ORIGINAL Article

IMPACT OF MATERNAL EDUCATION AND AGE ON WEIGHT OF CHILD AT BIRTH: USE OF MULTINOMIAL LOGISTIC MODEL

ABSTRACT

The World Health Organization (WHO) prescribed 2.5 kilograms to 4.2 kilograms as the standard for normal birth weight (NBW) and every child whose birth weight is below the lowest bound is regarded as low birth weight (LBW) while above the highest bound is regarded as macrosomia. The odds for a LBW child to die as reported is about 40 times high when compared to a NBW child and these overwhelming death records are higher in developing countries. Therefore, urgent research about the causes of LBW especially in developing countries is very necessary and this motivated this research in Nigeria. In this paper, the Multinomial Logistic Regression (MLR) model was applied to secondary data from the 2018 Nigerian Demographic and Health Survey (NDHS) report to predict the probability of giving birth to NBW and macrosomia babies referenced to LBW babies. The maternal education level and age were considered as the predictor variables. The data was naturally stratified by maternal education level, that is (1 = Higher Education, 2 = Secondary Education, 3 = Primary Education, and 4 = No Education). The equal sample allocation technique which assigns equal stratum sample sizes (n_i = 200 for the i^{th} maternal education level) was adopted. The 800 sample size was reduced to 735 after screening for outliers in the maternal age variable. Considering the 54 LBW babies, 57% (0.5741) were from mothers with no education. The results showed that maternal education level and age have causal effects on child birth weight in Nigeria. Younger mothers (less than 28years) are 96.5% likely to have LBW babies while mothers who attained a minimum of primary, secondary, and higher education are 88.00%, 82.00%, and 57.90% likely to have NBW babies respectively when compared to those with no formal education. The research recommends that mothers should acquire at least primary school education and early child marriage (less than 28years) of the girl child should be discouraged.

Keywords: Multinomial Logistic Regression; World Health Organization; Demographic and Health Survey; Low Birth Weight, Maternal education level

1. Introduction

The weight at birth of a baby usually serves as a reliable predictor of a baby's survival probability and psychosocial development. On average, European babies weigh 3.5kilograms which is NBW as prescribed by World Health Organization (2014)[1]. Every birth weight below the lower bound of the WHO standard is regarded as LBW (Park, 2007)[2]. There are many determinants of LBW but the most important is maternal social status, which can be measured as maternal education level Shi, 2004)[3]. It affects birth weight by enhancing the productivity of health investments. Ganchimeg et al. (2014)[4] found that there is an increased risk of adverse birth outcomes in younger mothers (10 – 19 years) when compared with adult mothers (20 – 24 years) after controlling for covariates. WHO (2014)[1] revealed that, out of

139 million live births in the world, more than 20 million LBW babies were delivered yearly, consisting of 15.5% of all live births, about 95.6% of them come from developing countries. Park (2007)[2] opined that 50% of all perinatal and 75% of all infant deaths occur in babies with LBW. These findings justify that the impact of maternal education level and age is worthy of research and further recommend ways to cushion their effects to reduce deaths amongst newborn babies in Nigeria.

The work of Currie and Moretti (2003)[5] also showed that maternal education has a causal effect on the use of prenatal care, improves the choice of life partner, and reduces smoking, thus reducing the incidence of low birth weight by 1%. Luis et al. (2017)[6] used Multinomial Logistics Regression (MLR) to reveal that moving from the reference category (deficient level) to other categories (reasonable, good, very good, and excellent) of General Health Perception is not significantly caused by stress but by burnout and some levels of depressive and sleeping. Mengasha et al. *(*2017)[7] studied the predictors of LBW and macrosomia in Tigray, Northern Ethiopia. The dependent variable in the MLR model had three nominal categories (low, normal, and macrosomia). The results showed that 10.5% and 6.68% incidence were recorded for LBW and macrosomia respectively. Fayehun and Asa (2020)[8] recently examined factors causing abnormal birth weights in urban areas of Nigeria. The findings suggested that the significant predictors of LBW were: geographical region, child characteristics (the type of birth), and household (wealth index) while the significant predictors of macrosomia were: geographical region, child characteristics, and maternal education, and health utilization. The work of Fayehun and Asa (2020)[8] is different from this present work because it was conducted for urban areas of Nigeria, but this present work extended the research to include both rural and urban residents and estimated the probabilities of NBW and macrosomia referenced to LBW in Nigeria.

This paper will build an MLR model to predict the probabilities of NBW and macrosomia referenced to LBW in Nigeria. The specific objectives are to:

i. estimate the relative risk in mother's age for giving birth to LBW versus NBW baby and macrosomia versus NBW baby,
ii. estimate the relative risk in the mother's education level on the weight of the child,
iii. generate the predicted probabilities for the birth weigh categories,
iv. investigate the changes in the predicted probability associated with maternal education levels and
v. plot the predicted probabilities against the maternal age scores.

2. MATERIAL AND METHODS

2.1 Binary Logistic Regression

Logistic regression is a statistical model that employs a function other than the usual least-squares approach to model a binary dependent variable. The function is called the logistic function and it models the probability of a certain dependent variable, class, or event such as on or off, pass or fail, win or lose, healthy or sick. Logistic regression is important in the area of Trauma and Injury Severity Score (TRISS) Boyd et al. (1987)[9], Infant disease modeling Orumie and Bartholomew (2022)[10], and insurance coverage prediction Orumie et al. 2021[11].

Consider a model with two independent variables say, x_1 and x_2, and one binary (Bernoulli) response variable Y, denoted as $\pi = P(Y=1)$. If it is assumed that there is a linear relationship between the independent variables and the log-odds (logit) of the response, then this linear relationship is represented mathematically in the following form

$$\xi = \log_b \frac{\pi}{1-\pi} = \beta_0 + \sum_{i=1}^{2} \beta_i x_i \qquad (1)$$

where

ξ is the log-odds, b is the base of the logarithm, and β_i is parameters of the model:
Exponentiating the logit gives the odds as expressed in equation (2)

$$\frac{\pi}{1-\pi} = b^{\left\{\beta_o + \sum_{i=1}^{2} \beta_i x_i\right\}} \qquad (2)$$

Dividing the numerator and denominator of (2) by $b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)}$, the probability that $Y=1$ is

$$\pi = \frac{b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)}}{b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)} + 1} = \frac{1}{1 + b^{-(\beta_0 + \sum_{i=1}^{2} \beta_i x_i)}} = S_b\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right) \qquad (3)$$

where

S_b is the sigmoid function with base b fixed.

Equation (3) states that, if β_i is fixed, then either the log-odds $Y=1$ for a given observation or the probability that $Y=1$ can be calculated.

2.2 Multinomial Logistic Regression (MLR)

MLR generalizes the logistic regression to more than two categories of problems. The multinomial logistic regression is simply a logistic model with more than two possible discrete outcomes for the outcome variable. This model was used in this study to predict the probabilities of the more than two possible outcomes of childbirth weight (low, normal, and

overweight) that has a nominal scale using maternal education level and age as predictor variables.
MLR uses a linear predictor function say $f(k,l)$ to predict the probability that an observation say i has outcome k, of the following form:

$$f(k,l) = \beta_{0,k} + \sum_{m=1}^{k} \beta_{1,k} x_{m,i} + \beta_{2,k} x_{2,i} + e_i \qquad i = 1, 2, ..., n ; \quad l = 1, 2, ..., m; \tag{4}$$

where

$k = Categories\, of$ birth weight

$f(k,l)$ is a linear prediction function that predicts the likelihood of observation $x_{m,i}$ that has an outcome as k
$\beta_{0,k}$ is the intercept term of the linear prediction function
$\beta_{1,k}$ is the regression parameter of the maternal education level at the kth outcome.
$\beta_{2,k}$ is the regression parameter of maternal age at the kth outcome
$x_{m,i}$ is the i^{th} observation of the m^{th} level of maternal education level variable
e_i is the i^{th} random error component associated with observation i

In this paper,

$x_{1,i}$ is Higher Education
$x_{2,i}$ is Secondary School
$x_{3,i}$ is Primary School
$x_{4,i}$ is No Education
This paper uses 735 data points and each data point consists of a set of 2 predictor variables (maternal education level and age) and an associated categorical outcome variable Y_i (weight of child). The predictor variables are categorical (maternal education level) and numerical (maternal age). The Y_i was coded into three groups (LBW, NBW, and Macrosomia). The NBW was chosen as the reference level in the dependent variable while No education level was chosen as a reference level in the categorical predictor variable. To arrive at the MLR model, for K possible outcomes of Y_i, running K-1 independent binary logistic regression models, in which one outcome is chosen as a "reference level" (NBW), and then the other K-1 outcomes are separately regressed against the reference level outcome.
If outcome K (NBW) is chosen as the pivot:

$$Ln\left(\frac{P_r(Y_i = 1)}{P_r(Y_i = K)}\right) = \beta_1 X_{m,i} \tag{5}$$

$$Ln\left(\frac{P_r\left(Y_i=2\right)}{P_r\left(Y_i=K\right)}\right)=\beta_2 X_{m,i}$$

.

.

.

$$Ln\left(\frac{P_r\left(Y_i=k-1\right)}{P_r\left(Y_i=K\right)}\right)=\beta_{k-1} X_{m,i} \tag{6}$$

Exponentiating both sides and solving for the probabilities in equations (5) and (6), we get:

$$P_r\left(Y_i=1\right)=P_r\left(Y_i=K\right)\exp\left(\beta_1 X_{m,i}\right)$$
$$P_r\left(Y_i=2\right)=P_r\left(Y_i=K\right)\exp\left(\beta_2 X_{m,i}\right)$$

.

.

.

$$P_r\left(Y_i=K-1\right)=P_r\left(Y_i=K\right)\exp\left(\beta_{k-1} X_{m,i}\right) \tag{7}$$

The probability of any K possible childbirth weight can be expressed as:

$$\begin{aligned} P_r\left(Y_i=K\right) &= 1-\sum_{k=1}^{k-1} P_r\left(Y_i=K\right) \\ &= 1-\sum_{k=1}^{k-1} P_r\left(Y_i=K\right)\exp\left(\beta_k X_{m,i}\right) \\ &= \frac{1}{\sum_{k=1}^{k-1}\exp\left(\beta_k X_{m,i}\right)+1} \end{aligned} \tag{8}$$

Other probabilities can be computed:

$$P_r\left(Y_i=1\right)=\frac{\exp\left(\beta_1 X_{m,i}\right)}{\sum_{k=1}^{k-1}\exp\left(\beta_k X_{m,i}\right)+1}$$

$$P_r\left(Y_i=3\right)=\frac{\exp\left(\beta_3 X_{m,i}\right)}{\sum_{k=1}^{k-1}\exp\left(\beta_k X_{m,i}\right)+1}$$

.

.

.

$$P_r\left(Y_i=K-1\right)=\frac{\exp\left(\beta_{K-1} X_{m,i}\right)}{\sum_{k=1}^{k-1}\exp\left(\beta_k X_{m,i}\right)+1} \tag{9}$$

The unknown parameters in each regression parameter vector β_k are typically jointly estimated by an extension of maximum likelihood using regularization of the weights. The solution is typically found using any of the following: iteratively reweighted least squares (IRLS), (Bishop, 2006)[12], gradient-based optimization algorithms such as L-BFGS (Malouf, 2002)[13], or specialized coordinate descent algorithms (Yu and Huang 2011)[14]. The iteratively reweighted least squares by Bishop (2006)[12], were implemented in this paper using the R statistical programming software, version 4.10.

3. RESULTS AND DISCUSSION

3.1 Data Source and Nature

Secondary data extracted from the 2018 Nigeria Demographic and Health Survey data was used for this study. The predictor variables are maternal education level and age while the outcome variable is childbirth weight. The dependent variable was recoded using the recommended WHO standards as LBW, NBW, and Macrosomia. The data was naturally stratified by maternal education levels (1 = Higher Education, 2 = Secondary Education, 3 = Primary Education, and 4 = No Education). The equal sample allocation technique was used as in (ni = 200 for the ith maternal education level). However, after removing the rows with possible outliers (in maternal age), the following stratum sample sizes were used (Higher Education level = 193, Secondary Education = 180, Primary Education = 169, and No Education = 193). The new outlier test after the deletion of rows containing outliers is shown in Figure 1.

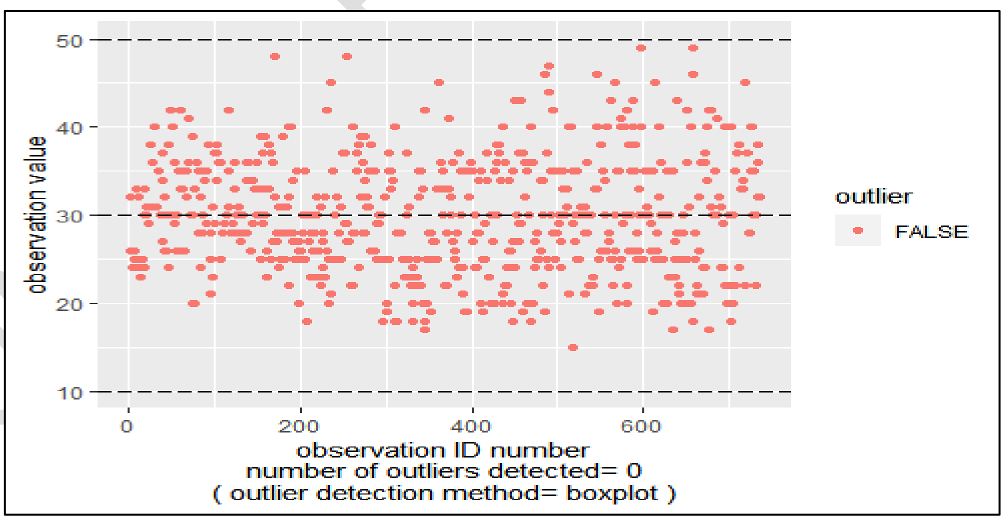

Fig. 1: The maternal age Box and Whisker's distribution.

Table 1 shows that the mean weight of all raw scores of the 735 sample points for birth weight was 3.2kilograms with a corresponding 0.59 standard deviation. The standard deviation value is very small which indicates that the individual birth weights are not very far from the mean value. The mean age of the mothers was approximately 30 years.

Table 1: Descriptive Statistics

	Mean	Std. Deviation	Skewness		Kurtosis		N
			Statistic	Std. Error	Statistic	Std. Error	
Weight of Child at Birth	3.1971	.58667	.202	.090	-.019	.180	735
Highest Education Level	2.4925	1.14108	-	-	-	-	735
Mother's Age	29.91	6.261	.290	.090	-.263	.180	735

The correlation values between the weight of the child at birth and the maternal education level and age are -0.247 and 0.136 respectively as shown in Tane 2. These correlation coefficients are significant at the alpha level of 5% which indicates that there exists a significant association between child birth weight and maternal education level and age. This satisfies the assumption of the MLR because the correlations do not necessarily need to be high.

Table 2 Correlation Matrix

		Birth weight	Maternal Education Level	Mother's Age
Pearson Correlation	Birth weight	1.000	-.247	.136
	Maternal Education Level	-.247	1.000	-.035
	Mother's Age	.136	-.035	1.000
p-value	Birth weight	.	**.000****	**.000****
	Highest Education Level	**.000****	.	.172
	Mother's Age	.000**	.172	.

****** means significant at 5%

The proportion of birth weight in each birth category against the maternal education level is presented in Table 3. The results show that 57% (0.57) of the 7.34% total LBW babies for this study were from mothers with No formal education while 75.4% of the total 88.03 NBW babies are from mothers with primary or secondary or tertiary education. This proportion shows that mothers with no formal education are more likely to bore LBW babies than their educated counterparts.

Table 3. Proportion of Birth weight by Mother's Education Level

Maternal Education	LBW	Proportion	NBW	Proportion	macrosoma	Proportion
Higher Education	13	0.24	164	0.253	16	0.471
Secondary School	6	0.12	159	0.246	15	0.441
Primary School	4	0.07	165	0.255	0	0.000
No Education	31	0.57	159	0.246	3	0.088
Total (%)	**54 (7.34%)**	**1.000**	**647 (88.03%)**	**1.000**	**34 (4.63%)**	**1.000**

The birth weight categories were cross-tabulated with the maternal education level at the mean maternal age to assess the distribution of the data set at the average age. The data distribution was displayed in Table 4.

Table 4. Mean Maternal Age at different Birth Weight and Maternal Education Levels

	Birth Weight Levels for mean age			
Maternal Education	LBW	NBW	macrosomia	Grand Total
Higher Education	29.54	31.23	32.44	31.22
Secondary School	27.50	28.16	32.87	28.53
Primary School	32.75	29.35	30.23	29.43
No Education	28.42	30.51	38.33	30.30
Grand Total	**28.91**	**29.82**	**33.15**	**29.91**

A diagnostic examination is conducted on the MLR model with two predictor variables. The standard errors of the predictor variables are between 0 and 2 (Table 5) suggesting no multicollinearity among the predictor variables.

Table 5. Multinomial Logistic Regression Output

Coefficients:					
	(Intercept)	Higher Educ.	Pri. Sch	Sec. Sch	Maternal Age
LBW	-0.626	-0.865	-2.120	-1.712	-0.034
Macrosomia	-7.300	1.732	-6.568	1.917	0.100
Std. Errors:					
	(Intercept)	Higher Educ.	Pri. Sch	Sec. Sch	Maternal Age
LBW	0.704	0.350	0.544	0.463	0.023
Macrosomia	1.247	0.646	1.640	0.659	0.030

The p-values of the coefficients of the MLR model in Table 5 are displayed in Table 6.

Table 6. Wald Statistic and Coefficient Significance Test Output

	(Intercept)	Higher Educ.	Pri. Sch	Sec. Sch	Maternal Age
LBW	0.790	6.088	15.135	13.683	2.137
Macrosomia	34.251	7.174	0.160	8.460	10.632
p-values					
	(Intercept)	Higher Educ.	Pri. School	Sec. School	Age
LBW	**3.74e-01****	**0.013****	**0.0001****	**0.0002****	0.1438
Macrosomia	**4.84e-09****	**0.007****	0.688	**0.0036****	**0.0011****

Bolded p-value indicates sig. at 5%

The model fitting information using the Likelihood ratio test is shown in Table 7. The results therein show that the MLR model with two predictor variables is better for predicting birth weight in Nigeria than the MLR model without the two predictor variables since the p-value is significant at 0.01.

Table 7. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	p-value
Intercept Only	336.637			
Final	263.020	73.617	8	**0.000****

The Goodness of fit test using the Pearson chi-square test statistics is displayed in Table 8. The p-value (0.994) and Deviance p-value (1.000) further indicates that the MLR model with two predictor variables is a good fit for the data. The Nagelkerke R-square value indicates that 16.1% of the total variations in birth weight occurred due to the variations among the two predictor variables.

Table 8. Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	160.552	208	.994
Deviance	145.699	208	1.000
Nagelkerke	0.161		

We further test for the significance of the predictor variables using the Likelihood ratio test. The results in Table 9 show that the two predictor variables are statistically significant in predicting birth weight in Nigeria.

Table 9 Likelihood Ratio Tests.

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	263.020	.000	0	.
Age	276.529	13.509	2	**0.001****
Education	326.290	63.270	6	**0.000****

Following equations (5) and (6), the logit models are as follow:

$$\begin{aligned} Ln\left(\frac{\text{weight}=\text{Low}}{\text{weight}=\text{normal}}\right) = \beta_{10} + \beta_{11_1}\ (\text{maternal edu.}=\text{Higher}) \\ +\ \beta_{11_3}(\text{maternal edu.}=\text{Primary}) \\ +\beta_{11_2}(\text{maternal edu.}=\text{Secondary}) \\ +\beta_{12}(\text{maternal Age.}) \end{aligned} \quad (10)$$

$$\begin{aligned} Ln\left(\frac{\text{weight}=\text{macrosoma}}{\text{weight}=\text{normal}}\right) = \beta_{20} + \beta_{21_1}\ (\text{maternal edu.}=\text{Higher}) \\ +\ \beta_{21_3}(\text{maternal edu.}=\text{Primary}) \\ +\beta_{21_2}(\text{maternal edu.}=\text{Secondary}) \\ +\beta_{22}(\text{maternal Age.}) \end{aligned} \quad (11)$$

Following equation (10) and coefficients in Table 5, we have that:

$$Ln\left(\frac{\text{weight}=\text{Low}}{\text{weight}=\text{normal}}\right)=-0.63\ -0.86(\text{maternal edu.}=\text{Higher}) \\ -2.12(\text{maternal edu.}=\text{Primary}) \\ -1.71(\text{maternal edu.}=\text{Secondary}) \\ -0.034\,(\text{maternal Age}) \quad (12)$$

Following equation (11) and coefficients in Tabe 5, we have that:

$$Ln\left(\frac{\text{weight}=\text{M}acrosoma}{\text{weight}=\text{normal}}\right)=-7.3+1.73(\text{maternal edu.}=\text{Higher}) \\ -6.57(\text{maternal edu.}=\text{P}rimary) \\ -1.92(\text{maternal edu.}=\text{Secondary}) \\ +0.101(\text{maternal A}ge.) \quad (13)$$

The exponent of the regression coefficients in equations (11) and (12) which represents the odds ratios (relative risk) is shown in Table 10.

Table 10. Exponents of the Multinomial Regression Parameters

	(Intercept)	Higher Educ.	Pri. Sch	Sec. Sch	Age
LBW	0.5348	0.4211	0.1200	0.1803	0.9665
Macrosomia	0.0007	5.6536	0.0014	6.800	1.105

Refer to equations (10), (11), (12), and (13), following the interpretations of MLR results in Ugwuanyim et al. (2020)[15], the interpretation follows:

Interpretation of the regression coefficients for LBW vs. NBW

β_{12} = A one-unit increase in maternal age is associated with the decrease in the log odds of giving birth to an LBW baby vs. an NBW baby in the amount of -0.034 (Table 5), this coefficient is not significant as the p-value is 0.1438 (Table 6). The relative risk as shown in Table 10, (exp(-0.034) = 0.9665)) implies that a one-unit increase in maternal age reduces the odds for LBW by (1 – 0.9665 = 0.0335)*100 = 3.35%.

β_{11_1} = The log odds of giving birth to an LBW baby vs NBW will decrease by -0.866 when a mother with no education attains higher education (Table 5). This coefficient is significant in predicting birth weight (p-value is 0.014, Table 6) at a 5% level of significance. The relative risk as shown in Table 10, (exp (-0.866) = 0.421), implies that mothers who move from no education to acquiring higher education are (1.000 – 0.421 = 0.579)*100 = 57.9% more likely to give birth to NBW baby.

β_{11_2} = The log odds of giving birth to an LBW baby vs an NBW baby will decrease by -1.71 when a mother moves from no education to secondary school (Table 5). This decrease is significant at 5% (p-value = 0.0002, Table 6). The relative risk as shown in Table 10, (exp (-1.71) = 0.18), implies that mothers who move from no education to secondary education are (1.000 – 0.18 = 0.82)*100 = 82% more likely to give birth to NBW babies.

β_{11_3} = The log odds of giving birth to LBW baby vs NBW baby will decrease by -2.12 when a mother moves from no education to primary school level of education (Table 5). This coefficient is significant at 5% (p-value = 0.001, Table 6). The relative risk as shown in Table 10, (exp (-2.12) = 0.12), also implies that mothers who move from no education to primary education are (1.000 – 0.120 = 0.88)*100 = 88.0% more likely to give birth to normal weight baby.

Interpretation of the regression coefficients for macrosomia vs. NBW

β_{22} = A one-unit increase in maternal age is associated with the increase in the log odds of giving birth to macrosomia vs. NBW baby in the amount of 0.100 (Table 5). The increase is significant at 5% (p-value = 0.001, Table 6). This simply means that one unit increase in maternal age increases the relative risk as shown in Table 10, (exp (0.100) = 1.106)) of giving birth to macrosomia baby by (1.105 - 1.000 = 0.106)*100 = 10.6%.

β_{21_1} = The log odds of giving birth to macrosomia vs NBW increases by 1.73 when a mother with no education attains Higher Education (Table 5). The increase is significant at 5% (p-value = 0.00740, Table 6). The relative risk in Table 10, (exp (1.73) = 5.65)) implies that mothers who move from no education to higher education are (5.65 – 1.000 = 4.65)*100 = 465% more likely to give birth to macrosomia baby.

β_{21_2} = The log odds of giving birth to macrosomia vs NBW baby will increase by 1.92 when a mother with no education attains a secondary school level of education (Table 5). The increase is significant at 5% (p-value = 0.0036, Table 6). The relative risk as shown in Table 10, (exp (1.92) = 6.820)), also implies that mothers with no education that attains secondary education are (6.82 - 1.000 = 5.82)*100 = 582% more likely to give birth to macrosomia babies.

β_{21_3} = The log odds of giving birth to macrosomia vs NBW baby will decrease by -6.57 when a mother with no education attains primary school level of education (Table 5). The decrease is not statistically significant at 5% (p-value = 0.688, Table 6). The relative risk as shown in Table 10, (exp (-6.57) = 0.00140)), also implies that mothers with no education that attains primary education are (1.000 – 0.00140 = 0.999)*100 = 99.9% more likely to give birth to NBW babies.

3.2 Predicted Probabilities (or Relative Risk) and Interpretation

The computed predicted probabilities for each of the outcome levels (birth weight) and the first six rows of the 735 rows are shown in Table 11.

Table 11. Predicted Probabilities for each level of childbirth weight

	Normal Weight	Low Weight	Macrosomia
1	0.8542138	0.06475142	0.08103480
2	0.8734275	0.08120511	0.04536743
3	0.8756458	0.08714508	0.03720917
4	0.8756458	0.08714508	0.03720917
5	0.8734275	0.08120511	0.04536743
6	0.8734275	0.08120511	0.04536743

To examine the changes in predicted probability associated with one of the two predictor variables, small datasets varying one variable while holding the other constant can be created. When maternal age and its mean (29 years) are held constant, the changes in the predicted probabilities for each level of maternal education are displayed in Table12. The probability of NBW baby increases but decreases for LBW baby as the maternal education levels move from higher to no education while holding maternal age at the average.

Table 12. Changes in predicted probabilities at mean maternal age

	Normal Birth Weight	Low Birth Weight	Macrosomia
1	0.86	0.07	0.07
2	0.89	0.03	0.08
3	0.98	0.02	0.00
4	0.83	0.16	0.01

1 = Higher, 2 = Secondary, 3 = Primary and 4 = No education

Table 13 showed the mean probability of the three categories of the outcome variable at each level of maternal education. It was observed that the probability was smaller for LBW for those mothers with higher education and the highest for those with no education. However, mothers with higher education had a high mean predicted probability for macrosomia babies classification more than others.

The plot of the predicted probabilities is shown in Figure 2. The likelihood that a mother will give birth to LBW baby decreases as the age of the mother increases and the mother attained at least a primary education because the curve is almost flattened for all levels of education other than for the no-education mothers. The plot also shows that as the age of the mother increases, the likelihood of such a mother giving birth to a macrosomia baby increases for all levels of education but remains constant for mothers with only primary school education.

Table 13. The Mean probabilities of child birth weight within each levels of education

	Normal Birth Weight	Low Birth Weight	Microsomia
Higher Education			
	0.58	0.03	0.39
Secondary School			
	0.56	0.01	0.43
Primary School			
	0.99	0.01	0.00
No Education			
	0.78	0.09	0.13

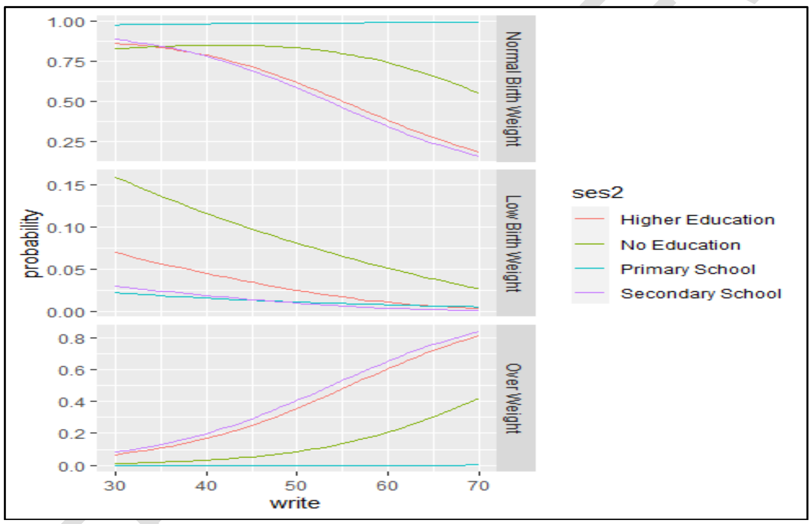

Figure 2: Plot of the predicted probabilities

4. CONCLUSION AND RECOMMENDATIONS

Table 14. Summary of findings

Variable	**Relative Risk**	**Interpretation**
Maternal Age	Low Birth Weight vs. Normal Birth Weight = 0.9665	Older mothers are 3.35% likely to have low-weight babies at birth. This implies that younger mothers are at risk.
	Microsomia vs. Normal Birth Weight = 1.10596	Younger mothers are 10.6% likely to have microsomia babies at birth. This implies that older mothers are at risk.
Higher Education	Low Birth Weight vs. Normal	Mothers who move from no education

	Birth Weight = 0.4211.	to higher education are 57.9% likely to give birth to a normal-weight baby at birth.
	Microsomia vs. Normal Birth Weight = 5.65	Mothers that switch from no education to higher education are 46.5% likely to give birth to babies at birth.
Primary School	Low Birth Weight vs. Normal Birth Weight = 0.12	Mothers that move from no education to primary school level of education are 88% likely to have normal birth weight babies at birth.
	Microsomia vs. Normal Birth Weight = 0.0014	Mothers who move from no education and attain primary school level of education are 99% likely to have normal-weight babies at birth.
Secondary School	Low Birth Weight vs. Normal Birth Weight = 0.18	Mothers that move from no education to secondary school level of education are 82% likely to have normal-weight babies at birth.
	Microsomia vs. Normal Birth Weight = 6.8	Mothers that move from no education to secondary school level of education are 82% likely to have overweight babies at birth.

Notes:

i. The weight of a child at birth is positively correlated with the mother's age. This finding is in agreement with Welcher and Mellits (1971)[16] that also reported a positive relationship between maternal age and infant birth weight.

ii. As we go up from no education to Higher education mothers, the likelihood to give birth to LBW decreases. This means that maternal education increases the chances for NBW children. This finding is in agreement with the findings of (Shi, 2004)[3] and Fayehun and Asa (2020)[8].

iii. LBW babies are associated more with no educated mothers and this likelihood decreases as maternal age increases (Figure 2)

Recommendations based on study findings are;

i. That early marriage of the girl child should be discouraged in Nigeria since LBW is associated with younger mothers (less than 28years) and children with LBW are more likely to die than those with normal weight.

ii. The girl child should at least acquire primary school education before marriage since maternal education has been shown in this paper to significantly affect child birth weight and the causal effect of education is identified for individuals with a low level of education rather than at the upper end of the education distribution.

ACKNOWLEDGEMENTS

We acknowledge Nigeria's Demographic and Health Survey for providing the data used in this research. The funds used in this research were mainly contributed by the authors. The reviewer's comments were highly appreciated

COMPETING INTERESTS
Authors have declared that no competing interests exist.

AUTHORS' CONTRIBUTIONS

" 'Author DCB' wrote the first draft of the manuscript and designed the study. 'Author OEB' and 'Author DE' performed the statistical analysis, wrote the protocol, and managed the analyses of the study. 'Author DCB' managed the literature searches…… All authors read and approved the final manuscript."

REFERENCES

[1] World Health Organization. "Global Nutrition Targets 2025: Low Birth Weight Policy Brief", WHO/NMH/NHD/14.5. (2014) Retrieved 12 April 2020.

[2] Park. K. "Park's Text Book of Preventive and Social Medicine". Jabalpur:*M/s. Banarsidas Bhanot Publishers* (2007) 17: 426–428.

[3] Shi L., Macinko J., Starfield B., Xu J., Regan J., and Politzer R., "Primary care, infant mortality, and low birth weight in the states of the USA". *J Epidemiol Community Health*.; (2004) 58.

[4] Ganchimeg T., Ota E., Morisaki N., Laopaiboon M., Lumbiganon P., and Zhang J. "Pregnancy and childbirth outcomes among adolescent mothers: a *World Health Organization multicountry study*". BJOG 2014; 121(Suppl 1):(2014), 40.

[5] Currie, J, and Moretti, E. "Mother's education and the intergenerational transmission of human capital: Evidence from college openings", *Quarterly Journal of Economics*, (2003) 118(4), 1495-1532.

[6] Luis, M.G., Helena, L.G., Sonia, P.G. and Ana, J.. Multinomial Logistic Regression in Worker's Health, *American Institute of Physics,* (2017) Conference paper in AIP Conference Proceedings.

[7] Mengesha, H.G., Wuneh, A.D., Weldearegawi, B. and Divya, L.S. Low Birth Weight and Macrosomia in Tigrary, Northern Ethiopia; who are the mothers at risk?, *BMC Pediatrics,* (2017) 17(144).

[8] Fayehun, O. and Asa, S. Abnormal Birth Weight in Urban Nigeria: An Examination of Related Factors, *PLOS one,* (2020) 15(11).

[9] Boyd, C. R.; Tolson, M. A. & Copes, W. S. "Evaluating trauma care: The TRISS method. Trauma Score and the Injury Severity Score". *The Journal of Trauma.* (1987) *27 (4): 370–378.*

[10] Orumie, UC and Bartholomew, DC. "Respiratory Syncytil Virus Infection in Infants: A comparative study using Discriminant, Probit and Logistic Regression Analysis". Asian Journal of Probaility and Statistics, (2022), 18(2), 18-31.

[11] Orumie UC, Bartholomew DC, Obite CP, Kiwu LC. Likelihood of Insurance Coverage on Damages Due To Level of Insecurity In Nigeria: Logistic Modeling Approach, Financial Risk and Management Reviews. 2021;7(1):50-59.

[12] Bishop, C.M. Pattern Recognition and Machine Learning. Springer. (2006). 206–209.

[13] Malouf, R. A comparison of algorithms for maximum entropy parameter estimation (PDF). Sixth Conf. on Natural Language Learning (CoNLL). (2002). 49–55.

[14] Yu, H.F and Huang, F.L. "Dual coordinate descent methods for logistic regression and maximum entropy models" (PDF). MachineLearning. (2011) 85 (1–2):41–75. doi:10.1007/s10994-010-5221-8.

[15] Ugwuanyim, G.U., Osuchukwu, C.O. Bartholomew, D.C. and Obite, C.P. "Medical Choices for a Wealthy Nation – A Multinomial Logistic Regression Model", Asian Journal of Probability and Statistics, (2020) 6(3): 1-12, ; Article no.AJPAS.54245.

[16] Welcher D.W., Lobl M. & Mellits E.D.. "Maternal age and intellectual functioning of offspring". *Johns Hopkins Med J*; (1971) 128:347-357.