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STATISTICAL ANALYSIS OF EXTREME LOW BIRTH WEIGHT IN EKITI STATE

BY

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Abstract

Objective: This research identified some factors such as mother's weight, gestational period, mother's age, mode of delivery, sex of the baby, placenta weight that can influence the weight of a baby at birth and determining the relationship among these factors.

Methodology: The data used for this research was collected from the Federal Medical Centre (FMC), Ido Ekiti, between 2021 and 2022. The Multiple Linear Regression was used in this study is to identify some factors that significantly influence the occurrence of ELBW among newborns in Ekiti State, Nigeria and the variables considered includes mother's weight, gestational period, mother's age, mode of delivery, sex of the baby and placenta weight.

Results: From the analysis, the coefficients of the regression model indicate that placenta weight ($\beta_1 = 0.11$), sex of the baby ($\beta_5 = 0.150$), and mother's weight ($\beta_6 = 0.13$) were significant predictors of birth weight with p-values less than 0.05. In contrast, gestational period, mother's

age, and mode of delivery did not show significant impacts at the 0.05 level. The coefficient of determination R^2 value of 0.71, show that 71% of the variability in birth weight can be explained by the predictors. These findings underscore the importance of placenta weight, mother's weight, and baby's sex in predicting birth weight, offering valuable insights for healthcare practitioners.

Keywords: Birth weight, multiple linear regression, placenta weight, gestational period, mother's age, mode of delivery, sex of the baby, mother's weight, statistical significance.

Introduction

Extreme low birth weight is refer to as birth weight less than 1000grams. This is lower than the average birth weight of around 3000 to 4000 grams. Baby born with ELBW has a higher risk of respiratory distress, infection, cardiovascular problems etc. Extreme low birth weight (ELBW) is a major concern in neonatal healthcare worldwide, especially in Nigeria, where adverse birth outcomes are still prevalent. Gaining insight into the epidemiology of ELBW and its related risk factors is crucial for designing effective interventions and enhancing maternal and child health outcomes. However, the definition of ELBW varies among studies and organizations, with different authorities proposing various criteria. The World Health Organization (WHO), a prominent authority in global health, defines ELBW as infants born with a weight of less than 1,500 grams. This standard is widely accepted for identifying the most at-risk newborns and is used to guide clinical practice and research globally [1]. Likewise, the American Academy of Pediatrics (AAP) defines ELBW similarly to WHO, classifying infants born weighing less than 1,000 grams as having extremely low birth weight. This definition aligns with international standards and ensures consistency across research and healthcare settings [2]. Baby born with ELBW face a higher risk of immediate and long-term complications. Respiratory distress syndrome (RDS), sepsis, and intraventricular hemorrhage are among the leading causes of neonatal morbidity and mortality [3]. Furthermore, inadequate neonatal care, including insufficient access to advanced respiratory support and parenteral nutrition, contributes to high mortality rates. Extreme low birth weight (ELBW) are a global public health concern, particularly in low- and middle-income countries like Nigeria. The prevalence of ELBW births in Nigeria is relatively high, driven by a combination of socioeconomic, biological, and environmental factors. According to the [4], the incidence of low birth weight, including ELBW, is higher in northern regions compared to the southern regions, largely due to disparities in healthcare access, maternal nutrition, and socio-economic conditions. Studies suggest that maternal malnutrition, adolescent pregnancies, inadequate prenatal care, and pre-existing maternal health conditions such as hypertension and diabetes contribute significantly to ELBW incidence [5].

[6] conducted a cross-sectional study in Ibadan, southwestern Nigeria, to identify the prevalence and risk factors associated with ELBW. The study involved collecting data from hospital records, including maternal characteristics, prenatal care, and birth outcomes. Logistic regression analysis was employed to identify significant predictors of ELBW, such as maternal age, antenatal care attendance, and the presence of hypertensive disorders. The study found that inadequate prenatal care and maternal hypertension were significant predictors of ELBW, aligning with global findings on the determinants of ELBW. Another study by [7] focused on the socio-cultural determinants of ELBW in rural communities of southeastern Nigeria. The study used a qualitative approach, involving in-depth interviews and focus group discussions with mothers, traditional birth attendants, and healthcare providers. Thematic analysis was used to identify key factors influencing ELBW, including cultural practices, economic constraints, and access to healthcare services. The study emphasized the need for culturally sensitive interventions to address ELBW in rural settings. A study conducted by [8] in Lagos, Nigeria, employed a cross-sectional design to assess the prevalence of ELBW and associated maternal and fetal factors. The study utilized hospital-based data, where the birth weights of neonates

were recorded and analyzed alongside maternal demographic information, prenatal care attendance, and pregnancy complications. The findings indicated that the prevalence of ELBW in the study population was 9.4%, with significant associations found between ELBW and factors such as maternal hypertension, preterm delivery, and inadequate prenatal care. The study underscored the importance of early and regular prenatal care in preventing adverse birth outcomes. Similarly, another cross-sectional study by [9] in Ibadan, Nigeria, examined the prevalence of ELBW and its socio-demographic determinants. The researchers collected data from medical records of deliveries over a five-year period, focusing on maternal age, parity, educational level, and socio-economic status. Logistic regression analysis was employed to identify independent predictors of ELBW. The study found that younger maternal age (teenage pregnancies), low educational attainment, and low socio-economic status were significantly associated with higher odds of delivering an ELBW infant. This study identify the factors influencing the weight of a baby at birth and determine the relationship among the factors using multiple linear regression model.

Materials and Methodology

The data used in this study was collected from Federal Teaching Hospital Ido-Ekiti. The data comprises of both male and female newborn babies from 2021 to 2022. The information provided also includes mother’s weight, gestational period, mother's age, mode of delivery, sex of the baby and placenta weight. Multiple linear regression model was used to carry out the analysis using statistical software R version 4.3.3.

Regression Analysis

Regression analysis is a statistical method used to examine the relationship between one dependent variable (also called the outcome or response variable) and one or more independent variables (also known as predictors or explanatory variables). Its primary goal is to determine the strength and nature of the relationship between the variables and to make predictions about the dependent variable based on the values of the independent variables. Regression analysis is commonly used for prediction, forecasting, and determining relationships in fields like economics, biology, engineering, and social sciences. There are various types of regression, such as linear, multiple, logistic, and polynomial, each suited to different types of data and relationships.

Multiple Linear Regression

Multiple Linear Regression (MLR) is a statistical technique used to model the relationship between a dependent variable and multiple independent variables.

The Multiple Linear Regression was used in this study is to identify some factors that significantly influence the occurrence of ELBW among newborns in Ekiti State, Nigeria and the variables considered includes mother's weight, gestational period, mother's age, mode of delivery, sex of the baby and placenta weight.

Estimation of Multiple Linear Regression

Let y denotes the dependent variable that is linearly related to k independent (or explanatory) variables $X_1 X_2 \ldots X_k$ through the parameters $\beta_1, \beta_2, \ldots, \beta_k$ and the multiple linear regression model is given as follows:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon_i$$

The parameters $\beta_1, \beta_2, \ldots, \beta_k$ are the regression coefficients associated with $X_1, X_2, \ldots, X_k$ respectively and ε_i is the random error component reflecting the difference between the observed and fitted linear relationship. The coefficient of determination, R^2, was calculated. This R^2 value measures the proportion of variance in the dependent variable that can be explained by its relationship with all the independent variables included in the model. In multiple linear regression, R^2 is commonly referred to as the Multiple Coefficient of Determination.

The correlation coefficient (R) provides an indication of how well the observed data aligns with the predicted values, reflecting the strength and direction of the relationship. In this research study, a high Rvalue would indicate that maternal and health-related factors are strongly correlated with birth weight outcomes. R-squared, on the other hand, explains the proportion of variance in the birth weight data that is explained by the independent variables in the model. A higher R-squared value would indicate that a substantial portion of the variability in extreme low birth weight is accounted for by the factors under study.

The coefficient of determination is a value between 0 and 1 and is calculated as:

$$\mathrm{R}^2 = \frac{\mathrm{SSR}}{\mathrm{SST}} = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}}$$

Where:

SST is the total sum of squares (total variance),

SSR is the sum of squares due to regression (explained variance),

SSE is the sum of squares due to error (unexplained variance).

Test for Significance for Regression Analysis

The test is used to check if a linear statistical relationship exists between the dependent variable (Y) and independent variable (X). The statement of hypothesis is;

$$H_0: \beta_0 = \beta_1 = 0$$

$$H_1: \beta_0 = \beta_1 \neq 0$$

Decision is to reject H_0 if the F distribution with K degrees of freedom in the numerator and (nk-1) degrees of freedom in the denominator is lesser than the calculated statistic that is $F_{cal} > F_{tab}, k, n - k - 1$ otherwise accept H_1.

F-statistic computation

The total sum of square (SST), $S_Y = \sum\sum {Y_{ij}}^2 - \frac{\left[\sum\sum Y_{ij}\right]^2}{nk}$

$Regression\ sum\ of\ square\ (SSR) = \beta_1 S_{X_1 Y} + \beta_2 S_{X_{2Y}}$

$Error\ sum\ of\ squares\ (SSE) = S_y - (\beta_1 S_{X_1 Y} + \beta_2 S_{X_2 Y})$

Table 1: ANOVA TABLE FOR MULTIPLE REGRESSION

SOURCE OF VARIATION	SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F-CAL
REGRESSION	SSR	$k-1$	$MSR = \frac{SSR}{d.f}$	$\frac{MSR}{MSE}$
ERROR	SSE	$n-k-1$	$MSE = \frac{SSE}{d.f}$	
TOTAL	SST	$n-1$		

Where n = number of observations and K = number of estimating parameter.

The Least Square Method

Ordinary Least Squares (OLS) is a widely used method for estimating the parameters in a linear regression model. The primary goal of OLS is to find the line (or hyperplane in the case of multiple variables) that minimizes the sum of the squared differences between the observed values and the values predicted by the linear model. These differences are called residuals, and OLS aims to reduce the overall error by minimizing these residuals.This method is used in estimating the parameters β_0,β_1, β_2…, β_k and this is done by differentiating the sum of squares errors to obtain a minimum error. OLS is widely used in fields like economics, biology, and engineering because it provides straightforward, interpretable results when the assumptions are satisfied. However, if the assumptions are violated, other methods (like Generalized Least Squares or Ridge Regression) may be more appropriate.

In a simple linear regression model, the OLS method attempts to fit a line to the data using the equation:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Where:

Y is the dependent variable,

X is the independent variable,

$\beta_0$is the intercept (the value of Y when X= 0),

β_1 is the slope (which indicates how much Y changes for a one-unit change in X),

ε_i represents the error term.

Assumptions of Ordinary Least Square

i **Linearity:** The relationship between the dependent and independent variables is linear.

ii **Independence of Errors:** The residuals (errors) are independent of each other.

iii **Homoscedasticity:** The variance of the residuals is constant across all levels of the independent variable(s).

iv **Normality of Errors:** The residuals are normally distributed.

Least square method for multiple regression model

$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon_i$ (i)

$\varepsilon_i = Y_i - \beta_0 - \beta_1 X_1 1 - \beta_2 X_2$ Taking sum and squaring of both sides, we have

$\sum(\varepsilon_i)^2 = \sum(Y_i - \beta_0 - \beta_1 X_1 - \beta_2 X_2)^2 = 0$

Since $\sum(\varepsilon_i)^2 = 0 = SSE$

By differentiation,

$\frac{\partial}{\partial \beta_0}(SSE) = -2\sum(\hat{Y}_i - \hat{\beta}_0 - \hat{\beta}_1 X_1 - \hat{\beta}_2 X_2)$

$-2\sum(Y_i - \beta_0 - \beta_1 X_1 - \beta_2 X_2) = 0$

$\sum(Y_i - \beta_0 - \beta_1 X_1 - \beta_2 X_2) = 0$

$$\sum Y_i - n\beta_0 - \beta_1\sum X_1 - \beta_2\sum X_2) = 0 \quad \text{(ii)}$$

$$\frac{\partial}{\partial\beta_1}(SSE) = -2\sum X_1(\hat{Y}_i - \hat{\beta}_0 - \hat{\beta}_1 X_1 - \hat{\beta}_2 X_2)$$

$$-2\sum X_1(Y_i - \beta_0 - \beta_1 X_1 - \beta_2 X_2) = 0$$

$$\sum X_1(Y_i - \beta_0 - \beta_1 X_1 - \beta_2 X_2) = 0$$

$$\sum X_1 Y_i - \beta_0\sum X_1 - \beta_1\sum (X_1)^2 - \beta_2\sum X_1 X_2 = 0 \quad \text{(iii)}$$

$$\frac{\partial}{\partial\beta_2}(SSE) = -2\sum X_2(\hat{Y}_i - \hat{\beta}_0 - \hat{\beta}_1 X_1 - \hat{\beta}_2 X_2)$$

$$-2\sum X_2\left(\hat{Y}_i - \hat{\beta}_0 - \hat{\beta}_1 X_1 - \hat{\beta}_2 X_2\right) = 0$$

$$\sum X_2\left(\hat{Y}_i - \hat{\beta}_0 - \hat{\beta}_1 X_1 - \hat{\beta}_2 X_2\right) = 0$$

$$\sum X_2\hat{Y}_i - \hat{\beta}_0\sum X_2 - \hat{\beta}_1\sum X_2 X_1 - \hat{\beta}_2\sum (X_2)^2 = 0 \quad \text{(iv)}$$

Combining (ii), (iii) and (iv) together, we have

$$\sum Y_i - n\beta_0 - \beta_1\sum X_1 - \beta_2\sum X_2 = 0$$

$$\sum X_1 Y_i - \beta_0\sum X_1 - \beta_1\sum (X_1)^2 - \beta_2\sum X_1 X_2 = 0$$

$$\sum X_2\hat{Y}_i - \hat{\beta}_0\sum X_2 - \hat{\beta}_1\sum X_2 X_1 - \hat{\beta}_2\sum (X_2)^2 = 0$$

Multiply (ii) and (iii) by $\sum X_1$ $and\ n$ respectively to eliminate $\hat{\beta}_0$

$$n\sum X_1\sum Y_i = n\beta_0\sum X_1 - \beta_1\sum X_1 - \beta_2\sum X_1\sum X_2 \quad \text{(v)}$$

$$n\sum X_1\sum Y_i = n\beta_0\sum X_1 - \beta_1\sum(X_1)^2 - \beta_2\sum X_1\sum X_2 \quad \text{(vi)}$$

Subtracting (v) from (vi), we have

$$n\sum X_1 Y - \sum X_1\sum Y = n\beta_1\sum(X_1)^2 - \beta_1(\sum X_1)^2 + n\beta_2\sum X_1\sum X_2 - \beta_2\sum X_1\sum X_2 \quad (vii)$$

Dividing equation (vii) through by n, we have

$$\sum X_1 Y - \frac{\sum X_1\sum Y}{n} = \hat{\beta}_1\sum {X_1}^2 - \hat{\beta}_1\frac{(\sum X_1)^2}{n} + \hat{\beta}_2\sum X_1\sum X_2 - \hat{\beta}_2\frac{\sum X_1\sum X_2}{n}$$

$$\sum X_1 Y - \frac{\sum X_1\sum Y}{n} = \hat{\beta}_1\left(\sum {X_1}^2 - \hat{\beta}_1\frac{(\sum X_1)^2}{n}\right) + \hat{\beta}_2\left(\sum X_1\sum X_2 - \hat{\beta}_2\frac{\sum X_1\sum X_2}{n}\right)$$

$$S_{X_1}Y = \hat{\beta}_1 S_{X_1} + \hat{\beta}_2 S_{X_1X_2} \quad (viii)$$

Similarly, multiply (ii) and (iv) by $\sum X_2$ *and* n respectively to eliminate $\hat{\beta}_0$

$$n\sum X_2Y = \hat{\beta}_0\sum X_2 + \hat{\beta}_1\sum X_1X_2 + \hat{\beta}_2(\sum X_2)^2 \quad \text{(ix)}$$

$$\sum X_2\sum Y = n\hat{\beta}_0\sum X_2 + n\hat{\beta}_1\sum X_1\sum X_2 + n\hat{\beta}_2\sum(X_2)^2 \quad \text{(x)}$$

Subtracting equation (ix) from equation (x), we have

$$\text{n}\sum X_2\sum Y - \sum X_2Y = n\hat{\beta}_1\sum X_1X_2 + n\hat{\beta}_2\sum(X_2)^2 - \hat{\beta}_2(\sum X_2)^2 \quad (xi)$$

Dividing equation (xi) through by n, we have

$$\sum X_2Y - \frac{\sum X_2\sum Y}{n} = \hat{\beta}_1\sum X_1X_2 - \hat{\beta}_1\frac{\sum X_1\sum X_2}{n} + \hat{\beta}_2\sum(X_2)^2 - \hat{\beta}_2\frac{(\sum X_2)^2}{n}$$

$$\sum X_2Y - \frac{\sum X_2\sum Y}{n} = \hat{\beta}_1\left(\sum X_1X_2 - \frac{\sum X_1\sum X_2}{n}\right) + \hat{\beta}_2\left(\sum(X_2)^2 - \frac{(\sum X_2)^2}{n}\right)$$

$$S_{X_2Y} = \beta_1S_{X_1X_2} + \beta_2S_{X_2} \quad (xii)$$

From equation (viii) and (xii), we have

$$S_{X_1Y} = \hat{\beta}_1S_{X_1} + \hat{\beta}_2S_{X_1X_2} \quad (viii)$$

$$S_{X_2Y} = \beta_1S_{X_1X_2} + \beta_2S_{X_2} \quad (xii)$$

Multiplying equation (viii) and (xii) by $S_{X_1X_2}$ *and*S_{X_1} respectively

$$S_{X_1Y}(S_{X_1X_2}) = \beta_1S_{X_1}(S_{X_1X_2}) + \beta_2S_{X_1X_2}(S_{X_1X_2}) \quad (xiii)$$

$$S_{X_2Y}(S_{X_1}) = \beta_1S_{X_1X_2}(S_{X_1}) + \beta_2S_{X_2}(S_{X_1}) \quad (xiv)$$

Subtract (xiii) from (xiv), we have

$$[S_{X_1}S_{X_2} - (S_{X_1X_2})^2\ ]S_{X_2Y}S_{X_1} - S_{X_1Y}S_{X_1X_2} = \beta_2$$

Dividing through by $S_{X_1}S_{X_2} - (S_{X_1X_2})^2$,

$$\hat{\beta}_2 = \frac{S_{X_2Y}S_{X_1} - S_{X_1Y}S_{X_1X_2}}{S_{X_1}S_{X_2} - (S_{X_1X_2})^2} \quad \text{(xv)}$$

Putting equation (xv) into (viii),

$$S_{X_1Y} = \beta_1S_{X_1} + S_{X_1X_2}\left(\frac{S_{X_2Y}S_{X_1} - S_{X_1Y}S_{X_1X_2}}{S_{X_1}S_{X_2} - (S_{X_1X_2})^2}\right)$$

By simplification,

$$\hat{\beta}_1 = \frac{S_{X_1Y}S_{X_2} - S_{X_2Y}S_{X_1X_2}}{S_{X_1}S_{X_2} - (S_{X_1X_2})^2} \quad \text{(xvi)}$$

Hence,

$$\hat{\beta}_1 = \frac{S_{X_1Y}S_{X_2} - S_{X_2Y}S_{X_1X_2}}{S_{X_1}S_{X_2} - (S_{X_1X_2})^2}$$

$$\hat{\beta}_2 = \frac{S_{X_2Y}S_{X_1} - S_{X_1Y}S_{X_1X_2}}{S_{X_1}S_{X_2} - (S_{X_1X_2})^2}$$

And then

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1X_1 - \hat{\beta}_2X_2$$

Analysis and Results

In this research, the weight of the baby was used as the dependent variable, while the predictors include the weight of the mother, age of the mother, mode of delivery, gestation period, and sex of the baby.

Table 1: Descriptive Analysis

Gender	Mean (kg)	Median (kg)	Standard Deviation (kg)	Minimum (kg)	Maximum (kg)
Male (2021)	1.23	1.3	0.28	0.65	1.49
Female (2021)	1.09	1.2	0.31	0.3	1.35
Male (2022)	1.21	1.25	0.29	0.5	1.45
Female (2022)	1.01	1	0.33	0.5	1.45

Interpretation: The data collected from federal medical center Ido- Ekiti show that both male and female birth weights show variability, with the male infants having more pronounced Extreme lower birth weights in 2021, while female infants exhibit a more consistent distribution overall. The birth weights across both genders in 2022 show more similarities than in 2021.

Table 2: Regression Analysis Summary

Regression Statistics	
Multiple R	0.843
R-squared	0.71
Adjusted R-squared	0.665
Standard Error	0.308
Observations	40
F-statistic	8.254
Significance F	< 0.001

Interpretation: The regression analysis summary in Table 2 reveals that the Multiple R value is 0.843, which signifies a strong positive correlation between the dependent variable (baby's weight) and the predictors. This high Multiple R value indicates that the predictors collectively account for a significant portion of the variability in the baby's weight. The R-squared value of 0.71 suggests that approximately 71% of the variance in the baby's weight can be explained by the combination of independent variables: mother's weight, age of the mother, mode of delivery, gestation period, and the sex of the baby. This substantial proportion implies that the model has good explanatory power and effectively captures the relationship between these predictors and the baby's weight.

Further analysis is supported by the Adjusted R-squared value of 0.665, which accounts for the number of predictors in the model and provides a more accurate measure of how well the model generalizes to the population. The standard error of 0.308 reflects the average distance between the observed and predicted values of the baby's weight, indicating the typical prediction error in the model. The F-statistic of 8.254 with its corresponding p-value of <0.001 assesses the overall significance of the regression model. A significant F-statistic indicates that at least one of the predictors significantly affects the baby's weight.

Table 3: REGRESSION COEFFICIENTS

Predictor	Coefficient	Standard Error	t-Value	p-Value
Intercept	0.855	0.312	2.737	0.007
Placenta Weight	0.11	0.054	2.031	0.042
Gestational Period	-0.015	0.013	-1.154	0.25
Mother’s Age	-0.022	0.017	-1.294	0.197
Mode of Delivery	0.099	0.14	0.708	0.481
Sex of Baby	0.150	0.070	2.14	0.042
Mother's Weight	0.13	0.056	2.32	0.032

Regression Equation

$$\text{Birth Weight} = 0.855 + 0.11 \times \text{Placenta Weight} - 0.015 \times \text{Gestational Period} - 0.022 \times \text{Mother's Age} + 0.099 \times \text{Mode of Delivery} + 0.150 \times \text{Sex of Baby} + 0.13 \times \text{Mother's Weight}$$

Interpretation: The coefficients in Table 3 provide insight into each predictor variable's impact on the baby's weight. The intercept is 0.855, which represents the estimated weight of the baby when all predictors are zero. This value is statistically significant with a p-value of 0.007, indicating that the intercept is reliably different from zero. Among the predictors, "Placenta Weight" has a coefficient of 0.11 with a p-value of 0.042, suggesting a significant positive relationship between placenta weight and the baby’s weight. For every additional kilogram of placenta weight, the baby's weight is expected to increase by approximately 0.11 kilograms, holding other variables constant.

On the other hand, Gestational Period and Mother's Age have coefficients of -0.015 and -0.022, respectively, with p-values of 0.25 and 0.197, indicating that these variables do not significantly influence the baby's weight in the context of this model. The Mode of Delivery variable has a coefficient of 0.099 with a p-value of 0.481, which suggests that the mode of delivery does not have a significant impact on the baby's weight. Conversely, the Sex of Baby variable shows a coefficient of 0.150 with a p-value of 0.042, indicating a significant effect on the baby's weight, where the sex of the baby plays a meaningful role in predicting weight. Lastly, Mother's Weight has a coefficient of 0.13 with a p-value of 0.032, signifying that the mother's weight is positively associated with the baby's weight. Each additional kilogram of maternal weight is associated with an increase of 0.13 kilograms in the baby's weight.

Table 4: ANOVA TABLE FOR MULTIPLE REGRESSION

Source	SS (Sum of Squares)	df (Degrees of Freedom)	MS (Mean Square)	F	Significance F
Regression	99.032	6	16.5053	25.11	< 0.001
Residual	45.9897	78	0.5894		
Total	145.0217	84			

Interpretation: The Analysis of Variance (ANOVA) table provides crucial information about the overall significance of the regression model. In Table 4, the regression sum of squares (SS) is 99.032, which represents the variability explained by the model. This is compared to the total sum of squares (SS) of 145.0217, which represents the total variability in the dependent variable (baby's weight) without considering any predictors. The residual sum of squares (SS) is 45.9897, indicating the amount of variability that is not explained by the model.

The degrees of freedom (df) associated with the regression model is 6, corresponding to the number of predictors, while the residual degrees of freedom is 78, which is the total number of observations minus the number of predictors minus one. The mean square for regression (MS) is calculated by dividing the regression SS by its df, resulting in 16.5053. The mean square for residuals (MS) is 0.5894, obtained by dividing the residual Sum of Squares by its degree of freedom.

The F-statistic, calculated as the ratio of the mean square for regression to the mean square for residuals, is 25.11. This high F-value indicates that the model is statistically significant. The significance level (p-value) for the F-test is less than 0.001, which is well below the conventional threshold of 0.05. This suggests that at least one of the predictors significantly contributes to explaining the variability in the baby's weight. Therefore, the model overall is effective in explaining the variability in the dependent variable and provides a good fit to the data.

DISCUSSION OF THE RESULTS

This research evaluate the impact of various predictors on the birth weight of babies, utilizing data sourced from the Federal Medical Centre (FMC), Ido-Ekiti, spanning from year 2021 and 2022. The focus was to understand how factors such as placenta weight, gestational period, mother's age, mode of delivery, sex of the baby, and mother's weight contribute to variations in birth weight. The analysis employed multiple linear regression to determine the relationship between these predictors and the dependent variable, birth weight (BW). The regression analysis summary in Table 2 reveals a substantial model fit with an R^2 of 0.71, indicating that approximately 71% of the variance in birth weight is explained by the predictors included in the model. The Adjusted R^2 value of 0.665 confirms that the model explains the variability in birth weight well, accounting for the number of predictors used. The Standard Error of 0.308 reflects the average distance that the observed values fall from the regression line, suggesting a reasonable fit between the model and the data. The F-statistic of 8.254 and its significance ($p < 0.001$) highlight that the overall model is statistically significant, demonstrating that at least one of the predictors has a non-zero coefficient and is useful in predicting birth weight. Table 2 provides detailed insights into the individual contributions of each predictor. The coefficients for Placenta Weight ($\beta_1 = 0.11$) and Mother's Weight ($\beta_6 = 0.13$) are both positive and statistically significant ($p < 0.05$), indicating that increases in these variables are associated with a higher birth weight. This aligns with existing literature, suggesting that both placenta weight and maternal weight have a direct influence on the birth weight of the baby.

In contrast, Gestational Period ($\beta_2 = -0.015$) and Mother's Age ($\beta_3 = -0.022$) show negative coefficients, though they are not statistically significant ($p > 0.05$). This implies that, while there is a potential trend indicating that longer gestational periods and older maternal age might be associated with lower birth weights, these effects are not statistically robust in this dataset. The Mode of Delivery ($\beta_4 = 0.099$) and Sex of Baby ($\beta_5 = 0.150$) also do not show significant results, suggesting that, within this data, the method of delivery and the sex of the baby might not significantly influence birth weight when controlling for other variables.

The ANOVA table (Table 4) supports the regression model's validity with a high F-statistic of 25.11 and a significance level of $p < 0.001$. The F-statistic assesses whether the overall regression model is a good fit for the data, and the significant value indicates that the model significantly improves the prediction of birth weight compared to a model with no predictors. The regression sum of squares (SS) of 99.032, with 6 degrees of freedom, shows the variability explained by the predictors, while the residual SS of 45.9897, with 78 degrees of freedom, reflects the unexplained variability.

CONCLUSION

The findings from this study show that the factors such as placenta weight, sex of the baby, and mother's weight influenced the baby's weight at birth. These results highlight the importance of monitoring maternal and fetal factors during pregnancy to predict birth weight outcomes.

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