JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. 10, No. 2, April 2026, pp. 634-646

A Bayesian Structural Causal Modeling Framework for Analyzing Childhood Stunting Factors

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Article History:
Received : 27-10-2025
Revised : 05-12-2025
Accepted : 07-12-2025
Online : 01-04-2026

Keywords:
Stunting;
Child;
Health;
Bayesian;
Path Analysis.

ABSTRACT

This quantitative study investigates the causal determinants of childhood stunting using a structured questionnaire as the primary research instrument. The analysis applies Bayesian path modeling to examine how Economic Level influences Child Nutritional Status both directly and indirectly through Children's Diet. Bayesian estimation is used to obtain stable and reliable parameter values, with convergence checks ensuring model adequacy. The overly technical explanations of MCMC procedures and specific sampling algorithms from the original version are condensed to maintain clarity in an abstract. The results show that Children's Diet plays a strong mediating role, indicating that economic improvements contribute more substantially to better nutritional outcomes when dietary practices are strengthened. These findings highlight clear policy implications, particularly the need to integrate dietary interventions with economic support programs. Overall, the study demonstrates that Bayesian path analysis provides a rigorous yet flexible approach for evaluating interconnected determinants of child nutrition and contributes evidence-based insights for stunting reduction strategies.

Crossref
https://doi.org/10.31764/jtam.v10i2.35966

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A. INTRODUCTION

Stunting, defined as impaired physical and cognitive development caused by chronic malnutrition, recurrent infections, and inadequate caregiving stimulation, continues to be a major global public health challenge. As reported by the World Health Organization (WHO, 2021), approximately 148 million children under five are affected, with the highest burden concentrated in low and middle income countries where nutritional insecurity and socioeconomic disparities remain pervasive. In Southeast Asia, stunting has long-term consequences for cognitive development, academic performance, productivity, and adult health, positioning it as a cross-sectoral development issue rather than merely a nutritional problem (UNICEF, 2015). In Indonesia, the 2022 Indonesian Nutrition Status Survey (SSGI) recorded a prevalence of 21.6%, which despite gradual improvement remains above the global target of <20% and far from the national medium-term target of 14% (Indonesia, 2021). These figures highlight the urgency of evidence-based strategies that address the multidimensional roots of stunting within diverse socioeconomic and environmental contexts (Akombi et al., 2017; Beal et al., 2018).

A substantial body of research has highlighted various determinants of stunting, including household income, maternal education, parenting and feeding practices, child dietary diversity, sanitation, and access to health services (Akombi et al., 2017; Beal et al., 2018). Although these studies provide important insights, many rely on classical statistical models such as linear regression and logistic regression, which tend to assess variables individually rather than capturing how multiple factors interact simultaneously within a causal system. Stunting is inherently multifactorial, shaped by intertwined nutritional, socioeconomic, environmental, and behavioral influences that evolve over time (Picauly et al., 2023). Because conventional analytical approaches often assume linear relationships, multivariate normality, and large sample sizes, their ability to represent complex causal pathways is limited (Byrne, 2010; Kline, 2016; Lei & Wu, 2007). Consequently, there remains a methodological gap in modelling the simultaneous direct and indirect pathways through which diverse risk factors affect child nutritional outcomes in heterogeneous populations.

Despite increasing recognition that stunting results from interdependent determinants, empirical studies employing modelling frameworks capable of capturing these relationships remain limited. Existing work on stunting predominantly utilizes frequentist structural equation modelling, with very few studies integrating Bayesian inference to analyze direct, indirect, and total effects in a unified system (Rahman et al., 2020). This represents a significant research gap, as Bayesian approaches are better able to accommodate non-normal data, small or moderate sample sizes, strong prior knowledge, and uncertainty quantification conditions frequently encountered in public health nutrition research (Gelman et al., 2013; Lee, 2012). The novelty of this study lies in addressing this empirical and methodological gap by constructing an integrative causal framework that simultaneously models economic status, caregiving practices, child diet, and nutritional status using Bayesian Path Analysis. Through this contribution, the study advances current knowledge by offering a more flexible, robust, and realistic representation of how multiple determinants interact to shape stunting.

Path analysis provides a conceptual and analytical foundation for modelling complex causal systems by estimating the magnitude and direction of direct and indirect relationships among variables (Fernandes & Solimun, 2021). Within this framework, variables are classified as exogenous, mediating endogenous, and purely endogenous, allowing researchers to examine how upstream social and economic conditions influence intermediate caregiving or dietary processes before ultimately affecting child health outcomes. While path analysis has been widely applied in social and health sciences, its classical formulation is sensitive to violations of multivariate normality, measurement error, and sample size requirements, which are common in stunting-related research (Byrne, 2010; Kline, 2016). Empirical studies using the classical approach also tend to treat relationships linearly, overlooking nonlinearity, prior expert knowledge, and parameter uncertainty (Lei & Wu, 2007). These limitations create the need for an alternative analytic strategy that can provide more reliable inference under realistic data conditions encountered in field-based public health studies.

Bayesian Path Analysis offers several advantages for addressing these challenges, as it integrates prior information with empirical data through Bayes' Theorem to generate full posterior distributions of model parameters (Gelman et al., 2013; Lee, 2012). This approach accommodates small samples, outliers, and non-normal distributions, making it highly suitable for stunting research where data quality and completeness often vary across regions. Bayesian estimation also provides credible intervals that are directly interpretable in probability terms, enabling clearer decision-making for policymakers (Qiu & Li, 2025). Additionally, model validation can be conducted using posterior predictive checks, which yield more nuanced assessments of model fit under uncertain data conditions. Given the multidimensional and context-dependent nature of stunting determinants, Bayesian Path Analysis represents an analytically rigorous and conceptually coherent method for examining how socioeconomic, behavioral, and nutritional factors jointly influence child outcomes (Rahman et al., 2020).

Building on these considerations, this study aims to develop and apply a Bayesian Path Analysis framework to identify and quantify the direct, indirect, and total effects among economic status, parenting practices, child dietary patterns, and child nutritional status in Indonesia. By integrating diverse determinants into a unified causal system and estimating the model through Bayesian inference, this research contributes both methodological and substantive advances to the field of public health nutrition. Methodologically, it demonstrates the capacity of Bayesian estimation to produce stable, flexible, and uncertainty-aware parameter estimates under realistic field data conditions (Gelman et al., 2013; Lee, 2012). Substantively, it provides a more holistic understanding of stunting pathways that can inform targeted and multisectoral intervention strategies, aligned with national stunting reduction priorities and international best practices (Picauly et al., 2023; UNICEF, 2015). This integrated perspective is expected to strengthen evidence-based policymaking toward reducing the persistence of stunting in Indonesia.

B. METHODS

1. Research Design

This study employed a quantitative explanatory design to examine causal relationships among economic level, children's eating patterns, and children's nutritional status. The analysis used Bayesian Path Analysis, a statistical modelling approach that allows for the estimation of both direct and indirect effects within a multidimensional framework. This method was selected because it can incorporate prior information, handle complex causal structures, and provide more interpretable probability-based estimates compared to frequentist approaches (Gelman et al., 2013; Lee, 2012).

2. Location and Time of Research

The research was conducted in Dadapan Village, Wajak District, Indonesia, using secondary data collected in 2024 as part of a prior community-based nutrition survey. Dadapan Village was selected due to its representation of typical rural demographics with a moderate prevalence of stunting in children under five, reflecting common socioeconomic characteristics of East Java.

3. Population and Sample

The population consisted of households with children under five years old in Dadapan Village. A total of 100 respondents were selected using judgment sampling based on the following inclusion and exclusion criteria:

a. Inclusion Criteria:
   1) Households with at least one child under the age of five.
   2) Parents or primary caregivers of children under five who were willing to participate in the study.
   3) Respondents who provided informed consent to participate.

b. Exclusion Criteria:
   1) Households with children over the age of five.
   2) Parents or caregivers who were not the primary decision-makers regarding children's nutrition.
   3) Respondents who refused to provide informed consent.

These criteria were applied to ensure that the sample was representative of the target population and that the data collected was relevant to the research objectives.

4. Research Variables and Indicators

The study analyzed three latent variables measured using a Likert scale, each with its corresponding indicators (Table 1).

Table 1. Research Variables and Indicators

Variable	Indicators
Economic Level (X_1)	Family Income ($X_{1,1}$), Family Expenses ($X_{1,2}$)
Children's Eating Patterns (Y_1)	Menu Preparation ($Y_{1,1}$), Processing ($Y_{1,2}$), How to Feed ($Y_{1,3}$)
Child Nutritional Status (Y_2)	Types of Food ($Y_{2,1}$), Total Food ($Y_{2,2}$)

5. Research Framework

The conceptual model (Figure 1) depicts the hypothesized causal pathways, where economic level influences children's eating patterns and nutritional status both directly and indirectly.

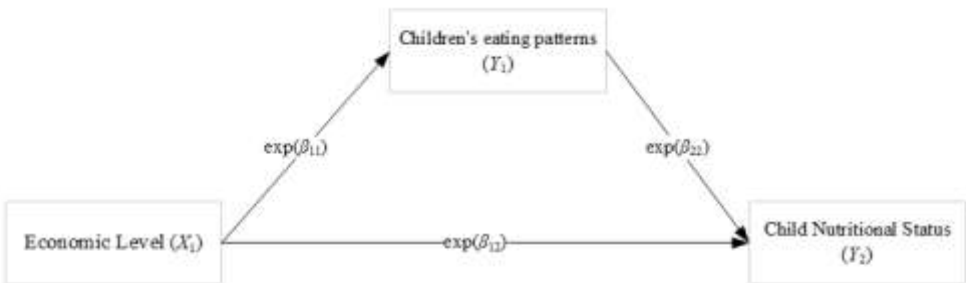

Figure 1. Research Conceptual Model

6. Data Collection

The dataset was derived from a validated questionnaire developed by the original study team. The instrument included a series of indicators designed to measure the key variables in the study, such as economic level, children's eating patterns, and child nutritional status. Each indicator was assessed using a 5-point Likert scale, ranging from "Strongly Disagree" to

"Strongly Agree" for attitudinal questions, and numerical scales for others (e.g., income level, food frequency).

Prior to implementation, the instrument underwent reliability and validity testing. Reliability was assessed using Cronbach's alpha to evaluate the internal consistency of the scales, with values above 0.7 indicating acceptable reliability. Validity was tested through content validity (ensuring the instrument covered all relevant aspects of the variables) and construct validity (using factor analysis to confirm the factor structure). The data were anonymized, and the variables were coded and entered into R statistical software for analysis.

7. Bayesian Approach

The Bayesian approach is a statistical method that utilizes the principle of Bayes' Theorem to integrate preliminary information with observed data (*likelihood*), resulting in parameter estimation through *posterior* distribution that reflects the current level of confidence in the parameter (Alvares et al., 2025). In path analysis, this approach is more flexible than classical methods as it can handle small sample sizes, abnormal data, and nonlinear relationships (Gelman et al., 2013). Mathematically, Bayes' Theorem is stated as follows Equation (1):

$$\pi(\theta|X) = \frac{P((X|\theta)\pi(\theta)}{P(X)} \propto P((X|\theta)\pi(\theta) \tag{1}$$

where is the $\pi(\theta|X)$ *posterior* distribution, is $\pi(\theta)$ *prior*, is $P((X|\theta)$ *likelihood*, and is $P(X)$ *a marginal likelihood* that acts as a normalizing factor. It is this posterior distribution that is used to infer the parameters after considering the actual data (Gelman et al., 2013); (Bernardo & Smith, 2004).

8. Operational Steps of Bayesian Path Analysis

The following steps outline the specific procedures used to implement the Bayesian Path Analysis model, detailing the structural model, prior selection, likelihood function, MCMC procedure, and convergence criteria.

a. Structural Model: The model includes three types of variables:
   1) Exogenous: Economic Level (X_1),
   2) Endogenous Pure: Child Nutritional Status (Y_2),
   3) Endogenous Mediating: Children's Eating Patterns (Y_1).

b. Prior: Informative priors were selected based on prior studies to align the model with prior knowledge and available data (Box & Tiao, 2011).
c. Likelihood Function: The likelihood function is used to update prior beliefs and generate posterior distributions. The likelihood is expressed as the product of distributions for each observation(Gelman et al., 2013).
d. MCMC Procedure: Gibbs sampling was employed to generate samples from the posterior distribution. MCMC was implemented with 10,000 iterations, using 2,000 burn-in iterations to ensure convergence (Ghosh et al., 2006).

e. Convergence Criteria**:** Convergence was assessed using trace plots**,** autocorrelation plots**,** and Gelman-Rubin diagnostic ($\hat{R}$)**.** Convergence is considered valid when $\hat{R}$ approaches 1 and trace plots show randomness (Astutik & Al., 2023; Schoot & al., 2021).

9. Posterior Distribution and Inference

Posterior distribution is a key component in Bayesian inference, as it provides up-to-date information regarding the distribution of parameters after considering actual data. Point estimation, credible intervals, and probability-based decision-making are carried out based on this distribution (Astutik et al., 2023). In many cases, the posterior distribution cannot be derived analytically so numerical methods such as the *Markov Chain Monte Carlo* (MCMC) are required. Through algorithms such as Metropolis-Hastings or Gibbs Sampling, samples from the posterior distribution can be generated and used to calculate estimates such as posterior means as Equation (3):

$$\hat{I} = \frac{1}{T}\sum_{t=1}^{T} f(\theta^{(t)}) \tag{3}$$

This value represents the expected estimate of the parameters, which is obtained through the average of the MCMC iterations after the convergence is achieved(Ghosh et al., 2006).

10. Credible Interval and HPD

Unlike confidence intervals in the frequency approach, credible intervals provide a direct probabilistic interpretation, for example "there is a 95% confidence that the parameter is within the interval [a, b]" (Eberly & Casella, 2003). One special form is the Highest Posterior Density (HPD) interval, which is the interval with the highest probability that includes the most likely parameter values, especially useful when the posterior distribution is asymmetrical (De Santis & Gubbiotti, 2021).

11. Convergence Checks

To ensure the validity of the inference results, it is important to evaluate the convergence of the MCMC chain. This examination can be done visually or quantitatively. Visualizations such as *trace plots* are used to ensure that the chain has achieved stationaryness. *Density plots* help evaluate posterior forms of distribution, while *autocorrelation plots* are used to assess independence between iterations (Schoot & al., 2021); (Astutik et al., 2023). Non-converging chains can result in biased and unstable estimates, so determining the *burn-in* period and chain length is an important aspect of MCMC implementation.

12. Model Feasibility Measures

The assessment of the feasibility of the model in the Bayesian approach is an important stage to ensure that the model built is not only in accordance with the data, but also has proportionate complexity. In this study, three main measures were used to assess the feasibility of the model, namely the Deviance Information Criterion (DIC), Root Mean Square Error (MSE), and Coefficient of Determination These three measures complement each other in providing information about the accuracy, efficiency, and explanatory power of the model (R^2).

a. Deviance Information Criterion (DIC)
   DIC is one of the model feasibility measures commonly used in Bayesian approaches, especially when parameter estimation is performed using the Markov Chain Monte Carlo (MCMC) method. This measure combines two important aspects, namely the model's fit for data (*model fit*) and model complexity (*model complexity*). DIC allows comparisons between several candidate models, thus facilitating the selection process of the best model (Spiegelhalter et al., 2002); (Cain & Zhang, 2019). DIC is calculated based on the following formula as Equation (6):

$$\boldsymbol{DIC = -2\log\left(p(x|\overline{\beta})\right) + 2p_D} \quad (6)$$

   The smaller the DIC value, the better the model, as it reflects the balance between the model's suitability to the data and the simplicity of the model's structure. The interpretation criteria for the absolute difference in DIC between models are presented in Table 2 below.

Table 2. Interpretation of DIC Values in Bayesian Model Evaluation

DIC value	Model Selection
< 5	The difference in performance between models is considered small, so a simpler model is chosen.
5 – 10	There is quite strong evidence that models with smaller DICs are better.
> 10	There is strong evidence that models with smaller DIC values are superior.

b. Root Root Mean Square Error (MSE)
   RMSE is used to measure the mean of the square of the error between the predicted value and the actual value. The smaller the RMSE value, the better the model's ability to represent the data. RMSE in the Bayesian approach is calculated based on expectations of the difference in the square of the estimated parameter with the actual value, as shown in the following formula (Sayed, 2023)as Equation (7):

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}} \quad (7)$$

   A low MSE indicates that the model has minimal prediction errors and can be used as an indicator of the model's numerical goodness.

c. Coefficient of Determination (R^2)
   The coefficient of determination is used to measure the proportion of variability in dependent variables that can be described by the model. In the context of a structural model, the total coefficient of determination indicates the extent to which the entire path

structure is able to explain endogenous variables. The total determination coefficient is calculated as follows Equation (8):

$$\boldsymbol{R^2_{T,adj} = 1 - \prod_{k=1}^{K}\left(1 - R^2_{k,adj}\right)} \qquad (8)$$

The interpretation of the value of the determination coefficient is presented in Table 3.

Table 3. Determinant Coefficient Interpretation Criteria

No	R^2	Criterion
1	$< 0,5$	Not Good
2	$0,5 - 0,75$	Enough
3	$> 0,75$	Good

C. RESULT AND DISCUSSION

1. Characteristics of Respondent

Table 4 presents the descriptive statistics of the observed indicators, including family income, family expenses, menu preparation, food processing, feeding methods, types of food consumed, and total food intake.

Table 4. Characteristics of Respondents

Indicators	Mean±SD	Min-Max
Family Income ($X_{1,1}$)	3.25±0.84	1-5
Family Expenses ($X_{1,2}$)	3.40±0.79	1-5
Menu Preparation ($Y_{1,1}$)	3.15±0.81	1-5
Processing ($Y_{1,2}$)	3.22±0.83	1-5
How to Feed ($Y_{1,3}$)	3.30±0.85	1-5
Types of Food ($Y_{2,1}$)	3.18±0.80	1-5
Total Food ($Y_{2,2}$)	3.28±0.78	1-5

The descriptive results indicate that all indicators fall within the moderate category, with mean scores ranging from 3.15 to 3.40 on a 1-5 scale. Economic indicators, namely family income and expenses, show slightly higher averages compared to feeding-related indicators, suggesting relatively stable economic conditions among respondents. However, feeding practice indicators, such as menu preparation, food processing, and feeding methods, remain moderate, indicating that improvements in caregiver practices are needed to optimize children's dietary quality. Similarly, consumption-related indicators including types of food and total food intake are moderate, highlighting that dietary diversity and intake have not yet reached optimal levels to fully support child nutritional status.

2. Measurement Model Results

The measurement model was assessed using Bayesian estimation. All factor loadings exceeded 0.50, indicating adequate construct validity, as shown in Table 5.

Table 5. Factor Loadings of Research Indicators

Variable	Indicators	Loading
Economic Level (X_1)	Family Income ($X_{1,1}$)	0.812
	Family Expenses ($X_{1,2}$)	0.798
Children's Eating Patterns (Y_1)	Menu Preparation ($Y_{1,1}$)	0.765
	Processing ($Y_{1,2}$)	0.781
	How to Feed ($Y_{1,3}$)	0.754
Child Nutritional Status (Y_2)	Types of Food ($Y_{2,1}$)	0.783
	Total Food ($Y_{2,2}$)	0.802

The construct validity of all indicators is strong, with factor loadings exceeding 0.50. The economic level construct showed the highest loadings, confirming that family income and expenses effectively measure household economic capacity. The indicators related to children's eating patterns and nutritional status also loaded strongly on their respective latent variables, validating that these variables appropriately capture feeding behaviors and dietary adequacy in relation to child nutrition.

3. Structural Model Result

Figure 2 shows the final structural model of the Bayesian Path Analysis, illustrating the relationships between variables.

Figure 2. Final Bayesian Path Model

4. Path Coefficient Estimation

The direct, indirect, and total effects between variables are presented in Table 6.

Table 6. Path Coefficient Estimates

Path	Estimate (β)	95% Credible Interval
$X_1 \rightarrow Y_1$	0.394	(0.239;0.545)
$Y_1 \rightarrow Y_2$	0.587	(0.458;0.706)
$X_1 \rightarrow Y_2$	0.201	(0.037;0.372)

All structural paths in the model were statistically supported under the Bayesian framework, as indicated by 95% credible intervals that exclude zero. Economic level shows a positive and meaningful effect on children's eating patterns (β=0.394), demonstrating that improvements in household financial capacity are associated with better feeding behaviors. The pathway from children's eating patterns to nutritional status (β=0.587) exhibits the strongest effect, emphasizing the critical role of dietary practices in determining stunting-related outcomes. Economic level also influences nutritional status directly (β=0.201), although the effect size is smaller compared to the indirect pathway. These findings suggest that while economic improvements contribute to better child health, their impact is substantially amplified when translated into improved dietary practices.

5. Estimation of Path Parameters with Bayesian Approach

Table .7 Estimation of Path Parameters with Bayesian Approach

Line	Posterior Average	Std. Deviation
$X_1 \rightarrow Y_1$	0.394	0.079
$Y_1 \rightarrow Y_2$	0.587	0.062
$X_1 \rightarrow Y_2$	0.201	0.089

All Bayesian path estimates were positive, demonstrating meaningful relationships among the variables. The children's eating patterns ($Y_1 \rightarrow Y_2$, β = 0.587) had the strongest influence on nutritional status, while the economic level ($X_1 \rightarrow Y_1$, β = 0.394) moderately affected feeding practices. The direct effect of economic level on nutritional status ($X_1 \rightarrow Y_2$, β = 0.201) was smaller, highlighting that improvements in nutrition are largely mediated through caregiver feeding behaviors.

6. MCMC Validation for Bayesian Path Model Parameters

Table 8. Summary of MCMC Validation for Bayesian Path Model Parameters

Parameters	Posterior Average	R-hat	Effective Sample Size (ESS)
β ($X_1 \rightarrow Y_1$)	0.394	0.079	1,237
β ($Y_1 \rightarrow Y_2$)	0.587	0.062	1,416
β ($X_1 \rightarrow Y_2$)	0.201	0.089	1,118

The MCMC diagnostics indicate that all Bayesian path estimates have converged properly. The R-hat values for all parameters are below 1.1, confirming chain convergence, and the Effective Sample Sizes (ESS) exceed 1,000, indicating sufficient independent samples for reliable posterior estimation. These results demonstrate that the posterior means of the path coefficients (X1→Y1, Y1→Y2, X1→Y2) are stable and robust, supporting the validity of the Bayesian path analysis results.

7. Model Quality Evaluation

Table 9. Results of Bayesian Path Model Quality Evaluation

Evaluation Size	Value
Deviance Information Criterion (DIC)	1051.10
Root Mean Square Error (RMSE)	0.039
Total Determination Coefficient	86.2%

The Bayesian path model demonstrates a good fit to the data. The Deviance Information Criterion (DIC = 1051.10) and low Root Mean Square Error (RMSE = 0.039) indicate strong model adequacy, while the high total determination coefficient (86.2%) shows that the model explains a substantial portion of the variance in child nutritional status. These metrics collectively confirm that the selected variables and specified paths effectively capture the key determinants of stunting in this study.

8. Implications and Comparison with Previous Studies

This study adds value by using the Bayesian approach, which provides more robust estimates, especially in the presence of small sample sizes and complex data structures. Unlike frequentist approaches, credible intervals in Bayesian analysis offer a direct probabilistic interpretation, allowing policymakers to make decisions based on confidence levels (Eberly & Casella, 2003). The MCMC procedure and DIC further validate the model, ensuring that the results are stable and reliable. In comparison to previous studies (Akombi et al., 2017), which primarily used frequentist methods, the results of this study align with findings that suggest economic factors influence feeding practices and that children's eating patterns play a significant role in improving nutritional outcomes. However, this study provides stronger statistical evidence for the mediating role of dietary practices through the Bayesian framework, reinforcing the importance of improving feeding behaviors to address stunting.

Practical Implications and Policy Recommendations: Given the significant role of dietary practices in improving nutritional status, policymakers should prioritize interventions aimed at enhancing caregiver feeding behaviors. Programs that focus on nutrition education for parents, combined with improvements in household economic conditions, can effectively reduce stunting rates. Additionally, future policy should consider the multidimensional nature of stunting and design integrated strategies that address both economic stability and nutritional education.

D. CONCLUSION AND SUGGESTIONS

This study makes several scientific contributions in understanding the causal mechanisms of childhood stunting. Theoretically, it advances the literature by integrating economic level, children's eating patterns, and child nutritional status within a Bayesian Path Analysis framework, providing a more flexible and robust approach to modelling complex causal relationships compared to traditional methods. Methodologically, it demonstrates the value of Bayesian estimation in handling small sample sizes and complex, non-linear relationships in public health research, offering an alternative to conventional frequentist approaches. Practically, the findings underscore the importance of combining economic empowerment with improved dietary practices to reduce stunting, emphasizing that policy interventions must address both economic conditions and caregiving behaviors to be effective.

The study also highlights the importance of children's diet as a dominant mediator between economic level and nutritional status, offering new insights into how household economic improvements can lead to better child health outcomes when accompanied by enhanced feeding practices. The strong performance of the Bayesian model, confirmed through convergence diagnostics and goodness-of-fit evaluation, further supports the validity of the identified causal relationships.

However, this study has certain limitations. The sample was drawn from a specific rural area (Dadapan Village), which may limit the generalizability of the findings to other regions or populations with different socioeconomic characteristics. Additionally, the study focused on a limited set of variables, excluding other potential determinants of stunting, such as maternal nutritional status, health service access, and environmental factors. These limitations should be considered when interpreting the findings. For future research, it is recommended to expand the model by incorporating additional determinants of stunting, such as maternal health, health service utilization, sanitation, and behavioral factors. These variables would provide a more comprehensive understanding of the multifactorial causes of stunting and strengthen the robustness of the model. Furthermore, future studies could explore the use of advanced Bayesian modelling techniques on larger and more diverse populations to increase the generalizability of the results and refine policy recommendations.

ACKNOWLEDGEMENT

The authors would like to thank all parties involved who have contributed to the completion of this research.

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