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Original Research Article

Predictive modeling and risk factors of under-five child mortality in India using NFHS-5 dataset: a parity-based analysis

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ABSTRACT

Background: Child mortality is one of the important public health issues in developing countries like India. Many previous studies found that there are several risk factors affecting child mortality namely; Socio-economic factors, Bio-demographic factors, etc. Therefore, in the present study, various variables associated with these factors were explored in relation to under-five child mortality. Additionally, three different models were compared to assess their suitability for estimating child mortality across different parity levels of women. This approach was adopted with the objective of framing more effective strategies to reduce child mortality rates in India.
Methods: For our purpose, binary logistic regression model was performed to describe the significant risk factors of mortality among under-five children. For finding a best predictive model, three different models are formulated and model fitting was observed by the method of MSE. First model was binomial distribution, second was beta-binomial distribution and third was poisson distribution model.
Results: The logistic regression result reveals that the factors like maternal health, education, and socio-economic conditions, rural areas, significantly influence child mortality and the method of comparison on the three different models describes that the beta-binomial distribution model shows the better fit on the data. The estimated values of probability of child deaths at higher parities; parity 3, parity 4, and parity 5, were obtained as 0.153, 0.279, 0.123, respectively.
Conclusions: According to this study we found that, child mortality is still a significant issue in India. Therefore, progress on socio economic, bio-demographic and environmental risk factors should be the focus of policymaker's intervention.

Keywords: Child mortality, Binomial, Beta-binomial, Poisson, Logistic regression models, NFHS data

INTRODUCTION

Mortality and morbidity in children below five years of age remains to be an area of concern across the world as well as in India. Child mortality is the death of children under the age of five.[1] The child mortality rate refers to the probability of dying between birth and exactly five years of age expressed per 1,000 live births.[2] Child mortality trend is declining over time but the rate is not decline fast. To examine the variations of a population over time, we need to analyse factors that influenced child death. India is one of the developing countries which are struggling to achieve low child mortality rate. Therefore, the rates of child death are not only important measures of the living and socio-economic conditions of a nation but also are powerful indicators of social-economic development and can be used to measure the overall health status of a nation.[3]

This study considers a demographic, socioeconomic and environmental characteristics as explanatory variables that have been recognized as important risk factors of under-five mortality in previous studies.[4-6] Several studies have examined that the child mortality remains high due to maternal and child factors.[3,7-11] Many authors found that mother's education affect child mortality, as per highly educated mothers may adopt good environmental practices regarding sanitation and hygienic practices in the home. Furthermore, education helps mothers to access gainful employment and empowers them to make healthcare decisions about themselves and their children. And children whose mothers had a higher educational level had a lower risk of child mortality.[7,10-12] Some studies have observed that the place of residence and wealth status of the household also directly affects to increase in child mortality.[4-8,12]

Many authors contributed in the direction of modeling of infant and child mortality. Tripathi et al used Bayesian method to found a best fitting model for assessment of child mortality under different parity.[13] Similarly, some authors were compared different probability models to found a better predictive model to estimate the child mortality.[14,15]

From previous studies, it was observed that most researchers had utilized the data available at that time to investigate the risk factors associated with child mortality. However, in order to assess whether any changes had occurred in these risk factors over time, the most recent data from the NFHS was employed in the present study. This was done to examine whether the previously identified risk factors continue to influence child mortality or whether improvements have been observed. Additionally, it was noted that most prior studies had compared only two models to identify the best predictive model. Therefore, in the current study, more than two models were compared to determine the most effective predictive model.

The present study has purpose to find out the relationship of different selected variables of socio-economic, bio-demographic and environmental factors with child mortality and also an attempt to find the best predictive model from already existing models to estimate the child mortality according to the parity of mothers in total reproductive life span of women. Three models have been taken into account to estimate the child mortality among different parity. The aim behind it was to determine the factors affecting child mortality that can be used by health professionals for forecasting the child death rates for timely interventions and possible reduction in factors causing high rates of child mortality. NFHS-5(2019) datasets have been used for getting our purpose of the study.

METHODS

For this study, publicly available survey, NFHS dataset, were utilized. The National Family Health Survey (NFHS-5) represents the fifth round of India's comprehensive health and family welfare survey, conducted under the aegis of the Ministry of Health and Family Welfare in collaboration with the International Institute for Population Sciences (IIPS). Critical data on a wide range of health and demographic indicators, including maternal and child health, nutrition, family planning, and sanitation, were collected. Information was gathered from 707 districts across 28 states and 8 union territories. In total, 636,699 households were surveyed and interviews were conducted with 724,115 eligible women aged 15-49 years and 101,839 eligible men aged 15-54 years.

This study used the child recode dataset file from the NFHS-5 survey. All eligible women aged 15-49 years old who were either permanent residents or visitors who were present in the home of the selected households were the respondents on behalf of their under-five children. A total of 232920 samples of eligible women were included in the NFHS-5 dataset. After removing missing values, duplicates and irrelevant data, the total sample size of this study is 88729. A total of seven independent variables is categorized into socioeconomic, biodemographic, and environmental factors of the under-five mortality. In this study, the mother's education, mother's age at 1st birth, child sex, source of drinking water, type of cooking fuel, place of residence and wealth index is included as the independent variables. The children who's died before reaching their five years of age is the dependent variable for this study. It is dichotomous coded as 1 if child died before reaching their fifth birthday and 0 if alive.

Random and Fixed effects models are powerful statistical approaches frequently employed to analyse the determinants of child mortality by accounting for unobserved differences across individuals, households, or communities. The random effects model assumes that the variability between groups is random and not correlated with the observed predictors, making it suitable for estimating the influence of both time-varying and stable risk factors. This model is often applied alongside count or overdispersed data models such as the Poisson, binomial, and beta-binomial distributions to predict the number of child deaths across different parities. In contrast, the fixed effects model controls for all unmeasured and constant characteristics within each group by allowing to have its own intercept.

This approach is especially suitable when such unobserved factors are likely to influence both the predictors and the possibility of child death, helping to isolate the true effect of key variables like maternal education, socio-economic status, etc. In logistic regression, fixed effects are useful for identifying the probability of under-five mortality while accounting for unobserved heterogeneity. These models enhance the precision of estimates and the validity of conclusions.

MODEL-I

The binomial distribution commonly employed in statistical analysis. It models the number of successes in a fixed number of independent trials, each with a constant probability of success. In terms of child mortality, it serves to estimate the number of child deaths occurring before the fifth birthday within a defined population of children. Suppose, we consider a group of n children and each child has a fixed probability p of dying (with a corresponding probability 1-p of survival), the number of child deaths, denoted by the random variable X, like, follows a binomial distribution: X~Bin(n,p), where, n is the number of trials, p is the probability of dying on a single trial and X is the discrete random variable representing the total number of child deaths. The probability of observing exactly k child deaths out of n trials is given by the binomial probability mass function:

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}, \text{ for } k = 0,1,2\ldots n$$

where $\binom{n}{k}$ denotes the binomial coefficient, representing the number of k child deaths from n trials. Within this framework, the mean number of under-five deaths is given by $E(X) = np$, which reflects the expected number of children who die before age five. The variance, expressed as $Var(X) = np(1-p)$, which quantifies the degree of variability in the number of child deaths across similar populations.

MODEL-II

The Beta-Binomial distribution arises as a compound distribution of the binomial distribution when the probability of success is not fixed but follows a Beta distribution. In the case of child mortality, the number of under-five deaths X, given a child mortality probability p, follows a binomial distribution: $X|p \sim \text{Bin}(n, p)$, and the probability p follows a Beta distribution: $p \sim \text{Beta}(\alpha, \beta)$, where $\alpha > 0$ and $\beta > 0$ are shape parameters that reflect the variability in child mortality risk across different groups. By integrating over the distribution of p, the resulting marginal distribution of X becomes:

$$P(X = k) = \binom{n}{k} \frac{B(k+\alpha,\ n-k+\beta)}{B(\alpha,\beta)}, \text{ for } k = 0,1\ldots n$$

Where; B(,) denotes the Beta function. The mean of the Beta-Binomial distribution, represents the expected number of under-five deaths, $E(X) = \frac{n\,\alpha}{(\alpha + \beta)}$ and the variance captures the additional variability due to heterogeneity in the child mortality probability,

$V(X) = \frac{n\,\alpha\,\beta\,(\alpha + \beta + n)}{(\alpha + \beta)^2\,(\alpha + \beta + 1)}$. This distribution denoted as: $X \sim \text{Beta-Bin}(n,\alpha,\beta)$.

MODEL-III

The Poisson distribution used to describe the number of occurrences of rare events over a fixed interval of time or space. In the context of under-five child mortality, it is employed to model the number of child deaths occurring within a defined population segment or time frame, under the assumption that these child deaths occur independently and at a constant average rate. If X represents the number of under-five deaths in a population, and λ denotes the expected number of deaths per unit of observation, then X is assumed to follow a Poisson distribution: $X \sim \text{Poisson}(\lambda)$. The probability of observing exactly k child deaths is given by the Poisson probability mass function:

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \text{ for } k = 0,1,2,\ldots n$$

Where, e is the base of the natural logarithm. In this model, the parameter λ serves as both the mean and the variance of the distribution, i.e., $E(X) = Var(X) = \lambda$. This property makes the Poisson distribution suitable for modeling of child mortality when the child death is rare.

MODEL-IV

Logistic regression used for modeling the relationship between a binary dependent variable and one or more independent variables. The model estimates the probability that a given input point belongs to a particular category using the logit function, which maps any real-valued number into the (0,1) interval. In the terms of child mortality, logistic regression can be employed to model the probability of a child's death compared with survival as a function of various socioeconomic, demographic, and health-related predictors. The model estimates the log-odds of child mortality as a linear combination of independent variables such as maternal education, household income, access to healthcare, and nutritional status. The logistic regression model is represented as:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)}}$$

where $P(Y = 1|X)$ is the probability of child mortality, $X_1, X_2, \ldots, X_k$, represent the predictor variables, and $\beta_0, \beta_1, \ldots, \beta_k$ are the model coefficients estimated through maximum likelihood estimation, which finds the set of criteria that makes the observed outcomes most probable under the model.

RESULTS

Table 1 highlights the distribution of child mortality across different background characteristics. Table 2 presents the distribution of women by parity and the number of child deaths based on NFHS-5 dataset. Table 3,4,5 compares the observed and expected frequencies of child deaths across parities 3 to 5 under the Binomial model (Model I), Beta-Binomial model (Model II) and Poisson model (Model III).

Table 1: Basics description of the data taken in the study.

Variable (n=88729)	Category	Child mortality, N (%)		Total
		Yes	No	
Place of residence	Urban	1282 (14.1)	18014 (22.6)	19296 (21.7)
	Rural	7811 (85.9)	61622 (77.6)	69433 (78.3)
Mother's education level	No education	3784 (41.6)	17389 (21.8)	21173 (23.9)
	Primary	1617 (17.8)	10579 (13.3)	12196 (13.7)
	Secondary	3304 (36.3)	40802 (51.2)	44106 (49.7)
	Higher	388 (4.3)	10886 (13.6)	11254 (12.7)
Source of drinking water	Water supply sources	3439 (37.8)	38570 (48.4)	42009 (47.3)
	Groundwater sources	5086 (55.9)	35033 (44.0)	40119 (45.2)
	Surface water sources	299 (3.3)	2699 (3.4)	2998 (3.4)
	Others	269 (3.0)	3334 (4.2)	3603 (4.1)
Cooking fuel	Modern cooking fuels	2987 (32.8)	37251 (46.8)	40238 (45.3)
	Biomass fuels	4654 (51.2)	33303 (41.8)	37957 (42.8)
	Agricultural/animal-derived fuels	1206 (13.3)	5997 (7.5)	7203 (8.1)
	Other	246 (2.7)	3085 (3.9)	3331 (3.8)
Gender of last child	Male	5347 (58.8)	47808 (60.0)	53155 (59.9)
	Female	3746 (41.2)	31828 (40.0)	35574 (40.1)
Mother's age at 1st birth	Less than and equal to 25	8469 (93.1)	69812 (87.7)	78281 (88.2)
	Above than 25	624 (6.9)	9824 (12.3)	10448 (11.8)
Wealth index	Poorest	3285 (36.1)	19076 (24.0)	22361 (25.2)
	Poorer	2327 (25.6)	17606 (22.1)	19933 (22.5)
	Middle	1687 (18.6)	16263 (20.4)	17950 (20.2)
	Richer	1195 (13.1)	14751 (18.5)	15946 (18.0)
	Richest	599 (6.6)	11940 (15.0)	12539 (14.1)

Table 2: Distribution of women taken from NFHS-5 data with parity.

Parity	Number (%) of child death						Total
	0	1	2	3	4	5	
3	19658 (88.2)	2552 (11.4)	78 (0.3)	5 (0.02)	-	-	22293 (100.0)
4	8049 (77.2)	2038 (19.5)	329 (3.2)	10 (0.1)	1 (0.009)	-	10427 (100.0)
5	3147 (66.4)	1203 (25.4)	330 (7.0)	52 (1.1)	5 (0.1)	1 (0.02)	4738 (100.0)

Table 3: Model-I (Binomial distribution).

Child death	Parity 3		Parity 4		Parity 5	
	Observed value	Expected value	Observed value	Expected value	Observed value	Expected value
0	19658	19661.85	8049	7969.037	3147	3022.21972
1	2552	2521.801	2038	2215.989	1203	1421.832035
2	78	107.8142	329	231.079	330	267.5657658
3	5	1.536456	10	10.70955	52	25.17577228
4	-	-	1	0.185601	5	1.184418171
5	-	-	-	-	1	0.0222686
Total	22293	22293	10427	10426.99	4738	4737.99
Prob.	0.0407		0.065		0.086	

Figure 1-3 displays the graphical representation for the same. Table 6 provides a comparison of the Binomial, Beta-Binomial, and Poisson models using Mean Square Error (MSE) as a measure of model fit across parities 3 to 5. Figure 4 highlights the MSE of these three models across the parities. It clearly shows that the Beta-Binomial model consistently yields the lowest MSE values across all parities, indicating the best fitting model except parity 3, in which the Binomial Model shows the better performance. In contrast, the Binomial model's error increases sharply with parity, while the Poisson model performs better than the Binomial but still worse than the Beta-Binomial.

Table 4: Model-II (Beta- Binomial distribution).

Child death	Parity 3		Parity 4		Parity 5	
	Observed value	Expected value	Observed value	Expected value	Observed value	Expected value
1	2552	2505.78	2038	2054.816	1203	1215.794
2	78	106.35	329	282.3498	330	310.1666
3	5	1.5	10	22.78201	52	56.69924
4	-	-	1	0.866206	5	6.909946
5	-	-	-	-	1	0.430211
Total	22293	22292.99	10427	10427	4738	4738
Prob.	0.0407		0.064		0.086	
1	2552	2505.78	2038	2054.816	1203	1215.794

Table 5: Model-III (Poisson distribution).

Child death	Parity 3		Parity 4		Parity 5	
	Observed value	Expected value	Observed value	Expected value	Observed value	Expected value
0	19658	19732.61258	8049	8031.719	3147	3079.032
1	2552	2407.378735	2038	2096.279	1203	1327.063
2	78	146.8501028	329	273.5644	330	285.982
3	5	5.971904181	10	23.8001	52	41.08608
4	-	-	1	1.552957	5	4.427025
5	-	-	-	-	1	0.38161
Total	22293	22292.81	10427	10426.91	4738	4737.97
Prob.	0.0407		0.065		0.086	

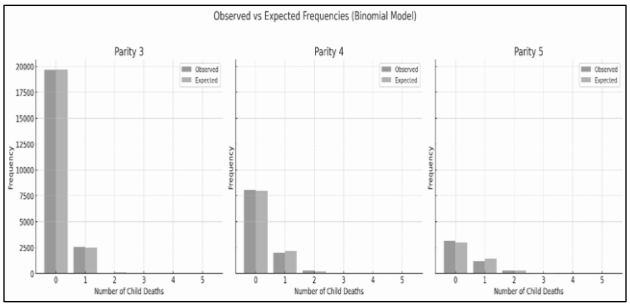

Figure 1: Comparisons of observed and expected values of child deaths under the Binomial model.

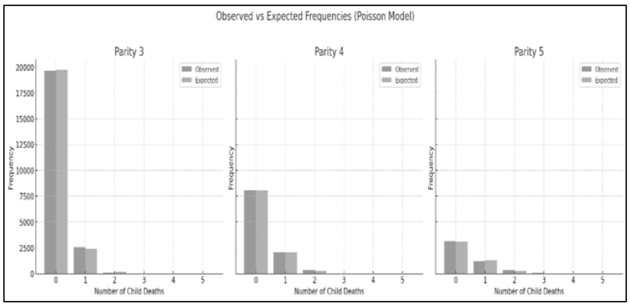

Figure 3: Comparisons of observed and expected values of child deaths under the Poisson model.

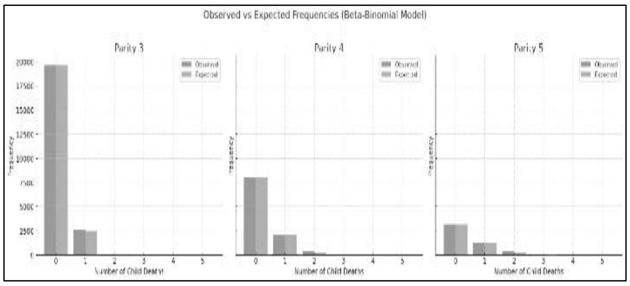

Figure 2: Comparisons of observed and expected values of child deaths under the Beta- Binomial model.

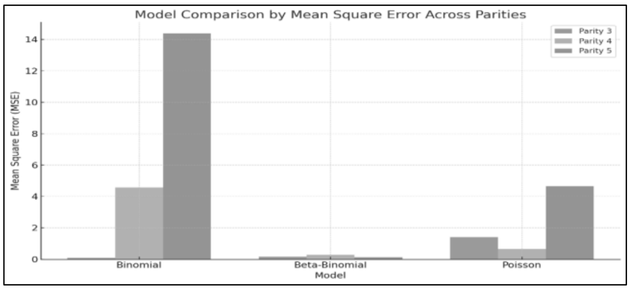

Figure 4: Models comparison by mean square error across different parities.

Table 7 presents the logistic regression results which reveal a significant association between our selected variables with child mortality. Children in rural areas have 1.09(CI:1.01-1.17) times higher odds of child mortality compared to those in urban areas. Mothers with no education have 4.01(CI:3.57-4.50) times higher odds of child mortality, while those with primary education and secondary education face 3.01(CI:2.67-3.39) and 1.78(CI:1.59-1.99) times higher odds of child mortality, compared to the mothers with higher education. Households using groundwater for drinking have 1.26(CI:1.19-1.32) times higher odds of child mortality compared to those using piped water. Interestingly, use of surface water shows 0.99(CI:0.87-1.13) times lower odds, indicating a possible protective factor after adjustment. With respect to cooking fuel, households using biomass fuels and agricultural/animal-derived fuels have 1.05(CI:0.99-1.12) and 1.39(CI:1.28-1.51) times higher odds of child mortality, respectively, than those using modern fuels. Children born to mothers whose first birth occurred after 25 years have 0.66(CI:0.61-0.72) times lower odds of child mortality, suggesting a strong protective effect. Finally, economic status shows a clear gradient compared to the richest households, the poorest household face 1.54(CI:1.39-1.72) times higher odds, while poorer, middle, and richer households have 1.40(CI:1.26-1.55), 1.27(CI:1.15-1.41) and 1.19(CI:1.07-1.32) times higher odds of child mortality, respectively.

Table 6: Comparison of the models.

Method	Model I (Binomial distribution)			Model II (Beta- Binomial distribution)			Model III (Poisson distribution)		
	Parity 3	Parity 4	Parity 5	Parity 3	Parity 4	Parity 5	Parity 3	Parity 4	Parity 5
Mean square error	0.081	4.571	14.371	0.153	0.279	0.123	1.400	0.667	4.658

Table 7: Logistics regression model.

Variable (n=88729)	Category	Child mortality, N (%)		P value	Crude Odds Ratio COR (CI)	Adjusted Odds Ratio AOR (CI)
		Yes	No			
Type of place of residence	Urban	1282(6.6)	18014(93.4)	<0.001	Ref	Ref
	Rural	7811(11.2)	61622(88.8)		1.78(1. 67,1.89)	1.09(1.01,1.17)
Mother's education level	No education	3784(17.9)	17389(82.1)	<0.001	6.09(5.47,6.78)	4.01(3.57, 4.50)
	Primary	1617(13.3)	10579(86.7)		4.28(3.81,4.79)	3.01(2.67,3.39)
	Secondary	3304(7.5)	40802(92.5)		2.26(2.03,2.52)	1.78(1.59,1.99)
	Higher	388(3.4)	10886(96.6)		Ref	Ref
Source of drinking water	Water supply sources	3439(8.2)	38570(91.8)	<0.001	Ref	Ref
	Groundwater sources	5086(12.7)	35033(87.3)		1.62(1.55,1.70)	1.26(1.19,1.32)
	Surface water sources	299(10.0)	2699(90.0)		1.24(1.09,1.40)	0.99(0.87,1.13)
	Others	269(7.5)	3334(92.5)		0.90(0.79,1.03)	0.97(0.70,1.36)
Type of cooking fuel	Modern cooking fuels	2987(7.4)	37251(92.6)	<0.001	Ref	Ref
	Biomass fuels	4654(12.3)	33303(87.7)		1.74(1.66,1.82)	1.05(0.99,1.12)
	Agricultura animal-derived fuels	1206(16.7)	5997(83.3)		2.50(2.33,2.69)	1.39(1.28,1. 51)
	Other	246(7.4)	3085(92.6)		0.99(0.86,1.13)	0.95(0.68,1.35)
Gender of last child	Male	5347(10.1)	47808(89.9)	0.024	Ref	Ref
	Female	3746(10.5)	31828(89.5)		1.05(1.00,1.10)	1.04(0.99,1.09)
Mother's age at 1st birth	Less than and equal to 25	8469(10.8)	69812(89.2)	<0.001	Ref	Ref
	Above than 25	624(6.0)	9824(94.0)		0.52(0.48,0. 56)	0.66(0.61,0.72)
Wealth index within state	Poorest	3285(14.7)	19076(85.3)	<0.001	3.43(3.13,3.75)	1.54(1.39,1.72)
	Poorer	2327(11.7)	17606(88.3)		2.63(2.40,2.89)	1.40(1.26,1.55)
	Middle	1687(9.4)	16263(90.6)		2.06(1.87,2.27)	1.27(1.15,1.41)
	Richer	1195(7.5)	14751(92.5)		1.61(1.46,1.78)	1.19(1.07,1.32)
	Richest	599(4.8)	11940(95.2)		Ref	Ref

DISCUSSION

The purpose of the present study was to find the best predictive model to predict the under-five child mortality and also find the significant influence of various selected variables on child mortality. The comparative model analysis further strengthens the findings by providing robust statistical support for model selection. The Binomial model demonstrated a reasonably good fit at lower parities but failed to accommodate the observed variability at higher child death counts. It significantly underestimated child deaths among higher-parity women, leading to increased MSE with rising parity levels. Conversely, the Beta-Binomial model showed excellent agreement between observed and expected frequencies across all categories, effectively capturing the overdispersion in the data. It yielded the lowest MSE values at all parities, validating its appropriateness for modeling on child mortality. The Poisson model performed moderately well, with a better fit for lower mortality frequencies but relatively less precision in predicting higher-order child deaths, as reflected in its intermediate MSE values. Most of the previous studies also compare the existing models to find the best predictive models for predicting under five child mortality.[13-15]

The present study also explores the critical determinants of child mortality by analysing demographic, environmental and socioeconomic variables using a statistical model. The initial descriptive analysis indicated clear disparities in child mortality associated with the selected variables. The logistic regression analysis identified maternal education, place of residence, water source, cooking fuel and household wealth index as critical factors influencing child mortality. Notably, the odds of child mortality were substantially higher among children born to mothers with no or low education, those residing in rural areas, and those from economically disadvantaged households. One of the most consistent findings across literature is the strong protective role of maternal education. Women with even a primary level of education experience a notably reduced risk of child mortality.[16] Kiross et al showed that mothers with primary education had 28% lower odds and those with secondary education had 45% lower odds of experiencing infant death compared to uneducated mothers.[17] This aligns with the findings from India, where Moradhvaj et al concluded that maternal education plays a critical role in child survival.[18] Furthermore, Dhakad et al, Jayathilaka et al and Kumar et al emphasized that rural residence is associated with higher under-five mortality due to disparities in access to healthcare, sanitation and clean water.[12,4,5] Child mortality remains higher in rural than urban India, with limited improvement in recent years. Household economic status further influences child mortality, as wealthier families can afford better healthcare, nutrition and sanitation.[19] These findings underscore the role of systemic inequalities in perpetuating health disparities among children. Furthermore, environmental conditions, such as the use of non-modern fuels and unsafe drinking water sources, also emerged as prominent contributors to increased child mortality risk, reinforcing the link between environmental health and child survival. Similarly, Naz et al and Ashish et al reported that indoor air pollution from cooking with solid fuels increased neonatal, post-neonatal and under-five mortality.[20,21] Additionally, Luo et al found that exposure to polluting fuels during pregnancy was associated with adverse birth outcomes, which may force into early childhood mortality risks.[22] Moreover, maternal age at first birth is another critical factor. Children born to mothers under the age of 25 face a substantially higher risk of death.[23-25] The findings of this study underline the importance of targeted interventions in reducing child mortality. First, promoting maternal education is critical, as it is strongly associated with improved child survival outcomes; policies must prioritize access to secondary and higher education for girls. Ensuring access to clean drinking water, particularly piped water, is essential given the higher risk associated with groundwater usage. Similarly, transitioning households away from biomass and animal-derived fuels toward clean energy sources like LPG can reduce child mortality risk linked to environmental exposures. Public health strategies should also focus on rural and socioeconomically disadvantaged populations through initiatives like conditional cash transfers, expanded nutrition programs and decentralized maternal and child health services. Delaying age at first birth through comprehensive reproductive education and contraceptive access can further mitigate risk. Additionally, although female children showed slightly lower odds of child mortality, ongoing efforts to ensure gender equity in child health and nutrition must be maintained.

The consistency between model-based predictions and regression outcomes strengthens the validity of these findings. The Beta-Binomial model's superior fit and the regression model's robust associations suggest that interventions targeting maternal education, improved water, fuel sources and poverty alleviation could significantly reduce child mortality. These results underscore the importance of multidimensional public health strategies that address not only medical and nutritional care but also the broader environmental and social determinants of child survival.

CONCLUSION

This study reaffirms under-five child mortality in India is influenced by socio-economic, demographic, and environmental factors. Among the statistical models evaluated, the Beta-Binomial model proved to be the most effective in estimating child mortality across higher parities, suggesting its utility in guiding predictive analytics and health planning. Children born to less-educated, lack of access to clean fuel and water sources, poor environmental conditions and economically disadvantaged mothers, particularly in rural areas, face a significantly higher risk of child mortality. The study emphasizes the urgent need for targeted policy interventions focusing on maternal education, rural health infrastructure, environmental hygiene, and economic upliftment to reduce child mortality rates. By aligning public health strategies with these critical determinants, India can make significant progress toward achieving child survival goals and improving overall public health outcomes.

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REFERENCES

1. World Health Organization. Child mortality and causes of death", 2019. Available at: https://www.who.int/data/gho/data/themes/topics/topic-details/GHO/child-mortality-and-causes-of-death. Accessed 26 November 2019.
2. UNICEF. UNICEF – Definitions, 2019. Available at: https://www.unicef.org/reports/levels-and-trends-child-mortality-report-2019. Accessed on 1 December 2025.
3. Abdelghffar FA, Saad Akram M, Aoami Al, Ambrka Al, Jamila DO. Determinants of Under-Five Mortality (U5MR) in Al-Bayda city by using the logistics regression model. Human J Int J Sci Res Methodol. 2022;20:242-57.
4. Jayathilaka R, Adikari H, Liyanage R, Udalagama R, Wanigarathna N. Cherish your children: socio-economic and demographic characteristics associated with child mortality. BMC Publ Heal. 2021;21(1):1217.
5. Kumar SG, Majumdar A, Kumar V, Naik BN, Selvaraj K, Balajee K. Prevalence of acute respiratory infection among under-five children in urban and rural areas of puducherry, India. J Nat Sci Biol Med. 2015;6(1):3.
6. Mukherjee A, Bhattacherjee S, Dasgupta S. Determinants of infant mortality in rural India: An ecological study. Ind J Publ Heal. 2019;63(1):27-32.
7. Alemayehu YK, Theall K, Lemma W, Hajito KW, Tushune K. The role of empowerment in the association between a woman's educational status and infant mortality in Ethiopia: Secondary analysis of demographic and health surveys. Ethio J Heal Sci. 2015;25(4):353-62.
8. Patel N, Olickal JJ. Maternal and child factors of under-five mortality in India. Findings from NFHS-4. Clin Epidemiol Glob Heal. 2021;12:100866.
9. Paul P, Saha R. Is maternal autonomy associated with child nutritional status? Evidence from a cross-sectional study in India. PLoS One. 2022;17(5):e0268126.
10. Shahraki M, Agheli L, Arani AA, Sadeghi H. The effect of mothers' education and employment on children's health. Jentashap J Heal Res. 2016;7(4):e30977.
11. Wu H. The effect of maternal education on child mortality in Bangladesh. Populat Developm Revi. 2022;48(2):475-503.
12. Moradhvaj M, Yildiz D, KC S. The Role of Maternal Education in Reducing Excess Deaths among Girls in India. 2023:1-31.
13. Tripathi A, Singh G, Singh A. Model for Assessment of child mortality under different parity: a Bayesian Swatch. J Biosci Medi. 2019;7:113-26.
14. Maheshwari S, Singh BP, Gupta PK. A new probability model for estimation of child mortality for fixed parity. Int J Heal. 2015;3(2015):34-7.
15. Singh BP, Dixit S, Maurya DK. Some probability models for age at infant death and estimation procedure. Demography India. 2022;51(2):25-44.
16. Tessema NS, Geda NR. Trends in maternal education-based inequalities in under-five mortality in Ethiopia: multilevel, decomposition and concentration index analyses. Discov Soci Sci Heal. 2024;4(1):59.
17. Kiross GT, Chojenta C, Barker D, Tiruye TY, Loxton D. The effect of maternal education on infant mortality in Ethiopia: A systematic review and meta-analysis. PloS one. 2019;14(7):e0220076.
18. Samir KC. Differential impact of maternal education on under-five mortality in rural and urban India. Health & Place. 2023;80:102987.
19. Uddin MF, Mim SA, Haque MA, Tariquajjaman M, Jabeen I, Latif MB, et al. Sociodemographic and maternal health-related factors associated with mortality among children under three in Bangladesh: an analysis of data from Bangladesh demographic and health survey 2017-18. BMC Publ Heal. 2024;24(1):3324.
20. Naz S, Page A, Agho KE. Household air pollution and under-five mortality in India (1992-2006). Environment Heal. 2016;15(1):54.
21. Kc A, Halme S, Gurung R, Basnet O, Olsson E, Malmqvist E. Association between usage of household cooking fuel and congenital birth defects-18 months multi-centric cohort study in Nepal. Arch Publ Heal. 2023;81(1):144.
22. Luo M, Liu T, Ma C, Fang J, Zhao Z, Wen Y, et al. Household polluting cooking fuels and adverse birth outcomes: An updated systematic review and meta-analysis. Fronti Publ Heal. 2023;11:978556.
23. Ahinkorah BO. Maternal age at first childbirth and under-five morbidity in sub-Saharan Africa: analysis of cross-sectional data of 32 countries. Arch Publ Heal. 2021;79(1):151.
24. Noori N, Proctor JL, Efevbera Y, Oron AP. The effect of adolescent pregnancy on child mortality in 46 low-and middle-income countries. BMJ Glob Heal. 2022;7(5).
25. Sinha S, Aggarwal AR, Osmond C, Fall CH, Bhargava SK, Sachdev HS. Maternal age at childbirth and perinatal and under-five mortality in a prospective birth cohort from Delhi. Ind Pediatr. 2016;53(10):871-7.

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