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The Influence of Informative Priors in the Estimation of MIMIC Model Parameters with Small Sample Sizes and Outliers

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Abstract

This study examined the performance of Bayesian and maximum likelihood estimation in MIMIC models when the latent factor contained outliers but the fitted model assumed latent normality. Using a simulation study with varying sample sizes and contamination proportions, we evaluated absolute relative bias, coverage probability, interval width, and power for the direct effect parameter. The results showed that the correctly centered informative Bayes approach consistently performed best, yielding the smallest bias, nominal or perfect coverage, and the highest power across conditions. A correctly centered informative coefficient prior with a naïve loading prior also performed well, although slightly worse than the fully correctly specified Bayesian model. In contrast, misspecified priors, especially misspecified loading priors and severely misspecified coefficient priors, led to poorer performance, and maximum likelihood estimation showed the weakest robustness overall. These findings suggest that informative priors can substantially improve estimation and inference in MIMIC models with outliers, but their benefits depend on accurate prior specification.

Keywords: Bayesian estimation, informative priors, small sample size, outliers, MIMIC model

1. Introduction

Maximum likelihood (ML) estimation is the most widely used method in structural equation modeling (SEM) and possesses desirable asymptotic properties under correct model specification. However, its performance depends on sufficiently large sample sizes, which are often unavailable in applied research contexts (Kline, 2023; MacCallum et al., 1996). Empirical reviews indicate that small samples are common in SEM applications, raising concerns about parameter stability, standard error accuracy, and inferential validity under ML estimation (MacCallum & Austin, 2000). Bayesian SEM offers an alternative framework by combining likelihood-based information with prior distributions, producing posterior inference that does not rely on large-sample approximations. Estimation is typically carried out using Markov chain Monte Carlo (MCMC) algorithms, which can yield improved estimation stability in small samples (Muthén & Asparouhov, 2012).

However, in small-sample settings, posterior inference becomes increasingly sensitive to prior specification. Prior informativeness in Bayesian SEM is governed by both the location (mean) and scale (variance) of the prior distribution. While the location reflects the expected value of the parameter, the scale determines the degree of uncertainty and regularization imposed by the prior. Prior research has shown that both components influence estimation, particularly in small samples (McNeish, 2016a, 2016b, 2017; Levy & McNeish, 2023). In this study, we focus specifically on prior location and examine the consequences of misspecifying prior means under latent distributional misspecification, while holding prior variance constant across conditions. Informative priors can improve estimation when they are reasonably centered near the true parameter values, whereas incorrectly specified

informative priors may bias posterior estimates when the data provide limited information. Finch and Miller (2019) examined the effects of correct and incorrect informative priors on Bayesian Multiple Indicators Multiple Causes (MIMIC) estimation under small-sample conditions and found that correctly specified informative priors improved parameter recovery. Moreover, under certain conditions, incorrectly centered informative priors on the MIMIC regression coefficient still yielded acceptable posterior estimates. Importantly, however, all simulation conditions in their study assumed that the latent factor was normally distributed. Consequently, it remains unclear whether these conclusions extend to settings in which the latent factor distribution itself has outliers.

The present study addresses this gap by investigating the recovery of the MIMIC regression coefficient under Bayesian estimation when the latent factor includes outliers. Specifically, the latent factor is generated from a two-component mixture distribution, while the fitted model continues to assume a single normally distributed latent factor, thereby introducing deliberate distributional misspecification. Sample sizes are intentionally small to moderate, reflecting conditions commonly encountered in applied SEM research (Finch & Miller, 2019). The proportion of individuals drawn from the mixture component is systematically varied, and posterior recovery of the MIMIC regression coefficient is evaluated under correctly specified and mis-specified informative priors. Performance is compared against ML estimation to assess the relative robustness of Bayesian and frequentist approaches.

2. Model

2. 1 General MIMIC Model

In this study, we use a single-factor MIMIC model, which includes both a measurement model and a structural model. Following the design in Finch and Miller (2019), there is one observed covariate X, which influences the single latent factor f, so the structural model is

$$f = \gamma X + \epsilon_f$$

where γ is the MIMIC regression coefficient gamma, and ϵ_f is the structural error term, which is assumed to be independent with X. Also, both X and ϵ_f are assumed normally distributed. The coefficient γ is manipulated to evaluate both error control and detection power. Under the non-null condition, γ enables evaluation of Absolute Relative Bias (ARB) and power.

To isolate the effects of latent contamination and prior misspecification, the factor loadings hold constant across conditions in this study, consistent with the simulation research by Finch & Miller (2019). Its measurement model for the observed indicators is

$$Y_i = \lambda f + \zeta_i$$

where Y_i is the observed indicator, λ is the factor loading linking observed indicator to the latent factor, ζ_i is the measurement error that is independent with ϵ_f and f, which also assumed normal. Substituting the structural model into the measurement model yields the combined MIMIC model

$$Y_i = \lambda\left(\gamma X + \epsilon_f\right) + \zeta_i$$

The implied mean and variance of Y_i are given by

$$E(Y_i) = \lambda\left(\gamma E(X) + E\left(\epsilon_f\right)\right) + E(\zeta_i)$$

$$Var(Y_i) = \lambda^2\left[\gamma^2 Var(X) + Var\left(\epsilon_f\right)\right] + Var(\zeta_i)$$

2. 2 Model with Outliers

To introduce latent contamination, in this study the structural error term or the residue of the latent factor ϵ_f is specified as a mixture distribution, indicating it has a small proportion of outliers. Specifically, we assume ϵ_f is from a two-component normal mixture distribution as

$$\epsilon_f \sim (1-p)\, N(\mu_1, {\sigma_1}^2) + p\, N(\mu_2, {\sigma_2}^2)$$

where $N(\mu_1, {\sigma_1}^2)$ represents the correctly specified normally distributed residue, $N(\mu_2, {\sigma_2}^2)$ represents outliers, p represents the proportion of outliers. The p here is small, thereby operationalizing increasing degrees of latent heterogeneity. Specifically, p = 0 corresponds to the case of no outliers so ϵ_f is a normal latent distribution $N(\mu_1, {\sigma_1}^2)$, satisfying the typical assumption imposed in MIMIC models. Bigger positive values of p reflect progressively larger proportion of outliers, ranging from mild to severe contamination. Robustness of the MIMIC model to violations of latent normality was systematically evaluated by varying the proportion of latent outlier p. The mean and variance of ϵ_f are

$$E(\epsilon_f) = (1-p)\mu_1 + p\mu_2$$

$$Var(\epsilon_f) = (1-p)({\sigma_1}^2 + \mu_1^2) + p({\sigma_2}^2 + \mu_2^2) - [(1-p)\mu_1 + p\mu_2]^2$$

$$= (1-p){\sigma_1}^2 + p{\sigma_2}^2 + (1-p)p(\mu_1 - \mu_2)^2$$

So the mean and variance of Y_i are

$$E(Y_i) = \lambda[\gamma E(X) + (1-p)\mu_1 + p\mu_2] + E(\zeta_i)$$

$$Var(Y_i) = \lambda^2[\gamma^2 Var(X) + (1-p){\sigma_1}^2 + p{\sigma_2}^2 + (1-p)p(\mu_1 - \mu_2)^2] + Var(\zeta_i)$$

This design enables a direct and systematic assessment of how escalating levels of latent factor contamination impact the statistical performance of the MIMIC regression coefficient, including estimation bias, statistical power, coverage probability, and Type I error rates under varying degrees of model misspecification (Curran et al., 1996).

3. Simulation Studies

3. 1 Design and Data-Generation

A Monte Carlo simulation study was conducted to evaluate the recovery of the MIMIC regression coefficient under Bayesian and ML estimation when the latent factor distribution is contaminated by outliers (non-normally distributed) while the fitted model continues to assume latent normality. ML estimation was included as a benchmark to facilitate direct comparison with Bayesian estimation under violations of latent normality. Observed covariate, structural error term, and measurement error were generated from standard normal distributions.

The simulation design follows a stress-testing approach, in which key factors are systematically varied to evaluate estimator performance under increasingly challenging conditions. In addition to various prior specification, the degree of latent factor contamination levels (5% and 10%) were selected to represent mild and moderate deviations from latent normality, enabling controlled assessment of robustness. Sample sizes were chosen to reflect small to moderate conditions typical in applied SEM contexts. The simulation design is summarized as in Table 1.

Table 1. Simulation Design

Component	**Details**
Model	MIMIC with one covariate and 10 indicators with factor loadings fixed at 1
Latent factor model	$f = \gamma X + \epsilon_f$
Structural Error	$\epsilon_f \sim (1-p)\, N(0,1) + p\, N(10,5)$ with $p \in \{0.05,\ 0.10\}$
Priors	Correctly centered Informative, Naïve, Incorrectly centered (±1, 2, 3 SD) Informative
Sample Sizes	30, 40, 60, 80, 100, 120, 160, 180
Replications	500 per condition
Estimation	Bayesian (MCMC) vs ML
Evaluation	ARB, Coverage, Power

(1) Sample sizes ranged from N = 30 to N = 180, reflecting small to moderate samples commonly encountered in applied SEM research (Finch & Miller, 2019).

(2) We assumed $\epsilon_f \sim (1-p)\, N(0,1) + p\, N(10,5)$, and the factor contamination level or the proportion of latent outlier, p, has two levels, $p \in \{0.05,\ 0.10\}$. Therefore,

$$E(\epsilon_f) = 10\,p$$

$$Var(\epsilon_f) = 1 + 104p - 100p^2$$

Specifically, when $p = 0$, $E(\epsilon_f) = 0$ and $Var(\epsilon_f) = 1$; when $p = 0.05$, $E(\epsilon_f) = 0.5$ and $Var(\epsilon_f) = 5.95$; and when $p = 0.10$, $E(\epsilon_f) = 1$ and $Var(\epsilon_f) = 10.40$.

(3) We assume the covariate $X \sim N(0, 1)$, the measurement error $\zeta_i \sim N(0, 1)$, the number of observed indicators was fixed at $J = 10$, the factor loadings are fixed at $\lambda = 1$, and the true magnitude of the MIMIC regression coefficient gamma γ is fixed at $\gamma = 0.5$, representing a moderate structural effect. Then we have

$$E(Y_i) = 10p$$

$$Var(Y_i) = 2.25 + 104p - 100p^2$$

Specifically, when $p = 0$, $E(Y_i) = 0$ and $Var(Y_i) = 2.25$; when $p = 0.05$, $E(Y_i) = 0.5$ and $Var(Y_i) = 7.20$; and when $p = 0.10$, $E(Y_i) = 1$ and $Var(Y_i) = 11.65$.

(4) Regarding the informative prior conditions, Table 2 lists the ten priors specified for the MIMIC regression coefficient, ranging from correctly centered priors to priors increasingly mis-specified by up to three standard deviations from the true value.

Table 2. Prior Distribution for Bayesian Estimation

Label	Meaning	Coefficient γ (true = 0.6)	Loading λ (true = 1)
InfB	Correctly centered informative prior for both parameters	Correct[a]: N(0.6, 0.1)	Correct: N(1, 0.1)
NBIL	Naïve Bayes prior with correctly centered informative loading prior	Naïve[b]: N(0, Inf)	Correct: N(1, 0.1)
IBNL	correctly centered informative coefficient prior with naïve loading prior	Correct: N(0.6, 0.1)	Naïve: N(0, Inf)
NB	Naïve prior for both parameters	Naïve: N(0, Inf)	Naïve: N(0, Inf)
IB1	Incorrectly centered coefficient Bayes prior (1 SD away) with naïve loading	Incorrect[c] 1 SD: N(0.5, 0.1)	Naïve: N(0, Inf)
IB2	Incorrectly centered coefficient Bayes prior (2 SD away) with naïve loading	Incorrect 2 SD: N(0.4, 0.1)	Naïve: N(0, Inf)
IB3	Incorrectly centered coefficient Bayes prior (3 SD away) with naïve loading	Incorrect 3 SD: N(0.3, 0.1)	Naïve: N(0, Inf)
IL1	Naïve coefficient prior with incorrectly centered loading prior (1 SD away)	Naïve: N(0, Inf)	Incorrect 1 SD: N(0.9, 0.1)
IL2	Naïve coefficient prior with incorrectly centered loading prior (2 SD away)	Naïve: N(0, Inf)	Incorrect 2 SD: N(0.8, 0.1)
IL3	Naïve coefficient prior with incorrectly centered loading prior (3 SD away)	Naïve: N(0, Inf)	Incorrect 3 SD: N(0.7, 0.1)

Note.
a Correctly centered informative priors.
b Naïve priors correspond to weakly informative specifications.
c Incorrect priors were centered at 1, 2, or 3 standard deviations away from the true parameter value while maintaining the informative prior variance.

3. 2 Implementation

All simulations were implemented in R (version 4.4.2). Bayesian estimation was conducted using MCMC procedures 2 chains with 3,000 burn-in iterations followed by 5,000 posterior samples per chain. Convergence was assessed through inspection of trace plots and evaluation of chain mixing across replications. ML estimation was conducted under conventional multivariate normality assumptions and served as a benchmark for evaluating the relative robustness of Bayesian estimation under latent factor contamination. Each simulation condition was replicated 500 times. We focused on the recovery of the MIMIC regression coefficient under latent factor mixture distributions. Performance was evaluated using absolute relative bias (ARB), coverage probabilities, and statistical power.

3. 3 Results

3.3.1 ARB of the MIMIC Regression Coefficient γ

Table 3 reports the ARB values for estimating γ in the MIMIC model with outliers across all sample sizes and both contamination proportions. Among them, the correctly centered informative Bayes approach (InfB) consistently produced the smallest ARB values. Specifically, InfB yielded ARB values ranging from 0.04 to 0.08 under 5% contamination and from 0.03 to 0.06 under 10% contamination. In contrast, MLE and NB showed substantially larger bias, particularly at smaller sample sizes. The correctly centered informative coefficient prior with naïve loading prior (IBNL) also performed well, with relatively small ARB values across conditions, though it was still slightly worse than InfB. Among the incorrectly centered coefficient priors, ARB increased as prior misspecification became more severe from IB1 to IB3, suggesting that larger degrees of prior misspecification led to greater estimation bias. A similar pattern was found for the incorrectly centered loading priors (IL1–IL3), which yielded particularly large ARB values at small sample sizes and under the higher contamination condition. In sum, these results suggest that correctly centered informative priors markedly reduced bias, whereas prior misspecification, including loading priors, could result in substantially weakened estimation accuracy.

Table 3: ARB[a] of MIMIC with outliers (true $\gamma = 0.5$, J = 10)

N	MLE[b]	NB[c]	InfB[d]	IB1[e]	IB2[e]	IB3[e]	IBNL[f]	IL1[g]	IL2[g]	IL3[g]	NBIL[h]
contamination proportion = 0.05											
30	0.86	0.76	**0.04**	0.27	0.43	0.63	0.09	0.71	0.81	0.90	0.67
40	0.64	0.69	**0.05**	0.22	0.4	0.57	0.08	0.61	0.67	0.77	0.58
60	0.53	0.50	**0.05**	0.19	0.37	0.54	0.07	0.51	0.57	0.65	0.47
80	0.46	0.43	**0.06**	0.19	0.37	0.52	0.07	0.54	0.47	0.53	0.44
100	0.41	0.40	**0.06**	0.17	0.34	0.51	0.07	0.42	0.41	0.47	0.37
120	0.37	0.37	**0.06**	0.17	0.35	0.50	0.06	0.39	0.41	0.43	0.36
160	0.32	0.29	**0.06**	0.16	0.33	0.47	0.07	0.33	0.33	0.38	0.30
180	0.28	0.29	**0.08**	0.17	0.31	0.46	0.07	0.29	0.29	0.35	0.31
contamination proportion = 0.10											
30	1.04	0.82	**0.03**	0.23	0.41	0.59	0.08	1.08	1.21	1.19	0.91
40	0.83	0.89	**0.03**	0.22	0.4	0.59	0.08	0.89	0.87	1.00	0.81
60	0.69	0.63	**0.04**	0.20	0.38	0.57	0.08	0.65	0.71	0.73	0.77
80	0.58	0.57	**0.04**	0.20	0.38	0.57	0.06	0.69	0.73	0.65	0.65
100	0.51	0.59	**0.04**	0.19	0.37	0.54	0.06	0.52	0.50	0.55	0.49
120	0.51	0.51	**0.05**	0.19	0.36	0.54	0.06	0.49	0.52	0.51	0.48
160	0.37	0.39	**0.05**	0.19	0.35	0.52	0.06	0.41	0.43	0.45	0.41
180	0.35	0.36	**0.06**	0.17	0.35	0.52	0.06	0.37	0.38	0.42	0.42

Note.
a ARB = Absolute Relative Bias $(\hat{\gamma} - \gamma)/\gamma$.
b MLE = Maximum Likelihood Estimation;
c NB = Naïve prior for both parameters;
d InfB = Correctly centered informative prior for both parameters;
e IB1–IB3 = Incorrectly centered coefficient prior (1–3 SD away) with naïve loading prior;
f IBNL = Correctly centered Informative coefficient prior with naïve loading prior;
g IL1–IL3 = Naïve coefficient prior with incorrectly centered loading prior (1–3 SD away);
h NBIL = Naïve coefficient prior with correctly centered informative loading prior.

3.3.2 Coverage Probability

Table 4 lists the coverage rates across all conditions. The correctly centered informative Bayes approach (InfB) achieved perfect coverage across all sample sizes under both contamination proportions, with coverage fixed at 1.00. MLE and NB also performed reasonably well, with coverage generally close to the nominal level and improving as sample size increased. Similarly, IBNL and NBIL showed consistently strong performance, with coverage mostly ranging from 0.94 to 1.00 across conditions. In contrast, the incorrectly centered coefficient priors showed substantial undercoverage, especially for IB2 and IB3. IB2 produced coverage values mostly between 0.38 and 0.66, whereas IB3 performed the worst, with coverage near 0.00 across most conditions and only slight improvement at larger sample sizes under 5% contamination. The incorrectly centered loading priors (IL1–IL3) generally maintained acceptable coverage, typically around 0.90 to 0.98, although they were slightly less stable than MLE, NB, InfB, IBNL, and NBIL. In sum, these findings suggest that correctly specified informative priors provided the most reliable interval estimation, whereas severely misspecified coefficient priors led to substantial deterioration in coverage performance.

Table 4: Coverage of MIMIC with outliers (true $\gamma = 0.5$, J = 10)

N	MLE[b]	NB[c]	InfB[d]	IB1[e]	IB2[e]	IB3[e]	IBNL[f]	IL1[g]	IL2[g]	IL3[g]	NBIL[h]
contamination proportion = 0.05											
30	0.93	0.76	**1.00**	0.88	0.38	0.00	0.97	0.94	0.96	0.93	0.95
40	0.94	0.87	**1.00**	0.96	0.42	0.00	0.98	0.98	0.96	0.96	0.96
60	0.96	0.96	**1.00**	0.99	0.52	0.02	1.00	0.96	0.96	0.93	0.96
80	0.93	0.92	**1.00**	0.98	0.50	0.01	1.00	0.93	0.94	0.96	0.94
100	0.94	0.92	**1.00**	0.98	0.60	0.03	0.99	0.95	0.96	0.92	0.96
120	0.96	0.92	**1.00**	0.98	0.52	0.04	1.00	0.96	0.93	0.94	0.95
160	0.94	0.94	**1.00**	0.96	0.56	0.08	1.00	0.94	0.96	0.90	0.96
180	0.96	0.95	**1.00**	0.96	0.66	0.10	1.00	0.94	0.95	0.91	0.96
contamination proportion = 0.10											
30	0.94	0.92	**1.00**	0.98	0.41	0.00	0.97	0.93	0.92	0.91	0.94
40	0.96	0.92	**1.00**	0.96	0.40	0.00	0.97	0.97	0.96	0.95	0.97
60	0.94	0.95	**1.00**	0.98	0.54	0.00	0.98	0.96	0.96	0.97	0.90
80	0.94	0.96	**1.00**	1.00	0.58	0.00	1.00	0.92	0.92	0.94	0.92
100	0.96	0.92	**1.00**	0.99	0.58	0.00	0.99	0.96	0.98	0.94	0.94
120	0.92	0.94	**1.00**	0.98	0.56	0.02	1.00	0.94	0.98	0.96	0.97
160	0.99	0.96	**1.00**	0.98	0.51	0.04	1.00	0.94	0.94	0.95	0.92
180	0.96	0.96	**1.00**	1.00	0.59	0.02	1.00	0.96	0.96	0.95	0.93

Note. The same as in Table 3.

Figure 1 illustrates the coverage probability and interval width. Coverage probabilities for NB, InfB, IBNL, NBIL, and most incorrectly centered loading-prior conditions remained close to the nominal 0.95 level across sample sizes, whereas IB2 showed clear undercoverage and IB3 performed especially poorly, with coverage near zero throughout. This pattern was similar under both contamination levels, although coverage under 10% contamination appeared slightly more stable for several methods. For interval width, all methods showed narrower intervals as sample size increased. InfB, IB1, IB2, IB3, and IBNL produced the smallest interval widths and changed very little across sample sizes, whereas NB, NBIL, and the incorrectly centered loading-prior conditions (IL1–IL3) yielded much wider intervals, especially at smaller sample sizes. Among these wider-interval methods, IL3 tended to have the largest interval widths, followed by IL2 and IL1, and the gap gradually narrowed as sample size increased. Comparing the two contamination conditions, interval widths were generally larger under 10% contamination than under 5% contamination, particularly for NB, NBIL, and IL1–IL3. Taken together, the figure suggests that some methods achieved nominal coverage partly at the cost of wider intervals, whereas the severely misspecified coefficient prior condition (IB3) combined very narrow intervals with extremely poor coverage.

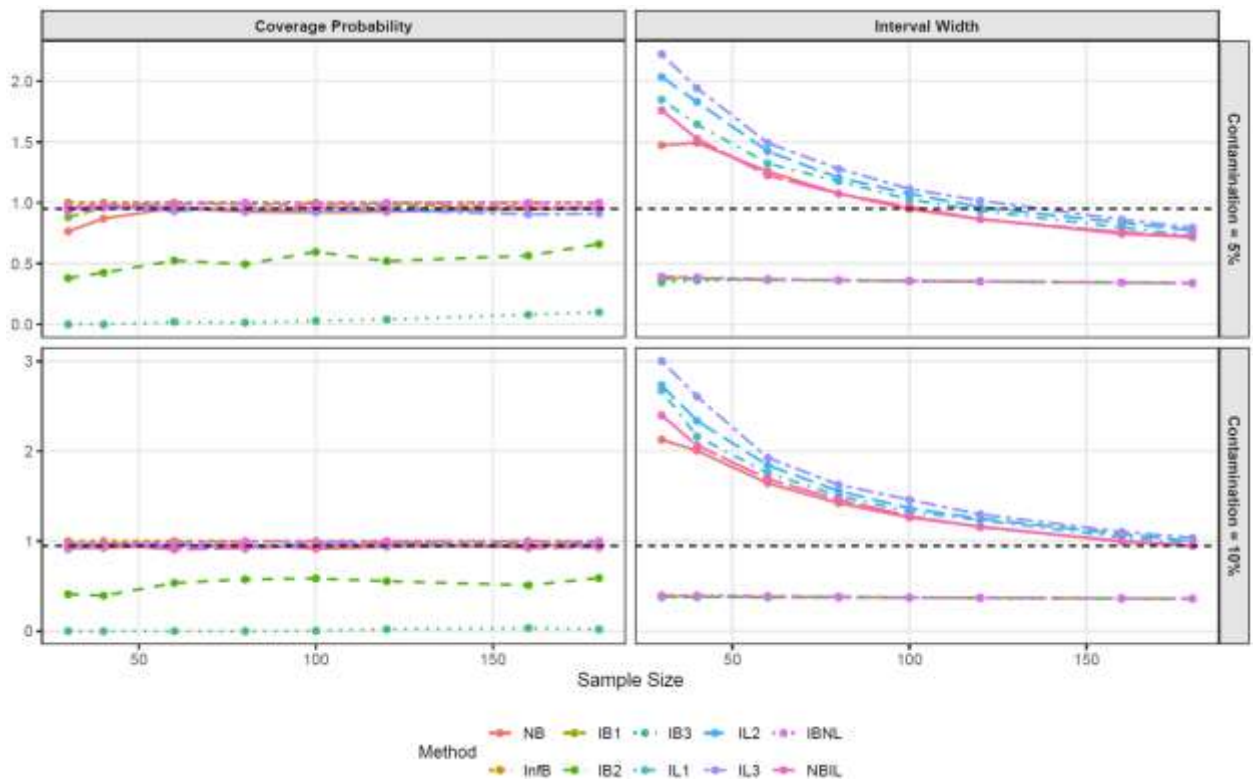

Figure 1: Coverage probabilities (left panels) and interval widths (right panels) for the MIMIC coefficient across sample sizes and contamination levels.

3.3.3 Statistical Power

Table 5 presents the statistical power for detecting γ in the MIMIC model with outliers across all sample sizes and both contamination proportions. The correctly centered informative Bayes approach (InfB) consistently achieved near-ceiling power (1.00), indicating the strongest performance. The incorrectly centered coefficient prior conditions (IB1–IB3) and the correctly centered informative coefficient prior with naïve loading prior (IBNL) also showed very high power overall, with most values close to or equal to 1.00, although IB3 was slightly lower than IB1 and IB2 under some smaller-sample conditions. In contrast, MLE and NB had substantially lower power, especially at smaller sample sizes, but both generally improved as sample size increased. The incorrectly centered loading prior conditions (IL1–IL3) performed notably worse than the coefficient-prior conditions, with relatively low power at small sample sizes and only moderate improvement as sample size increased. This pattern was

especially pronounced under the higher contamination proportion of 0.10, where IL1–IL3 showed clear reductions in power compared with the 0.05 contamination condition. In sum, the results indicate that correctly centered informative priors provided the greatest sensitivity for detecting γ, whereas misspecification in loading priors was particularly harmful to statistical power.

Table 5: Power of MIMIC with outliers (true γ = 0.5, J = 10)

N	MLE[b]	NB[c]	InfB[d]	IB1[e]	IB2[e]	IB3[e]	IBNL[f]	IL1[g]	IL2[g]	IL3[g]	NBIL[h]
contamination proportion = 0.05											
30	0.17	0.29	**1.00**	0.98	0.95	0.80	0.98	0.29	0.30	0.28	0.28
40	0.30	0.23	**1.00**	0.98	0.98	0.89	0.98	0.31	0.26	0.32	0.32
60	0.35	0.34	**1.00**	1.00	0.98	0.92	0.99	0.40	0.44	0.45	0.39
80	0.38	0.54	**1.00**	0.99	0.98	0.94	0.98	0.47	0.48	0.52	0.46
100	0.58	0.56	**1.00**	1.00	1.00	0.97	0.99	0.54	0.56	0.56	0.55
120	0.63	0.62	**1.00**	1.00	1.00	0.94	1.00	0.60	0.68	0.63	0.63
160	0.70	0.74	**1.00**	1.00	1.00	1.00	1.00	0.73	0.68	0.77	0.70
180	0.79	0.74	**1.00**	1.00	1.00	0.98	1.00	0.74	0.78	0.81	0.74
contamination proportion = 0.10											
30	0.13	0.18	**1.00**	0.98	0.98	0.84	1.00	0.16	0.16	0.14	0.16
40	0.17	0.20	**1.00**	0.98	0.98	0.84	1.00	0.20	0.15	0.17	0.18
60	0.22	0.22	**1.00**	0.98	1.00	0.84	0.98	0.20	0.24	0.21	0.22
80	0.28	0.30	**1.00**	0.98	0.97	0.84	0.98	0.29	0.38	0.26	0.26
100	0.29	0.41	**1.00**	0.99	0.98	0.91	0.98	0.32	0.30	0.30	0.33
120	0.42	0.37	**1.00**	0.98	0.99	0.88	0.98	0.40	0.42	0.41	0.42
160	0.50	0.48	**1.00**	1.00	1.00	0.94	0.99	0.50	0.47	0.53	0.48
180	0.54	0.59	**1.00**	1.00	1.00	0.94	0.98	0.53	0.54	0.58	0.55

Note. The same as in Table 3.

4. Conclusions, Limitations and Future research

This study suggests that informative Bayesian estimation offers substantial advantages when priors are well-centered across the ARB, coverage, and power results. The correctly centered informative Bayes approach consistently showed the strongest and most stable performance. It produced the smallest bias, maintained nominal or perfect coverage, and achieved the highest power across sample sizes and contamination conditions. The model with a correctly centered informative coefficient prior and naïve loading prior also performed well overall, indicating that correctly specifying the coefficient prior alone can still provide substantial benefit. In contrast, misspecified priors, especially incorrectly centered loading priors and severely misspecified coefficient priors, led to clear deterioration in performance. The loading-prior misspecification conditions were associated with noticeably larger bias and weaker power, while the most severely misspecified coefficient prior condition resulted in serious undercoverage despite its relatively narrow intervals. MLE exhibited the weakest robustness. These findings show that informative priors can substantially improve estimation and inference, but these advantages depend heavily on whether the priors are correctly centered.

Several limitations should be noted. First, the current simulation design was restricted to a MIMIC structure with a fixed coefficient and a fixed number of indicators. Therefore, the findings may not generalize to other cases or more complex latent structures. Second, only two contamination proportions were examined in this study, and the form of contamination was limited to the structural error. Other types of outliers or nonnormality may affect the methods differently. Third, the study focused primarily on ARB, coverage, and power. Although these are important

criteria, additional indices such as RMSE, Type I error, and sensitivity to prior variance choices would provide a more complete evaluation. Finally, the priors were manipulated through centering conditions of specific magnitudes, but other forms of prior misspecification, such as incorrect variance specification or structural misspecification, were not explored.

Future research should extend this work in several directions. One useful next step would be to vary the true coefficient values, number of indicators, and severity or form of contamination to assess the robustness of these findings under broader conditions. It would also be valuable to examine alternative design choices, pilot-based models, or more complex models, such as multiple latent variables, multiple direct effects, or models with categorical indicators. In addition, future studies could investigate how different degrees of prior informativeness and prior variance misspecification influence estimation accuracy and interval performance. Comparing these Bayesian approaches with additional robust frequentist and Bayesian alternatives would also strengthen the practical implications of the results. Finally, applying these methods to empirical datasets would help demonstrate how informative priors operate in realistic settings where prior information may be partially correct rather than perfectly specified.

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