Heliyon 9 (2023) e18961

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Multilevel modelling of neonatal mortality in Ghana: Does household and community levels matter?

Wisdom Kwami Takramah [a,b,*], Justice Moses K. Aheto [b,c]

[a] Department of Epidemiology and Biostatistics, School of Public Health, University of Health and Allied Sciences, Ho, Ghana
[b] Department of Biostatistics, School of Public Health, University of Ghana, Accra, Ghana
[c] WorldPop, University of Southampton, United Kingdom

ARTICLE INFO

Keywords:
Neonatal mortality
Multilevel modelling
Logistic regressionmodel
Ghana

ABSTRACT

Background: Neonatal mortality accounts for an increasing share of under-five deaths, and they are declining at a slower rate than postnatal deaths. Apparently, neonatal mortality is increasingly becoming a major public health problem in Ghana and the world over. The current study sought to analyze neonatal mortality as a function of predictor variables and to estimate and understand unobserved household and community-level residual effects on neonatal mortality to provide data driven evidence to shape informed policies and interventions aimed at reducing the neonatal mortality burden.
Methods: The current study extracted three-level complex data on 5884 children born in the five years preceding the 2014 Ghana Demographic and Health Survey. A two-level and three-level multilevel logistic models were applied to estimate unobserved household and community-level variations in neonatal mortality in the presence of set of predictor variables. Sampling weights were incorporated in both the descriptive and inferential analysis since the data used emanated from a complex survey. Model fit statistics such as AIC scores for a weighted two-level and three-level random intercept logistic models were compared. The model with the lowest AIC score was considered the most preferred model.
Results: The household-level random intercept model suggested that the odds of neonatal mortality was higher among multiple births [OR = 3.15 (95% CI: 1.17, 8.50)], babies born to mothers who received prenatal care from non-skilled worker [OR = 5.88 (95% CI: 2.90, 11.91)], babies delivered through caesarian section [OR = 2.47 (95% CI: 1.06, 5.79)], a household with 1–4 members [OR = 10.23 (95% CI: 4.17, 25.50)], a short preceding birth interval (<24 months) [OR = 3.05 (95% CI: 1.18, 7.88)], and preceding birth interval between 24 and 47 months [OR = 2.88 (95% CI: 1.41, 5.91)]. Substantial unobserved household-level residual variations in neonatal mortality were observed.
Conclusion: The findings of the current study provide an actionable information to be used by government and other stakeholders in the health sector to renew commitment to reduce neonatal mortality to an acceptable level. There is the need to intensify maternal health education by health providers to encourage pregnant women to visit antenatal clinics at least four times so they could benefit substantially from ANC services.

* Corresponding author. Department of Epidemiology and Biostatistics, School of Public Health, University of Health and Allied Sciences, Ho, Ghana.

E-mail address: takramah@uhas.edu.gh (W.K. Takramah).

https://doi.org/10.1016/j.heliyon.2023.e18961
Received 2 February 2022; Received in revised form 30 July 2023; Accepted 3 August 2023
Available online 6 August 2023
2405-8440/© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

The key health metrics for health care quality evaluation and health policy formulation such as maternal and infant mortality are major public health problems Ghana is grappling with in recent years. However, adverse birth outcomes are the main drain on human capital due to death and disability [1]. The global average of neonatal mortality stands at 18 per 1000 live births and constitutes 47% of deaths among children under five in 2017 [2]. As mortality among children under five declines globally, deaths among these children are more concentrated in the first days of life. More so, neonatal mortality accounts for an increasing share of under-five deaths, and they are declining at a slower rate than child deaths overall [3]. To this end, there is a need to pay more attention to this group of children.

A review of the literature revealed that newborn health and stillbirths are part of the unfinished agenda of the Millennium Development Goals (MDGs) for maternal and child health [4]. The Sustainable Development Goals (SDGs) target 3.2 was set to challenge all countries to reduce neonatal mortality to 12 deaths per 1000 live births and under-5 mortality to 25 deaths per 1000 live births by 2030 [5]. However, seven years into the SDGs implementation, available data shows that it is impossible to reduce neonatal mortality to 12 per 1000 by 2030 in all countries. Thus, in the quest to achieve SDG 3.2 (reduction in neonatal deaths) there is the need to have deeper understanding of potential risk factors, unobserved household and community-level residual effects on neonatal mortality.

In Ghana, a newborn baby dies every 15 min, and newborn deaths contribute to 50% of all infants' deaths in 2015 [6]. Thus, this presupposes that close to half of under-five deaths are attributable to neonatal mortality. Neonatal mortality rate for five years preceding 2017 Ghana Maternal Health Survey (GMHS) was 25 deaths per 1000 live births, whereas post-neonatal mortality was 12 deaths per 1000 live birth [7]. Furthermore, 68% of all deaths among children under-5 years in Ghana occurred before a child's first birthday, with 48% occurring during the first month of life [8].

These staggering statistics on neonatal deaths are disturbing and pose a significant challenge to a country's socio-economic development and quality of life. Thus, this is a clear indication that the management and delivery of maternal and child health care services in Ghana is not yielding positive results. Several initiatives and frameworks have been developed and implemented by the health sector to discover sustainable solution to high under-5 mortality in Ghana. Nonetheless, the reality is that most of the interventions under these frameworks have focused more on the post-neonatal period with little attention to newborn care [9]. The Ministry of Health (MOH), Ghana Health Service, and development partners should renew efforts to reduce neonatal and under-five mortality rates significantly to improve the quality of maternal and child health care.

A plethora of public health surveys has been conducted over the years to model neonatal mortality and identify its risk factors [10–13]. It is evident from previous studies that complex multiple risk factors such as mothers with a history of previous children who died in the first year of life, hospitalization during pregnancy, and low birth weight [14], preterm labor and intrapartum asphyxia [15], belonging to the poorest household wealth index quintile, male infants, first rank baby, smaller than average birth size and mothers with delivery complications [10], residing in a rural area, being a large body size baby and a mother experiencing pregnancy complication [16] were identified to increase the risk of neonatal mortality. However, most of these studies [17–20] have applied a single-level modeling approach to the data ignoring the hierarchical data structure. Neonatal mortality cannot be explained entirely by individual-level effects because persistent group effects vary across higher levels. Thus, traditional regression models that assume independence of observations and ignore the hierarchical structure of the data and the group effects cannot be applied to fit multilevel data. The multilevel modeling approach takes into account the individual as well as the group level effects [21]. Thus, there is a need to identify and understand why children from certain households and communities are more likely to die before age 28 days while simultaneously adjusting for potential predictors using multilevel analysis approach. The findings will provide essential and actionable information for making informed policy decisions and intervention strategies related to child health and survival.

2. Materials and methods

2.1. Data source and study population

The current study used the 2014 Ghana Demographic and Health Survey (GDHS) dataset. The 2014 GDHS is a nationally representative household sample survey. Complex survey design such as stratified and cluster involving two-stage sampling technique with the unequal probability of sample selection was used in the 2014 GDHS. The first stage sampling involved the selection of enumeration areas (EAs). The second stage involved a systematic sampling technique to select households (Secondary Sampling Units) from each cluster (EAs) at random [22] with known and non-zero probabilities to obtain unbiased parameter estimations. The 2010 population and Housing census frame was used as a reference to select the enumeration areas (EAs)|. The 2014 GDHS successfully interviewed 11385 occupied households comprising 9396 women aged 15–49 and 4388 men aged 15–49. However, this study reviewed the birth history data collected using the children under-5 year's questionnaire data on 5884 children born in the five years preceding the 2014 GDHS [22].

2.2. Outcome variable

The outcome variable is neonatal mortality. Neonatal mortality is the death of the infant within 28 days of life. Neonatal deaths within 28 days of life were categorized as 'dead' and coded as '1'. Those who survived 28 days of life were alive and coded as '0'.

2.3. Independent variables

The conceptual framework for the study of child survival in developing countries [23] was the reference material for selecting predictor variables that influence neonatal mortality. The current study also extracted the predictor variables from previous studies on neonatal and infant mortality [24], and those available in the 2014 GDHS were also selected. Individual-level and household level explanatory variables included sex of child, birth type, preceding birth interval, size of a child, maternal age, ever terminated pregnancy, mode of delivery, parity, and prenatal care assistance, household size, maternal religion, wealth index, maternal marital status, health insurance status of the mother. Community-level factors consist of the type of place of residence, ethnic group, and region.

2.4. Statistical analysis

Data cleaning and validation were done to ensure data quality before analysis was carried out using STATA/MP version 15.1. Since the design of the GDHS is complex, svyset command in STATA was used to declare survey design characteristics for the dataset, incorporating all information about the primary sampling unit (PSU), sampling weight, and stratification in the "svyset" syntax. Descriptive statistics were performed to compute weighted simple frequency to display and summarize categorical explanatory variables while weighted mean and standard deviation were computed to summarize the quantitative explanatory variables.

A multilevel model was applied in the second part of the analysis. This is because the data emanated from a complex survey where individuals were nested within households and households nested within clusters (communities). The sampling technique used in the 2014 GDHS resulted in a complex hierarchical data structure. Furthermore, an application of classical logistic regression model to the hierarchical data, will lead to bias estimation of standard error of parameters because it does not take into account the higher levels (i.e., household and community levels) which could subsequently lead to spurious statistical significance for risk factors under consideration. To address this concern, the multilevel model was chosen as the most appropriate statistical method because it adjusts for the sampling design and properly accounts for dependence attributable to the hierarchical structure of the DHS data to avoid potential spurious statistical significance.

The multilevel model specified in this study predicted neonatal mortality (binary outcome) as a function of risk factors and unobserved household and community-level effects, producing odd ratios and their associated 95% confidence intervals, including household- and community-level residual effect variances. First, we set up a weighted two-level (household-level) variance component model where no risk factors were included and then extended this model to simultaneously adjust for available risk factors. Secondly, we extended the two-level model to a three-level (i.e., child, household- and community-levels) model while adjusting for the risk factors. In all the multilevel models fitted to the data in this study, we allowed only the intercept to vary across households and/or communities, allowing for the estimation of the unobserved household- and community-level residual variation in neonatal mortality in Ghana.

2.5. Multilevel model for three-level complex survey data

The variance component only model is expressed in the form:

$$\eta_{ijk} = \log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \gamma_{000} + \upsilon_{00k} + \mu_{0jk} \tag{1}$$

$$\mu_{0jk} \sim N\left(0, \sigma_{\mu}^2\right)$$

$$\upsilon_{00k} \sim N\left(0, \sigma_{\nu}^2\right)$$

where η_{ijk} represents the odds of a neonate dying within 28 days of life, γ_{000} is the overall intercept of odds of a neonate dying within 28 days of life across all communities, υ_{00k} represent the random effect of community k, μ_{0jk} is the random effect of household j within community k, it is assumed that the random effects, μ_{0jk} and υ_{00k}, are independent and normally distributed with the means equal to zero (0) and constant variances σ_{μ}^2 *and* σ_{ν}^2, respectively [25]. More so, the individual-level variance of a traditional logistic model is expressed as $\frac{\pi^2}{3}$ which is approximately 3.29 [26].

The variance component model would help to observe the variance in neonatal mortality at the household- and community-level. However, since our interest is in the influence of the predictor variables on the odds of neonatal mortality, the three-level random intercept model that incorporates predictor variables at the individual-level was specified. Thus, the random intercept model has both fixed and random parts.

To fit three-level random intercept model predictor variables were added to the single-level model (child-level – i.e., level-1). Substituting level-2 model and level-3 model into level-1 model created a combined equation or mixed model. The three-level random intercept model with multiple explanatory variables, where $X_1, \ldots, X_p$ denote explanatory variables could be expressed in the form:

$$\eta_{ijk} = \log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \gamma_{000} + \gamma_{100}X_{1ijk} + \ldots + \gamma_{p00}X_{pijk} + \upsilon_{00k} + \mu_{0jk} \tag{2}$$

The variance partitioning coefficient (VPC) which coincides with the Intra-class correlation coefficient (ICC) in the random intercept model explains the proportion of variation in neonatal mortality that is due to between households or between community-level differences were used to measure dependency in the data. A higher value of ICC or VPC is interpreted as a higher cluster effect. Two types of intra-class correlation were considered for the models. They are correlation across households within the same community (Intra-community correlation) and Correlation between children within the same household and living in the same community (Intra-household correlation). ICC is expressed mathematically as:

$$\text{Intra} - \text{community correlation} = \rho(comm) = \frac{\sigma_v^2}{\sigma_\mu^2 + \sigma_v^2 + \pi^2/3} \tag{3}$$

$$\text{Intra} - \text{household correlation} = \rho(Household, \text{comm}) = \frac{\sigma_\mu^2 + \sigma_v^2}{\sigma_\mu^2 + \sigma_v^2 + \pi^2/3} \tag{4}$$

The model parameters were estimated using the adaptive Gaussian quadrature (AGQ) algorithm by integration over quadrature points. The adaptive Gaussian quadrature (AGQ) algorithm depends on the number of random effects in the model. The algorithm suffers a convergence problem as the number of random effects in the mode increases [27].

The bounds-and-leaps method or information criterion-based procedures for variable selection such as the Log-Likelihood (LL), Akaike Information Criterion (AIC), and the Schwarz's Bayes Information Criterion (BIC) [28] were applied. The information criterion-based procedures select the optimal model with the relevant number of variables that best fit the data. A lower AIC or BIC

Table 1
Weighted Percentage Distribution of Neonatal Mortality by Risk factors selected for births within five years preceding the 2014 Ghana demographic and Health Survey (0–59 months).

Study Variable	Weighted Frequency	Neonatal Death	Study Variable	Weighted Frequency	Neonatal Death
	n(%)	n(%)		n(%)	N(%)
NEONATAL FACTORS			**Maternal Age**		
Sex of child			15–24	1175(20.6)	29.0(2.5)
male	2970(52.2)	88.8(3.0)	25–34	2839(49.9)	70.4(2.5)
female	2725(47.8)	70.8(2.6)	35–49	1681(29.5)	60.2(3.6)
Size of child			**Household Wealth Index**		
Average/large	4799(84.3)	116.6(2.4)	Poor	2459(43.2)	69.3(2.8)
Small	895.5(15.7)	43.0(4.8)	Medium	1114(19.6)	25.8(2.3)
Low birth weight			Rich	2122(37.3)	64.5(3.0)
No	3107(90.5)	21.1(0.7)	**Maternal Highest Level of Education**		
Yes	327.6(6.1)	9.2(2.8)	No Education	1561(27.4)	39.2(2.5)
Type of birth			Primary Education	1141(20.0)	36.8(3.2)
Single birth	5403(94.9)	130.0(2.4)	Secondary Education	2739(48.1)	80.1(2.9)
Multiple birth	291.8(5.1)	29.6(10.1)	Higher Education	253.9(4.5)	3.4(1.4)
MATERNAL FACTORS			**Maternal Occupation**		
Preceding Birth Interval			Employed	4679(82.4)	135.9(2.9)
<24 month	561.5(13.0)	27.5(4.9)	Unemployed	1002(17.6)	23.4(2.3)
24-47	2203(51.1)	72.6(3.3)	**Household size**		
48+ month	1544(35.8)	20.4(1.3)	1-4 members	2118(37.2)	73.1(3.4)
Covered by Health Insurance			5-7 members	2634(46.3)	60.3(2.3)
No	1847(32.4)	32.8(1.8)	8+ members	943.1(16.6)	26.2(2.8)
Yes	3847(67.6)	126.8(3.3)	**Maternal Religion**		
Ever terminated Pregnancy			No religion	238.6(4.2)	2.0(0.8)
No	4235(74.4)	116.2(2.7)	Christian	4303(75.6)	129.6(3.0)
Yes	1460(25.6)	43.4(3.0)	Islam	969.8(17.0)	26.8(2.8)
Mode of Delivery			Traditional	183.4(3.2)	1.1(0.6)
No Caesarean Section	4966(87.2)	124.3(2.5)	**Community Level Factors**		
Caesarean Section	728.7(12.8)	35.3(4.9)	**Place of Residence**		
Children ever Born			Urban	2563(45.0)	71.4(2.8)
1	944(16.6)	16.3(1.7)	Rural	3132(55.0)	88.2(2.8)
2	1213(21.3)	24.6(2.0)	**Ethnicity**		
3	1108(19.5)	28.0(2.5)	Akan	2701(47.4)	82.6(3.1)
4	827.2(14.5)	28.6(3.5)	Ga/Dangme	353.4(6.2)	7.6(2.2)
5+	1603(28.1)	62.0(3.9)	Ewe	735.5(12.9)	24.0(3.3)
Prenatal care by			Mole-Dangbani	985.5(17.3)	25.1(2.5)
Non-Skilled Worker	1664(29.2)	101.8(6.1)	Grusi/Gurma	624.6(11.0)	10.7(1.7)
Skilled Worker	4031(70.8)	57.8(1.4)	Other	294.4(5.2)	9.6(3.3)
SOCIO-DEMOGRAPHIC FACTORS					
Maternal Marital Status					
Single	436.6(7.7)	11.1(2.6)			
Currently Married	4879(85.7)	141.2(2.9)			
Formally Married	379.4(6.7)	7.3(1.9)			

value indicates a better fit.

The model fit statistics such as Akaike Information Criterion (AIC) and the Schwarz's Bayes Information Criterion (BIC) scores were computed to evaluate the performance of the fitted models.

The model with the lowest value of AIC score was the most preferred model. The estimated area under the curves (AUC) scores for each model were compared to evaluate the predictive accuracy of the models. The model with the highest AUC score was selected as the model with the best predictive ability. Brier score was used to evaluate the calibration and accuracy of probabilistic prediction of the models [29–31]. The lower the value of the Brier score, the better the prediction. A p-value <0.05 was considered for statistical significance.

2.6. Ethics approval

The 2014 GDHS protocol was reviewed and approved by the Ghana Health Service Ethical Review Committee and the Institutional Review Board of ICF International. Thus, ethical per-mission for the current study was not needed since the required GDHS dataset was available publicly. However, ethical procedures were strictly observed at the time of the GDH surveys to ensure that human rights were protected as required by US Department of Health and Human Services. Detail information on DHS data and ethical standards can be accessed at: http://goo. gl/ny8T6X.

3. Results

3.1. Sample characteristics

Table 1 depicts the relationship between neonatal mortality and risk factors. It is evident that the majority of babies (84.3%) who were included in the sample were average or large body size. Here again, single births constituted 94.9% of the babies surveyed, 67.6% of mothers were covered by health insurance, and 82.3% of mothers were employed. The results of the descriptive statistics also indicated that neonatal mortality is more pronounced among babies with small size bodies (4.8%) relative to babies with average or large body size. Additionally, the neonatal mortality recorded for multiple births is five times the neonatal mortality recorded among single births. The findings also showed that the majority of neonatal mortality was registered among babies born through cesarean section 35.3(4.9%) compared to those born via vaginal delivery 124.3 (2.5%). The results presented in Table 1 also revealed that the risk of neonatal mortality was higher among mothers who received prenatal care from the non-skilled worker (6.1%), multiple births (10.1%), under 24 months preceding birth interval (4.9%), and household size of 1–4 members (3.3%)

3.2. Variable selection for the models using leaps-and-bounds method

Table 2 displays the bounds-and-leaps methods for variable selection and its associated statistics. The results of the variable selection procedure indicated that 16 predictor variables were initially entered into the model. The model with 8 predictor variables was favored by AIC while the model with 6 predictor variables was favored by BIC. Even though any one of these two-predictor variable optimal models can be selected to fit the data, we consider the model with 8 predictor variables as the most plausible choice. Thus, multilevel models were applied to investigate the contribution of the 8 predictor variables (i.e., child size, prenatal care assistants, household size, number of children ever born, type of birth, preceding birth interval, mode of delivery and health insurance status of mother) selected by AIC.

Table 2
Optimal models for variable selection.

No. of Predictors	Optimal Models		
	LL	AIC	BIC
1	−504.851	1013.702	1026.531
2	−491.532	989.0644	1008.309
3	−476.579	961.1569	986.8167
4	−464.999	939.9974	972.0721
5	−459.523	931.0453	969.535
6	−454.145	922.2909	**967.1954**
7	−451.543	919.0869	970.4064
8	−450.125	**918.2501**	975.9845
9	−449.325	918.6496	982.799
10	−448.714	919.4287	989.993
11	−448.227	920.4543	997.4336
12	−448.081	922.1623	1005.556
13	−448.026	924.0524	1013.862
14	−447.977	925.9537	1022.178
15	−447.96	927.9192	1030.558
16	−447.954	929.9071	1038.961

3.3. Evaluating calibration and predictive accuracy of the models

Table 3 depicts the models' performance test results of predictive accuracy of the two-level random intercept model, and the weighted three-level random intercept model. The AUC score computed for the weighted two-level random intercept model is 0.963 and the AUC score for the weighted three-level random intercept model is 0.932. The predictive ability of the weighted two-level random intercept model is better than the weighted three-level random intercept model.

Fig. 1 shows a 93.2% likelihood that the weighted three-level random intercept model would accurately predict the odds of neonatal mortality. The predictive ability of the weighted two-level random intercept model is 96.3%. Thus, both the two- and three-level random intercept models exhibit an outstanding predictive accuracy of the odds of predicting neonatal mortality in this group of children with model 2 providing the best predictive accuracy.

Table 4 displays the results of the evaluation of calibration and accuracy of probabilistic predictions or forecasting of the models. The results show that the Brier score for the weighted two-level and three-level random intercept model stands at 0.018 and 0.020 respectively. It is clear from the results that both models have the same probability predictive accuracy of 2.6% and are well-calibrated. However, the two-level random intercept model had better calibration with the lowest Brier score (0.018) than the three-level model. The calibration of the models was measured using metric statistics such as Spiegelhalter's z-statistic, Sanders-modified Brier score, Sanders resolution, Outcome index variance, and Murphy resolution.

3.4. Measure of variation and intra-class correlation

The intra-class correlation coefficients (ICC) for the weighted two-level and three-level random intercept models were computed to measure clustering effect (correlation) in the data both at the household level (level-2 ICC) and community level (level-3 ICC) (Table 5).

The ICC computed for weighted two-level null model was 46.97% which means that 47% of the total variation in neonatal mortality was accounted for by the household level differences. On the other hand, the ICC computed for weighted two-level random intercept model with fixed effect predictors was positive (ICC = 49.64%). This means that with fixed effect predictors, about 50% of total variation in neonatal mortality was explained by household which each neonate belongs to and individual-level fixed effect predictors. It is observed that adding fixed effect predictors to the two-level random intercept model had increased the ICC from 46.97% to 49.64% with significant household level residual, and this justifies the need for performing multilevel modeling (Table 5) instead of the classical single-level logistic regression model.

The results of the current study also show that conditional on the fixed effect predictors in the three-level model, there is almost no correlation (ICC = 9.35 × 10^-34) in neonatal mortality between neonates in the same community. Thus, the study did not find significant unobserved community-level residual effects in neonatal mortality after adjusting for the household level and the fixed effect predictors.

3.5. Assessing model fit

The model fit statistics such as AIC indicated that the weighted two-level random intercept model (AIC = 810.06) fit the data better than the weighted three-level random intercept model (AIC = 856.27) and the empty two-level variance component model (AIC = 1362.00). Thus, the most preferred model choice for the current study based on the lowest AIC score is the weighted two - level random intercept model (Table 5). We therefore interpret the results from the weighted two-level random intercept model.

3.6. Risk factors associated with neonatal mortality

Table 5 displays results of modeling risk factors of neonatal mortality using a weighted two-level random intercept model and weighted three-level random intercept model. The weighted two-level random intercept model reveals that the small body size babies are more likely to die within 28 days of life relative to large body size babies [OR = 1.70 (95% CI: 0.79,3.67)]. It is observed in the weighted two-level random intercept model that there is a higher probability of neonatal death among multiple births [OR = 3.15 (95% CI: 1.17, 8.50)], babies delivered through caesarian section [OR = 2.47 (95% CI: 1.06, 5.79)], a short preceding birth interval (<24 months) [OR = 3.05 (95% CI: 1.18, 7.88)] and preceding birth interval between 24 and 47 months [OR = 2.88 (95% CI: 1.41, 5.91)], babies born to mothers who received prenatal care from non-skilled worker [OR = 5.88 (95% CI: 2.90, 11.91)] and household with 1–4 members [OR = 10.23 (95% CI: 4.17, 25.50)]

Table 3
Model evaluation using area under the receiver operating characteristic (ROC) curves.

Model	n	ROC (AUC)	SE	95% CI		Chi Square	Pvalue
Model 2	4514	0.963	0.007	0.950	0.976	15.63	<0.001
Model 3	4514	0.932	0.011	0.911	0.952		

model 2 = weighted two-level random intercept model, **Model 3** = weighted three-level random intercept model.

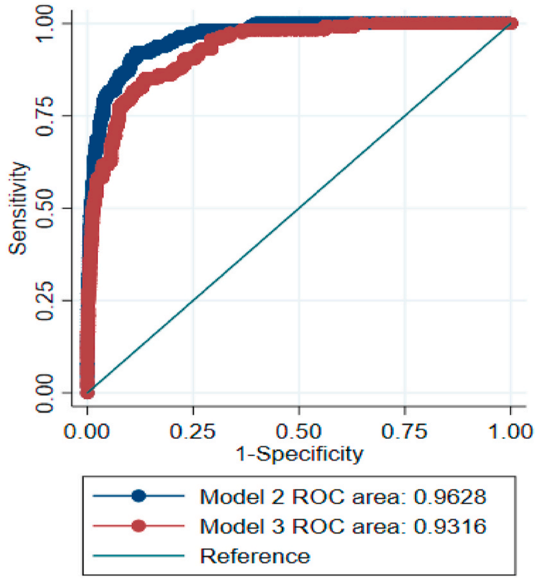

Fig. 1. Area under the ROC curve comparing the predictive ability of weighted two-level random intercept model (Model 2) and weighted three-level random intercept model (Model 2).

Table 4
Calibration and accuracy of probability predictions of the models.

	Model 2	Model 3
Mean probability of outcome	0.026	0.026
Forecast	0.012	0.017
Correlation	0.577	0.526
Brier score	0.018	0.020
Spiegelhalter's z-statistic	7.781	2.944
Spiegelhalter's pvalue	0.000	0.002
Sanders-modified Brier score	0.022	0.022
Sanders resolution	0.021	0.021
Outcome index variance	0.025	0.025
Murphy resolution	0.004	0.003
Reliability-in-the-small	0.002	0.001
Forecast variance	0.003	0.002
Excess forecast variance	0.002	0.001
Minimum forecast variance	0.001	0.001
Reliability-in-the-large	0.000	0.000
2*Forecast-Outcome-Covar	0.010	0.007

model 2 = weighted two-level random intercept model, **Model 3** = weighted three-level random intercept model.

4. Discussion

The current study investigated the residual household and community-level effects, and the contribution of predictor variables to the odds of neonatal mortality in Ghana, incorporating random effects by allowing the intercept to vary both at the household- and the community-levels. The weighted two-level random intercept model also revealed that the unobserved residual variation at the household level accounted for 49.64% of the total variance in neonatal mortality. The presence of substantial (i.e., significant) unobserved residual variation in neonatal mortality at the household level justified the need for the multilevel modeling approach in this study. The large proportion of variance in the neonatal mortality was accounted for by households because of different data generating processes or some underlying phenomenon. Thus, this finding has policy implications because any interventions targeted at reducing neonatal mortality in Ghana may or may not work for some households. Furthermore, there is almost no residual variability in the probability of neonatal mortality between neonates across communities after we adjusted for the household-level random effects and predictor variables in the model. In other words, there is no similarity in neonatal mortality among neonates from the same community after adjusting for the household-level random effects and the predictor variables in the three-level model. Our two-level (AUC value = 96.2%) and three-level (AUC value = 93.2%) random effect models show outstanding predictive accuracy [32] of the odds of predicting neonatal mortality with the two-level model providing a better fit to the data.

Table 5
Weighted two- and three-level random intercept logit model for predicting the Odds of Neonate Dying within 28 days of Life.

Variable	Model 1	Model 2		Model 3	
	Parameters (95%CI)	OR (95%CI)	p-value	OR (95%CI)	p-value
Neonatal factors					
Size of child					
large		1.00(Ref)		1.00(Ref)	
Small		1.70 (0.79,3.67)	0.175	1.76 (0.86,3.61)	0.124
Type of birth					
Single birth		1.00(Ref)		1.00(Ref)	
Multiple birth		3.15 (1.17, 8.50)	0.023	1.82 (0.70,4.76)	0.219
Maternal Factors					
Preceding Birth Interval					
<24 months		3.05 (1.18, 7.88)	0.021	3.58 (1.56,8.22)	0.003
24-47		2.89 (1.41, 5.91)	0.004	3.08 (1.63,5.81)	0.001
48+ month		1.00(Ref)		1.00(Ref)	
Covered by Health Insurance					
No		1.00(Ref)		1.00(Ref)	
yes		2.47 (1.27,4.82)	0.008	2.73 (1.46,5.10)	0.002
Number of children ever born		1.45 (1.28, 1.66)	<0.0001	1.40 (1.22,1.60)	<0.0001
Mode of Delivery					
No Caesarean Section		1.00(Ref)		1.00(Ref)	
Caesarean Section		2.47 (1.06, 5.79)	0.037	3.13 (1.34,7.27)	0.008
Prenatal care by					
Skilled worker		1.00(Ref)		1.00(Ref)	
Non-Skilled Worker		5.88 (2.90, 11.91)	<0.0001	5.12 (2.69,9.76)	<0.0001
Socio-Demographic Factors					
Household size					
5-7 members		1.70 (0.78, 3.73)	0.183	1.61 (0.77,3.34)	0.202
1-4 members		10.23 (4.17, 25.10)	<0.0001	7.51 (3.08,18.33)	<0.0001
8+ members		1.00(Ref)		1.00(Ref)	
Random effects Parameters					
Household level variance (SE)	2.91 (0.52)	3.24 (0.95)		1.32 (0.76)	
Community level variance (SE)				4.31 × 10^-33 (4.34 × 10^-33)	
ICC OR VPC					
Household level ICC (%)	46.97	49.64		28.6	
Community level ICC (%)				9.35 × 10^-34	
Model fit statistics					
AIC	1362.00	810.06		856.27	
BIC	1375.36	887.04		933.24	
−2 log likelihood	−679.00	−393.03		−440.77	

model 1 = weighted two-level null model, Model 2 = Weighted two-level random intercept with covariates, model 3 = Weighted three-level random intercept with covariates.

Comparing the findings from a weighted single level logistic multivariable regression model used in our previous study [20] and the findings from a weighted two-level random intercept model used in the current study, notable differences were observed. For example, type of birth was not significant in our previous study but significant in the present study. Furthermore, remarkable varying effect sizes and level of uncertainty were observed for the predictors between the two studies. The results obtained from the weighted single level logistic multivariable regression and weighted two-level random intercept model differ because the former assumes independent observations and does not take into account clusters which in effect leads to underestimation of coefficients and standard error of the parameter estimates, narrow confidence interval, and erroneous rejection of the null hypothesis. The current study used multilevel data which presented correlation between observations.

The fixed effects part of the two-level random intercept model suggests that there is higher odds of neonatal death among multiple births [OR = 3.15 (95% CI: 1.17, 8.50)] compared to single births. The results of the current study is consistent with the results of a similar study carried out in Jimma Zone, Southwest Ethiopia [12]. Other previous studies including [33,34] confirmed the results of the current study and further explained that multiple births had an increased risk of low birth weight which in the long run would result in neonatal mortality if proper care is not given.

It is evident from the results that babies delivered through cesarean section have a higher probability of dying within 28 days of life relative to vagina delivery [OR = 2.47 (95% CI: 1.06, 5.79)]. Similar studies supported the findings of the current research findings (32,40). A review of the literature showed that cesarean sections have the likelihood of impacting negatively on the health of the mother, her child, and future pregnancies over a short and long period [35]. In this vein, it is prudent for a pregnant woman to avoid any health and health-related issues that will increase the risk of delivery through cesarean section. Pregnancy related conditions such as preeclampsia and eclampsia are highly associated with maternal outcomes and neonatal deaths. Thus, interventions such as low-dose aspirin and dietary supplementation with calcium which were identified to effectively reduce the risk of preeclampsia and eclampsia should be administered to pregnant women with hypertension [36,37]. The risk of postpartum hemorrhage should also be reduced by administering uterotonics. Prophylactic oxytocin and misoprostol given during the third stage of labor were identified as effective interventions for treating and preventing postpartum hemorrhage [38,39] Most importantly, the odds of neonatal mortality is monotonically related to household size (Table 5). A previous study identified family size as a risk factor of neonatal mortality [46–47] and this corroborated the findings from the current study. Further research is needed to elucidate the findings in this regard.

Practically, for a unit increase in parity the odds of neonatal mortality increases by 45% [OR = 1.45 (95% CI: 1.28, 1.66)]. The results of the current study agreed with the results obtained in a previous study [40]. The most plausible explanation adduced concerning this result could be that mothers who lost their babies few days after delivery or during delivery might resume sex almost immediately even though they are not properly healed and would eventually become pregnant again in the process [48]. Besides, women who married at an older age might want to have several children at a very short interval. To this end, this will likely impact negatively on the health of the fetus and live births which could lead to both maternal and neonatal deaths if not properly managed.

Furthermore, the odds of babies born to mothers who received prenatal care provided by non-skilled workers dying within 28 days of life is over 5 times the odds of mothers who received prenatal care provided by a skilled worker [OR = 5.88 (95% CI: 2.90, 11.91)]. Similarly, recent studies reported that a pregnant woman who visits an antenatal clinic at least four times is less likely to lose her baby within 28 days of life in sub-Saharan Africa [12,35]. The possible explanation for this is that antenatal clinics or health facilities and trained midwives in deprived and rural communities are not available. On the other hand, cultural and religious beliefs might be barriers to receiving prenatal care provided by skilled and well-trained health personnel. Thus, to ensure that pregnant women stay healthy, they must be encouraged through maternal health education to attend the antenatal clinic so that trained health personnel such as a nurse or midwife could monitor their fetal development and conduct routine checks to prevent and manage any health challenge that might lurk its ugly head.

5. Conclusion

The weighted two-level random intercept model was the best performing and probabilistic prediction model for accurately predicting neonatal mortality, suggesting the need for multilevel modeling approaches used in this study. Substantial differences in the probability of neonatal mortality across households were found. The fixed effects part of the weighted two-level random intercept model suggested an increased odds of neonatal mortality among children born multiple, shorter proceeding birth intervals, delivered through caesarean section, prenatal care assisted by non-skilled worker and belonging to small size households. The findings obtained from this study will arm the health policymakers and managers with actionable and insightful information for data-driven policy formulation and to put strategies in place to target households and the identified risk factors to reduce the risk of neonatal mortality.

The significant unobserved household level residuals in neonatal mortality found in this study warrant further investigation to identify as yet factors that might be responsible for this. Also, our finding that children belonging to mothers who possessed health insurance and smaller household sizes had increased odds of neonatal mortality needs further examination.

Ethics approval and consent to participate

Not applicable.

Author contribution statement

Wisdom Kwami Takramah: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Justice Moses K. Aheto: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Special thanks go to DHS program for providing access to the datasets used in the current study. We thank Profs. Adanu, Yawson and Fobil for their insights.

Abbreviation

AUC	area under curve

AIC	Akaike Information Criterion
BIC	Bayes Information Criterion
DHS	Demographic and Health Surveys
EAs	Enumeration Areas
GDHS	Ghana Demographic and Health Survey
PSU	primary sampling unit
CI	Confidence Interval
OR	Odds Ratio
ICC	Intraclass Correlation Coefficients
ROC	Receiver Operating Characteristics
AUC	Area under Curve
VPC	Variance Partition Coefficient
IUGR	Intrauterine Growth Restriction

References

[1] WHO, UNICEF, Reaching the 2020 Every Newborn Milestones: Country Progress , Plans and Moving Forward, May 2018, p. 2018. Available from: https://www.healthynewbornnetwork.org/hnn-content/uploads/Summary-Every-Newborn-progress-report-2018.pdf.
[2] W.H.O. Global, Strategy for Women's, Children's and adolescents' health 2016-2030 [Internet], Implementation in the African Region (2016). Available from: https://reliefweb.int/report/world/global-strategy-women-s-children-s-and-adolescents-health-2016-2030-implementation?gclid=CjwKCAjw8ZKmBhArEiwAspcJ7tIx_L8Gk9LtqDPLZhcLA1NKaQBYcMZc36i5Mcw9GPaLeEHw_J9KSxoCenIQAvD_BwE.
[3] A. Sobanjo-ter Meulen, J. Liljestrand, J.E. Lawn, J. Hombach, J. Smith, K.E. Dickson, et al., May 3–4, 2018. In: Vaccine, in: Preparing to Introduce New Maternal Immunizations in Low- and Lower-Middle-Income Countries: A Report from the, Bill & Melinda Gates Foundation Convening "Allies in Maternal and Newborn Care", Elsevier Ltd, 2020, p. 4355, 61..
[4] WHO, UNICEF, Every Newborn: an Action Plan to End Preventable Deaths [Internet], World Health Organization, Geneva, 2014. Available from: https://apps.who.int/iris/handle/10665/127938.
[5] UNICEF. Looking ahead, Child Survival and the Sustainable Development, Goals [Internet], 2017. Available from: https://data.unicef.org/topic/child-survival/child-survival-sdgs/.
[6] UNICEF. EVERY CHILD ALIVE, The Urgent Need to End Newborn Deaths [Internet], 2018. Available from: https://www.unicef.org/indonesia/reports/every-child-alive-urgent-need-end-newborn-deaths.
[7] G.H.S. GSS, Ghana Maternal Health Survey 2017: Key Indicators Report. Accra, Ghana, GSS, GHS, and ICF, 2017.
[8] [Internet], Ghana Statistical Service (GSS) Ghana Health Service (GHS), ICF International. Demographic and Health Survey 2014, GSS, GHS, and ICF International, Rockville, Maryland, USA, 2015. Available from: http://www.statsghana.gov.gh/gssmain/fileUpload/pressrelease/2014 (GDHS Report.pdf).
[9] Ministry of Health, –4, Ghana National Newborn Health Strategy and Action Plan 2014 – 2018. 2014 (July 2014) 1. Available from: https://extranet.who.int/mindbank/item/6005.
[10] Y Bin Nisar, M.J. Dibley, Determinants of Neonatal Mortality in Pakistan : Secondary Analysis of Pakistan Demographic and Health Survey 2006 – 07 vol. 14, BMC Public Health, 2014, p. 663.
[11] E.O. Adewuyi, Determinants of neonatal mortality in rural and urban Nigeria : evidence from a population-based national survey, Pediatr Int. 2021 59 (2017) 190–200.
[12] G.T. Debelew, M.F. Afework, A.W. Yalew, Determinants and causes of neonatal mortality in Jimma Zone , southwest Ethiopia : a multilevel analysis of prospective, Follow Up Study 9 (9) (2014).
[13] S.B. Kassar, A.M.C. Melo, S.B. Coutinho, M.C. Lima, P.I.C. Lira, Determinants of neonatal death with emphasis on health care during pregnancy , childbirth and reproductive history ☆, J. Pediatr. 89 (3) (2013) 269–277.
[14] J.O. Akinyemi, E.A. Bamgboye, O. Ayeni, Trends in neonatal mortality in Nigeria and effects of bio-demographic and maternal characteristics, BMC Pediatr. 15 (1) (2015) 1–12.
[15] I. Jehan, H. Harris, S. Salat, A. Zeb, N. Mobeen, O. Pasha, et al., Neonatal Mortality , Risk Factors and Causes : a Prospective Population-Based Cohort Study in Urban Pakistan, vols. 130–8, 2009.
[16] T. Dahiru, Determinants of early neonatal mortality in Nigeria: results from 2013 Nigeria DHS, J Pediatr Neonatal Care 2 (5) (2015).
[17] A.K. Andegiorgish, M. Andemariam, S. Temesghen, L. Ogbai, Z. Ogbe, L. Zeng, Neonatal mortality and associated factors in the specialized neonatal care unit Asmara, Eritrea. BMC Public Health 20 (1) (2020) 1–9.
[18] A. Weddih, M.L.C.B. Ahmed, M. Sidatt, N. Abdelghader, F. Abdelghader, A. Ahmed, et al., Prevalence and factors associated with neonatal mortality among neonates hospitalized at the national hospital Nouakchott, Mauritania, Pan Afr Med J 34 (2019) 1–7.
[19] A. Woday Tadesse, Y. Mekuria Negussie, S.B. Aychiluhm, Neonatal mortality and its associated factors among neonates admitted at public hospitals, pastoral region, Ethiopia: a health facility based study, PLoS One [Internet] 16 (3) (2021), e0242481, https://doi.org/10.1371/journal.pone.0242481.
[20] W.K. Takramah, J.M.K. Aheto, Predictive model and determinants of odds of neonates dying within 28 days of life in Ghana. Heal Sci Reports 4 (1) (2021) 1–11.
[21] R.-O.-S. Hrițcu, Multilevel models: conceptual framework and applicability, AUDŒ [Internet] 11 (5) (2015) 1–10. https://journals.univ-danubius.ro/index.php/oeconomica/article/view/2959/html.
[22] (DHS) Key Findings [Internet], Ghana Statistical Service (GSS) Ghana Health Service (GHS), ICF International. 2014 Ghana Demographic and Health Survey, GSS, GHS, and ICF International, Rockville, Maryland, USA, 2015. Available from: https://dhsprogram.com/pubs/pdf/sr224/sr224.pdf.
[23] W. Henry Mosley, L.C. Chen, An Analytical Framework for the Study of Child Survival in Developing Countries. 2009 10 (1984) 25–45.
[24] J.M.K. Aheto, Predictive model and determinants of under-five child mortality : evidence from the 2014 Ghana demographic and health survey (2019) 1–10.
[25] G. Leckie, Three-level multilevel models - concepts, LEMMA VLE Module 11 11 (2013) 1–47. Available from: http://www.bristol.ac.uk/cmm/learning/course.html;.
[26] J. Merlo, B. Chaix, H. Ohlsson, A. Beckman, K. Johnell, P. Hjerpe, Logistic Regression to Investigate Contextual Phenomena, 2006, pp. 290–297.
[27] F. Steele, Introduction to multilevel modelling concepts, Lemma Module 5 [Internet] 5 (2008). Available from: http://www.cmm.bris.ac.uk/lemma.
[28] C. Lindsey, S. Sheather, Best subsets variable selection in nonnormal regression models, STATA J. 15 (4) (2015) 1046–1059.
[29] J. Wong, M. Abrahamowicz, D.L. Buckeridge, R. Tamblyn, Derivation and validation of a multivariable model to predict when primary care physicians prescribe antidepressants for indications other than depression, Clin. Epidemiol. 10 (2018) 457–474.
[30] A.E.L. Houd, Brier score, Understanding Model Calibration (2021) 1–11.
[31] Y. Huang, W. Li, F. Macheret, R.A. Gabriel, L. Ohno-Machado, A tutorial on calibration measurements and calibration models for clinical prediction models, J. Am. Med. Inf. Assoc. 27 (4) (2020) 621–633.

[32] E.O. Adewuyi, Y. Zhao, R. Lamichhane, E.O. Adewuyi, A. Eo, I.J. Contemp, et al., Socioeconomic , bio-demographic and health/behavioral determinants of neonatal mortality in Nigeria, a multilevel analysis of 2013 demographic and health survey 3 (2) (2016) 311–323.
[33] J.L. Kiely, The epidemiology of perinatal mortality in multiple births, Obstet. Gynecol. Surv. 46 (7) (1991) 449–451.
[34] S De Souza, E. Duim, F.K. Nampo, Determinants of neonatal mortality in the largest international border of Brazil, a case-control study (2019) 1–9.
[35] K. Singh, P. Brodish, E. Haney, Postnatal care by provider type and neonatal death in sub-Saharan Africa: a multilevel analysis, BMC Publ. Health 14 (1) (2014) 1–7.
[36] L. Duley, S. Meher, H. Ke, S. Al, A. Lm, Antiplatelet Agents for Preventing Pre-eclampsia and its Complications Antiplatelet Agents for Preventing Pre-eclampsia and its, vols. 1–3, 2019.
[37] G.J. Hofmeyr, E.D. Hodnett, Antenatal care packages with reduced visits and perinatal mortality : a secondary analysis of the WHO antenatal care trial - comentary : routine antenatal visits for healthy pregnant women do make a difference, Reprod. Health 1–2 (2013).
[38] Ö. Tunçalp, H. Gj, G. Am, Prostaglandins for preventing postpartum haemorrhage (Review). Cochrane Database Syst Rev 8 (2012).
[39] J. Salati, S. Leathersich, M. Williams, A. Cuthbert, J. Tolosa, Internet prophylactic oxytocin for the third stage of labour to prevent postpartum haemorrhage review), Cochrane Database Syst. Rev. 4 (4) (2019) 2. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6487388/pdf/CD001808.pdf.
[40] G.A. Kayode, E. Ansah, I.A. Agyepong, M. Amoakoh-coleman, D.E. Grobbee, K. Klipstein-grobusch, Individual and community determinants of neonatal mortality in Ghana : a multilevel analysis, BMC Pregnancy Childbirth [Internet 14 (165) (2015) 1–12, https://doi.org/10.1186/1471-2393-14-165.