International Journal of Reproduction, Contraception, Obstetrics and Gynecology
Zamanah E et al. Int J Reprod Contracept Obstet Gynecol. 2025 Jul;14(7):2102-2110
www.ijrcog.org

pISSN 2320-1770 | eISSN 2320-1789

DOI: https://dx.doi.org/10.18203/2320-1770.ijrcog20251954

Original Research Article

Bayesian logistic regression of stillbirth cases in the Bolgatanga Municipality of Ghana, West Africa

Ernest Zamanah[1]*, Suleman Nasiru[2]

[1]Department of Biometry, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Ghana
[2]Department of Statistics and Actuarial Science, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Ghana

Received: 14 May 2025
Revised: 14 June 2025
Accepted: 16 June 2025

***Correspondence:**
Dr. Ernest Zamanah,
E-mail: ezamanah@yahoo.com

ABSTRACT

Background: Stillbirth, as an adverse outcome of pregnancy, represents a growing worldwide public health challenge. The risks of stillbirth have been reported to exhibit considerable variation across different factors due to variability in socio-economic and geographical settings. Thus, this study was aimed at modelling the risk of stillbirth in the Bolgatanga Municipality of the Upper East region of Ghana and identifying some possible risk factors.

Methods: A retrospective cohort study design was utilized in this work. Thus, all the data were obtained from the medical recorded histories of all single birth outcomes at Bolgatanga Regional hospital in Ghana from September 2023 to December 2024. Bayesian logistic regression was applied in fitting the data on stillbirth in this study. R studio was the statistical software that was utilized in analysing the data.

Results: Based on the results of the posterior estimation of the Bayesian logistic regression, maternal age, educational level and hypertension status were established as significant risk factors of stillbirth in the Bolgatanga Municipality. Overall, women with low maternal age (<20 years) and those with advanced maternal age (≥35 years), women with no formal education, and women with hypertension during pregnancy were established to have a higher risk of stillbirth in the Bolgatanga Municipality.

Conclusions: The study concluded by indicating the need for various agencies of healthcare in the Bolgatanga Municipality to institute targeted interventions that will help control the effects of the risk factors and enhance improved overall pregnancy outcomes.

Keywords: Posterior estimation, Bayesian approach, Logistic regression, Stillbirth, Priors

INTRODUCTION

Stillbirth is an adverse outcome of pregnancy, defined as the death of a fetus after a gestational period of 28 weeks or more with a birth weight of 1000 gram or more.[1-3] Aside the attendant loss of earnings because of time taken off work, stillbirth often results in psychological related trauma in addition to adverse economic repercussions in relation to funeral costs among others.[2]

Stillbirths represent a growing worldwide public health challenge with a global estimated number of approximately 2 million stillbirths among which three out of four are noted to occur in Sub-Saharan Africa (SSA) or Southern Asia.[4,5] Majority of stillbirths are noted to occur in low and middle-income countries (LMICs). For example, in 2019, LMICs accounted for approximately 84% of all stillbirths around the world.[6] LMICs are thus noted to bear a greater proportion of the global burden of stillbirths.[7]

Global stillbirth rates have been shown to characterize with a decreasing trend over the years. Evident from 2000 to 2019, stillbirth rates are noted to have declined from 24.7 per 1000 births to 13.9 per 1000 births.[8] Across different sub-Saharan African countries, still birth rates have been shown to exhibit considerable variation. In 2014 and 2015 for example, stillbirth rates were shown to vary from 20.3 per 1000 births to 118.1 per 1000 births across different African countries. Variation in stillbirth rates has also been shown to be exhibited across different regions in Ghana. For example, between 2013 through to 2017, stillbirth rates were shown to range between 27 per 1000 births and 105.6 per 1000 births across various regions in Ghana.[7]

The risk of stillbirth has been reported to exhibit considerable variation across different factors due to variability in socio-economic and geographical settings.[9] Disease conditions such as diabetes, hypertension or HIV/AIDS have been reported as possible factors that influence the likelihood of stillbirths. Alcohol usage, smoking and educational level have also been identified as possible underlying factors among others that influence the risk of stillbirths among women.[5] In the context where birth outcome is either stillbirth or live birth, the classical logistic regression model has been utilized to determine possible risk factors of stillbirths in many applied studies. For example, the classical logistic regression model was applied in modelling the risk factors of stillbirth in Northern Ghana.[10] Several other research works have also applied the classical logistic regression.[1,8,11-16]

Practical data sets are however often biased by sampling methods or inadequacies of sample size among others and are usually considered incomplete compared to reality. As a result, the accuracy of estimation results is often affected in the applications of traditional models such as the classical logistic regression model. The Bayesian procedure provides a robust approach of modelling that utilizes prior knowledge or information together with observed data to update and refine available information through the process of posterior inference. Regardless of the sample size, the Bayesian procedure results in more accurate estimation results with better precision than traditional methods.[17]

Using an appropriate statistical procedure in the modelling process will ensure that possible underlying risk factors are appropriately identified.[18] Thus, the study focussed on applying the Bayesian approach as a robust modelling procedure in modelling the risk of stillbirth in the Bolgatanga Municipality of the Upper East region of Ghana and identifying possible associations of some risk factors of stillbirth.

An outline of the remaining part of the article is given as follows: Section 2 gives a presentation of the materials and methods. In section 3, the results and discussions are outlined. The article is then concluded with some recommendations in section 4.

METHODS

Study design

A retrospective cohort study design was utilized in this work.

Study area

The Bolgatanga municipality of the upper East Region of Ghana represented the study area of this work. The Bolgatanga municipality is the administrative capital of the upper East Region of Ghana and home to the Bolgatanga Regional Hospital. The hospital serves as a referral center for all private health facilities within the municipality and also provides healthcare services to all patients within the municipality and beyond.

Study population

All birth outcomes that were recorded at the Bolgatanga Regional Hospital from September 2023 to December 2024 were included the study.

Inclusion criteria

All single birth outcomes with a gestational age of 28 weeks or more were included in the study.

Exclusion criteria

Birth outcomes were excluded from the study where information on gestational age was not available.

Data collection

Secondary data were obtained from the Bolgatanga Regional Hospital of the upper East region of Ghana by reviewing the medical histories of all single birth outcomes from September 2023 to December 2024. Thus, a total of 410 recorded single birth outcomes were used for the study. Birth outcome, defined as stillbirth or live birth representing a binary outcome was the variable of interest in the study. Other variables such as hypertension status of mother, maternal age, foetal sex and educational level of mother were used as independent variables in the study.

Ethical approval

The research did not involve direct participation of pregnant women. Thus, ethical clearance was not required for the study. Personal or identification information on the birth outcomes were excluded from the data thereby ensuring confidentiality in the use of the data that were obtained for the study.

Study variables

Dependent variable

The response variable for this study was birth outcome defined as stillbirth or live birth. Thus, the variable of interest was classified as a dichotomous variable in the study.

Independent variables

Maternal age

As a categorical variable referring to the age of the pregnant woman at time of delivery, three categories (<20 years, 20-34 years and ≥35 years) were defined for maternal age.

Foetal sex

As a categorical variable, foetal sex refers to male and female categories of the foetus.

Educational level

Four categories (No education, Primary, Secondary and Tertiary) were defined for educational level of mother of each birth outcome.

Hypertension status

For the hypertension status of the mother of each birth outcome, two categories (Yes and No) were defined.

Statistical analysis

Bayesian inference

Consider that w_j, $j=1,\dots,n$ represent the birth outcomes of pregnant women and a random variable has a probability function given by $P\left(w_j|\boldsymbol{\varphi}\right)$ where $\boldsymbol{\varphi}=\left(\varphi_1,\varphi_2,\dots,\varphi_n\right)$ is a parameter space. The likelihood function is defined by

$$L(\boldsymbol{\varphi})=\prod_{j=1}^{n} P\left(w_j|\boldsymbol{\varphi}\right).$$

The Bayesian approach of modelling makes use of prior distributions of the unknown parameters $\boldsymbol{\varphi}$ in the likelihood function. Prior distributions provide knowledge of existing information about the parameter space $\boldsymbol{\varphi}$, before the sample w_j, is observed. Considered as stochastic, appropriate distributions known as prior distributions are assigned to all the parameters $\boldsymbol{\varphi}$ within the Bayesian framework.[19]

In a posterior inference, a probability distribution known as the posterior distribution is obtained through a combination of the likelihood function of the sample and the prior distributions.[19] Given the observed data, the posterior distribution, denoted by $P\left(\boldsymbol{\varphi}|w_j\right)$ is the conditional distribution of the parameters. The posterior distribution $P(\boldsymbol{\varphi})$, defined as the product of the likelihood function and the prior distributions is given by

$$P\left(\boldsymbol{\varphi}|w_j\right)\propto P\left(w_j|\boldsymbol{\varphi}\right)P(\boldsymbol{\varphi}). \qquad (1)$$

By assigning a distribution for each parameter under the assumption of the parameter estimates being random could generate informative priors resulting in misleading statistical inferences.[20] Conjugate or non-informative priors allow for more efficiency in estimating the coefficients of the posterior distributions within the approach of Bayesian framework.[21] Thus, conjugate priors were utilized in this study.

To assess the adequacy of the Bayesian model, trace and density plots of the posterior distributions parameter estimates were utilized to determine model convergence through Markov Chain Monte Carlo (MCMC) procedures.

Likelihood function

Consider a random sample of independently and identically distributed outcomes $\mathbf{w}=\left(w_1,w_2,\dots,w_n\right)'$, with a probability function $f\left(w_j|\boldsymbol{\varphi}\right)$, where $\boldsymbol{\varphi}$ is a parameter space. The joint probability function which is the likelihood function of the sample is defined in (2).[22]

$$L(\boldsymbol{\varphi}|\mathbf{w})=f\left(w_1,w_2,\dots,w_n|\boldsymbol{\varphi}\right)=\prod_{j=1}^{n} f\left(w_j|\boldsymbol{\varphi}\right). \qquad (2)$$

Bayesian analysis using logistic regression model

Consider a random sample of birth outcomes $\mathbf{w}=\left(w_1,w_2,\dots,w_n\right)'$, in which each individual birth outcome is defined as stillbirth or live birth. Then the distribution of w_j is Bernoulli with values 0 or 1. The Bernoulli distribution with a parameter η has a probability mass function defined in (3).[22,23]

$$f\left(w_j|\eta\right)=\eta^{w_j}\left(1-\eta\right)^{1-w_j}, \qquad (3)$$

where $\eta=P\left(w_j=1\right)$.

Using the logit link function, the logistic regression is defined such that

$$\eta=\frac{\exp(X\varphi)}{1+\exp(X\varphi)},$$

where X' is a $k \times 1$ vector of explanatory variables and φ is a $k \times 1$ vector of regression coefficients. This therefore gives the likelihood function as

$$L = \prod_{j=1}^{n} \left[\left(\frac{\exp(X\varphi)}{1+\exp(X\varphi)} \right)^{w_j} \times \left(1 - \frac{\exp(X\varphi)}{1+\exp(X\varphi)} \right)^{1-w_j} \right]. \qquad (4)$$

By choosing a Gaussian prior for the regression coefficient such that $\varphi_i \sim N(0, \sigma_0^2)$, the joint posterior distribution is obtained by applying the Bayes theorem. This gives

$$P(\varphi | X, w_j) \propto L(w_j | \varphi, X) P(\varphi). \qquad (5)$$

That is,

$$P(\varphi | X, w_j) \propto \prod_{j=1}^{n} \left[\left(\frac{\exp(X\varphi)}{1+\exp(X\varphi)} \right)^{w_j} \times \left(1 - \frac{\exp(X\varphi)}{1+\exp(X\varphi)} \right)^{1-w_j} \right] \times \prod_{i=1}^{I} \frac{1}{\sigma_o \sqrt{2\pi}} \exp\left(-\frac{\varphi_i^2}{2 \times \sigma_0^2} \right). \qquad (6)$$

RESULTS

Summary statistics

Table 1 shows the descriptive statistics which illustrate the distribution of the birth outcomes across various categories of the predictor variables. Table 1 shows that 64.15% of the birth outcomes were females and 35.85% were males. Again, majority of the mothers of the birth outcomes representing 94.15% were aged between 20 and 34 years whereas 2.68% aged less than 20 years and 3.17% aged above 34 years. Among the birth outcomes, very few of the mothers representing 1.95% received primary education whereas 4.15% received no formal education. Majority of the mothers attained higher levels of education with 68.29% being secondary level and 25.61% being tertiary level. Finally, the prevalence of hypertension was evident among 6.34% of the mothers in the study.

Table 1: Descriptive statistics of birth outcomes based on some predictor variables.

Variable	Category	Frequency (%)
Birth outcome	Live birth	387 (94.39)
	Stillbirth	23 (5.61)
Foetal sex	Female	236 (64.15)
	Male	174 (35.85)
Maternal age (in years)	<20	11 (2.68)
	20-34	386 (94.15)
	≥35	13 (3.17)
Educational level	No education	17 (4.15)
	Primary	8 (1.95)
	Secondary	280 (68.29)
	Tertiary	105 (25.61)
Hypertension status	Yes	26 (6.34)
	No	384 (93.66)

Table 2: Parameter estimates of Bayesian logistic regression on the stillbirth data.

Parameter		Estimates	Standard error	95% credible interval	Rhat	Bulk_ESS	Tail_ESS
Intercept		8.45	5.56	(-0.73, 21.07)	1.00	8288	8427
Maternal age (in years)	20-34	-9.94	4.98	(-20.95, -1.53)	1.00	7332	9147
	≥35	-3.86	5.46	(-15.06, 6.62)	1.00	8893	9629
	<20 (Ref)	-	-	-	-	-	-
Foetal sex	Male	0.55	2.97	(-5.25, 6.59)	1.00	11301	10449
	Female (Ref)	-	-	-	-	-	-
Educational level	Primary	-4.47	4.42	(-13.57, 4.04)	1.00	8882	10581
	Secondary	-11.67	4.40	(-21.54, -4.30)	1.00	7813	9850
	Tertiary	-12.88	5.08	(-24.10, -4.50)	1.00	7855	9892
	None (Ref)	-	-	-	-	-	-
Hypertension status	Yes	6.87	3.78	(0.33, 15.42)	1.00	7073	7793
	No (Ref)	-	-	-	-	-	-

Ref means reference category

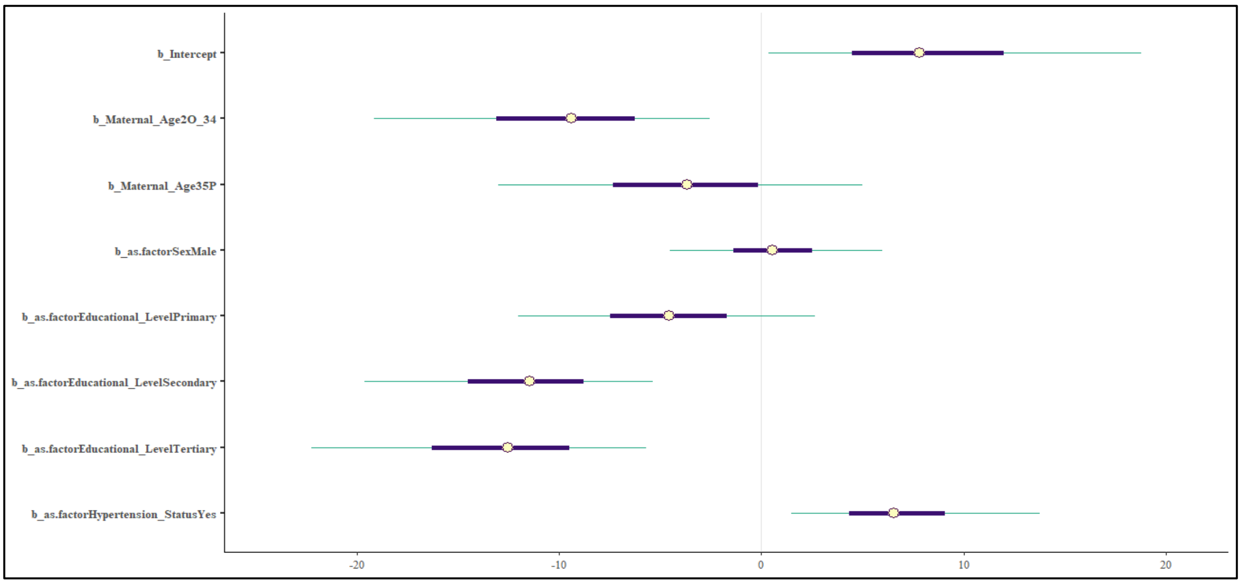

Figure 1: Caterpillar plot of Bayesian logistic regression.

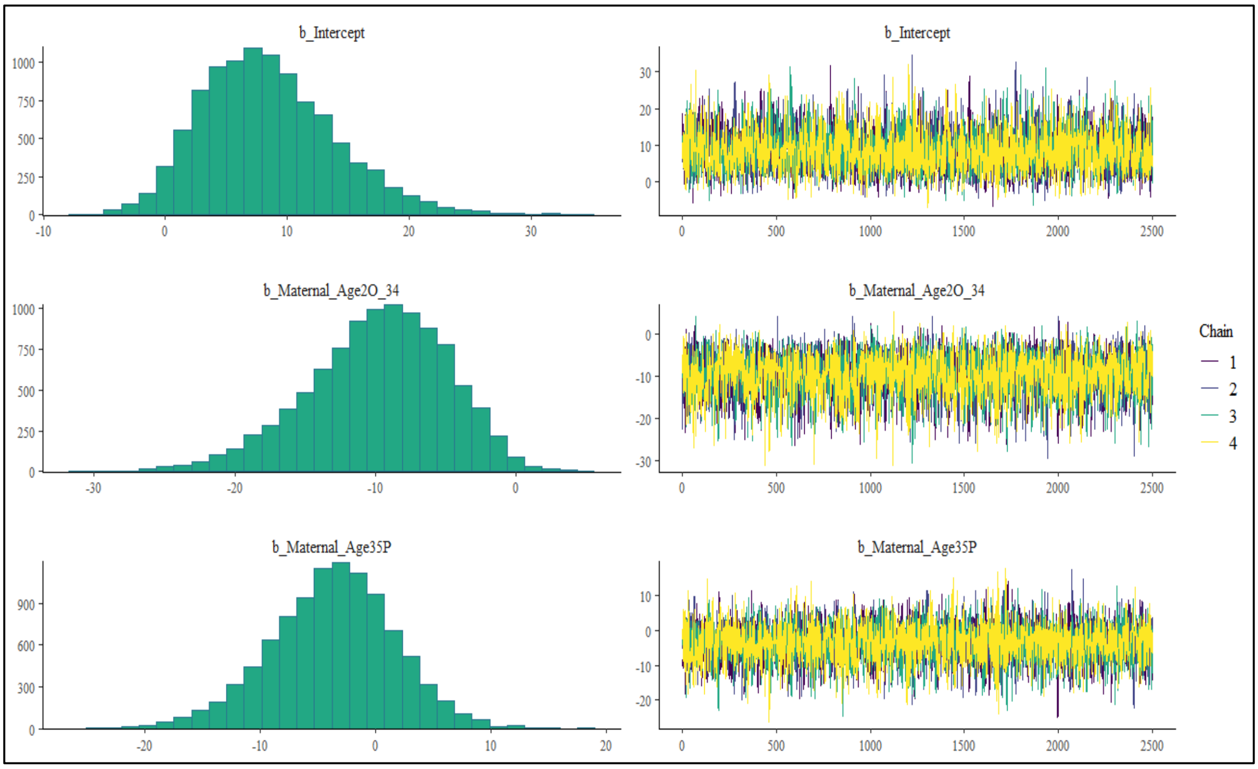

Figure 2: Density and trace plot of Bayesian logistic regression parameters.

Table 2 shows the parameter estimates of the posterior distribution for the Bayesian logistic regression model. Among the predictors, the results showed maternal age, educational level and hypertension status to be statistically significant at 95% confidence level. Foetal sex is however shown to be statistically insignificant. The Rhat values are all 1.0 for all the parameters and the effective sample size (Bulk_ESS and Tail_ESS) values are all greater than 1000 indicating that there was satisfactory model convergence of the posterior distribution of the Bayesian logistic regression.

Figure 1 shows the caterpillar plot of the Bayesian logistic regression model. The results support the finding that whilst foetal sex is statistically insignificant, maternal age, educational level and hypertension status are statistically significant at 95% confidence level.

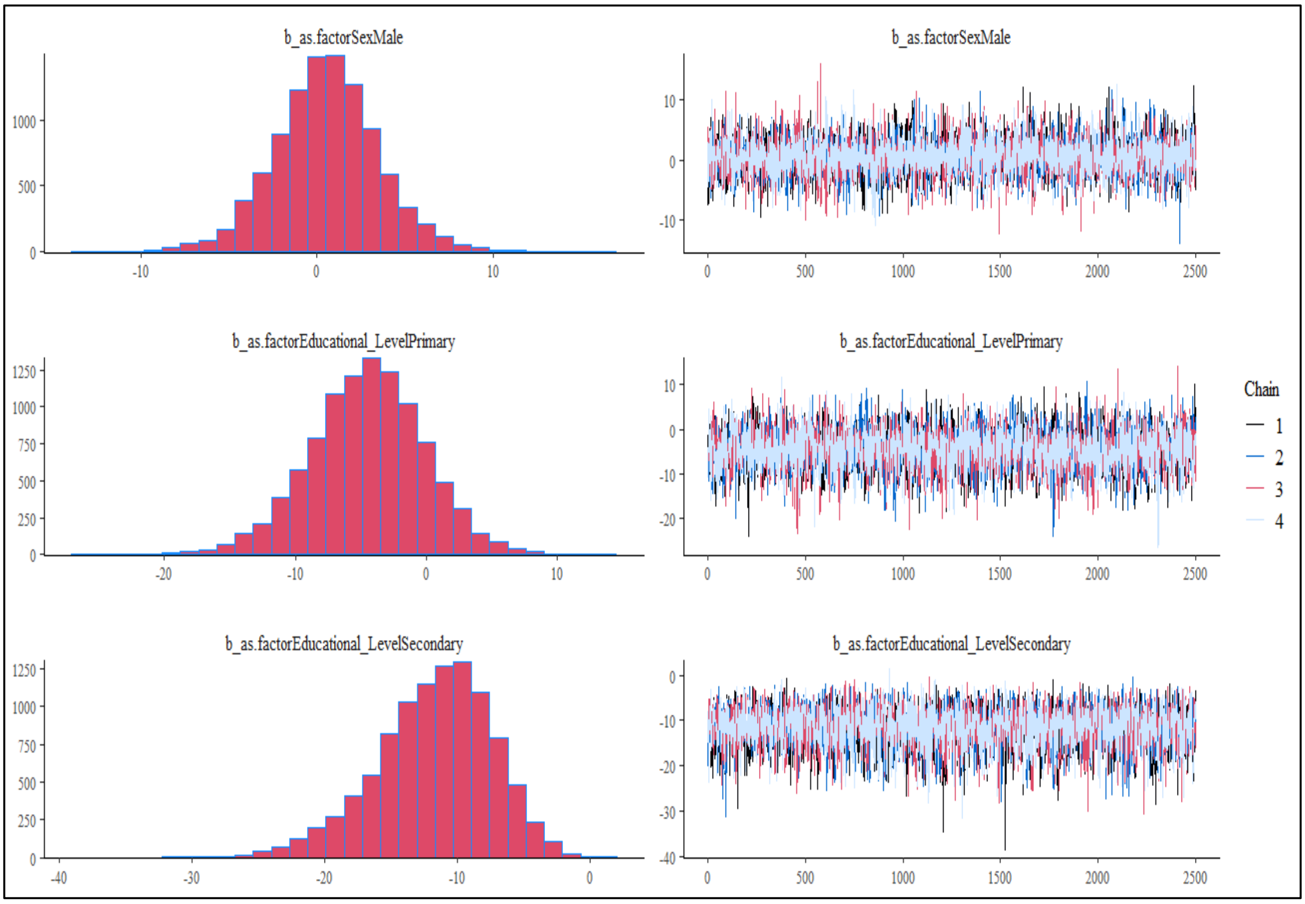

Figure 3: Density and trace plot of Bayesian logistic regression parameters.

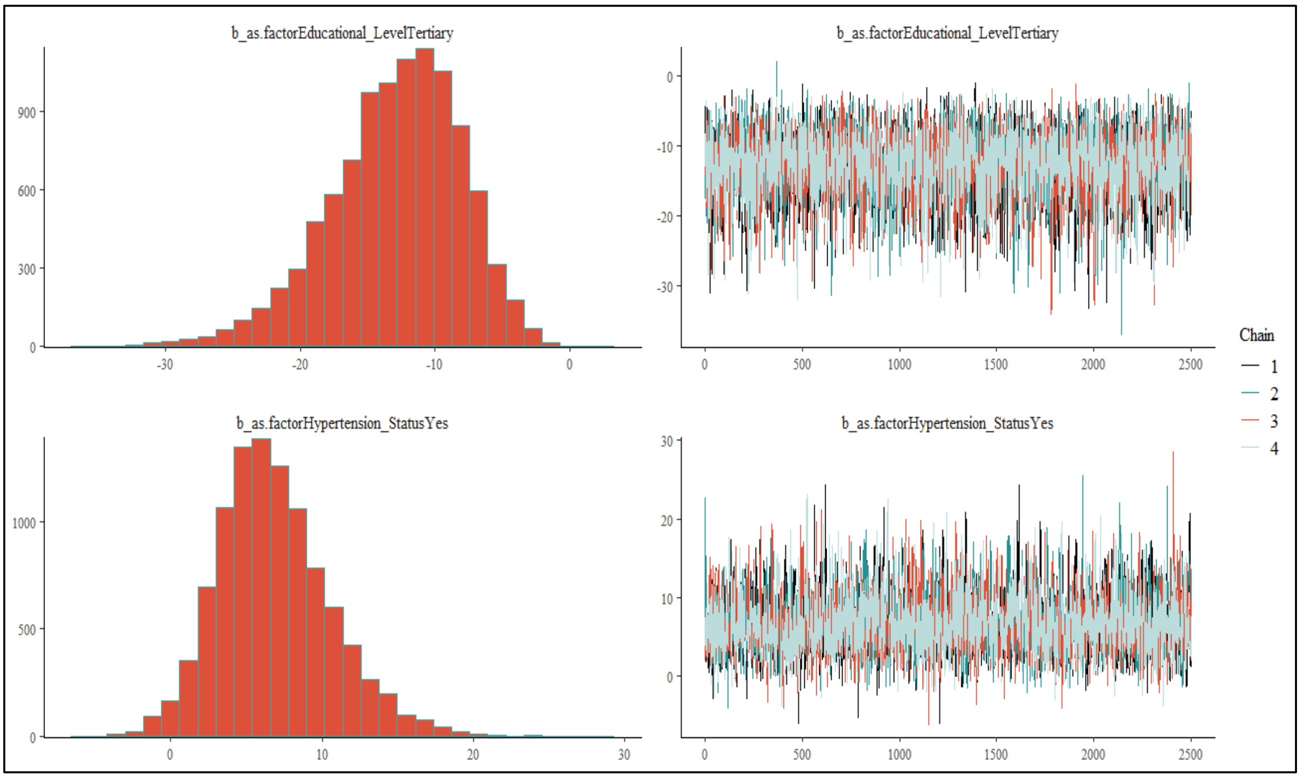

Figure 4: Density and trace plot of Bayesian logistic regression parameters.

Figure 5: Posterior predictive plot of Bayesian logistic regression.

Model diagnostic checks

The adequacy of the fitted Bayesian logistic regression model is investigated in this section to determine whether there was satisfactory model convergence. Figures 2, 3 and 4 show the trace and density plots of the parameters of the fitted regression model. The results showed an overlay of the chains, and this illustrates a good mixing of the four chains for all the parameters. The results confirm that the Monte Carlo Markov Chain simulation converged satisfactorily to the target posterior distribution in the estimation of the parameters. This finding is supported by the results in Table 2 with the Rhat values being 1 for all the parameters of the model.

Further, the posterior predictive plot in Figure 5 shows an overlap of the posterior and replicated distributions having the same trend. The results confirm that the posterior predictive capability of the Bayesian logistic regression model was adequate in modelling the risk of stillbirth in the Bolgatanga municipality.

DISCUSSION

In this paper, the risk of stillbirth in the Bolgatanga Municipality of the Upper East region of Ghana was investigated, with a dichotomous variable, defined as stillbirth or live birth being the response variable. Among a sample of birth outcomes, the summary statistics showed the prevalence of hypertension evident among 6.34% of the mothers in the study.

The Bayesian framework as a robust modelling approach was utilized in modelling the response variable in this study. Thus, the response variable defined with binary outcomes was studied by applying the Bayesian logistic regression model.

The posterior estimation results of the fitted Bayesian logistic regression identified maternal age, educational level and hypertension status as statistically significant risk factors of stillbirth at 95% confidence level. However, foetal sex showed no statistical significance.

At the 95% confidence level, the results illustrated a statistically significant difference in the risk of stillbirth for different age categories of mothers. Specifically, it was empirically established that the risk of stillbirth is higher for mothers who are aged less than 20 years compared to mothers who are aged between 20 and 34 years. For women who are aged less than 20 years and those aged above 34 years, the results however showed no significant difference in the risk of stillbirth. This shows that women who are less than 20 years old and those with advanced maternal age (≥ 35 years) have a higher risk of stillbirth than women within the age category of 20-34 years. The finding is consistent with other reported observations that women with advanced maternal age have a higher risk of stillbirth.[3,25]

Across different educational levels, the findings indicated a statistically significant difference in the risk of stillbirth between mothers with no formal education and those with higher educational levels. Specifically, the results illustrated that women with higher educational levels (secondary and tertiary) have a lower risk of stillbirth compared to those with no formal education. This finding is similar to observations of other studies that women with higher educational status have a lower risk of stillbirth.[25,26]

Empirically, the findings further established a statistically significant difference in the risk of stillbirth between women with hypertension during pregnancy and those without hypertension during pregnancy. Specifically, the findings indicated that women with hypertension during pregnancy have a higher risk of stillbirth compared to women without hypertension during pregnancy. The finding is consistent with observations of other studies that women with hypertension during pregnancy have a higher risk of stillbirth than women without hypertension during pregnancy.[1-3]

Study limitations

The use of secondary data was a limitation to the choice of variables in this study. Consequently, important variables such as smoking status and alcohol usage which could influence the risk of stillbirth could not be captured in the current study. Nonetheless, the findings of this study are useful and have implications towards public health policy in the Bolgatanga Municipality.

CONCLUSION

This study was aimed at modelling the risk of stillbirth in the Bolgatanga municipality of the upper East region of Ghana and identifying some possible risk factors. To this end, Bayesian logistic regression model was utilized in fitting the stillbirth data in this study. Based on the results of the posterior estimation of the Bayesian logistic regression, maternal age, educational level and hypertension status were established as significant risk factors of stillbirth in the Bolgatanga Municipality. Overall, women with low maternal age (<20 years) and those with advanced maternal age (≥35 years), women with no formal education, and women with hypertension during pregnancy were established to have a higher risk of stillbirth in the Bolgatanga municipality.

Recommendations

Based on the findings of this study, it is recommended for various agencies of healthcare in the Bolgatanga Municipality to institute targeted interventions that will ensure adequate access to healthcare through which conditions such as hypertension during pregnancy can be detected and managed. Pregnant women can also be sufficiently educated on recommended practices during pregnancy. Again, pregnant women within the high-risk age categories can also be identified and the needed medical assistance offered. These will help control the effects of the risk factors and enhance improved overall pregnancy outcomes in the Bolgatanga Municipality.

ACKNOWLEDGEMENTS

The authors are grateful to the staff of the Records Department of the Bolgatanga Regional Hospital for their support in providing the data for this research work.

Funding: No funding sources
Conflict of interest: None declared
Ethical approval: The study was approved by the Institutional Ethics Committee

REFERENCES

1. Jamie AH. Prevalence and determinants of stillbirth in attended deliveries in University Hospital, Eastern Ethiopia in 2021. Caspian J Reprod Med. 2022;8(1):9-14.
2. Egbe TO, Ewane EN, Tendongfor N. Stillbirth rates and associated risk factors at the Buea and Limbe regional hospitals, Cameroon: a case-control study. BMC Pregnancy Childbirth. 2020;20(75):1-8.
3. Kasa GA, Woldemariam AY, Adella A, Alemu B. The factors associated with stillbirths among sub-saharan African deliveries: a systematic review and meta-analysis. BMC Pregnancy Childbirth. 2023;23(835):1-18.
4. United Nations. UN-IGME-2020-Stillbirth-Report. 2020.
5. Nakamya P, Komakech A, Migamba SM, Biribawa C, Kwesiga B, Bulage L, et al. Trends and geospatial distribution of stillbirths in Uganda, 2014–2020. BMC Pregnancy Childbirth. 2024;24(249):1-14.
6. Mahmood NH, Kadir DH, Yahya RO, Birdawod HQ. The significance of delivery methods and fetal gender in reducing stillbirth rate: Using the generalized regression model. Clin Epidemiol Glob Health. 2024;29:1-9.
7. Dah AK, Osarfo J, Ampofo GD, Appiah-Kubi A, Mbroh H, Azanu WK, et al. Stillbirth incidence and determinants in a tertiary health facility in the Volta Region of Ghana. PLos One. 2023;18(12):e0296076.
8. Hug L, You D, Blencowe H, Mishra A, Wang Z, Fix MJ, et al. Global, regional, and national estimates and trends in stillbirths from 2000 to 2019: a systematic assessment. Lancet. 2021;398(10302):772-85.
9. Saleem S, Tikmani SS, McClure EM, Moore JL, Azam SI, Dhaded SM, et al. Trends and determinants of stillbirth in developing countries: results from the Global Network's Population-Based Birth Registry. Reprod Health. 2018;15(100):23-30.
10. Nonterah EA, Agorinya IA, Kanmiki EW, Kagura J, Tamimu M, Ayamba EY, et al. Trends and risk factors associated with stillbirths: A case study of the Navrongo War Memorial Hospital in Northern Ghana. Plos One. 2020;15(2):e0229013.
11. Tesema GA, Tessema ZT, Tamirat KS, Teshale AB. Prevalence of stillbirth and its associated factors in East Africa: generalized linear mixed modeling. BMC Pregnancy Childbirth. 2021;21(414):1-10.
12. Nwoga HO, Ajuba MO, Igweagu CP. Still birth in a tertiary health facility in Enugu state South-East Nigeria: a hidden tragedy. Int J Reprod Contracept Obstet Gynecol. 2021;10(7):2584-90.
13. Milton R, Modibbo F, Gillespie D, Alkali FI, Mukaddas AS, Kassim A, et al. Incidence and sociodemographic, living environment and maternal health associations with stillbirth in a tertiary healthcare setting in Kano, Northern Nigeria. BMC Pregnancy Childbirth. 2022;22(692):1-14.
14. Vanotoo L, Dwomoh D, Laar A, Kotoh AM, Adanu R. Modeling clinical and non-clinical determinants of intrapartum stillbirths in singletons in six public hospitals in the Greater Accra Region of Ghana: a case–control study. Sci Rep. 2023;13(1013):1-12.

15. Mallam I, Abubakar I, Yakubu A. Application of multivariate logistic regression and decision trees to assess factors influencing prevalence of abortion and stillbirth in yankasa sheep. Animal Sci Genet. 2023;19(4):17-27.
16. Gwacham-Anisiobi U, Opondo C, Cheng TS, Kurinczuk JJ, Anyaegbu G, Nairl M. Rates and risk factors for antepartum and intrapartum stillbirths in 20 secondary hospitals in Imo state, Nigeria: A hospital-based case control study. PLOS Glob Public Health. 2024;4(10):e0003771.
17. Rastegar M, Nazar E, Nasehi M, Sharafi S, Fakoor V, Shakeri MT. Bayesian estimation of the time-varying reproduction number for pulmonary tuberculosis in Iran: a registry-based study from 2018 to 2022 using new smear-positive cases. Infect Dis Model. 2024;9(3):963-74.
18. Gemechu LL, Debusho LK. Bayesian spatial modelling of tuberculosis-HIV co-infection in Ethiopia. PLos One. 2023;18(3):e0283334.
19. Blangiardo M, Cameletti M. Spatial and spatio-temporal Bayesian models with R-INLA. John Wiley & Sons; 2015.
20. Hahn U. The Bayesian boom: good thing or bad? Front Psychol. 2014;5(765):1-12.
21. Robert CP, Rousseau JM. A special issue on Bayesian inference: challenges, perspectives and prospects. Phil Trans R Soc A. 2023;381:1-4.
22. Lukman PA, Abdullah S, Rachman A. Bayesian logistic regression and its application for hypothyroid prediction in post-radiation nasopharyngeal cancer patients. J Phys Conf Ser. 2021;1725:1-10.
23. Uspensky JV. Introduction to Mathematical Probability. New York: McGraw-Hill; 1937.
24. Farhin, S. and Khan, A. A. Bayesian survival analysis of acute encephalitis syndrome with censoring mechanism using brms package. J Stat Appl Probab. 2022;11(3):963-80.
25. Amani A, Nansseu JR, Ndeffo GF, Njoh AA, Cheuyem FZL, Libite PR, et al. Stillbirths in Cameroon: an analysis of the 1998-2011 demographic and health surveys. BMC Pregnancy Childbirth. 2022;22:736.
26. Regassa Y, Lemi H, Charkos TG. Determinants of stillbirth among mothers who gave birth at Bishoftu General Hospital, Ethiopia: using a Bayesian logistic regression model. Front Glob Women's Health. 2024.

Cite this article as: Zamanah E, Nasiru S. Bayesian logistic regression of stillbirth cases in the Bolgatanga Municipality of Ghana, West Africa. Int J Reprod Contracept Obstet Gynecol 2025;14:2102-10.