

## Prevalence and Determinants of Morbidity among Under-Five Children in Bangladesh: A Bayesian Approach Using Demographic and Health Survey Data

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### Abstract

Child morbidity remains a major barrier preventing Bangladesh from achieving the Sustainable Development Goals (target 3.2), despite notable reductions in child mortality. Consequently, greater attention to child health-related conditions is essential. Accordingly, this study seeks to examine the prevalence of morbidity among children under five years of age in Bangladesh and to identify the factors associated with it. This study utilized secondary cross-sectional data from the Bangladesh Demographic and Health Survey 2017–2018, which employed a two-stage systematic sampling framework to collect information. Following tests of association, a Bayesian binary logistic regression model was applied to determine significant risk factors for morbidity among under-five children, and convergence of the simulation was assessed using trace plots. The prevalence findings indicate that more than one-third of under-five children in Bangladesh experienced at least one child health-related condition, with the highest proportion of morbidity observed in the Barisal division (approximately 42%). Results from the Bayesian logistic regression suggest that increasing child age and higher levels of maternal education are linked to a reduced likelihood of child morbidity in Bangladesh. Furthermore, male children exhibited a 7% greater risk of morbidity compared with female children. In addition, underweight children were found to have a 31% higher risk of fever, diarrhea, or acute respiratory infection (ARI)-related conditions than their counterparts. The findings of this study demonstrate that child morbidity continues to pose a serious challenge in Bangladesh. Therefore, policymakers should prioritize interventions targeting key risk factors, including maternal education and child nutritional status.

**Keywords:** Child morbidity, Child nutritional, Children under five, Bayesian logistic regression

### Introduction

Child morbidity refers to the experience of ill health resulting from particular diseases or conditions and reflects the burden of health problems affecting children's well-being [1]. Infectious illnesses such as pneumonia, diarrhea, and malaria remain the leading causes of death among children under five worldwide [2]. Disturbingly, nearly two-thirds of global child deaths occur in low-income and underdeveloped countries [3].

Consequently, reducing child morbidity in low- and middle-income countries is an urgent priority, particularly in regions struggling to meet the Sustainable Development Goal related to child mortality reduction (target 3.2), which aims to reduce under-five mortality to 25 deaths per 1,000 live births by 2030 [4].

Although global under-five mortality has declined substantially in recent decades [5], progress in developing and underdeveloped areas, including Africa and Bangladesh, has been inadequate [6]. According to the World Health Organization, Sub-Saharan Africa and South Asia together account for roughly 80% of child deaths worldwide [5]. A recent study from Tanzania reported an estimated 63 child deaths per 1,000 live births in 2016, despite a 42% decline [7]. Another study conducted in Tanzania using data from 35 hospitals identified respiratory distress as the leading cause of

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early neonatal mortality, responsible for about 21% of cases [8].

Bangladesh continues to face considerable challenges related to child morbidity, with a large number of child deaths reported each year. A nationally representative survey, the Bangladesh Demographic and Health Survey, estimated that approximately 45 children die before reaching their fifth birthday [9]. Pneumonia alone accounts for about 19% of annual child deaths in Bangladesh [10]. Another study from Bangladesh reported that nearly 17% of children under five experienced diarrhea, while over 20% suffered from colds and fever [3]. Fever is also recognized as a common pediatric condition that places a substantial burden on the global public health system [11]. Collectively, these findings highlight the necessity of sustained and comprehensive efforts to further reduce child mortality and enhance child well-being in order to meet the SDG targets.

Promoting child well-being can improve survival outcomes, and strengthening child health remains a key policy priority for governments, particularly in developing nations [12]. Therefore, conducting research on child health issues and identifying influential risk factors for morbidity is essential. Numerous studies have investigated child morbidity prevalence and associated factors using traditional binary logistic regression methods [13, 14]. More recently, a study in Bangladesh employed a machine-learning-based logistic classifier to determine risk factors for child morbidity [15]. However, classical estimation methods relying on maximum likelihood may be biased when sample sizes are small [16], making Bayesian approaches a suitable alternative. Evidence from prior research suggests that Bayesian inference can yield more accurate estimates than classical likelihood-based methods when prior information is available [17]. Although many studies adopt flat or non-informative priors in Bayesian analyses, this study differs by applying informative priors [18, 19]. By incorporating informative priors derived from historical data, the accuracy of the model was enhanced, and parameter estimates were improved. Consequently, the Bayesian results obtained in this study are more robust and reliable than those produced by conventional classical inference techniques [20]. Despite extensive research on child morbidity, limited attention has been given to the application of Bayesian methods in the Bangladeshi context. To address this gap, this study pursues two main objectives: first, to assess the influence of demographic

factors on child morbidity; and second, to identify associated risk factors using Bayesian logistic regression with informative prior distributions.

A comprehensive understanding of child morbidity and its determinants is vital for effective policymaking and targeted interventions. Addressing child morbidity, particularly in vulnerable settings such as Bangladesh, has the potential to substantially reduce global child mortality. This study aims to contribute meaningful evidence to the field of child health, supporting progress toward the SDG targets and advancing the overall well-being of children worldwide.

## Materials and Methods

### *Data source*

This investigation was carried out using data from the nationally representative Bangladesh Demographic and Health Survey (BDHS) 2017–2018. The survey was implemented in Bangladesh with financial support from the United States Agency for International Development (USAID). The complete dataset is openly accessible and can be downloaded from: <https://dhsprogram.com/data/available-datasets.cfm>.

### *Sample design and sample size*

The BDHS employed a stratified two-stage sampling methodology to obtain survey participants. At the initial stage, a total of 675 Enumeration Areas (EAs) were selected. Subsequently, 30 households were systematically chosen from each EA during the second stage. Overall, the 2017–2018 BDHS included 20,250 residential households. From these households, 8,421 mothers or primary caregivers of living children under five years of age were successfully interviewed.

### *Dependent variable*

Morbidity among children under five years of age was evaluated based on the presence of three common childhood illnesses: fever, diarrhea, and acute respiratory infection (ARI). Since the study population consisted of mothers or caregivers of under-five children, respondents were asked whether their child had experienced any of these three conditions. The definitions, response categories, and coding schemes for these morbidity indicators are presented in **Table 1**.

**Table 1.** The module of under-five child morbidity

Illness	Definition	Coding
Fever	Experienced fever during the two weeks preceding the survey	1 = Yes 0 = No
Diarrhea	Suffered from diarrhea in the two weeks prior to the survey	1 = Yes 0 = No

ARI	Exhibited symptoms of respiratory difficulty in the two weeks before the survey	1 = Yes 0 = No
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A child who experienced at least one of the aforementioned conditions was classified as having morbidity; otherwise, the child was categorized as not having morbidity [15]. Consequently, the dependent variable used in this study was binary and is defined as:

$$\text{Child Morbidity} = \begin{cases} 1; \text{Yes, child is being experienced at least one health problem} \\ 0; \text{No, child is not being experienced any of these health problems} \end{cases} \quad (1)$$

#### Independent variable

Several sociodemographic characteristics that may influence morbidity among children younger than five years in Bangladesh were selected as explanatory

variables. A detailed description of these independent variables is provided in **Table 2**.

**Table 2.** Description of independent variables

Variable	Categories
Age of child (months)	<12, 12–35, 36–59
Sex of child	Male, Female
Child underweight	Yes, No
Birth type	Single, Multiple
Mother's educational level	None, Primary, Secondary, Higher
Mother's employment status	Yes, No
Household wealth index	Poor, Middle, Rich
Religious affiliation	Muslim, Others
Exposure to mass media	Yes, No
Place of residence	Urban, Rural

#### Statistical analysis and software

The analytical strategy of this study consisted of three sequential stages: descriptive analysis, bivariate analysis, and multivariate analysis. Descriptive statistics were used to summarize the percentage distributions of all

study variables. To assess associations between selected explanatory variables and under-five child morbidity, bivariate analysis was conducted. The chi-square test was applied to evaluate the relationship between categorical variables. The chi-square statistic ( $X^2$ ) is defined as:

$$X^2 = \sum \frac{(\text{Observed frequency} - \text{Expected frequency})^2}{\text{Expected frequency}} \sim X^2_{(r-1)(c-1)} \quad (2)$$

where  $r$  indicates the number of categories of the independent variable and  $c$  denotes the number of categories of the dependent variable.

For multivariate analysis, logistic regression techniques were used to estimate the effects of explanatory variables on morbidity status among under-five children. Specifically, Bayesian binary logistic regression with

informative prior distributions was employed to identify significant risk factors for child morbidity in Bangladesh. The traditional binary logistic regression model is commonly applied to model the probability of a dichotomous outcome as a function of explanatory variables [13, 14]. However, Bayesian binary logistic regression incorporates prior information, which can result in more efficient and precise estimates than

classical estimation approaches [16]. Accordingly, Bayesian binary logistic regression is formulated using Bayes' theorem, which can be expressed as, "".

$$f(\beta | Y_i, X_{ip}) = f(Y_i | \beta) \times f(\beta) \quad (3)$$

Here,  $f(\beta | Y_i, X_{ip})$  denotes the posterior distribution of the parameter vector  $\beta$ ,  $f(Y_i | \beta)$ , represents the likelihood function, which expresses the probability of observing the data ( $Y_i$ ) given particular values of the unknown parameters( $\beta$ ); and  $f(\beta)$  refers to the prior distribution, reflecting prior beliefs or existing knowledge about the parameter  $\beta$ , which may be derived from earlier studies. In this analysis, child morbidity  $Y_i$  is treated as a binary outcome variable, while  $X_{i1}, \dots, X_{ip}$  represent a collection of explanatory variables. The response variable is assumed to follow a Bernoulli distribution with parameter  $\pi_i$ . Accordingly, the corresponding link function can be expressed as,

$$\text{logit}(\pi_i) = \log \frac{\pi_i}{1 - \pi_i} = \beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip} \quad (4)$$

where,

$$\pi_i = \frac{\exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})}{1 + \exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})} \quad (5)$$

Using the value of  $\pi_i$ , the likelihood function  $f(Y_i | \beta)$  can be written as (for a given sample size  $n$ ,

$$f(Y_i | \beta) = \prod \binom{M_i}{Y_i} (\pi_i)^{Y_i} (1 - \pi_i)^{M_i - Y_i} \quad (6)$$

Here,  $\beta_i$  represents unknown parameters that are estimated through the specification of prior distributions. In Bayesian analysis, two main categories of prior information are typically considered: (a) flat or non-informative priors and (b) informative priors. In the present study, an informative prior was adopted, referred to as a "historical prior distribution," which was derived from earlier survey data (specifically, the Bangladesh Demographic and Health Survey 2014, available at <https://dhsprogram.com/data/available-datasets.cfm>).

The use of such historical priors can enhance the precision of estimates for unknown parameters [20, 21]. Accordingly, the most commonly applied prior forms for logistic regression coefficients were employed, which can be written as,

$$\beta_j \sim N(\mu_j, \sigma_j^2). \quad (7)$$

To obtain estimates for  $\mu$  and  $\sigma_j^2$ , unknown parameters were first derived from earlier survey data using the maximum likelihood estimation technique. Following this, a parametric bootstrap resampling approach was applied to efficiently construct the Bayesian prior distributions [22].

In many applied settings, deriving an exact analytical form of the posterior distribution is impractical, particularly when models become statistically complex. Consequently, approximation techniques such as Markov Chain Monte Carlo (MCMC) simulations are widely adopted to estimate marginal posterior distributions for unknown parameters. Through repeated sampling from the posterior distribution, MCMC enables reliable statistical inference and parameter estimation. Readers interested in a detailed explanation of computational strategies for estimating posterior distributions in Bayesian statistics are referred to [23].

Regarding the simulation setup, convergence was achieved after 150,000 iterations for each chain, following an initial burn-in of 500 iterations. Thinning was performed by retaining every 99th sampled value. A total of four Markov chains were run in the analysis. Model estimates are presented as odds ratios together with 95% credible intervals. In Bayesian inference, credible intervals quantify uncertainty around parameter estimates and are obtained directly from the posterior distribution by combining prior information with observed data.

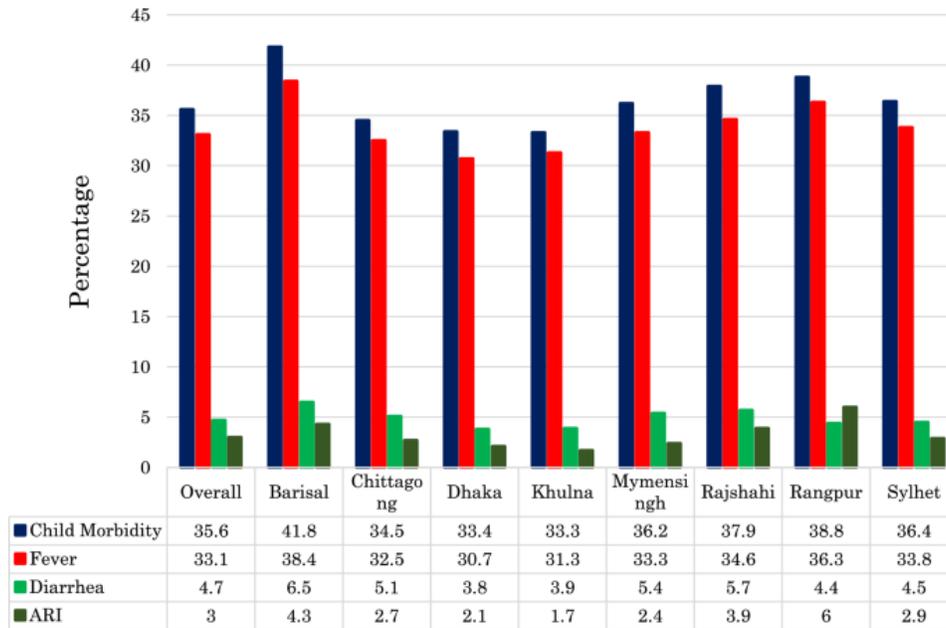
The conventional MCMC estimation procedure was implemented using the "bayesmh" command in STATA version 16, which was used to generate marginal posterior distributions for all parameters.

## Results and Discussion

### *Prevalence of child morbidity*

**Figure 1** depicts the geographic distribution of child morbidity across Bangladesh. Among the 8,421 mothers or caregivers of living children under five years of age included in the sample, 35.6% reported that their child experienced at least one morbidity condition. Fever was identified as the most frequent illness, affecting 33.1% of children, followed by diarrhea (4.7%) and acute respiratory infection (ARI) (3.0%). Regionally, the Barisal division exhibited the highest overall burden of

child morbidity, with a prevalence of 41.8%, along with elevated rates for other morbidity outcomes.



**Figure 1.** Spatial illustration of prevalence of child morbidity in Bangladesh

#### *Association between socio-demographic factors on child morbidity*

**Table 3** displays the percentage distribution of selected socioeconomic and demographic variables among the 8,421 study participants. Most children belonged to the 12–35 month (39.9%) and 36–59 month (38.8%) age categories. Slightly more than half were male (52.1%), while females accounted for 47.9%. The majority of children were not classified as underweight (78.2%), whereas 21.8% were underweight. Nearly all children were single births (98.4%). In terms of maternal education, secondary schooling was reported for 48.5% of mothers, while 28.6% had completed primary education. Most mothers were not engaged in

employment (59.4%). Regarding household economic status, 41.6% of children came from poor households and 39.6% from wealthy households. Most children were raised in Muslim families (92.0%). Access to mass media was reported by 54.7% of households, whereas 45.3% lacked such access. Additionally, a substantial proportion of children resided in rural areas (72.6%), compared with 27.4% living in urban locations. Results from the chi-square ( $X^2X^2$ ) test of independence presented in **Table 3** indicate that child morbidity was significantly associated with child age, sex, underweight status, maternal education level, household wealth index, religion, and place of residence in Bangladesh.

**Table 3.** Percentage distribution and association between selected covariates and child morbidity among under-five children in Bangladesh

Variable	Frequency (%)	No morbidity (%)	Yes morbidity (%)	$\chi^2$ value (p-value)
Age of child (months)				92.26 (<0.001)
< 12	1789 (21.2)	61.6	38.4	
12–35	3363 (39.9)	59.8	40.2	
36–59	3269 (38.8)	70.6	29.4	
Sex of child				6.60 (0.01)
Male	4389 (52.1)	63.1	36.9	
Female	4032 (47.9)	65.8	34.2	

Child underweight				17.21 (<0.001)
Yes	1753 (21.8)	59.5	40.5	
No	6288 (78.2)	64.9	35.1	
Birth type				0.23 (0.63)
Single	8288 (98.4)	64.4	35.6	
Multiple	133 (1.6)	62.4	37.6	
Mother's education				16.83 (<0.001)
None	611 (7.3)	66.6	33.4	
Primary	2407 (28.6)	64.0	36.0	
Secondary	4085 (48.5)	62.8	37.2	
Higher	1318 (15.6)	68.8	31.2	
Mother's working status				2.72 (0.1)
Yes	3415 (40.6)	65.4	34.6	
No	5006 (59.4)	63.7	36.3	
Household wealth index				7.24 (0.03)
Poor	3502 (41.6)	63.6	36.4	
Middle	1587 (18.8)	62.6	37.4	
Rich	3332 (39.6)	66.1	33.9	
Religious affiliation				13.90 (<0.001)
Muslim	7749 (92.0)	63.8	36.2	
Others	672 (8.0)	71.0	29.0	
Access to mass media				1.41 (0.24)
Yes	4609 (54.7)	64.9	36.3	
No	3812 (45.3)	63.7	35.1	
Place of residence				7.28 (<0.01)
Rural	6113 (72.6)	63.5	36.5	
Urban	2307 (27.4)	66.7	33.3	

#### Identify factors contributing to child morbidity using Bayesian logistic regression

A Bayesian binary logistic regression framework, combining likelihood functions with prior information, was applied in this study. Informative prior distributions, referred to as “historical priors,” were derived using data from the Bangladesh Demographic and Health Survey 2014, which were then used to construct the posterior distribution. Parameter estimation was carried out using Markov Chain Monte Carlo (MCMC) simulation based on the Metropolis–Hastings algorithm. Four parallel chains were executed, and convergence was achieved

after 150,000 iterations per chain, following a burn-in of 500 samples and thinning by selecting every 99th iteration.

Findings from the Bayesian analysis presented in **Table 4** indicate that child age exhibited a statistically significant positive association with morbidity. Children younger than 12 months had a 1.51-fold higher likelihood of experiencing morbidity, while those aged 12–35 months showed an approximately 48% increased risk (OR = 1.48, 95% CI: 1.36, 1.58) compared with children aged 36–59 months.

**Table 4.** Odds ratios (OR) and 95% credible interval (95% CI) from Bayesian (informative prior) logistic regression

Variable	Odds Ratio	95% Credible Interval	
		Lower	Upper
Age of child (months)			
< 12	1.51	1.38	1.65
12–35	1.48	1.36	1.58

36–59 (Ref.)	1		
Sex of child			
Male	1.07	1.01	1.15
Female (Ref.)	1		
Child underweight			
Yes	1.31	1.21	1.40
No (Ref.)	1		
Mother's education			
None	1.21	1.04	1.40
Primary	1.30	1.15	1.43
Secondary	1.30	1.19	1.43
Higher (Ref.)	1		
Household wealth index			
Poor	1.03	0.94	1.12
Middle	1.07	0.98	1.19
Rich (Ref.)	1		
Religious affiliation			
Muslim	1.25	1.11	1.39
Others (Ref.)	1		
Place of residence			
Rural	1.03	0.96	1.12
Urban (Ref.)	1		

Ref. = Reference category

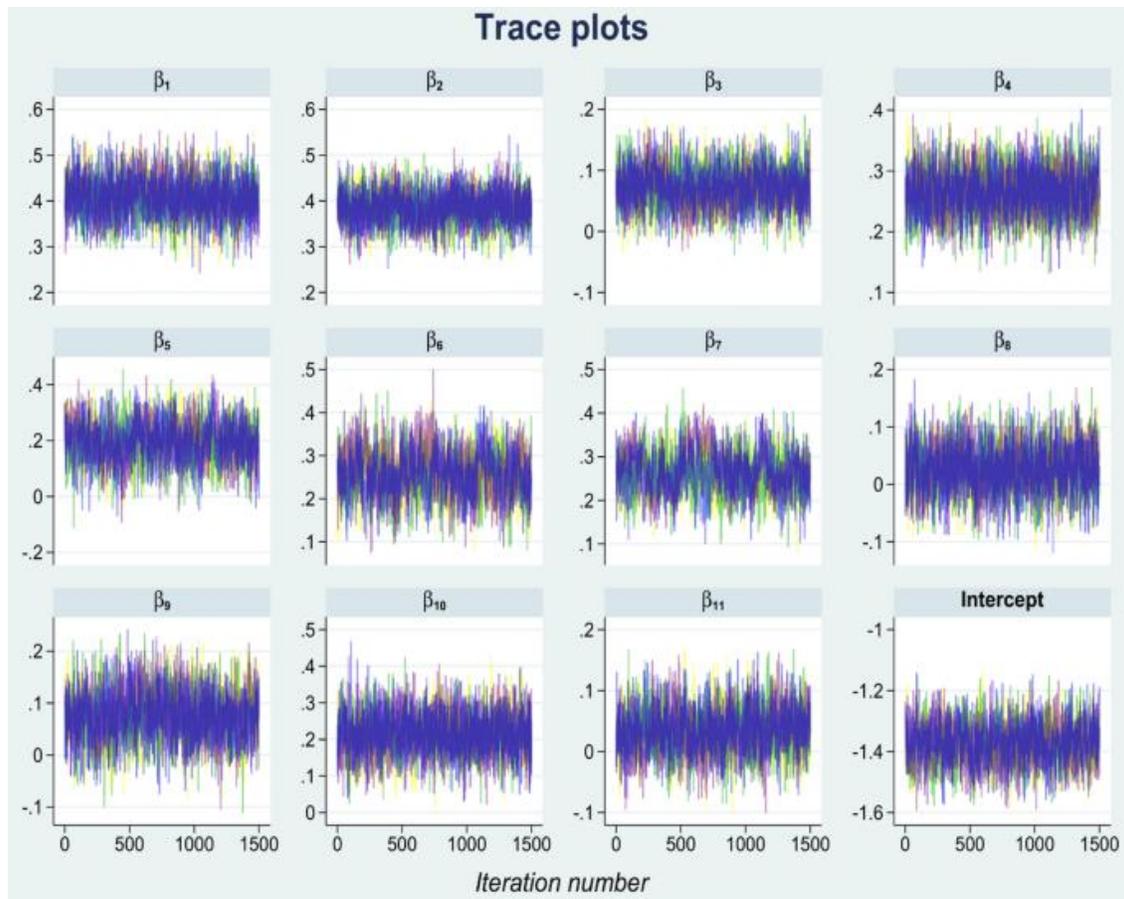
Male children were found to have a significantly higher likelihood of experiencing child morbidity, with an odds ratio of 1.07 compared to female children. Additionally, children who were underweight had 31% greater odds (OR = 1.31, 95% CI: 1.21, 1.40) of suffering from morbidity conditions relative to children with normal weight.

Maternal educational attainment was also significantly associated with child morbidity. Children whose mothers had no formal education faced a 21% increased risk (OR = 1.21, 95% CI: 1.04, 1.40) of developing morbidity conditions. Children whose mothers had either primary or secondary education showed a 1.30-fold higher likelihood of being affected by morbidity.

Bayesian analysis further indicated that children from Muslim families had a 25% higher chance (OR = 1.25, 95% CI: 1.11, 1.39) of experiencing child morbidity compared to children from families of other religious affiliations.

To assess the convergence of the MCMC sampling, trace plots were utilized, as these visually demonstrate the

stability and mixing of the sampled distributions. **Figure 2** illustrates the posterior distributions for model coefficients under the informative normal priors. The trace plots indicate proper mixing of the samples, confirming the success of the Bayesian inference and the reliability of the informative priors. Convergence of the Markov chains was further evaluated using the Gelman-Rubin diagnostic. If the Gelman-Rubin statistic ( $R_{cR_c}$ ) is below 1.1 for all parameters ( $\beta$ ), convergence can be considered achieved [24]. In this study,  $R_{cR_c} < 1.1$  for all  $\beta_i, i = 1, \dots, 11$ , confirming full convergence. Here,  $\beta_1$  = <12 months,  $\beta_2$  = 12–35 months,  $\beta_3$  = male children,  $\beta_4$  = underweight children,  $\beta_5$  = uneducated mother,  $\beta_6$  = primary educated mother,  $\beta_7$  = secondary educated mother,  $\beta_8$  = poor wealth status,  $\beta_9$  = middle wealth status,  $\beta_{10}$  = Muslim family,  $\beta_{11}$  = rural residence.



**Figure 2.** Trace plots for model parameters of the Bayesian logistic regression model with informative prior

Bangladesh has made notable strides in child health over recent decades [25], leading to a reduction in under-five mortality by more than 65% between 1990 and 2017 [26]. However, progress in reducing child morbidity has been less successful. This highlights that child health challenges persist and require continued policy attention. The primary objective of this study was to identify key determinants of child morbidity using Bayesian logistic regression with informative priors, providing evidence to support health policy decisions. The MCMC simulation and corresponding trace plots confirm the validity of the Bayesian inference and the convergence of the chains. The study revealed that over one-third of children in Bangladesh experienced at least one morbidity condition, such as fever, diarrhea, or ARI. These findings are consistent with previous national studies [27], confirming the persistent prevalence of these conditions. Regional analysis showed that Barisal division had the highest morbidity rates, which may be linked to disparities in healthcare access for common childhood illnesses [28].

Several socio-demographic factors were found to influence child morbidity significantly. Age was a major determinant: children under 12 months and those aged 12–35 months were more likely to suffer from morbidity compared to the 36–59 months group. This pattern aligns with previous research [29, 30], likely because younger children have higher exposure to infectious agents due to frequent contact with others [31]. Male children also showed higher morbidity risk than females, which is consistent with earlier nationally representative surveys [15, 32]. Biological evidence suggests that females often mount stronger humoral and cellular immune responses, providing some protection against infections [33]. Child nutrition status was another critical factor. Underweight children faced higher odds of morbidity compared with well-nourished peers, which aligns with findings from studies in Cambodia demonstrating the link between poor nutrition and increased susceptibility to illness [34]. Maternal education strongly influenced child health outcomes. Children of less educated mothers had

elevated risks of fever, diarrhea, and ARI compared to children of highly educated mothers. This is consistent with the notion that educated mothers are better informed about child health, preventive care, and appropriate use of healthcare services [35]. Similar findings were reported in studies conducted in Africa [36] and Nepal [37].

Finally, children of Muslim mothers had a higher likelihood of experiencing morbidity than those of non-Muslim mothers. Evidence from 15 sub-Saharan African countries has similarly shown lower immunization coverage among Muslim families, which may contribute to higher morbidity risks [38].

#### *Strengths and limitations of the study*

A key strength of this study is that it utilized data from a large-scale, nationally representative survey. Another methodological advantage is the application of Bayesian logistic regression incorporating informative priors derived from historical survey data from Bangladesh. To enhance the precision and reliability of these prior distributions, a resampling approach, specifically “bootstrapping,” was applied, allowing accurate estimation of means and variances from the historical dataset. Previous research conducted in Bangladesh has shown that using historical priors provides more precise parameter estimates compared to flat priors [20].

Despite these strengths, several limitations should be noted. First, the cross-sectional nature of the data prevents establishing causal relationships between identified risk factors and child morbidity. Future studies should consider longitudinal or experimental designs to better address causality. Additionally, due to data constraints, this study could not account for certain influential factors, such as environmental conditions, patterns of healthcare utilization, and other relevant variables.

#### **Conclusion**

The findings of this study indicate that child morbidity remains a major public health concern in Bangladesh. Bayesian binary logistic regression with MCMC simulation was employed to identify key risk factors, leveraging information from previous surveys. Important determinants affecting child morbidity included age, sex, nutritional status, maternal education, and household wealth.

To mitigate the risk of child illnesses, it is essential to expand child health programs. Based on these results, we recommend implementing health education and awareness campaigns targeting parents and caregivers, emphasizing child nutrition, timely healthcare-seeking behaviors, and overall preventive care. Moreover, improving maternal education is critical for reducing morbidity rates. Given that this study applied a bootstrap method to derive priors from the BDHS 2014 dataset, future research could explore alternative prior specifications through Bayesian meta-analytic approaches [39].

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