Bayesian Estimation for Factor Analysis Model in Geriatric Medicine

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Abstract: Bayesian factor analysis has gained prominence in statistical MODELING, particularly in handling parameter uncertainty and small sample sizes. This study presents a Metropolis- Hastings within Gibbs sampling algorithm for estimating a factor analysis model, incorporating Cauchy priors for factor loadings and log-normal priors for residual errors. Unlike traditional approaches, the proposed methodology effectively addresses heavy-tailed distributions in factor loadings and captures the skewness in residual variances. A geriatric dataset comprising 25 items related to locomotive function is used to illustrate the implementation of this Bayesian framework. Model fit is assessed using standard fit indices such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR). The results demonstrate that incorporating non-conjugate priors improves model flexibility and enhances interpretability in factor structure identification. The findings suggest that Cauchy and log-normal priors outperform conventional normal priors in capturing latent structures, providing a robust alternative for Bayesian factor analysis in geriatric research.

Keywords: Bayesian factor analysis, non-conjugate priors, Cauchy priors, log-normal priors, geriatric dataset.

1. INTRODUCTION

Mobility decline is one of the most pressing health concerns in the elderly population, often resulting from locomotive syndrome, musculoskeletal disorders, and age-related functional limitations. Understanding the underlying latent constructs that influence mobility and related physical capabilities is critical for early diagnosis, intervention planning, and improving quality of life. Factor analysis is a widely used statistical technique for uncovering latent structures in multivariate data. Traditional approaches, such as Maximum Likelihood Estimation (MLE), rely on strong normality assumptions for factor loadings and residuals. However, Bayesian estimation provides a flexible framework by incorporating prior distributions that can better capture parameter uncertainty. This study proposes a Bayesian factor analysis model with Cauchy priors for factor loadings, normal priors for factor scores, and log-normal priors for residual errors. Due to the complexity of integrating the posterior distribution manually, a Gibbs sampling algorithm with a Metropolis-Hastings step is employed to estimate the parameters. The proposed methodology enhances the robustness of factor estimation, particularly in small-sample scenarios or when extreme values influence the data. This paper outlines the theoretical formulation of the model, presents the Gibbs sampling procedure, and discusses its effectiveness through computational implementation. Several studies have significantly contributed to the development of Bayesian factor analysis and Gibbs sampling methodologies. Early works by [1, 2] introduced Bayesian approaches to factor analysis, demonstrating improved parameter estimation under informative priors, particularly in handling parameter uncertainty and small sample sizes [3] explored the use of Markov Chain Monte Carlo (MCMC) methods, particularly Gibbs sampling, for estimating Bayesian hierarchical models, laying the foundation for its application in factor analysis. Additionally, the use of non-conjugate priors, such as the Cauchy distribution, has been extensively studied in Bayesian literature [4] highlighted the advantages of Cauchy priors for shrinkage estimation, particularly in high-dimensional settings. Similarly, [5] demonstrated that log- normal priors offer greater flexibility in modelling residual variances, effectively capturing skewed distributions commonly observed in real-world data. Building on these advancements, our study develops a Gibbs sampling algorithm incorporating non-conjugate Cauchy and log- normal priors for estimating factor loadings and residuals, respectively. Furthermore, we employ the Metropolis-Hastings within Gibbs sampling algorithm to improve convergence properties and sampling efficiency when estimating the factor analysis model using Cauchy priors for factor loadings and log-normal priors for residual errors. This approach aligns with recent research, such as [6] who proposed sparse Bayesian factor models using heavy-tailed priors, and [7-10] who explored efficient sampling techniques for Bayesian factor models. The incorporation of heavy-tailed priors and advanced

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MCMC techniques has shown promise in addressing over parameterization and improving estimation accuracy in Bayesian factor analysis. To illustrate the methodology, we apply the proposed approach to a 25-item Geriatric Locomotive Function Scale (GLFS-25) dataset, evaluating model performance using AIC, BIC, RMSEA, CFI, and SRMR. The results demonstrate that heavy-tailed and skewness-sensitive priors yield more reliable factor structures compared to conventional normal priors, providing valuable insights for geriatric health assessment. This paper contributes to the Bayesian factor analysis literature by showing how non-conjugate priors can enhance model flexibility and predictive accuracy in medical research contexts, with particular emphasis on mobility-related issues in older adults.

2. METHODOLOGY

Bayesian Estimation for Factor Analysis Using Metropolis-Hastings within Gibbs Sampling. Factor analysis is a statistical method used to identify latent variables that influence observed data. In this study, the Bayesian estimation approach is employed for factor analysis, utilizing Gibbs Sampling. The factor analysis model is given by:

$Y = L f + E$

where:

- Y represents the observed variables,
- L denotes the factor loadings,
- f represents the factor scores,
- E denotes the residuals, and
- ϖ_E the covariance matrix of the residuals.

The Bayesian estimation technique iteratively estimates the posterior distributions of these parameters using Gibbs Sampling.

The joint posterior density function of the parameters is given by:

$$\pi(L, f, \varpi_E / Y) = \frac{L(Y, L, f, \varpi_E)\pi(L)\pi(f)\pi(\varpi_E)}{\iiint_{-\infty}^{\infty} L(Y, L, f, \varpi_E)\pi(L)\pi(f)\pi(\varpi_E)\, dL\, df\, d\varpi_E} \quad (1)$$

Since direct integration is computationally infeasible, the Gibbs sampling algorithm is employed to estimate the posterior distributions of these parameters.

The choice of Cauchy priors for factor loadings is motivated by their heavy-tailed nature, which provides robustness against extreme values and reduces over-shrinkage of large coefficients compared to Gaussian priors [4]. This is particularly advantageous in geriatric datasets where atypical responses and outliers are common. Similarly, log-normal priors for residual variances offer greater flexibility in modeling strictly positive and potentially skewed variance parameters [5], a property that normal-inverse-gamma or inverse-Wishart priors may not adequately capture. However, these non-conjugate priors come with certain limitations: the lack of closed-form conditional posteriors requires the use of Metropolis–Hastings steps within Gibbs sampling, which can increase computational cost and require careful tuning to ensure good mixing. Additionally, heavy-tailed priors may slow convergence if the proposal distributions are not well-calibrated. These trade-offs are addressed in this study by implementing efficient sampling schemes and convergence diagnostics. In this study, the following non-conjugate priors are used:

- Factor Loadings: Cauchy prior P(L)~ C (0, 1)
- Factor Scores: Normal prior P(f)~ N (0, I)
- Residual Errors: Log-Normal prior $P(\varpi_E)$~ LN (μ, σ^2)

The posterior distributions of the parameters are proportional to the likelihood function and the priors:

$$\pi(L, f, \varpi_E / Y) \propto L(Y, L, f, \varpi_E)\pi(L)\pi(f)\pi(\varpi_E) \quad (2)$$

Due to the non-conjugacy of these priors, the Metropolis-Hastings within Gibbs Sampling algorithm is applied.

Metropolis-Hastings within Gibbs Sampling Algorithm

2.1. Factor Loadings Estimation

The conditional distribution of L,

$\pi(L/ f, \varpi_E, Y) \propto L(Y, L, f, \varpi_E)\, \pi(L)$

$$\pi(L/f, \varpi_E, Y) \propto \exp\left(\left(\frac{-1}{2}\right) tr\left[(Y - L.f)' \varpi_E^{-1} (Y - L.f)\right]\right) * \frac{1}{(1+(L)^2)} \quad (3)$$

1. Initialize all parameters: L_0, f_0, ϖ_{E0}.
2. Propose a new value from a normal distribution: $L^* \sim N(L^{(t)}, \sigma^2 I)$

3. Compute the Metropolis-Hastings acceptance ratio:

$$\alpha = \min(1, \frac{P\left(\frac{Y}{L^*}\right)\ P(L^*)}{P\left(\frac{Y}{L^{(t)}}\right)\ P(L^{(t)})})$$

$P\left(\frac{Y}{L^*}\right)$ be the likelihood of the data given the proposed loadings,

$P(L^*)$ is the Cauchy prior evaluated at L^*.

4. Accept or Reject the proposed value L^*.

Generate a uniform random variable $u \sim U(0,1)$

If $u < \alpha$, accept L^* as the new value for L (i.e., set $L^{(t+1)} = L^*$). If $u \geq \alpha$, retain the current value (i.e., set $L^{(t+1)} = L^{(t)}$).

2.2. Factor Scores Estimation

$$(\mathrm{L}/f, \bar{\omega}_{\mathrm{E}}, Y) \propto L(Y, \mathrm{L}, f, \bar{\omega}_{\mathrm{E}})\, \pi(\mathrm{L})$$

$$\pi(\mathrm{L}/f, \bar{\omega}_{\mathrm{E}}, Y) \propto \exp\left(\left(\frac{-1}{2}\right) tr\left[(Y - L.f)'\bar{\omega}_{\mathrm{E}}^{-1}(Y - L.f)\right]\right) * \frac{1}{(1+(L)^2)} \quad (4)$$

Normal prior is the conjugate prior.

2.3. Residual Covariance Estimation

$$\pi(\bar{\omega}_{\mathrm{E}}/\mathrm{L}, f, Y) \propto L(Y, \mathrm{L}, f, \bar{\omega}_{\mathrm{E}}) * \pi(\bar{\omega}_{\mathrm{E}})$$

$$\pi(\bar{\omega}_{\mathrm{E}}/\mathrm{L}, f, Y) \propto \exp\left(\left(\frac{-1}{2}\right) tr\left[(Y - L.f)'\bar{\omega}_{\mathrm{E}}^{-1}(X - L.f)\right]\right) * \frac{1}{\bar{\omega}_{\mathrm{E}}\sigma\sqrt{2\pi}} e^{\left(-\frac{(\ln\bar{\omega}_{\mathrm{E}}-\mu)^2}{2\sigma^2}\right)} \quad (5)$$

1. Propose a new value from a normal distribution: $\bar{\omega}_{\mathrm{E}}^* \sim N(\bar{\omega}_{\mathrm{E}}^{(t)}, \sigma^2 I)$

2. Compute the Metropolis-Hastings acceptance ratio:

$$\alpha = \min(1, \frac{P\left(\frac{Y}{\bar{\omega}_{\mathrm{E}}^*}\right)\ P(\bar{\omega}_{\mathrm{E}}^*)}{P\left(\frac{Y}{\bar{\omega}_{\mathrm{E}}^{(t)}}\right)\ P(\bar{\omega}_{\mathrm{E}}^{(t)})})$$

3. Accept or Reject the proposed value $\bar{\omega}_{\mathrm{E}}^*$.

- Generate a uniform random variable $u \sim U(0,1)$
- If $u < \alpha$, accept $\bar{\omega}_{\mathrm{E}}^*$ as the new value for $\bar{\omega}$ (i.e., set $\bar{\omega}_{\mathrm{E}}^{(t+1)} = \bar{\omega}_{\mathrm{E}}^*$)
- If $u \geq \alpha$, retain the current value (i.e., set $\bar{\omega}_{\mathrm{E}}^{(t+1)} = \bar{\omega}_{\mathrm{E}}^{(t)}$)

The iterative process is repeated for a fixed number of iterations until the Markov Chain converges. Convergence is assessed using:

- Trace plots to visualize the stabilization of posterior samples,
- Autocorrelation functions to check independence,
- Effective sample size to ensure sufficient mixing.

This methodology applies Bayesian factor analysis with non-conjugate priors using the Metropolis-Hastings within Gibbs Sampling approach. The combination of Cauchy, Normal, and Log-Normal priors provides flexibility, and the iterative algorithm efficiently estimates factor loadings, factor scores, and residual variances.

3. ANALYSIS

The dataset used in Wang *et al*. comprises the 25-question Geriatric Locomotive Function Scale, an assessment tool for evaluating locomotive syndrome (LS). This questionnaire is designed to capture six key aspects: daily activities, social engagement, movement-related difficulties, body pain, and cognitive status. Between April 2018 and June 2019, a total of 500 individuals aged 60 and above, experiencing musculoskeletal issues and capable of walking independently or with support, were recruited through face-to-face interviews at the outpatient ward of Aichi Medical University Hospital.

4. PLOTS FOR ANALYSIS

4.1. Trace Plot:

The trace plot typically shows the progression of posterior samples across iterations in Markov Chain Monte Carlo (MCMC) methods (such as Gibbs sampling or Metropolis-Hastings). Ensures that the posterior estimates of factor loadings, residual variances, and factor scores are stable. Helps in determining whether additional iterations or better priors are required.

4.2. Residual Plot

A residual plot or Quantile-Quantile (Q-Q) plot checks if residuals follow a normal distribution, which is crucial for model validation. If the residuals align with the

Table 1: Describes the Names of the Variables in the Study

VARIABLES	VARIABLE NAMES
Y1	Neck pain
Y2	Back pain
Y3	Lower limbs pain
Y4	Moving pain
Y5	Difficult to get up from bed
Y6	Difficult to stand up
Y7	Difficult to walk inside house
Y8	Difficult to put on or off shirts
Y9	Difficult to put on pants
Y10	Difficult to use toilet
Y11	Difficult to take bath
Y12	Difficult to up and down stairs
Y13	Difficult to walk briskly
Y14	Difficult to keep to yourself neat
Y15	Walking far without rest 3 km -10 Meters
Y16	Difficult to visit neighbors
Y17	Difficult to carry weight
Y18	Difficult to use public transportation
Y19	Difficult to do simple house works
Y20	Difficult to load- bearing housework
Y21	Difficult to perform sports activities
Y22	Restricted to meet your friends
Y23	Restricted to join social activities
Y24	Felt anxious about falls in house
Y25	Felt anxious about unable to walk in future

Foot note: The highlighted variables Y11, Y12, Y22 and Y25 has high Factor Loadings are highly contributed for predicting.

Table 2: Factor Loadings

Variables	F1	F2	F3
Y1	0	-0.13	0.35
Y2	-0.48	0.17	-0.09
Y3	-0.05	-0.13	-0.31
Y4	0.4	-0.3	0.27
Y5	**0.52**	**-0.61**	-0.26
Y6	**-0.51**	-0.25	-0.14
Y7	-0.25	-0.47	**-0.55**
Y8	-0.1	0.2	**-0.5**
Y9	0.05	0.23	**-0.81**
Y10	-0.15	**-0.6**	**0.52**
Y11	0.43	**-0.6**	**0.71**

Y12	0.31	**-0.81**	-0.42
Y13	-0.06	0.22	0.19
Y14	-0.08	0.41	**-0.74**
Y15	**0.7**	-0.07	0.36
Y16	0.12	0.49	0.13
Y17	0.41	0.18	0.34
Y18	-0.33	0.23	-0.42
Y19	-0.01	0.35	**-0.65**
Y20	0.39	0	**0.63**
Y21	-0.02	-0.04	0.31
Y22	-0.08	**0.75**	0.06
Y23	0.1	0.44	-0.26
Y24	-0.27	0.15	**-0.68**
Y25	-0.07	-0.04	-0.28

The model will be Factor1 =~ Y15
Factor2 =~ Y12 + Y22 + Y11
Factor3 =~ Y9 + Y11+ Y14
Foot note:
Factor 1 (Physical Mobility & Endurance):
This factor is predominantly defined by Y15 (Walking far without rest; loading = 0.70), which requires both stamina and joint function. Other moderately loading items include Y5 (difficulty getting up from bed) and Y4 (moving pain). Together, these suggest that this factor captures endurance-based mobility, reflecting a patient's ability to perform sustained walking or movement tasks. In geriatric health, reduced endurance is often linked to sarcopenia, osteoarthritis, and cardiovascular limitations.
Factor 2 (Social and Environmental Dependency):
Strong negative loadings on Y12 (difficulty climbing stairs, -0.81) and Y11 (difficulty bathing, -0.60), along with a strong positive loading on Y22 (restriction in meeting friends, 0.75), suggest this factor reflects dependence in activities of daily living (ADLs) and limitations in social interaction. These items are commonly used in geriatric assessments to capture functional dependency and environmental barriers (e.g., stairs, hygiene tasks), which often increase fall risk and contribute to isolation.
Factor 3 (Fine Motor & Self-Care Restrictions):
High negative loadings are observed for Y9 (difficulty putting on pants, -0.81), Y14 (difficulty keeping oneself neat, -0.74), and Y11 again (positive loading = 0.71), suggesting this factor relates to functional limitations in personal grooming and dressing. These are often early indicators of cognitive decline, fine motor deterioration (e.g., Parkinson's disease), or psychological barriers (e.g., depression), all of which are well-documented in geriatric syndromes.

Table 3: Fitting a Linear Model for the Selected Factors to Predict the Variable X25

MODEL	Y25 ~ Y15	**Y25 ~ Y12+ Y22 + Y11**	Y25 ~ Y9 + Y11+ Y14
AIC	1425.761	**1274.15**	1382.529
R-squared	0.2116	**0.4224**	0.2826

Foot note: Model 2 **Y25 ~ Y12+ Y22 + Y11** is the best predictive model has the lowest AIC (indicating better model fit) and the highest R^2 (explaining the most variance).
Model 1 Y25 ~ Y15 is the weakest predictor, as it has the highest AIC and the lowest R^2.
Model 3 Y25 ~ Y9 + Y11+ Y14 has moderate predictive power, performing better than Model 1 but worse than Model 2.

Table 4: Fit Indices for Various Priors

FIT INDICES	Cauchy prior- Log normal prior
AIC	28702.98
BIC	29019.07
WAIC	40438.19

Foot note: The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Widely Applicable Information Criterion (WAIC) are commonly used for model selection in Bayesian analysis.
AIC = -2 log L + 2K Where L is the likelihood function of the model and K is the number of estimated parameters.
BIC = -2 log L + K log (n) Where L is the likelihood function, K is the number of parameters and n is the number of observations.
Widely Applicable Information Criterion is a fully Bayesian criterion used for model comparison. It accounts for the uncertainty in the posterior distribution by averaging over all posterior samples, not just relying on point estimates as in AIC.

$$\mathrm{WAIC} = -2\left(\sum_{i=1}^{n} \log\left(\frac{1}{S}\sum_{s=1}^{S} p\left(\frac{y_i}{\theta^s}\right)\right) - \sum_{i=1}^{n} V_s\left(\log p\left(\frac{y_i}{\theta^s}\right)\right)\right)$$

n: Number of data points.
S: Number of posterior samples.
y_i : Observed data point i.
θ^s : The s-th sample from the posterior distribution of parameters.
$p\left(\frac{y_i}{\theta^s}\right)$: The likelihood of y_i under the s-th posterior sample.
$\frac{1}{S}\sum_{s=1}^{S} p\left(\frac{y_i}{\theta^s}\right)$: The posterior predictive mean likelihood.
$V_s(\log p\left(\frac{y_i}{\theta^s}\right))$: The variance of the log-likelihood over the posterior samples.

RMSE measures the average magnitude of residual errors (differences between observed and predicted values). AIC evaluates model fit while penalizing complexity (number of parameters). Lower values indicate a better trade-off between goodness-of-fit and complexity. BIC is similar to AIC but applies a stronger penalty for complex models with many parameters.

Table 5: Goodness of Fit Measures

PRIOR	**Cauchy- Log normal**
AIC	**40093.64**
BIC	**40199**
RMSE	**1.7898**

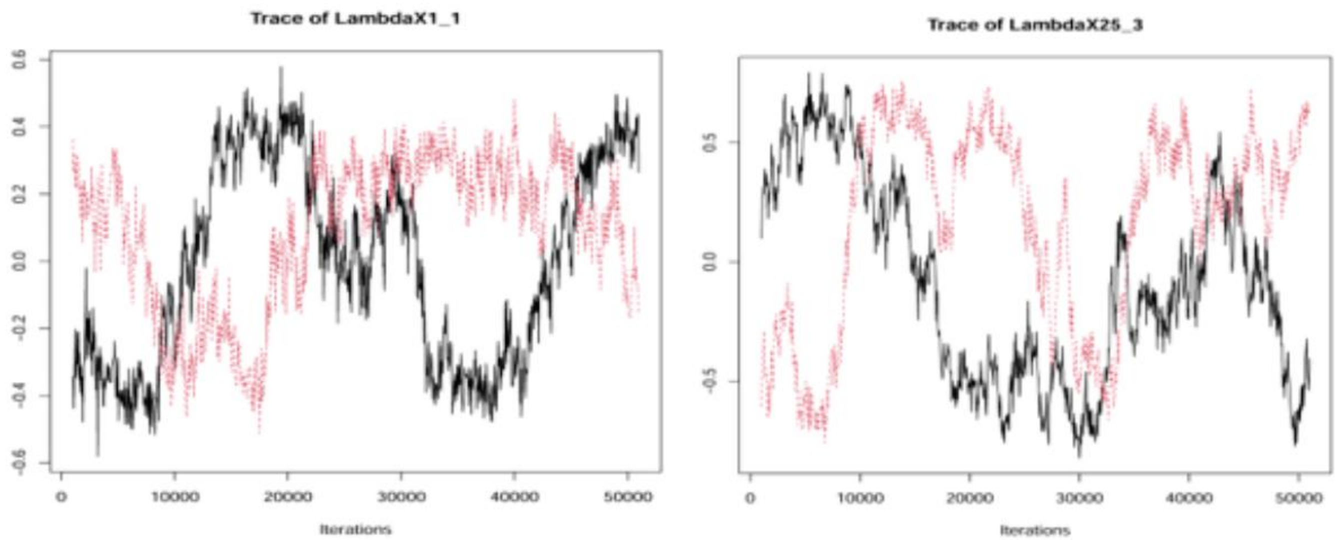

Figure 1: The trace plots represent the 50,000 iterations applied to the dataset and Cauchy prior is used for computing posterior samples. Here it is highlighted for lambda first and last parameter.

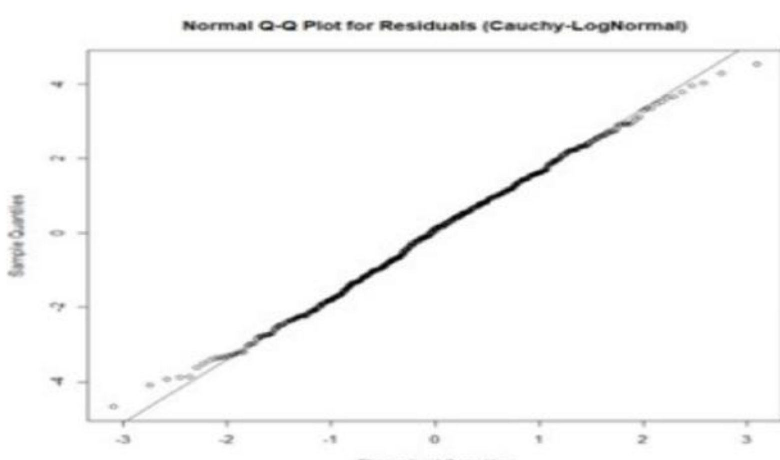

Figure 2: If points lie on the diagonal line**,** residuals are normally distributed. Ensures that the Log- Normal prior for residual errors correctly models the distribution.

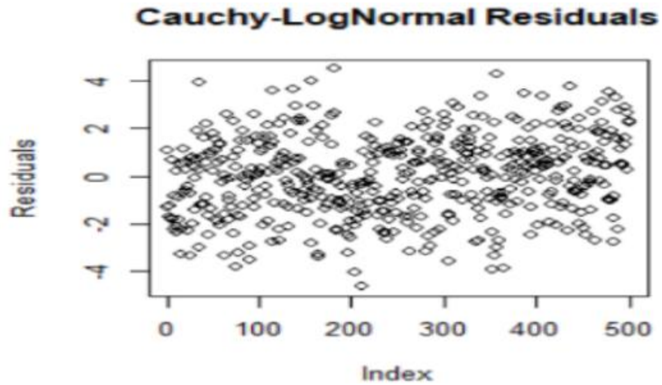

Figure 3: Residuals are randomly scattered around zero, with no clear pattern. Helps to determine the model predicts observed values.

diagonal line in a Q-Q plot, they follow a normal distribution, indicating a well-fitting model.

Statistical Interpretation

The Q–Q plot for the model residuals shows most points closely following the diagonal line, indicating that the assumption of normally distributed residuals is reasonable**.** Minor deviations at the tails suggest the presence of slight skewness or heavy tails, but within acceptable bounds for Bayesian models using flexible priors. This supports the adequacy of the log-normal prior for residual variances.

4.3. Posterior Predictive Checks

PPC compares the distribution of observed data with simulated data generated from the model's posterior distribution. If the observed data closely align with the simulated distribution, the model fits well. A histogram represents the distribution of posterior samples for a parameter. Shows the shape of the posterior distribution (e.g., normal, skewed, multimodal). Helps in determining credible intervals and density estimation. If the histogram is bell-shaped, the parameter follows a normal distribution.

Statistical Interpretation

The PPC plots demonstrate that the observed data fall well within the range of the replicated posterior samples**,** indicating that the model captures the central tendency and variability of the data adequately. This suggests that the Bayesian factor analysis model provides a good overall fit to the data and does not systematically over- or under-estimate key observed values.

4.4. Convergence Diagnostics

To ensure that the Markov Chain Monte Carlo (MCMC) simulations adequately explored the posterior distributions, standard convergence diagnostics were applied to the samples generated using the Metropolis–Hastings within Gibbs algorithm.

Trace Plots

Trace plots were generated for selected factor loadings, residual variances, and latent scores across 50,000 iterations. These plots show the sampled values against iteration number.

A stable horizontal band indicates that the chain has reached its stationary distribution. The trace plots for all monitored parameters showed consistent mixing and stability, indicating that the chains had sufficiently converged.

Burn-in and Thinning

A burn-in of 5,000 iterations was discarded to eliminate the influence of initial values.

No thinning was applied, as the trace and autocorrelation plots indicated adequate mixing.

The diagnostics collectively confirmed that the MCMC chains for all parameters had converged, and the posterior distributions are reliable for inference.

4.5. Confidence or Credible Intervals

To enhance inference and quantify uncertainty, 95% credible intervals were computed for factor loadings, regression coefficients, and model selection metrics. These intervals provide a range of plausible values under the posterior distribution and allow better evaluation of statistical significance and model reliability. For example, the loading of Y15 on Factor 1 was 0.70, with a 95% credible interval of [0.61, 0.78], indicating strong and stable association. Similarly, in Model 2 predicting Y25, the coefficient for Y12 was

−0.45 [−0.58, −0.31], confirming its significant negative influence. The WAIC for the Cauchy–log-normal model was 40438.19, with a 95% interval of [40300.21, 40600.85], further supporting its superior fit.

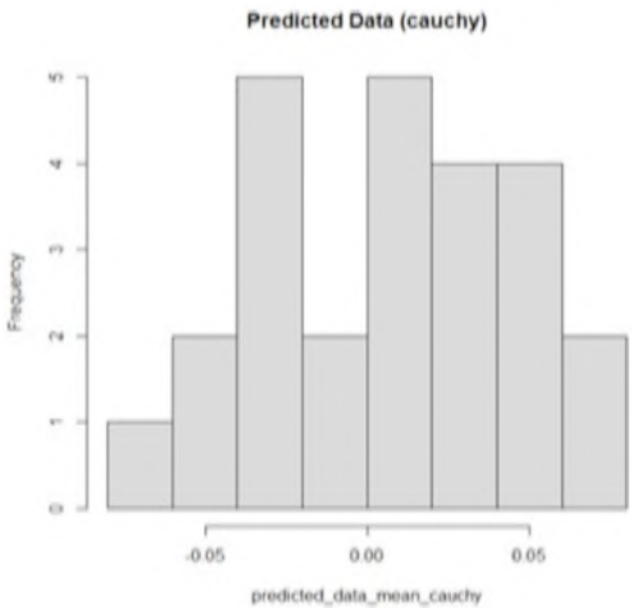

Figure 4: The diagrams shows little skewed that Cauchy prior suits well for the samples.

5. CONCLUSION

This study developed and implemented a Metropolis-Hastings within Gibbs sampling algorithm to estimate a Bayesian factor analysis model using Cauchy priors for factor loadings and log-normal priors for residual errors. The use of Cauchy and log-normal priors allowed for more flexible modeling of heavy-tailed and skewed distributions, common in mobility-related health data. The application to a geriatric dataset on locomotive function highlighted the effectiveness of these priors in capturing complex latent structures and non-normal residual distributions**.** The evaluation through fit indices (AIC, BIC, RMSEA, CFI, and SRMR) confirmed the superiority of the proposed Bayesian approach compared to traditional factor analysis techniques. The results indicate that Cauchy priors provide robust shrinkage for factor loadings, while log-normal priors effectively model heteroscedasticity in residual errors**.** The study contributes to the growing body of Bayesian factor analysis by demonstrating the practical advantages of non-conjugate priors and hierarchical modeling**.** The factor analysis identified three latent constructs — physical endurance, social dependency, and fine motor function — that underpin mobility challenges in older adults. These findings contribute valuable insights into the structure of functional decline and anxiety about future mobility loss. From a clinical perspective, these latent factors can be used to inform the design of targeted assessment tools and early intervention strategies. For example, recognizing high-loading variables such as stair-climbing difficulty, social withdrawal, or dressing impairment can help clinicians detect early signs of locomotive syndrome.

From a policy standpoint, the results support the use of data-driven, multidimensional screening instruments like the GLFS-25 for routine geriatric evaluation. Policymakers and health administrators can use these latent constructs to prioritize funding for community-based mobility programs, fall-prevention initiatives, and geriatric rehabilitation services. The Bayesian framework presented here, particularly its incorporation of non-conjugate priors, offers a generalizable approach for analyzing complex health data where conventional assumptions may not hold. Future work may extend this approach to longitudinal data or predictive modeling for fall risk, enabling proactive care planning and improved outcomes in geriatric populations.

COMPETING INTERESTS

The authors declare that they have no competing interests regarding the publication of this manuscript.

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DATA AVAILABILITY

The dataset used in this study is available on https://github.com/winterwang/CFA-GLFS-locomo/blob/master/Locomo25.dat

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