REVIEW ARTICLE

Statistical Modelling for the Assessment of Low Birth Weight in Tertiary Care Settings (2019-2024)

Shivam Dixit[1], Jagdish Prasad[2], Satish Saroshe[3], Deepa Joshi[4], Namita Drivastava[5]

[1,2]Department of Amity School of Applied Sciences, Amity University Rajasthan, Jaipur, Rajasthan

[3]Department of Community Medicine, Mahatma Gandhi Memorial Medical College, Indore, Madhya Pradesh

[4]Department of Obstetrics & Gynaecology, Mahatma Gandhi Memorial Medical College, Indore, Madhya Pradesh

[5]Department of Statistics, St. John's College, Agra, Uttar Pradesh

CORRESPONDING AUTHOR

Dr. Satish Saroshe, Associate Professor, Department of Community Medicine, Mahatma Gandhi Memorial Medical College, Indore, Madhya Pradesh – 452001

Email: drsatishsaroshe123@gmail.com

CITATION

Dixit S, Prasad J, Saroshe S, Joshi D, Drivastava N. Statistical Modelling for the Assessment of Low Birth Weight in Tertiary Care Settings (2019-2024). Indian J Comm Health. 2025;37(5):653-658.

https://doi.org/10.47203/IJCH.2025.v37i05.004

ARTICLE CYCLE

Received: 10/07/2025; Accepted: 07/10/2025; Published: 31/10/2025

Abstract

LBW is a major public health concern worldwide, particularly in developing countries, and is defined as a birth weight of less than 2,500 grams. It is essential to properly evaluate and manage LBW infants because this practice minimizes newborn health complications. This analysis reviews the application of statistical models (2019-2024) which evaluate risk components and treatment results for LBW cases found in tertiary medical facilities. Research uses logistic regression along with machine learning models in accord to survival analysis to discover maternal indicators alongside clinical indicators & socioeconomic indicators that predict LBW. Multiple risk factors are successfully integrated through advanced learning approaches starting from classical regression methods as the review demonstrates. Findings suggest that ensemble methods and deep learning models demonstrate superior predictive performance compared to conventional statistical approaches. The studies indicate that integrating machine learning methods with traditional biostatistics offers a more nuanced understanding of LBW risk. However, the need for interpretable models in clinical settings remains paramount.

Keywords

Low Birth Weight, Statistical Model, Logistic Regression, Machine Learning, Multiple linear Regression, Bayesian Method, Structural Equation Modeling

Introduction

The medical definition of a newborn being considered low birth weight happens when their birth weight falls below 2,500 grams. Data from one of the UN reports in 2020 shows that restricted birth weight and premature births exist in 19.8 million cases and 13.4 million cases annually and create a higher death risk particularly within the newborn period.(1) This represents a significant worldwide public health issue. The risk of infant death together with life-threatening diseases and permanent health complications becomes higher when birth weight is below average. The correct evaluation of risk factors that lead to LBW combined with successful predictive models creates powerful tools to enhance maternal health results as well as child development outcomes. The detection and assessment of low birth weight in tertiary care facilities becomes an imperative step for delivering suitable interventions and making proper resource allocations. Neonatal progress has not solved the LBW issue which continues as a significant problem mostly affecting hospitals that manage complex medical cases. The studies under review investigate multiple statistical methods for LBW data research from 2019 to 2024. The study reviews multiple research methods together with their analysis approaches along with their resulting findings. Over the past five years, significant advancements at statistical modeling have enhanced our ability in predicting and assessing LBW risk factors accurately. This review aims to:

- Examine the evolution of statistical methodologies for LBW assessment
- Compare the effectiveness of different modeling approaches
- Identify key predictors consistently found significant across studies
- Talk about the real-world effects of using these models in medical settings.

Material & Methods

Types of Studies

Recent studies on LBW in tertiary care hospitals have employed a range of study designs to identify and model risk factors. The predominant study types include:

Cohort Studies: The research consists of long-term investigations of successive maternal-infant relationships that monitor how maternal characteristics (including age, nutritional state and disease presence) impact the health outcomes of newborns, including birth weight, illness factors, and mortality rates. They include: -

Retrospective Cohort Studies- These studies typically utilize existing hospital records to identify patterns and correlations between maternal characteristics and LBW outcomes, offering valuable insights into tertiary care settings and to develop predictive models. Mukosa *et al.* (2022) analyzed records of some 28,800 pregnancies and 9,000 births per year between January 1, 2018, and September 30, 2019 in Zambia, Africa and underlined the significance of successful interventions for mothers and newborns. in Zambia and other similar settings to lessen the risk of morbidity & mortality in newborn LBWs.(2)

Prospective Studies- Longitudinal studies following pregnant women through their gestational period. Zhen Liu *et al.* (2022) found that the mother's height and pre-pregnancy body mass index (BMI) were significant predictors of infant birth weight in a prospective study aimed at identifying early predictors of LBW. Additionally, they found that interpretable machine learning holds promise as a birth weight prediction tool.(3)

Case-Control Studies: These studies compare LBW infants with normal-weight infants to identify the differences in maternal, socioeconomic, and environmental factors. Comparing LBW cases with normal birth weight controls to identify significant risk factors. A notable study by Anil KC *et al.* (2020) employed this design the main risk determinants for LBW include sharing household with a kitchen combined with iron supplementation under 180 tablets and limited maternal weight gain of < 6.53 kg in 2nd and 3rd trimesters, and co-morbid conditions while pregnancy and pre-term birth.(4)

Cross-Sectional Studies: These studies evaluate the prevalence of LBW and its contributing factors by analyzing data from a particular time point. For example, a cross-sectional study by Gupta *et al.* (2024) revealed strong correlations between birth weight and the mother's socioeconomic status, weight gain during pregnancy, number of ANC visits, interval between pregnancies, poor obstetric history, pregnancy complications, and gestation age at delivery.(5)

Randomized Controlled Trials (RCTs): Although less common, RCTs have been used to test specific interventions aimed at reducing LBW in high-risk populations, providing valuable data for statistical modeling. Christian P *et al.* in their controlled trials found that improving food intake during pregnancy effectively lessening the possibility of having LBW children.(6)

Statistical Methods

A variety of statistical methods have been used to develop predictive models for LBW. Some common approaches include:

1. Traditional Statistical Methods

Logistic Regression: Remains widely used for its interpretability. Linear, logistic, the relationship between LBW and predictor variables is often investigated using Cox proportional hazards regression. For continuous birth weight predictions to account for confounders, multivariate regression models have been employed. P Thapa *et al.* (2022) concluded that maternal health services, such as prenatal care and adherence to the recommended dose of maternal micronutrients, had a significant impact on birth weight using multivariate logistic regression. To lessen the detrimental effects of the gestation period, these factors should be considered in newborn and maternal health programs.(7)

Multiple Linear Regression: Multiple Linear Regression models allow researchers to adjust for multiple variables simultaneously and better assess the independent effects of each factor on LBW. Mondal B et al. in their multi-logistic regression analyses, they found that factors such as gender, maternal age, gestation period, economic status and educational attainment had independent effects on risk of LBW.(8)

Cox Proportional Hazards Models: It is often used for brainstorming purposes, in conjunction with event-specific brainstorming. In a study by Md Islam *et al.* (2024The effects of risk factors on infant mortality and low birth weight were evaluated using Cox proportional hazards and binary logistic regression models, and it was concluded that these models and knowledge of prenatal care may potentially reduce risk of infant mortality and low birth weight.(9)

Machine Learning Approaches- Over the last few years, To increase the precision of LBW predictions, machine learning techniques like support vector machines, random forests, and decision trees have been introduced. These models provide a more accurate risk assessment because they can manage big datasets and intricate variable interactions. These include: -

Random Forests: Shows improved predictive accuracy over traditional methods

Support Vector Machines: Effective for non-linear relationships, these algorithms can effectively classify LBW cases and non-LBW cases, even with nonlinear relationships.

Artificial Neural Networks: Particularly useful for complex pattern recognition

Borson *et al.* (2020) used predictive models of machine learning and concluded that these models can provide guidance to health professionals and researchers on the examination of low birth weight babies, which can assist the general public in comprehending and taking the appropriate action to prevent any such occurrence when a baby is born below the average birth weight.(10)

Recent studies Ranjbar *et al.* 2023, and Wang *et al.* 2023 have stated that more investigation is necessary to draw a more accurate conclusion about how well machine learning models predict LBW.(11,12)

Bayesian Methods: Bayesian statistical approaches have been applied to update prior knowledge on LBW risk factors with new data. These methods allow for more flexible model building and can incorporate uncertainty into predictions, making them useful in complex clinical settings. Avwerhota, O. O. *et al.* (2024) used Bayesian spatial analysis of risk determinants affecting LBW in Nigeria and found that the higher performance of the Bayesian STAR model proposes that spatial and non-parametric considerations give a more profound insight into LBW risking factors. The study also emphasized the multifaceted nature of low birth weight, highlighting the importance of maternal education support, healthcare access, and socioeconomic status.(13)

Structural Equation Modeling (SEM): To evaluate the direct and indirect effects of maternal care, some studies have used SEM, clinical, and environmental factors on LBW. This method is particularly useful in exploring latent variables that are not directly measured but influence birth outcomes. V N Maniragaba *et al.* in 2023 in their study "Modeling the Risk Factors of Undernutrition among Children below Five Years of Age in Uganda Using Generalized Structural Equation Models", the various characteristics and pathways of risk factors that affect undernutrition in children under five years of age, including perceived low birth weight, were validated using generalized structural equations, breastfeeding lesser than six months, lack of formal education by mothers, and frequent diarrhoea were among the most common.(1)

Miscellaneous models- Some researchers have utilized miscellaneous models including mixed bag approach utilizing different models simultaneously. Patterson *et al.* (2023) Five predictive models were tested: logistic regression, support vector multiple regression, random forest, decision tree, and K-nearest neighbor. According to their study, insufficient prenatal clinical variables in low- and middle-income nations result in adequate identification of birth outcomes for LBW babies with good sensitivity rates. They also found that this modelling is a first step in developing a clinical diagnose aiding tool to help providers in deciding to refer these women before delivery.(15)

RESULTS

Risk factors involved in LBW analysis

Some important conclusions are drawn from a thorough review of the literature on low-birth-weight risk factors over the previous five years.:

Maternal factors: Maternal age, parity, socioeconomic status, and pre-existing medical conditions are consistently identified as important risk factors for LBW.

Antenatal care: Adequate antenatal care, including regular check-ups and early detection of risk factors, is associates with reduced LBW rates.

Environmental factors: Exposure to environmental pollutants, such as air pollution and heavy metals, having linked to increased LBW risk.

Genetic factors: Genetic variations may contribute to LBW susceptibility, although further study is needed to elucidate their specific role.

Many reviews have time and again worked on these and other factors. For example, Hoda Arabzadeh *et al.* (2024) reviewed many risk factors including drug usage (e.g. cocaine or crack), infertility, periodontal disease, smoking, caffeine, depression and anemia as risk determinants for LBW in pregnancy. The research determined that pregnant women who practice dental care combined with proper eating habits and balanced stress management alongside abstention from tobacco and alcohol consumption lower their risk of delivering underweight babies.(16)

Similarly, A Bhagat *et al.* (2024) found that for reducing the prevalence of LBWs in tribal areas in Indian districts, maternal education, nutrition, ANC services and midwives should be addressed. Prenatal care is a major element of newborn monitoring services.(17)

Muluneh et al. found that maternal marital status, residence, educational background, ANC visits, smoking during pregnancy, iron supplementation, diabetes during pregnancy and maternal anaemia were significant and associates with low birth weight.(18)

Statistical models developed in recent studies have demonstrated varying degrees of accuracy in predicting LBW. While fewer models have achieving promising performance, further refinement and validation are necessary to ensure their clinical utility.(19,20)

Discussion

Recent studies emphasize the growing importance of developing statistical models to assess LBW amongst tertiary hospital setting. Shaohua *et al.* (2022) discovered that pregnancy-related hypertension and LBW were positively correlated with marital status, and gestational age and low birth rate in a logistic regression model.(21)

Similarly, Khazaei *et al.* (2022) used univariate and multivariate models and demonstrated that low birth weight is a multi-factorial phenomenon. They found that factors associated with LBW were history of pregnancy bleeding, gestational age, maternal BMI, pregnancy appetite and level of healthcare provided.(22)

The evolution of statistical modeling for LBW prediction has seen significant advancements in recent years. Ahammed *et al.* (2020) identifying LBW risk factors with a multivariate logistic regression model and descriptive statistics, demonstrated that incorporating socioeconomic factors alongside demographic gaps needs to be addressed through proper policy action while using these models.(23)

Mizuno *et al.* (2023) stressed the importance of using AI-based LBW models for pre-term and term-birth cohorts, using environmental lifestyle factors and genetics. They concluded that their prediction model, due to its accuracy and generalization, this system presents opportunities to help assess LBW risk in early pregnancy as well as manage LBW risks throughout the term period. Their model possesses the potential to provide precise forecasts of deaths in newborns through genetic analysis during premature birth.(24)

Several studies have explored the integration of novel data sources. Singh *et al.* (2023) included the National Family Health Survey 5 (2019–2021), or NFHS-5, while Devaguru A et al. (2023) investigated the global nutrition monitoring framework as reported by WHO in LBW estimation. (25,26)

The controversy in this field focuses on how model sophistication relates to interpretability levels in medical applications. Exceptional predictive abilities associated with deep learning models face limitations in the clinical practice, because of the inability to provide transparent explanations. Hybrid approaches, as proposed by Bekele *et al.* (2022) attempt to balance accuracy with interpretability.(27)

Some non- Bayesian methods have gained traction in LBW studies, particularly utilizing Akaike Information Criterion (AIC) value. Manzor *et al.* (2024) used a LBW determinants are found using a binary logit function in a generalized stable and linear mixed model. Their final model was modified to account for covariates like gestational age at birth, employment status, and ethnicity. A sequential forward selection method based on a lower Akaike Information Criterion (AIC) was used to choose the best model from among the randomly chosen health clinics.(28)

To lessen the burden of LBW, the majority of studies and researchers believe that better neonatal care facilities, infection control procedures, and focused interventions are essential. To improve birth weight outcomes, interventions targeted at preventing these risk factors should be given top priority. The problem of low birth weights can be reduced and effective early childhood and home care services with maximum use of breastfeeding can be provided because the majority of these factors are easily addressed by providing adequate care, with emphasis on educating mothers and family members.(29,30,31)

Many recent studies have incorporated various new models and outcomes in the field of the Low Birth Weight prediction modeling. R Kumar et al concluded that Logistic have better accuracy than decision tree model. Decision tree excels at capturing patterns but may overfit and hence should be used with caution. In the era of Artificial Intelligence and Machine Learning, many authors have utilized it and developed many LBW prediction models. The concept of explainable artificial intelligence (XAI) has been utilized by Pavanya et al(32) and L Chen et al.(33) On the other hand Mursil et al have utilized the latest Tabnet model of AI for LBW prediction modeling.(34)

Thus the advent of Artificial Intelligence and Machine Learning has paved the way for introduction of new modeling strategies in the field of prediction modeling of Low Birth Weight.

Conclusion

Different studies from 2019 through 2024 have significantly progressed our understanding of LBW statistical modeling in tertiary care hospitals. Logistic regression continues being the primary tool for risk assessment, at the same time machine learning and Bayesian methods gain extensive practical use. The predictive models make improvements to LBW forecasting in addition to enhancing the understanding of the complex interaction between maternal, economic and clinical factors that impact results. The combination of modern statistical techniques with established practices leads to better clinical decisions which produces superior results for newborns in tertiary medical facilities. Continued research should develop these technological models through additional validation tests using various population samples for wider application purposes.

Future Research

A crucial tool for identifying high-risk pregnancies and predicting LBW is statistical modeling. By incorporating various risk factors & employing appropriate researchers, statistical methods have developed models that can provide valuable insights for clinical decision-making. The models having significant constraints which encompass complex biological processes and data collection biases together.

Research should primarily tackle the current boundaries of prediction models and establish new creative methods to identify LBW. This could entail creating customized risk assessment tools, integrating dynamic risk factors that vary over time, and integrating longitudinal data. The clinical value of LBW prediction models needs better evaluation together with their effectiveness in medical settings.

Recommendation

NA

Limitation of the Study

NA

Relevance of the Study

It reviews Statistical Modelling for the Assessment of Low Birth Weight in Tertiary Care Settings.

Authors Contribution

All authors have contributed equally.

Financial Support and Sponsorship

None

Conflict of Interest

None

Acknowledgement

None

Declaration of Generative AI and AI Assisted Technologies in the writing Process

Used ChatGPT for review but entire article is self-written.

References

1. Okwaraji YB, Bradley E, Ohuma EO, Yargawa J, Suarez-Idueta L, Requejo J, et al. National routine data for low birthweight and preterm births: systematic data quality assessment for United Nations member states (2000–2020). BJOG. 2024;131(7):917-928.
2. Mukosha M, Jacobs C, Kaonga P, Musonda P, Vwalika B, Lubeya MK, et al. Determinants and outcomes of low birth weight among newborns at a tertiary hospital in Zambia: a retrospective cohort study. Ann Afr Med. 2023;22(3):271-278.
3. Liu Z, Han N, Su T, Ji Y, Bao H, Zhou S, et al. Interpretable machine learning to identify important predictors of birth weight: a prospective cohort study. Front Pediatr. 2022;10:899954.
4. KC A, Basel PL, Singh S. Low birth weight and its associated risk factors: health facility-based case-control study. PLoS One. 2020;15(6):e0234907.
5. Gupta S, Jatav P, Saroshe S, Shukla H, Bansal SB. A cross-sectional study to assess factors affecting low birth weight at tertiary care center, Indore. Indian J Public Health Res Dev. 2024;15(3):[pages].
6. Christian P, West KP Jr, Khatry SK, LeClerq SC, Pradhan EK, Katz J, et al. Effects of maternal micronutrient supplementation on fetal loss and infant mortality: a cluster-randomized trial in Nepal. Am J Clin Nutr. 2003;78(6):1194-1202.
7. Thapa P, Poudyal A, Poudel R, Upadhyaya DP, Timalsina A, Bhandari R, et al. Prevalence of low birth weight and its associated factors: hospital-based cross-sectional study in Nepal. PLOS Glob Public Health. 2022;2(11):e0001220.
8. Mondal B. Risk factors for low birth weight in Nepali infants. Indian J Pediatr. 2000;67:477-482.
9. Islam MJ, Chowdhury MH, Rahman MM, Rahman Z. Risk factors of children's low birth weight and infant mortality in Bangladesh: evidence from binary logistic regression and Cox PH models. Health Sci Rep. 2024;7(8):e70009.
10. Borson NS, Kabir MR, Zamal Z, Rahman RM. Correlation analysis of demographic factors on low birth weight and prediction modeling using machine learning techniques. In: Proc 4th World Conf Smart Trends Syst Secur Sustain (WorldS4); 2020 Jul 27; India. IEEE; 2020. p. 169-173.
11. Ranjbar A, Montazeri F, Farashah MV, Mehrnoush V, Darsareh F, Roozbeh N. Machine learning-based approach for predicting low birth weight. BMC Pregnancy Childbirth. 2023;23(1):803.
12. Wang Q, Gao W, Duan Y, Ren Z, Zhang Y. Exploring predictors of interaction among low-birth-weight infants and their caregivers: a machine learning-based random forest approach. BMC Pediatr. 2024;24(1):648.
13. Avwerhota OO, Avwerhota M, Daniel EO, Popoola TA, Popoola IO, Ogun AA, et al. Bayesian spatial analysis of

risk factors affecting low birth weight in Nigeria. J Fam Med Health Care. 2024;10(3):40-50.
14. Maniragaba VN, Atuhaire LK, Rutayisire PC. Modeling the risk factors of undernutrition among children below five years of age in Uganda using generalized structural equation models. Children (Basel). 2023;10(12):1926.
15. Patterson JK, Thorsten VR, Eggleston B, Nolen T, Lokangaka A, Tshefu A, et al. Building a predictive model of low birth weight in low- and middle-income countries: a prospective cohort study. BMC Pregnancy Childbirth. 2023;23(1):600.
16. Arabzadeh H, Doosti-Irani A, Kamkari S, Farhadian M, Elyasi E, Mohammadi Y. The maternal factors associated with infant low birth weight: an umbrella review. BMC Pregnancy Childbirth. 2024;24(1):316.
17. Bhagat AK, Mehendale AM, Muneshwar KN, Bhagat A. Factors associated with low birth weight among the tribal population in India: a narrative review. Cureus. 2024;16(2):eXXXXX.
18. Muluneh MW, Mulugeta SS, Belay AT, Moyehodie YA. Determinants of low birth weight among newborns at Debre Tabor referral hospital, Northwest Ethiopia: a cross-sectional study. SAGE Open Nurs. 2023;9:23779608231167107.
19. Mursil M, Rashwan HA, Cavallé-Busquets P, Santos-Calderón LA, Murphy MM, Puig D. Maternal nutritional factors enhance birthweight prediction: a super learner ensemble approach. Information (Basel). 2024;15(11):714.
20. Islam Pollob SA, Abedin MM, Islam MT, Islam MM, Maniruzzaman M. Predicting risks of low birth weight in Bangladesh with machine learning. PLoS One. 2022;17(5):e0267190.
21. Shaohua Y, Bin Z, Mei L, Jingfei Z, Pingping Q, Yanping H, et al. Maternal risk factors and neonatal outcomes associated with low birth weight. Front Genet. 2022;13:1019321.
22. Khazaei Z, Bagheri MM, Goodarzi E, Moayed L, Abadi NE, Bechashk SM, et al. Risk factors associated with low birth weight among infants: a nested case-control study in Southeastern Iran. Int J Prev Med. 2021;12:159.
23. Ahammed B, Maniruzzaman M, Ferdausi F, Abedin MM, Hossain MT. Socioeconomic and demographic factors associated with low birth weight in Nepal: data from 2016 Nepal demographic and health survey. Asian J Soc Health Behav. 2020;3(4):158-165.
24. Mizuno S, Nagaie S, Tamiya G, Kuriyama S, Obara T, Ishikuro M, et al. Establishment of early prediction models of low-birth-weight reveals influential genetic and environmental factors: a prospective cohort study. BMC Pregnancy Childbirth. 2023;23(1):628.
25. Singh D, Manna S, Barik M, Rehman T, Kanungo S, Pati S. Prevalence and correlates of low birth weight in India: findings from National Family Health Survey-5. BMC Pregnancy Childbirth. 2023;23(1):456.
26. Devaguru A, Gada S, Potpalle D, Eshwar MD, Purwar D. Prevalence of low birth weight among newborn babies and its associated maternal risk factors: a hospital-based cross-sectional study. Cureus. 2023;15(5):eXXXXX.
27. Bekele WT. Machine learning algorithms for predicting low birth weight in Ethiopia. BMC Med Inform Decis Mak. 2022;22(1):232.
28. Mansor E, Ahmad N, Mohd Zulkefli NA, Lim PY. Incidence and determinants of low birth weight in Peninsular Malaysia: a multicentre prospective cohort study. PLoS One. 2024;19(7):e0306387.
29. Dhivar NR, Gandhi R, Murugan Y, Vora H. Outcomes and morbidities in low-birth-weight neonates: a retrospective study from Western India. Cureus. 2024;16(6):eXXXXX.
30. Mfipa D, Hajison PL, Mpachika-Mfipa F. Predictors of low birthweight and comparisons of newborn birthweights among different groups of maternal factors at Rev. John Chilembwe Hospital, Malawi: a retrospective record review. PLoS One. 2024;19(8):e0291585.
31. Bansal P, Garg S, Upadhyay HP. Prevalence of low birth weight babies and its association with socio-cultural and maternal risk factors among institutional deliveries in Bharatpur, Nepal. Asian J Med Sci. 2019;10(1):77-85.
32. Pavanya M, Chadaga K, J V, et al. Prediction of birthweight with early and mid-pregnancy antenatal markers utilising machine learning and explainable artificial intelligence. Sci Rep. 2025;15:26223.
33. Chen L, Shao H, Zhang J, et al. Developing predictive models for full-term low birth weight infants using ten machine learning algorithms. BMC Pediatr. 2025;25:820.
34. Mursil M, Rashwan HA, Khalid A, Cavallé-Busquets P, Santos-Calderon L, Murphy MM, et al. Interpretable deep neural networks for advancing early neonatal birth weight prediction using multimodal maternal factors. J Biomed Inform. 2025;166:104838.