from preregistration for better comparability in study 2 under varying regression weights: $\sqrt{\frac{(\bar{T}-\theta)^2+S_T^2}{\theta^2}}$
- Empirical coverage levels of 95% confidence intervals (CIs): Proportion of observed data sets where the constructed CIs included the true value. (Not reported to limit the scope)

7. Monte Carlo Uncertainty of the Estimated Performance Measures

Monte Carlo uncertainty was calculated (manually in deviation from the preregistration) for the absolute and relative metrics: $\sqrt{\frac{S_T^2}{K}}$ and $\sqrt{\frac{S_T^2}{K\theta^2}}$ for bias and relative bias, and $\sqrt{\frac{K-1}{K}\sum_{j=1}^{K}\left(\text{RMSE}_{(j)}-\text{RMSE}\right)^2}$ and $\sqrt{\frac{K-1}{K}\sum_{j=1}^{K}\left(rRMSE_{(j)}-rRMSE\right)^2}$ for RMSE and relative RMSE.

8. Simulation Repetitions

- Replicating Rosseel & Loh (2022) study 1 consisted of 5000 repetitions per condition.
- Replicating Dhaene & Rosseel (2023) study 2 will consisted of 10000 repetitions per condition.
- Study 3 entailed 5000 repitiions as this resulted in sufficiently small Monte Carlo standard errors for the performance measures.

9. Missing Values due to non-convergence or other reasons

As mentioned above convergence rates were captured and only converged propper solutions were used for performance measure computation.

10. Software and Libraries

The simulation was set up and conducted in R Core Team (2023) using the `lavaan` package for generating data based on the population models as well as for applying SEM estimation methods (Rosseel (2012)) as well as the `furrr` ((**davis_furrr_2022?**)) package for parallel simulation execution. A full list of libraries and dependencies can be found on GitHub

11. Computational Environment

The simulations were conducted using the TARDIS high-performance computing cluster at the Max Planck Institute for Human Development. The computational environment was set up in R, utilizing a suite of packages for analysis and parallel computing. Key libraries included:

- Analysis and Data Manipulation Packages: `MASS`, `dplyr`, `tidyr`, `lavaan`, `purrr`, and `Matrix`.
- Parallel Computing Packages: `future`, `furrr`, `parallel`, `future` and `batchtools`.

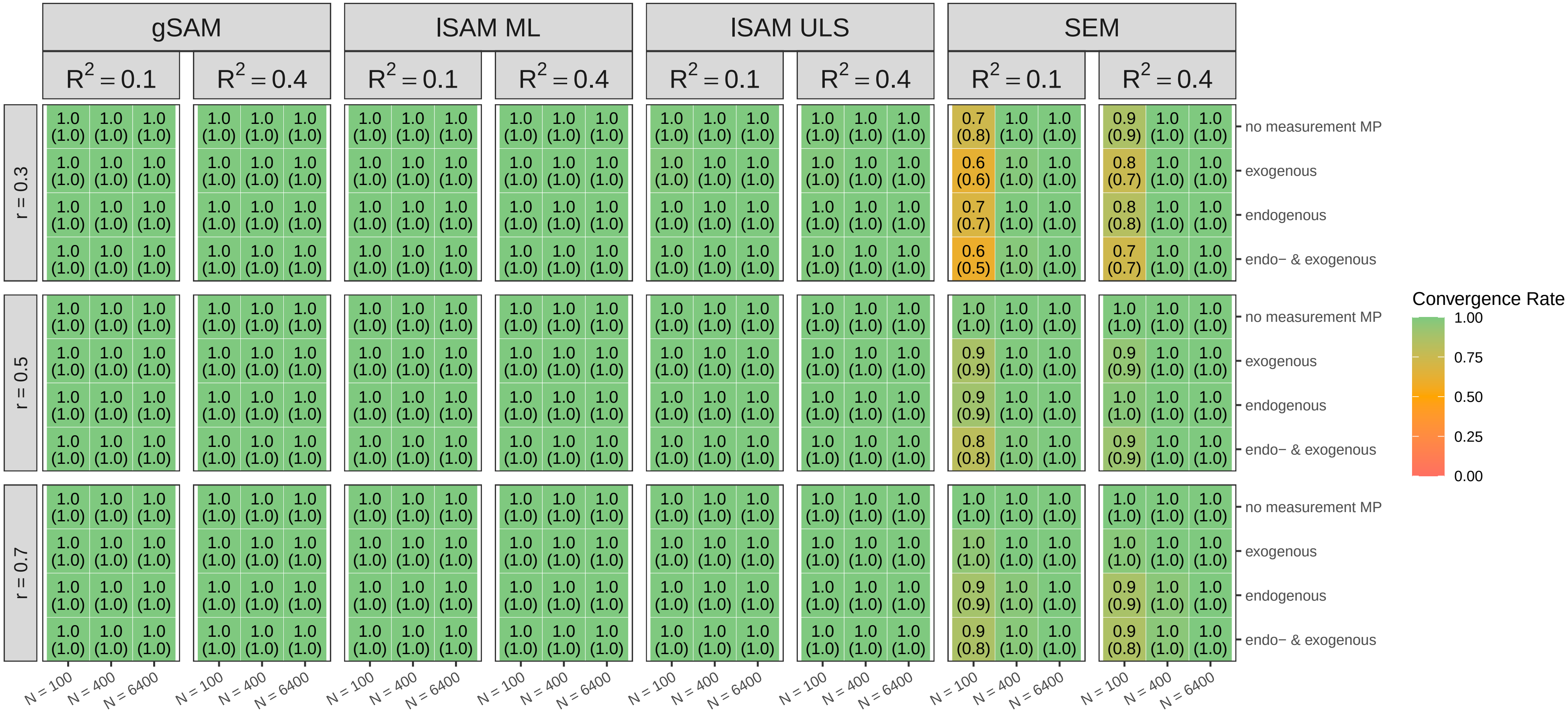
12. Reproducibility

The code of the simulation was made available on [GitHub] (https://github.com/valentinkm/AdversarialSimulation). A pre-generated list of seeds was used for all replications to ensure reproducibility and avoid synchronization in parallelized computations. As a examplary replication the simulation can be reproduced in this GitHub action here.

Appendix B: Supplementary Figures

Figure B1

Convergence Rate and Rate of Proper Solutions in Study 2



Note. Convergence and proper solutions (in parentheses) rates across sample sizes (N), reliability (r), and model misspecification location for global SAM (gSAM), local SAM with Maximum Likelihood (lSAM-ML), Unweighted Least Squares (lSAM-ULS), and SEM.

Appendix C: Detailed Error and Warning Messages

In the following, all different warning and error messages raised during the studies are listed (see Table C1) and shown how often they occurred under various fitting conditions (see Table C2). sdlkfjs

Table C1

List of Unique Warnings and Errors

ID	Message
1	lavaan WARNING: some estimated ov variances are negative
2	lavaan WARNING: the optimizer warns that a solution has NOT been found!
3	lavaan WARNING: the optimizer (NLMINB) claimed the model converged, but not all elements of the gradient are (near) zero; the optimizer may not have found a local solution use check.gradient = FALSE to skip this check.
4	lavaan WARNING: some estimated lv variances are negative
5	lavaan WARNING: some estimated ov variances are negative, lavaan WARNING: some estimated lv variances are negative
6	number of items to replace is not a multiple of replacement length
7	lavaan WARNING: Could not compute standard errors! The information matrix could not be inverted. This may be a symptom that the model is not identified., lavaan WARNING: some estimated ov variances are negative
8	lavaan WARNING: covariance matrix of latent variables is not positive definite; use lavInspect(fit, "cov.lv") to investigate.
9	lavaan WARNING: The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue is smaller than or close to zero. This may be a symptom that the model is not identified., lavaan WARNING: some estimated ov variances are negative
10	lavaan WARNING: Could not compute standard errors! The information matrix could not be inverted. This may be a symptom that the model is not identified., lavaan WARNING: some estimated lv variances are negative
11	lavaan WARNING: Could not compute standard errors! The information matrix could not be inverted. This may be a symptom that the model is not identified., lavaan WARNING: some estimated ov variances are negative, lavaan WARNING: some estimated lv variances are negative

Table C1

List of Unique Warnings and Errors (continued)

ID	Message
12	lavaan WARNING: some estimated ov variances are negative, lavaan WARNING: covariance matrix of latent variables is not positive definite; use lavInspect(fit, ”cov.lv”) to investigate.
13	lavaan WARNING: Could not compute standard errors! The information matrix could not be inverted. This may be a symptom that the model is not identified.
14	lavaan WARNING: The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue is smaller than or close to zero. This may be a symptom that the model is not identified., lavaan WARNING: covariance matrix of latent variables is not positive definite; use lavInspect(fit, ”cov.lv”) to investigate.
15	lavaan WARNING: Could not compute standard errors! The information matrix could not be inverted. This may be a symptom that the model is not identified., lavaan WARNING: covariance matrix of latent variables is not positive definite; use lavInspect(fit, ”cov.lv”) to investigate.
16	lavaan WARNING: the covariance matrix of the residuals of the observed variables (theta) is not positive definite; use lavInspect(fit, ”theta”) to investigate.
17	lavaan WARNING: The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue is smaller than or close to zero. This may be a symptom that the model is not identified.

Note. This table lists all unique warnings and errors encountered during the simulation studies.

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 1	1.3	100	0.3	SEM	Warning	6860	1
Study 1	1.2	100	0.5	SEM	Warning	3575	1
Study 1	1.3	100	0.5	SEM	Warning	2923	1
Study 1	1.2	100	0.7	SEM	Warning	2903	1
Study 1	1.2	100	0.3	SEM	Warning	2769	1
Study 1	1.1	100	0.3	SEM	Warning	2700	1
Study 1	1.4	100	0.3	SEM	Warning	2577	1
Study 1	1.2	100	0.3	SEM	Warning	2037	2
Study 1	1.1	100	0.3	SEM	Warning	1258	2

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 1	1.4	100	0.3	SEM	Warning	1133	2
Study 1	1.2	100	0.3	SEM	Warning	729	3
Study 1	1.3	100	0.3	SEM	Warning	692	3
Study 1	1.3	100	0.7	SEM	Warning	688	1
Study 1	1.3	400	0.3	SEM	Warning	606	1
Study 1	1.3	100	0.3	SEM	Warning	507	2
Study 1	1.2	400	0.3	SEM	Warning	450	1
Study 1	1.2	400	0.5	SEM	Warning	429	1
Study 1	1.2	100	0.3	SEM	Warning	417	4
Study 1	1.2	400	0.7	SEM	Warning	248	1
Study 1	1.1	100	0.3	SEM	Warning	242	3
Study 1	1.4	100	0.3	SEM	Warning	223	3
Study 1	1.2	100	0.5	SEM	Warning	203	2
Study 1	1.1	100	0.5	SEM	Warning	197	1
Study 1	1.4	100	0.5	SEM	Warning	183	1
Study 1	1.2	100	0.3	lSAM-ULS	Warning	150	1
Study 1	1.2	100	0.3	SEM	Warning	146	5
Study 1	1.4	100	0.3	lSAM-ULS	Warning	62	1
Study 1	1.1	100	0.3	lSAM-ULS	Warning	52	1
Study 1	1.2	100	0.3	gSAM	Warning	50	4
Study 1	1.4	100	0.3	SEM	Warning	50	4
Study 1	1.2	100	0.5	SEM	Warning	42	3
Study 1	1.2	100	0.3	lSAM-ULS	Error	38	6
Study 1	1.1	100	0.3	SEM	Warning	29	4
Study 1	1.1	100	0.3	lSAM-ULS	Error	25	6
Study 1	1.4	100	0.3	lSAM-ULS	Error	24	6
Study 1	1.2	100	0.3	SEM	Warning	23	7
Study 1	1.2	400	0.3	SEM	Warning	15	2

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 1	1.1	100	0.3	SEM	Warning	14	7
Study 1	1.2	100	0.3	gSAM	Error	14	6
Study 1	1.1	100	0.3	SEM	Warning	12	5
Study 1	1.4	100	0.3	SEM	Warning	11	5
Study 1	1.4	100	0.3	SEM	Warning	9	7
Study 1	1.2	100	0.7	SEM	Warning	7	2
Study 1	1.4	100	0.7	SEM	Warning	7	1
Study 1	1.2	100	0.3	SEM	Warning	5	8
Study 1	1.1	100	0.5	SEM	Warning	4	2
Study 1	1.3	100	0.5	SEM	Warning	4	3
Study 1	1.1	100	0.3	SEM	Warning	3	9
Study 1	1.1	100	0.7	SEM	Warning	3	1
Study 1	1.2	100	0.3	SEM	Warning	3	10
Study 1	1.2	100	0.3	SEM	Warning	3	11
Study 1	1.1	100	0.3	gSAM	Error	2	6
Study 1	1.1	100	0.3	gSAM	Warning	2	4
Study 1	1.1	400	0.3	SEM	Warning	2	1
Study 1	1.2	100	0.3	SEM	Warning	2	12
Study 1	1.2	100	0.3	lSAM-ULS	Warning	2	3
Study 1	1.2	100	0.5	SEM	Warning	2	4
Study 1	1.2	400	0.3	SEM	Warning	2	3
Study 1	1.3	100	0.5	lSAM-ULS	Error	2	6
Study 1	1.3	100	0.5	lSAM-ULS	Warning	2	1
Study 1	1.4	100	0.3	SEM	Warning	2	9
Study 1	1.4	100	0.3	gSAM	Error	2	6
Study 1	1.4	100	0.3	gSAM	Warning	2	4
Study 1	1.4	100	0.5	lSAM-ULS	Error	2	6
Study 1	1.1	100	0.3	SEM	Warning	1	11
Study 1	1.1	100	0.3	lSAM-ULS	Warning	1	3

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 1	1.1	100	0.5	lSAM-ULS	Warning	1	1
Study 1	1.2	100	0.3	SEM	Warning	1	9
Study 1	1.2	100	0.3	gSAM	Warning	1	8
Study 1	1.2	100	0.5	lSAM-ULS	Error	1	6
Study 1	1.2	100	0.5	lSAM-ULS	Warning	1	1
Study 1	1.3	100	0.3	SEM	Warning	1	7
Study 1	1.3	100	0.3	lSAM-ULS	Warning	1	1
Study 1	1.3	100	0.5	SEM	Warning	1	2
Study 1	1.3	400	0.5	SEM	Warning	1	1
Study 1	1.4	100	0.3	SEM	Warning	1	10
Study 1	1.4	100	0.3	lSAM-ULS	Warning	1	3
Study 1	1.4	100	0.3	lSAM-ULS	Warning	1	2
Study 1	1.4	100	0.5	lSAM-ULS	Warning	1	1
Study 2	2.2_both	100	0.3	SEM	Warning	5265	1
Study 2	2.2_exo	100	0.3	SEM	Warning	4622	1
Study 2	2.2_endo	100	0.3	SEM	Warning	3615	1
Study 2	2.2_both	100	0.7	SEM	Warning	2904	1
Study 2	2.2_both	100	0.5	SEM	Warning	2743	1
Study 2	2.1	100	0.3	SEM	Warning	2701	1
Study 2	2.2_endo	100	0.7	SEM	Warning	2336	1
Study 2	2.2_exo	100	0.5	SEM	Warning	1814	1
Study 2	2.2_both	100	0.3	SEM	Warning	1625	2
Study 2	2.2_exo	100	0.3	SEM	Warning	1624	2
Study 2	2.2_endo	100	0.5	SEM	Warning	1252	1
Study 2	2.2_endo	100	0.3	SEM	Warning	1211	2
Study 2	2.1	100	0.3	SEM	Warning	1121	2
Study 2	2.2_exo	100	0.7	SEM	Warning	702	1
Study 2	2.2_both	100	0.3	SEM	Warning	675	3

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 2	2.2_both	400	0.7	SEM	Warning	599	1
Study 2	2.2_endo	400	0.7	SEM	Warning	588	1
Study 2	2.2_exo	100	0.3	SEM	Warning	559	3
Study 2	2.2_endo	100	0.3	SEM	Warning	305	3
Study 2	2.2_exo	100	0.3	lSAM-ULS	Warning	286	1
Study 2	2.2_both	100	0.3	SEM	Warning	242	4
Study 2	2.2_both	400	0.3	SEM	Warning	239	1
Study 2	2.1	100	0.3	SEM	Warning	220	3
Study 2	2.2_exo	400	0.3	SEM	Warning	195	1
Study 2	2.2_exo	100	0.3	SEM	Warning	175	4
Study 2	2.1	100	0.5	SEM	Warning	165	1
Study 2	2.2_endo	100	0.3	SEM	Warning	157	4
Study 2	2.1	100	0.3	lSAM-ULS	Warning	138	1
Study 2	2.1	100	0.3	SEM	Warning	132	4
Study 2	2.2_both	400	0.5	SEM	Warning	130	1
Study 2	2.2_both	100	0.3	lSAM-ULS	Warning	128	1
Study 2	2.2_exo	100	0.3	lSAM-ULS	Error	121	6
Study 2	2.2_both	100	0.5	SEM	Warning	105	2
Study 2	2.2_exo	100	0.5	SEM	Warning	93	2
Study 2	2.2_endo	100	0.3	lSAM-ULS	Warning	78	1
Study 2	2.2_exo	400	0.5	SEM	Warning	77	1
Study 2	2.2_both	100	0.3	SEM	Warning	57	5
Study 2	2.1	100	0.3	lSAM-ULS	Error	44	6
Study 2	2.2_exo	100	0.3	SEM	Warning	43	5
Study 2	2.2_both	100	0.3	lSAM-ULS	Error	41	6
Study 2	2.2_endo	400	0.5	SEM	Warning	40	1
Study 2	2.2_both	100	0.3	gSAM	Warning	31	4

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 2	2.2_endo	400	0.3	SEM	Warning	29	1
Study 2	2.2_endo	100	0.3	SEM	Warning	26	5
Study 2	2.2_endo	100	0.3	gSAM	Warning	26	4
Study 2	2.2_exo	100	0.3	gSAM	Warning	20	4
Study 2	2.1	100	0.3	gSAM	Warning	18	4
Study 2	2.2_both	100	0.5	SEM	Warning	18	3
Study 2	2.2_both	100	0.5	lSAM-ULS	Warning	17	1
Study 2	2.2_exo	100	0.5	lSAM-ULS	Warning	16	1
Study 2	2.1	100	0.3	SEM	Warning	15	5
Study 2	2.1	100	0.3	SEM	Warning	14	7
Study 2	2.2_exo	100	0.5	SEM	Warning	14	3
Study 2	2.2_endo	100	0.3	lSAM-ULS	Error	14	6
Study 2	2.2_endo	100	0.5	SEM	Warning	13	2
Study 2	2.2_exo	100	0.3	SEM	Warning	10	7
Study 2	2.2_exo	400	0.3	SEM	Warning	10	2
Study 2	2.2_both	100	0.3	SEM	Warning	10	7
Study 2	2.2_both	400	0.3	SEM	Warning	8	2
Study 2	2.2_exo	100	0.3	lSAM-ULS	Warning	7	3
Study 2	2.2_both	100	0.3	gSAM	Error	7	6
Study 2	2.2_exo	100	0.3	SEM	Warning	6	10
Study 2	2.2_exo	100	0.5	lSAM-ULS	Error	5	6
Study 2	2.2_both	100	0.5	lSAM-ULS	Error	5	6
Study 2	2.2_exo	400	0.7	SEM	Warning	4	1
Study 2	2.2_endo	100	0.3	SEM	Warning	4	7
Study 2	2.1	100	0.3	SEM	Warning	3	10
Study 2	2.1	100	0.5	lSAM-ULS	Warning	3	1
Study 2	2.2_exo	100	0.3	SEM	Warning	3	11
Study 2	2.2_both	100	0.3	SEM	Warning	3	10

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 2	2.2_both	100	0.3	SEM	Warning	3	11
Study 2	2.2_both	100	0.7	SEM	Warning	3	2
Study 2	2.1	100	0.7	SEM	Warning	2	1
Study 2	2.2_exo	100	0.3	gSAM	Error	2	6
Study 2	2.2_exo	100	0.3	lSAM-ULS	Warning	2	2
Study 2	2.2_exo	100	0.7	SEM	Warning	2	2
Study 2	2.2_exo	400	0.3	SEM	Warning	2	3
Study 2	2.2_endo	100	0.5	SEM	Warning	2	3
Study 2	2.2_both	100	0.3	gSAM	Warning	2	3
Study 2	2.2_both	100	0.5	SEM	Warning	2	4
Study 2	2.1	100	0.3	gSAM	Error	1	6
Study 2	2.1	400	0.3	SEM	Warning	1	1
Study 2	2.2_exo	100	0.3	SEM	Warning	1	13
Study 2	2.2_exo	100	0.3	SEM	Warning	1	12
Study 2	2.2_exo	100	0.5	lSAM-ULS	Warning	1	3
Study 2	2.2_exo	100	0.7	SEM	Warning	1	3
Study 2	2.2_exo	400	0.3	lSAM-ULS	Error	1	6
Study 2	2.2_endo	100	0.3	SEM	Warning	1	9
Study 2	2.2_endo	100	0.3	lSAM-ULS	Warning	1	3
Study 2	2.2_endo	100	0.5	lSAM-ULS	Error	1	6
Study 2	2.2_endo	100	0.5	lSAM-ULS	Warning	1	1
Study 2	2.2_endo	400	0.3	SEM	Warning	1	2
Study 2	2.2_both	100	0.3	lSAM-ULS	Warning	1	2
Study 2	2.2_both	100	0.3	lSAM_ML	Error	1	6
Study 2	2.2_both	100	0.5	lSAM-ULS	Warning	1	2
Study 2	2.2_both	100	0.7	lSAM-ULS	Warning	1	1

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 2	2.2__both	400	0.3	SEM	Warning	1	3
Study 2	2.2__both	400	0.3	SEM	Warning	1	4
Study 3	3.1	50	0.3	lSAM-ULS	Warning	248	1
Study 3	3.1	50	0.3	gSAM	Warning	209	4
Study 3	3.1__negative	50	0.3	lSAM-ULS	Warning	208	1
Study 3	3.1__negative	50	0.3	gSAM	Warning	164	4
Study 3	3.2	50	0.3	lSAM-ULS	Warning	82	1
Study 3	3.2__negative	50	0.3	lSAM-ULS	Warning	82	1
Study 3	3.1__negative	50	0.3	lSAM-ULS	Error	79	6
Study 3	3.1	50	0.3	lSAM-ULS	Error	72	6
Study 3	3.2	50	0.3	SEM	Warning	71	8
Study 3	3.2__negative	50	0.3	SEM	Warning	71	8
Study 3	3.1	100	0.3	lSAM-ULS	Warning	62	1
Study 3	3.1__negative	50	0.3	SEM	Warning	61	8
Study 3	3.1	50	0.3	SEM	Warning	53	8
Study 3	3.1__negative	100	0.3	lSAM-ULS	Warning	52	1
Study 3	3.1	50	0.5	lSAM-ULS	Warning	51	1
Study 3	3.1__negative	50	0.3	gSAM	Error	47	6
Study 3	3.1__negative	50	0.5	lSAM-ULS	Warning	37	1
Study 3	3.1	50	0.3	gSAM	Error	36	6
Study 3	3.2	50	0.3	SEM	Warning	31	14
Study 3	3.2	100	0.3	lSAM-ULS	Warning	31	1
Study 3	3.2__negative	50	0.3	SEM	Warning	31	14

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 3	3.2_negative	100	0.3	lSAM-ULS	Warning	31	1
Study 3	3.1	100	0.3	lSAM-ULS	Error	28	6
Study 3	3.2	50	0.3	lSAM-ULS	Warning	19	2
Study 3	3.2_negative	50	0.3	lSAM-ULS	Warning	19	2
Study 3	3.1	50	0.5	lSAM-ULS	Error	18	6
Study 3	3.2	50	0.3	lSAM-ULS	Warning	18	3
Study 3	3.1_negative	100	0.3	lSAM-ULS	Error	18	6
Study 3	3.2_negative	50	0.3	lSAM-ULS	Warning	18	3
Study 3	3.1	100	0.3	gSAM	Warning	17	4
Study 3	3.2	50	0.3	lSAM-ULS	Error	17	6
Study 3	3.1_negative	50	0.3	SEM	Warning	17	14
Study 3	3.2_negative	50	0.3	lSAM-ULS	Error	17	6
Study 3	3.1_negative	50	0.5	lSAM-ULS	Error	13	6
Study 3	3.1_negative	100	0.3	gSAM	Warning	12	4
Study 3	3.2	100	0.3	lSAM-ULS	Warning	11	3
Study 3	3.2_negative	100	0.3	lSAM-ULS	Warning	11	3
Study 3	3.1	50	0.3	SEM	Warning	10	15
Study 3	3.1	50	0.3	gSAM	Warning	10	3
Study 3	3.2	50	0.3	gSAM	Warning	10	4
Study 3	3.1_negative	100	0.3	SEM	Warning	10	8
Study 3	3.2_negative	50	0.3	gSAM	Warning	10	4
Study 3	3.1	50	0.3	gSAM	Warning	9	8

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 3	3.2	100	0.3	lSAM-ULS	Error	9	6
Study 3	3.2_negative	100	0.3	lSAM-ULS	Error	9	6
Study 3	3.1	50	0.5	gSAM	Warning	8	4
Study 3	3.1	50	0.7	lSAM-ULS	Warning	7	1
Study 3	3.2	100	0.3	lSAM-ULS	Warning	7	2
Study 3	3.2_negative	100	0.3	lSAM-ULS	Warning	7	2
Study 3	3.1	50	0.3	SEM	Warning	6	14
Study 3	3.1	100	0.3	SEM	Warning	6	8
Study 3	3.2	50	0.3	SEM	Warning	6	15
Study 3	3.1_negative	50	0.3	SEM	Warning	6	15
Study 3	3.1_negative	50	0.3	gSAM	Warning	6	8
Study 3	3.1_negative	50	0.7	lSAM-ULS	Warning	6	1
Study 3	3.2_negative	50	0.3	SEM	Warning	6	15
Study 3	3.1	50	0.7	lSAM-ULS	Error	5	6
Study 3	3.2	50	0.5	lSAM-ULS	Warning	5	1
Study 3	3.1_negative	100	0.3	gSAM	Error	5	6
Study 3	3.2_negative	50	0.5	lSAM-ULS	Warning	5	1
Study 3	3.1	50	0.3	lSAM-ULS	Warning	4	2
Study 3	3.2	50	0.5	lSAM-ULS	Error	4	6
Study 3	3.2	100	0.3	SEM	Warning	4	8
Study 3	3.1_negative	50	0.3	lSAM-ULS	Warning	4	2
Study 3	3.1_negative	50	0.5	SEM	Warning	4	8

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 3	3.2_negative	50	0.5	lSAM-ULS	Error	4	6
Study 3	3.2_negative	100	0.3	SEM	Warning	4	8
Study 3	3.1	50	0.3	lSAM-ULS	Warning	3	16
Study 3	3.1_negative	50	0.3	gSAM	Warning	3	3
Study 3	3.1_negative	100	0.5	lSAM-ULS	Warning	3	1
Study 3	3.1	50	0.3	lSAM-ULS	Warning	2	3
Study 3	3.1	50	0.5	SEM	Warning	2	8
Study 3	3.1	100	0.3	gSAM	Error	2	6
Study 3	3.1	100	0.5	lSAM-ULS	Error	2	6
Study 3	3.1	250	0.3	lSAM-ULS	Warning	2	1
Study 3	3.2	100	0.3	SEM	Warning	2	14
Study 3	3.1_negative	50	0.3	lSAM-ULS	Warning	2	3
Study 3	3.1_negative	50	0.3	lSAM-ULS	Warning	2	16
Study 3	3.1_negative	50	0.5	gSAM	Warning	2	4
Study 3	3.1_negative	100	0.3	SEM	Warning	2	14
Study 3	3.1_negative	100	0.3	lSAM-ULS	Warning	2	3
Study 3	3.2_negative	100	0.3	SEM	Warning	2	14
Study 3	3.1	50	0.5	gSAM	Error	1	6
Study 3	3.1	50	0.5	lSAM-ULS	Warning	1	3
Study 3	3.1	50	0.5	lSAM-ULS	Warning	1	2
Study 3	3.1	100	0.3	SEM	Warning	1	14
Study 3	3.1	100	0.3	gSAM	Warning	1	8
Study 3	3.1	100	0.3	lSAM-ULS	Warning	1	3

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 3	3.1	100	0.5	lSAM-ULS	Warning	1	1
Study 3	3.1	250	0.3	lSAM-ULS	Error	1	6
Study 3	3.2	50	0.3	gSAM	Error	1	6
Study 3	3.2	50	0.3	lSAM-ULS	Warning	1	16
Study 3	3.2	50	0.5	gSAM	Warning	1	4
Study 3	3.2	50	0.5	lSAM-ULS	Warning	1	3
Study 3	3.2	50	0.7	lSAM-ULS	Warning	1	1
Study 3	3.2	250	0.3	lSAM-ULS	Warning	1	3
Study 3	3.2	250	0.3	lSAM-ULS	Warning	1	2
Study 3	3.2	250	0.3	lSAM-ULS	Warning	1	1
Study 3	3.2	400	0.3	lSAM-ULS	Warning	1	1
Study 3	3.1_negative	50	0.5	gSAM	Error	1	6
Study 3	3.1_negative	50	0.5	lSAM-ULS	Warning	1	16
Study 3	3.1_negative	50	0.7	lSAM-ULS	Error	1	6
Study 3	3.1_negative	50	0.7	lSAM-ULS	Warning	1	3
Study 3	3.1_negative	100	0.3	SEM	Warning	1	13
Study 3	3.1_negative	100	0.3	SEM	Warning	1	17
Study 3	3.1_negative	100	0.3	gSAM	Warning	1	8
Study 3	3.1_negative	250	0.3	lSAM-ULS	Error	1	6
Study 3	3.1_negative	250	0.3	lSAM-ULS	Warning	1	1
Study 3	3.2_negative	50	0.3	gSAM	Error	1	6

Table C2

Summary of Warnings and Errors by Condition with ID for All Studies (continued)

Study	Model Type	N	Reliability	Method	MessageType	Count	Message ID
Study 3	3.2_negative	50	0.3	lSAM-ULS	Warning	1	16
Study 3	3.2_negative	50	0.5	gSAM	Warning	1	4
Study 3	3.2_negative	50	0.5	lSAM-ULS	Warning	1	3
Study 3	3.2_negative	50	0.7	lSAM-ULS	Warning	1	1
Study 3	3.2_negative	250	0.3	lSAM-ULS	Warning	1	3
Study 3	3.2_negative	250	0.3	lSAM-ULS	Warning	1	2
Study 3	3.2_negative	250	0.3	lSAM-ULS	Warning	1	1
Study 3	3.2_negative	400	0.3	lSAM-ULS	Warning	1	1

Note. This table summarizes the count of warnings and errors for each condition in all three simulation studies with the respective ID number corresponding to Table 1.