International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Exploring the Impact of Maternal Prenatal History on Newborn Weight, in Antenatal Unit of Specialist Hospital Bauchi

[1]Mahmood M. M., [2] K. E Lasisi., [3]Abbas U. F., [4]Hauwa'u I.

[1,2,3,4]Department of Mathematical Sciences, Abubakar Tafawa Balewa University, Bauchi, Nigeria

ABSTRACT

The birth weight of the newborn determines the health and survival of the newborn. Birth weight depends upon maternal factors such as the nutritional status of the mother, maternal age, weight, parity, gestational age, hemoglobin status, blood sugar, and blood pressure. Methods it's a retrospective study conducted at medical college and hospital. Data collection was drawn on 100women for the age of the mother at the time of delivery, parity, gestational age, hemoglobin status and the weight of the mother, weight of the newborn, blood sugar, and blood pressure from January 2022- December 2022.Results: In our study low birth weight seems to be associated with Weight of child at birth is dependent variable (Y), 0 and 1 i.e. (Abnormal and Normal). A variable in the Equation shows that the impact of each independent variable on the response variable. However, it was observe that only X_2 = weight of mother and X_3= gestational age are significance at 5% level of significance while the other independent variable are insignificance with p-value>0.05. Predicted WOCAB is 58 abnormal, 98% and 40 normal, 97% from the Classification table with p-value ofp = .000. The null hypothesis was rejected at the 5% level of significance in respect to the decision rule and we therefore conclude that there is a significant difference between child's weight at birth and mother's prenatal history. Awareness about complications in teenage and young age pregnancy and neonatal outcomes can be emphasized in textbooks for young parents.

Keywords: Low birth weight; maternal age, weight, parity, gestational age, hemoglobin status, blood sugar, and blood pressure

1. Introduction

Low birth weight, defined as a birth weight of less than 2,500 grams, is a significant public health concern worldwide. Low birth weight is associated with an increased risk of neonatal mortality and morbidity, as well as long-term developmental delays, chronic health conditions, and reduced quality of life (Kozuki and 2015WHO, 2014).

Several maternal prenatal factors have been identified as contributing to low birth weight, including maternal age, smoking during pregnancy, gestational diabetes, hypertension, and maternal obesity. Kominiarek, 2017).

Maternal age is a risk factor for low birth weight, with teenage mothers and mothers over the age of 35 being at increased risk. Smoking during pregnancy is also a well-established risk factor for low birth weight, with infants born to mothers who smoke during pregnancy being on average 200 grams lighter than infants born to non-smoking mothers. Maternal obesity is also a risk factor for low birth weight, with infants born to obese mothers being at increased risk of both small for gestational age and large for gestational age (Kominiarek, 2017).

Data on the weight, height, age, number of live births and number of miscarriages of pregnant women were collected during antenatal; the weight and height are used to calculate BMI (body mass index). Women who are underweight before pregnancy (BMI less than $18.5kg/m^2$) are at significantly greater risk of having premature, low birth weight new born. Overweight and obese women (BMI greater than $25kg/m^2$) have a higher risk for preterm births. Every pregnancy carries its risks, but good prenatal care and support can help minimize those risks. Factors like age and overall health status can increase a woman's chances of experiencing complications during pregnancy. A child that has weight less than 2.4kg at birth has a low birth weight, and about one in 12 babies' fall into that category. A mother's health can also affect growth in the womb, high blood pressure, diabetes, heart problems and lungs conditions can restrict growth. If a mother smokes, drinks or uses illicit drugs, it can also lead to low birth weight. Certain infections or being pregnant with twins, triplets, or multiples can also lead to low child weight too. The immediate dangers of a child born with low child weight can experience symptoms immediately after delivery. Low child-weight babies might not take in adequate amounts of oxygen and their bodies might not be able to maintain a normal body temperature. Low-weight babies can have a hard time feeding. Children born with low child weight are also at a higher risk for infection, respiratory problems, bleeding in the brain, intestinal problems, increased risk of long-term disabilities, and sudden infant death syndrome. A baby with a low birth weight can experience health problems into adulthood. Adults who were classified as low child weight are at higher risk for high blood pressure, type2 diabetes and heart diseases. Aside from significant associations with infant mortality, low birth weight also has other negative effects particularly on physical and mental development of children. Barker's Hypothesis states that "conditions in the maternal womb have a programming effect (fetal programming) on fetal physiology." For instance, when a fetus is deprived of adequate nutrient supply in the womb, it will develop a thrifty phenotype causing smaller body size and lowered metabolic rate to name a few (Barker, 2000).

2. Statement of the Problem

Despite advances in medical technology and increased attention to maternal health during pregnancy, low birth weight remains a significant public health concern worldwide (Kumar.2022). Most of the studies are find out that, less than 50% of the child's are low weights at birth and low weight birth babies often have problems. The baby's tiny body is not as strong as a baby of normal birth weight. They may have a harder time eating, gaining weight, fighting infection at end to death. Low birth weight can lead to a number of complications. In this study, we trying find out that, the mothers' health status and nutritional intake affect or influence to reduce child's low weights at birth (data obtained from babies immediately after delivery). In our study we intend to use logistic regressions models to assess the contributing factor to child's birth weight, considering maternal age, weight, parity, gestational age, hemoglobin status, blood sugar, and blood pressure is the main task of this work.

3.0 Aim and Objectives of the Study

The aim of this study is to examine the application of logistic regressions on the relationship between child's weights at birth in the antenatal unit of Specialist Hospital, Bauchi State. The objectives of the Study are:

- To determine the relationship between child's weights at birth onMaternal age, weight, parity, gestational age, hemoglobin status, blood sugar, and blood pressure of the mother's
- To investigate the effective low weight at birth between child's and mother's
- To fit a logistic regression model for prediction and validate the model

4.0 Brief Literature Review

Multivariable methods of statistical analysis commonly appear in general health science literature (Bagley, White, & Golomb, 2001). The terms "multivariate analysis" and "multivariable analysis" are often used interchangeably in the literature. In the strict sense, multivariate analysis refers to simultaneously predicting multiple outcomes and multivariable analysis uses multiple variables to predict a single outcome (Katz, 1999).

Examined the multivariate analysis of relationship between Child's Weight and Length at birth and the Mother's antenatal history using Canonical Correlation Analysis which seeks to identify and quantify the association between two sets of variables (Nwabude, 2015).

The independent effect of pre-pregnancy weight, gestational weight gain (GWG), and there important risk factors on newborn birth weight. Methods Baseline data of 435 adult women and their singletons born between January and February 2012 at a public hospital in Brazil were used. Logistic regression was applied to determine the independent importance of pre-pregnancy weight and GWG for large for gestational age (LGA) newborns (Marco F. Mastroeni., 2017).

Carried out a study on "Application of multiple linear regression analysis in accessing the effect of weight at birth and mothers' antenatal history" this is aimed at determining the weight at birth and mothers' antenatal history (Victor, 2015). Examined the infant mortality rate (IMR) of tertiary hospital in Adamawa state, Nigeria. (Aminu, 2017). To study the independent effect of pre-pregnancy weight, gestational weight gains (GWG), and other important risk factors on newborn birth weight (Marco F. Mastroeni., 2016). Maternal Carbohydrate Intake Having an Impact on Newborn Birth Weight (Pathirathna, M.L.; Nandasena, H.M.R.K.G., 2023).

Impact of maternal determinants in rural areas influencing birth weight of newborn. The birth weight of the newborn determines the health and survival of the newborn. Birth weight depends upon maternal factors such as the nutritional status of the mother, gestational age, multiple gestations, hemoglobin status, weight of the mother, complications of labour such as diabetes, hypertension, seizures, cardiac defects, bleeding manifestations, chronic illness and substance abuse (Rajendiran and Brethis, 2022).

5.0 METHODOLOGY

Methodology refers to the study descriptions, synthesis of methods, their strengths, limitations, speculations and generalizations that have been utilized during the study. Hence, method refers to the process of research work. In this chapter, we shall consider the method used in collecting the data, the process of analyzing and estimating the parameter of the model in the logistic regression equation. Logistic regression, like any other model building technique in statistics is aimed at finding the best fitting and most economical and yet sensible modelto assess the relationship between a response **variables** and at least one independent variables. It differs from the linear regression in that, it can be applied when the dependent variable is categorical and that it does not require rigorous assumptions to be met (Al-Ghamdi, 2011).

5.1 Variables to be measured

The variables to be used in this research work are as follows; dependent variable Y (weight of child's at birth) and the independent variables are (i.e. X1= Maternal age, X2= Weight, X3= gestational age, X4= Parity, X5 = hemoglobin status, X6 = blood sugar, and X7 =blood pressure).

5.2 The Model

It expresses the proportion of the variation in the dependent variable explained by the independent variable. It is also the square of the correlation coefficient R that is, the measure of how well one variable is explained by another.

The most commonly used ordinal logistic model was described in Walker and Duncanand later called the *proportional odds (PO) model* by Mc- Cullagh. The PO model is beand Duncan and later called the proportional odds (PO) model. The PO model is best stated as follows, for a response variable having levels 0, 1, 2. . . K:

Where j = 1, 2. . . k. Some authors write the model in terms of Y ≤ j. Our formulation makes the model coefficients consistent with the binary logistic model. There are k intercepts (αs). For fixed j, the model is an ordinary logistic model for the event Y ≥ j. By using a common vector of regression coefficients β connecting probabilities for varying j, the PO model allows for parsimonious modeling of the distribution of Y.

The simple logistic regression to multiple predictors, one may construct a complex logistic regression as

logit (y) = $\ln(\frac{P}{1-P}) = a + \beta_1 \chi_1 + ... + \beta_k \chi_k$

Therefore,

$$P = p\ (Y = \text{interested outcome}/X_1 = \chi_1 ... X_k = \chi_k)$$

$$= \frac{e^{a+\beta_1\chi_1+\cdots+\beta_k\chi_k}}{1+e^{a+\beta_1\chi_1+\cdots+\beta_k\chi_k}} = \frac{1}{1+e^{-(a+\beta_1\chi_1+\cdots+\beta_k\chi_k)}}$$

The parameters for estimation are

Where, = Intercept, = Coefficient of the Independent Variables.

$X_1, X_2, X_3, X_4, X_5, X_6$ and X_7 Respectively against weight of the child as our response variable Y

5.3 Method of Parameter Estimation

Logistic regression uses the Maximum Likelihood Estimation method to estimate the model coefficients.

$1-\pi i = \frac{1}{1+e^{-(a+\beta_1\chi_1+\cdots+\beta_k\chi_k)}}$ and $\log_e(\frac{\pi i}{1-\pi i}) = \beta 0 + \beta 1 xi$

Therefore, $log_e(\beta 0, \beta j) = \sum_{j=1}^{k} Y(\beta 0 + \beta j xj) - \sum_{j-1}^{k} log_e [1 + exp(\beta 0 + \beta j Xj)]$

We are trying to find $\beta 0$ and βj to maximize the log-likelihood function:

$ln = log_e(\beta 0, \beta j) = \sum_{j=1}^{k} Y(\beta 0 + \beta j xj) - \sum_{j-1}^{k} log_e [1 + exp(\beta 0 + \beta j Xj)]$.

5.4 Method of Data Analysis

The statistical technique that is used in this research work is logistic regression analysis.The data will be analyzed using SPSS-Package version 22.0. In this study, we considered seven independent (explanatory) variables i.e maternal age, weight, parity, gestational age, hemoglobin status, blood sugar, and blood pressure of a mother as our X1, X2, X3, X4, X5, X6 and X7 respectively against weight of the child as our response variable Y.

The logistic Binary model

Model the dependent variable, we classified;

$$Y_i = \begin{cases} 1 \ if\ weight\ at\ birth\ is\ normal \\ 0 \ \ if\ low\ weight\ at\ birth\ is\ abnormal \end{cases}$$

5.5 Assumptions of Logistic Regression

Logistic regression is not dependent on stringent assumptions to be met as compared to linear regression. The fact that logistic regression analysis does not require a lot of assumptions renders it more preferable in some instances to other methods. The following details show it differs from other techniques:

1. The error terms are with a mean of zero and a variance of $\pi(x)[1-\pi(x)]$. (Hosmer and Lemeshow, 2000).
2. Binary logistic regression assumes that the dependent or outcome variable is dichotomous.
3. The outcomes are independent and mutually exclusive

4. Logistic regression requires large samples to be accurate: a minimum of 60 total cases. These requirements need to be satisfied.

6.0 RESULTS AND DISCUSSION

6.1 RESULTS

Results were presented in tables. Logistic regression Model (Binary Logistic), Chi-square test and percentages. Were used to establish relationship between child's weights at birth CWB with other variable of the mother's history in the antenatal unit of Specialist Hospital, Bauchi State.

Table [a,b] 1:Classification WOCAB

	Observed		Predicted		
			WOCAB		Percentage Correct
			Abnormal	NormaL	
Step 0	WOCAB	Abnormal	59	0	100.0
		NormaL	41	0	.0
	Overall Percentage				59.0

a. Constant is included in the model.

b. The cut value is .500

Table2: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.364	.203	3.204	1	.073	.695

Table3: Variables not in the Equation

			Score	Df	Sig.
Step 0	Variables	MAGE	1.586	1	.208
		WOM	65.151	1	.000
		GAGE	31.915	1	.000
		PARI	.343	1	.558
		HSTA	11.429	1	.001
		BSUG	23.983	1	.000
		BPRE	40.895	1	.000
	Overall Statistics		76.493	7	.000

Table 4: Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	123.280	7	.000
	Block	123.280	7	.000
	Model	123.280	7	.000

Table[a]5: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	12.091[a]	**.709**	.955

Table[a] 6: Classification WOCAB

	Observed		Predicted		
			WOCAB		Percentage Correct
			Abnormal	NormaL	
Step 1	WOCAB	Abnormal	58	1	98.3
		NormaL	1	40	97.6
	Overall Percentage				98.0

a. The cut value is .500

Table[a] 7: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	MAGE	.236	.130	3.300	1	.069	1.267
	WOM	**.512**	**.201**	**6.520**	**1**	**.011**	**1.669**
	GAGE	**3.514**	**1.747**	**4.044**	**1**	**.044**	**33.581**
	PARI	-.765	.555	1.903	1	.168	.465
	HSTA	.187	.372	.253	1	.615	1.206
	BSUG	.711	.584	1.482	1	.224	2.037
	BPRE	.348	1.383	.063	1	.801	1.417
	Constant	-168.281	78.364	4.611	1	.032	.000

a. Variable(s) entered on step 1: MAGE, WOM, GAGE, PARI, HSTA, BSUG, BPRE.

Table8: Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	121.556	7	.000
	Block	121.556	7	.000
	Model	121.556	7	.000

Table9: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	13.816[a]	**.703**	.948

Table[a]10: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	LOGMAGE	25.732	24.784	1.078	1	.299	149644774519.322
	LOGWOM	**74.012**	**29.089**	**6.474**	**1**	**.011**	1390632912807134800000000000000000.000
	LOGGAGE	**271.473**	**131.917**	**4.235**	**1**	**.040**	7.933E+117
	LOGPARI	-10.226	10.637	.924	1	.336	.000
	LOGHSTA	1.000	9.001	.012	1	.912	2.718
	LOGBSUG	11.294	7.941	2.023	1	.155	80342.068
	LOGBPRE	5.981	7.080	.714	1	.398	395.905
	Constant	-596.443	279.963	4.539	1	.033	.000

a. Variable(s) entered on step 1: LOGMAGE, LOGWOM, LOGGAGE, LOGPARI, LOGHSTA, LOGBSUG, and LOGBPRE.

6.2 Testing for overall fitness of the model, using chi-square test i.e

Hypothesis

Vs

Level of significance $\alpha = 0.05$

Decisionrule: we reject H_0 if p-value < 0.05, otherwise we accept H_0.

Conclusion: Since P-value (.000) < 0.05, we reject H_0 and conclude that the data fit the model.

6.2.1 Testing for individual variables

Hypothesis

Vs

Level of significance $\alpha = 0.05$

Decisionrule: we reject H_0 if p-value < 0.05, otherwise we accept H_0.

Hypothesis

Vs

Level of significance $\alpha = 0.05$

*Decisionrule***:** we reject H_0 if p-value < 0.05, otherwise we accept H_0.

Conclusion**:** We conclude that the variable x_2= (weight of mother) and

X3= (gestational age) contributes significantly to the model at $\alpha = 0.05$.

From the Model Summary table 4.8; the value of Cox & Snell R Square and Nagelkerke R Square is 70.3 and 94.8 which is the variation in the dependent variable jointly explained by the independent variables (Predictors: X_2 = weight of mother and X_3= gestational age) is 121.556 and 123.280From the Omnibus Tests of Model Coefficients with a p-value of p = .000. The null hypothesis was rejected at the 5% level of significance in respect to the decision rule and we therefore conclude that there is a significant difference between child's weight at birth and mother's prenatal history. From the coefficient table above it can be seen that the coefficients of the predictors: weight of child at birth (Y), weight of mother (X_2), gestational age (X_3), are.512and 3.514 with p-values of:.011 and 0.044. The fitted logistic regression model will become.

7.0 Conclusion

From the study, the marginal effect of National demography and maternal health correlates with birth weight shows that socially and economically impoverished mothers are more likely to have babies with weight less than 2.5kg. And the variation between birth weights associated with mothers prenatal history shows that only maternal age and weight of mother are significant.

REFERENCES

Antti-JussiÄmmälä (2020) Maternal stress or sleep during pregnancy are not reflected on telomere length of newbornsdoi.org/10.1038/s41598-020-71000-2.

Banerice A. (2009) Correlation between infant birth weight and mother's periodontal status.Journal of clinical Periodontology 32(3):299-304.

Barker J.P. (2000) The incubator and the medical discovery of the premature infant. Journal of perinatology: official journey of the California Perinatal Association, 20(5), 321-328.

Batty D. (2008).Impact of an initial miscarriage on the next ongoingpregnancy.*International Journal of Obstetrics and Gyology. 116(Suppl 1), 49-59.*

Blencowe H, Krasevec J, de Onis M, et al. National, regional, and worldwide estimates of low birth weight in 2015, with trends from 2000: a systematic analysis. Lancet Glob Health. 2019;7(7):e849-e860. doi:10.1016/S2214-109X(19)30170-9.

Blumfield, M.L., Hure, A.J.(2021). Maternal pre-pregnancy body mass index and gestational weight gain on offspring outcomes: A systematic review and meta- analysis.European Journal of Epidemiology, 36(2), 127-151.

Carlo W. (2011) The high risk infant. In:Wiegman, ed. Nelson Textbook of Pediatrics. 19th edition. Amsterdam, the Netherlands. Elsevier; 201:522-564.

Chamberlain, C.,O'Mara-Eves (2002). Psychosocial interventions for supporting women to stop smoking in pregnancy. Cochrane Database of Systematic Reviews,(4), CD001055. doi: 10.1002/14651858.CD001055.

De Onis, M., Blössner, M.(2017). Levels and patterns of intrauterine growth retardation in developing countries.European Journal of Clinical Nutrition, 71(3), 285-291.

Fretts R. (2015) Etiology and prevention of stillbirth.American journal of Obstetrics and Gynecology. Volume 193, Issue 6, Pages 1923-1935.

Gortmaker, S.L., Wise, P.H. (1985). Adolescent pregnancy: The impact on the health of the mother, the child, and society. Journal of Adolescent Health Care, 6(4), 263-278

Kami L. Schwerdtfeger (2017) Intergenerational Transmission of Trauma: ExploringMother–Infant Prenatal AttachmentDOI: 10.1002/jts.20179.

Keith T. S. Tung (2021) Influence of Maternal Infection and Pregnancy Complications on Cord Blood Telomere Lengthdoi.org/10.1155/2021/3339456.

Kominiarek, M.A.(2017). Association between gestational weight gain and perinatal outcomes.Obstetrics & Gynecology, 129(4), e1-e10.

Kozuki N, Katz J (2023) Mortality risk in preterm and small-for-gestational-age infants in low-income and middle-income countries: a pooled country analysis. Lancet.2013;382(9890):417-425. doi:10.1016/S0140-6736(13)60993-9.

Lawn JE, Cousens S, ZupanJ(2005) Lancet Neonatal Survival Steering Team. 4 million neonatal deaths: when? Where? Why? Lancet.;365(9462):891-900. doi:10.1016/S0140-6736(05)71048-5.

Marco F. Mastroeni(2018)The Independent Importance of Pre-pregnancy Weight and Gestational Weight Gain for the Prevention of Large-for Gestational Age Brazilian NewbornsMatern Child Health J DOI 10.1007/s10995-016-2156-0.

Maria Herlin(2019Exploring telomere length in mother– newborn pairs in relation to exposure to multiple toxic metals and potential modifying effects by nutritional factors) BMC Medicine*doi.org/10.1186/s12916-019-1309-6.*

Rajendiran, R., Brethis, (2022). Impact of maternal determinants in rural areas influencing birthweightofnewborn. International,JournalofHealthSciences,6(S9),32413249.https://doi.org/10.53730/ijhs.v6nS9.1326.