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Applying Logit Model to Manage Maternal Mortality in Kazaure Emirate

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Abstract*:* *Maternal mortality remains a significant public health challenge in Kazaure Emirate, Nigeria, necessitating evidence-based strategies to address its underlying causes. This study applies a logit model to identify the determinants of maternal mortality and propose targeted interventions. Data were collected from 1000 women of reproductive age, focusing on socioeconomic, medical and environmental factors such as such as maternal place of residence, maternal age at birth, husband occupation, maternal occupation, husband level of income, maternal level of income, maternal level of education, husband level of education, antenatal care, protein level, glucose level, prolonged labor, anemia, care rendered by an unskilled health practitioner, socio-cultural belief, place of delivery, domestic violence, access to healthcare facilities, infection after delivery, pregnancy-induced hypertension, miscarriage and other ailments or underlying diseases. The logit model revealed that low reproductive age, low education attainment by women or their households, rural residence, low level of income of women or their households, husband occupation, non-business mindset of women or their households, abnormal glucose level in women, bleeding, prolonged labor, anemia, care rendered by unskilled personnel, home delivery, access to healthcare facilities, pregnancy-induced hypertension, miscarriage and other ailments are significant predictors of maternal deaths. The model demonstrated strong predictive power, with a Nagelkerke R Squarevalue of 0.621 and an AUC of 0.918. These findings underscore the importance of improving healthcare access and promoting maternal education to reduce maternal mortality in Kazaure Emirate. Policy recommendations include expanding healthcare infrastructure, implementing community-based education programs and increasing investment in maternal health services. This study provides a data-driven framework for managing maternal mortality and offers actionable insights for policymakers and healthcare providers to improve maternal health outcomes in the region*

Keywords: Logit Model, Maternal Mortality**,** Pregnant Women, AUC and Model Predictive Power

I. INTRODUCTION

Maternal mortality remains a significant public health challenge in Kazaure Emirate, Nigeria. Shah and Say, (2007) reported that the primary reason for the loss of women of reproductive age has for many years been the epidemic of maternal death. There are notable regional variations in maternal mortality across the globe (Ward *et al.,* 2024). Nigeria accounts for a disproportionate amount of maternal fatalities worldwide. Nigeria's MMR increased from 917 deaths per 100,000 live births in 2017 to an expected 1,047 deaths per 100,000 live births in 2020 (WHO, 2023).Ronsmans *et al.,* (2006) reported that women in underdeveloped nations have a one in six lifetime risk of dying during pregnancy or delivery, compared to a reported one in 30,000 in Northern Europe. Similarly, Ebiede, (2019) opined that there are 58,000 maternal fatalities per 100,000 live births in Nigeria each year, compared to 239 per 100,000 live births worldwide in developing nations and 12 per 100,000 live births in developed nations. Ujah *et al*., (2005) also reported that women in developing nations have a lifetime risk of maternal death that is more than 200 times higher than that of women in Western Europe and North America. According to a research in Nigeria, the MMR for Jigawa State is 1,012 deaths for every 100,000 live births (Sharma *et al*., 2017).Many research works believed that factors responsible for these alarming statistics are either environmental, medical or social. For example, Hussein *et al.,* (2020) reported that

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maternal place of residence is a significant risk factor for maternal death of expectant women who attended the Ahmadu Bello university teaching hospital in 2019. Furthermore, Abe and Omo-Aghoja (2008) discovered that parity, low literacy, and poverty had a substantial impact on maternal mortality at the main hospital in Benin City, Nigeria.

The diversity of these causes and their different nature from one community to another necessitate a radical approach to the problem as it relates to Kazaure Emirate. One modeling technique that can be applied for this purpose is logit modeling (Suárez et al., 2017). Unlike linear regression where the dependent variable is a continuous value like blood pressure, the logit model uses a binary event as the dependent variable, such as alive vs. dead. According to Tetrault *et al*., (2008), the most popular univariable method in the field of health science is logit model. The United Nations Sustainable Development Goal 3 (SDG 3) which seeks to lower the worldwide maternal death ratio to less than 70 per 100,000 live births by 2030, is in line with global health priorities, including reducing maternal mortality (Olea-Ramirez et al., 2024). It will take coordinated efforts to enhance maternal health services globally in order to meet this goal. To sum it up, controlling maternal mortality is essential for maintaining family welfare, protecting women's health, and promoting sustainable development in Kazaure Emirate achievable by developing good healthcare system, expanding access to trained birth attendants, and using predictive models like the logit model. Therefore, this study specifically attempts to apply logit modeling techniques to manage maternal mortality in Kazaure Emirate by identifying the factors that influence it through logit model fitting framework and its evaluation principles. The study then recommends the necessary actions to be taken against the same risk factors.

II. MATERIALS AND METHODS

A. Materials

The study area is Kazaure Emirate. The Emirate consists of four local government areas. The study utilizes a retrospective research design in which it followed up pregnant women who aged 15-19 years. The data for the study were sourced through surveys. The survey covers four local governments of the study area. 250 women who are seven months pregnant were chosen purposely from each local government area. The participants were followed-up for 42 days after delivery. The information obtained was analyzed using logit model.

The explanatory (independent) variables of interest in this study include demographic factors, medical factors, environmental factors, and socio-economic factors. The response (dependent) variable is dichotomous; it is maternal mortality status (dead:1/alive:0) of the participants. The explanatory variables whose effect on the maternal mortality in Kazaure Emirate the study seeks to assess include: Maternal place of residence (MPR)(Rural area, Urban), Maternal age at birth (MAB) (Metric), Husband's Occupation (HO) (Farmer, Civil Servant, Business Man), Maternal Occupation (MO) (None, Civil Servant, Business Woman), Husband's Level of Income (HLI) (Metric), Maternal Level of Education (MLI) (Informal, Primary, Secondary, Postsecondary), Husband's Level of Education (HLE) (Informal Education, Primary, Secondary, Postsecondary), Antenatal Care Attendance (Never Attend, Attend Irregularly, Attend Regularly), Protein Level (Abnormal, Normal), Glucose (GL) (Abnormal, Normal), Bleeding (Yes, No), Prolonged labour (PLB) (Yes, No), Anaemia (Yes {<12.0 gm/dl}, No{>12.0gm/dl}), Care rendered by an unskilled health practitioner (CRUSP) (Yes, No), Socio-cultural belief and Practices (SCB) (Yes, No), Place of delivery (PD) (Home, Hospital), Domestic violence (DV) (Yes, No), Access to healthcare facilities (AHF) (No, Yes), Infection after delivery (IAD) (Yes, No), Pregnancy-induced hypertension (PIH) (Yes, No), Miscarriage (Yes, No) and other underlying ailments or diseases (OA) (Yes, No).

B. Methods

Concepts of Logit Model

Logit model analyzes the relationship between many independent factors and a dichotomous dependent variable, and calculates the likelihood of occurrence of an event. The logit model predicts the probability of an event occurring over the probability of an event not occurring.

Odds

The ratio of the likelihood that an event will occur to the probability that it will not occur is known as the event's odds. If the likelihood of an event occurring is p, the likelihood of it not occurring equals $(1 - p)$. The corresponding odds is thus a value determined by

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Odds of (Event) $= \frac{p}{1-p}$

The impact of independent variables is frequently expressed in terms of chances since the logit model estimates the likelihood of an event occurring over the probability of an event not occurring.

The mean of the response variable p in terms of an explanatory variable x is modeled with logit model by connecting p and x using the equation $p = \alpha + \beta x$. Unfortunately, this is a bad model since extreme values of x will result in values of $\alpha + \beta x$ that are not between 0 and 1. The natural logarithm is used to transform the odds in the logit model solution to this problem (Peng *et al.,* 2002). We model the natural log chances as a linear function of the explanatory variable using logit model:

$$Logit(y) = In(Odds) = In\left(\frac{p}{1-p}\right) = \alpha + \beta x \quad (1)$$

where x is the explanatory variable and p is the probability interested outcome. The logit model parameters are α and β This is the simplest logistic regression model.

Taking the antilog of equation (1) on both sides, an equation for predicting the probability of an interested outcome can be derived as:

$$p = P(Y = interestedoutcome/X = \chi, aspecificvlaue) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} = \frac{1}{1+e^{-(\alpha+\beta x)}} \quad (2)$$

By extending the logic of the simple logistic regression to several predictors, a complicated logit model can be constructed as follows:

$$Logit(y) = In(Odds) = In\left(\frac{p}{1-p}\right) = \alpha + \beta_1 x_1 + \cdots + \beta_k x_k \quad (3)$$

Therefore,

$$p = P(Y = interested\ \text{outcome}/X_1 = x_1, \ldots X_k = x_k) = \frac{e^{\alpha+\beta_1 x_1+\cdots+\beta_k x_k}}{1+e^{\alpha+\beta_1 x_1+\cdots+\beta_k x_k}} = \frac{1}{1+e^{-(\alpha+\beta_1 x_1+\cdots+\beta_k x_k)}} \quad (4)$$

Odds Ratio

The odds ratio (OR) is a metric that compares two odds for two different events. The corresponding probabilities of A occurring relative to B occurring for two events A and B are

$$oddsratio\{Avs.B\} = \frac{odds\{A\}}{odds\{B\}} = \frac{\frac{P_A}{1-P_A}}{\frac{P_B}{1-P_B}} \quad (5)$$

An OR is a measure of the relationship between an exposure and an outcome. The OR compares the chances of an outcome (e.g. sickness or disorder) occurring in the absence of a specific exposure (e.g. health behavior, medical history) to the odds of the outcome occurring in the presence of that exposure. The regression coefficient (b_1) is the estimated increase in the logged odds of the outcome per unit increase in the value of the independent variable in a logit model. In other words, the OR associated with a one-unit increase in the independent variable is the exponential function of the regression coefficient (e^{b_1}). The OR can also be used to see if a specific exposure is a risk factor for a specific outcome, as well as to compare the size of different risk factors for that outcome. $OR = 1$ denotes that exposure has no effect on the likelihood of a positive outcome. $OR > 1$ suggests that there is a link between exposure and a better chance of success. $OR < 1$ denotes a link between exposure and a reduced chance of success. One technique to generalize the OR beyond two binary variables is to use logit model (Peng & So, 2002). Assume we have a binary response variable $Y$and a binary predictor variable X, as well as other binary and non-binary predictor variables Z_1, ...,Z_k. The predicted coefficient b_x for X is related to a conditional OR if we apply multiple logit model to regress $YonX$, Z_1, ...,Z_k. At the population level, in particular,

$$e^{b_x} = \frac{P(Y=1/X=1,Z_1,\ldots,Z_k)/P(Y=0/X=1,Z_1,\ldots,Z_k)}{P(Y=1/X=0,Z_1,\ldots,Z_k)/P(Y=0/X=0,Z_1,\ldots,Z_k)} \quad (6)$$

As a result, e^{b_x} is a conditional odds ratio estimate. When the values of Z_1, ...,Z_k are held constant, e^{b_x} is interpreted as an estimate of the OR between $YandX$.

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The Logistic Curve

When y consists of binary coded (0, 1--failure, success) data, logit model is a method for fitting a curve, $y = f(x)$. Logit model fits a logistic curve to the connection between x and y when the answer is a binary (dichotomous) variable and x is numerical. A logistic curve is a sigmoid or S-shaped curve that is commonly used to describe population expansion (Eberhardt & Breiwick, 2012). A logistic curve begins with sluggish, linear growth, then accelerates to an even faster pace before slowing down to a steady rate. This formula defines a simple logistic function.

$$y = \frac{e^{x}}{1+e^{x}} = \frac{1}{1+e^{-x}} \quad (7)$$

which is graphed in Figure 1.

To provide flexibility, the logistic function can be extended to the form:

$$y = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} = \frac{1}{1+e^{-(\alpha+\beta x)}} \quad (8)$$

where α and β determine the logistic intercept and slope.

Logit model fits α and β, the coefficients. When α and β are 0 and 1, respectively, Figure 1 depicts the logistic function. The logit function is used to convert a 'S'-shaped curve into a nearly straight line and to modify the proportion range from 0 to 1 to $-\infty to \infty$ needed.

$$Logit(y) = In(Odds) = In\left(\frac{p}{1-p}\right) = \alpha + \beta x \quad (9)$$

where p denotes the likelihood of an interested outcome, α is the intercept parameter, β is a regression coefficient, and χ is a predictor.

Assumptions of Logit Model

Many of the fundamental assumptions of linear regression models based on the ordinary least square method, such as the linearity of the relationship between the dependent and independent variables, normality of the error distribution, homoscedasticity of the errors, and measurement level of the independent variables, are not required in logistic regression. Because it uses a non-linear log transformation of the linear regression, logit model can handle non-linear relationships between the dependent and independent variables.

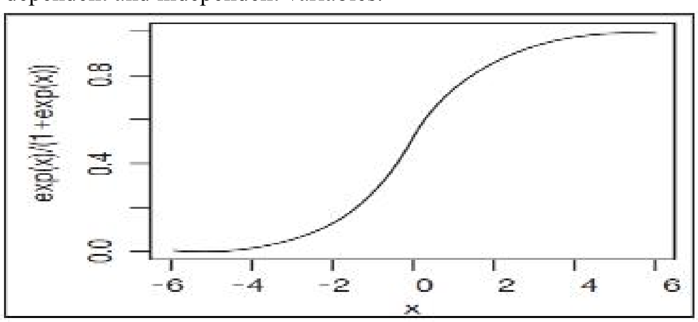

Fig. Graph of logistic curve where $\alpha = 0$ and $\beta = 1$

First, logistic regression requires a dichotomous dependent variable. Second, because logistic regression evaluates the probability of an event occurring ($P(Y = 1)$), the dependent variable must be coded correctly. That is, 1 should be coded as the desired outcome. Third, the model must be properly fitted. With the useless variables provided, it should not be overfitted. It should also not be underfitted with important variables left out. Fourth, logistic regression necessitates the independence of each observation. Multicollinearity should be minimal or non-existent in the model. Independent variables are not linear functions of each other, in other words. Fifth, while logistic regression does not necessitate a linear relationship between the dependent and independent variables, it does necessitate a linear relationship between the independent variables and the log probabilities of an occurrence. Finally, because maximum likelihood estimates are less powerful than conventional least squares for predicting unknown parameters in a linear regression model, logistic regression necessitates high sample sizes.

Fitting the Logit Model

Although the logistic regression model, $logit\ (y) = \alpha + \beta\chi$, appears to be similar to a simple linear regression model, the underlying distribution is binomial, and the parameters cannot be estimated in the same way. Rather, the parameters are often computed using the maximum likelihood of observing the sample values (Menard, 2001 and Healy, 2006). Maximum likelihood will provide you settings for α and β that optimize your chances of getting the data set. It necessitates the use of computer software for repeated computing (Healy, 2006).

If $Yi\ = 1$ for each individual in our n-person sample, an event occurs for the i^{th} subject; otherwise, $Y_i\ = 0$. $Y_1 \ldots, Y_n$ and $X_1 \ldots, X_n$ are the observed data. The likelihood (joint probability) of the data is given by (Healy, 2006):

$$L = \prod_{i=1}^{n} P(y/x)^{Y_i}\left(1 - P(y/x)\right)^{1-Y_i} = P(y/x)^{\sum_{i=1}^{n} Y_i}\left(1 - P(y/x)\right)^{n-\sum_{i=1}^{n} Y_i}$$

Natural logarithm of the likelihood is

$$l = log(L) = \sum_{i=1}^{n} Y_i log\left[P\left(\frac{y}{x}\right)\right] + \left(n - \sum_{i=1}^{n} Y_i\right) log\left(1 - P(y/x)\right)$$

In which:

$$P(y/x) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} \qquad (10)$$

The first derivatives of log-likelihood are used to estimate the parameters α and β, and they are solved for α and β. Iterative computing is employed for this. The coefficients are first given an arbitrary value (typically 0). The log-likelihood is then calculated, and the variance in coefficient values is noted. The process is then repeated until the value of l is maximized (equivalent to maximizing L). The maximum likelihood estimates of α and β are the outcomes.

The Likelihood Ratio Test

The overall fit of a model indicates the strength of the link between all of the independent variables and the dependent variable. It can be determined by comparing the fit of two models with and without independent variables. If a logistic regression model with k independent variables (the given model) shows an improvement over a model with no independent variables, it is said to provide a better fit to the data (the null model). A likelihood ratio test, which examines the null hypothesis, can be used to assess the overall fit of the model with k coefficients (Healy, 2006 and Sur *et al.,* 2019).

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_k = 0.$$

To do so, the deviation of the null model with just the intercept (-2 log likelihood) is compared to the deviance with the k independent variables (-2 log likelihood of the given model).

The difference of these two yields a goodness of fit index G, χ^2 statistic with k degrees of freedom (Bewick *et al.,* 2005). This is a measure of how well all of the independent variables affect the outcome or dependent variable.

$$G = \chi^2 = (-2\ loglikelihoodofnullmodel) - (-2\ loglikelihoodofgivenmodel) \qquad (11)$$

An equivalent formula sometimes presented in the literature is

$$G - 2log\frac{likelihoodofthenullmodel}{likelihoodofthegivenmodel} \qquad (12)$$

where the ratio of the maximum likelihood is calculated before taking the natural logarithm and multiplying by -2. This test is referred to as a 'likelihood ratio test.' If the total model fit statistic's p-value is smaller than the customary 0.05, reject H_0, concluding that at least one of the independent variables contributes to the outcome prediction.

Equation (12) is equivalently written as:

$$G = -2In\frac{L_0}{L_1} = -2(InL_o - InL_1) \qquad (13)$$

The likelihood ratio test compares the likelihood of acquiring data when the parameter is zero (L_0) to the likelihood (L_1) of obtaining data when the parameter is evaluated at its MLE.

Chi-Square Goodness of Fit Tests

Instead of using R^2as the overall fit statistic for a linear regression model, deviance between observed and anticipated values is employed in logistic regression. The residuals in linear regression are defined as $y_i - \hat{y}_i$ where y_i is the

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observed dependent variable for the i^{th} subject and $\hat{y}_i$ is the corresponding model prediction. The same principle applies to logistic regression, in which y_i is either 1 or 0, and the model's prediction is as follows:

$$\hat{y}_i = \frac{exp(\alpha+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})}{1+exp(\alpha+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} \qquad (14)$$

Chi-square test can be based on the residuals, $y_i - \hat{y}_i$ (Peng & So, 2002). A standardized residual can be defined as:

$$r_i = \frac{y_i-\hat{y}_i}{\sqrt{\hat{y}_i(1-\hat{y}_i)}} \qquad (15)$$

where the standard deviation of the residuals is $\hat{y}_i(1-\hat{y}_i)$. Using equation (15), one can then form a χ^2 statistic as

$$\chi^2 = \sum_{i=1}^{n} r_i^2 \qquad (16)$$

This statistic follows a χ^2 distribution with $n-(k+1)$ degrees of freedom, so that p-values can be calculated.

Hosmer-Lemeshow Test

The purpose of the Hosmer–Lemeshow test is to see if the observed proportions of events match the anticipated probability of occurrence in subgroups of the model population. The Hosmer-Leme show test compares predicted and observed frequencies in a 2-by-10 table by splitting predicted probability into deciles (10 groups based on percentile ranks) and producing a Pearson Chi-square (Nattino *et al*., 2020). The significance of test statistics is:

$$H = \sum_{g=1}^{10} \frac{(O_g-E_g)^2}{E_g} \qquad (17)$$

where O_g and E_g represent observed and predicted events for the g^{th} risk decile group, respectively. Asymptotically, the test statistic has a χ^2 distribution with 8 (number of groups -2) degrees of freedom. Small values with a large p-value around 1 imply a good fit to the data and, as a result, a good overall model fit. A poor fit to the data is indicated by large values (with $p < 0.05$). When the$n$ is less than 400, Hosmer and Leme show that this test should not be used.

Statistical Significance of Individual Coefficients

If the overall model is successful, the next step is to determine the importance of each of the independent variables. The change in the projected log odds of having an outcome for one-unit change in the i^{th} independent variable, all other things being equal, is shown by the logistic regression coefficient for the i^{th} independent variable. That is, if the i^{th} independent variable is altered by one unit while the other predictors remain constant, the log probabilities of outcome should change by two units. The likelihood ratio test and the Wald statistic are two tests used to determine the significance of an independent variable in logistic regression (Menard, 2001).

Wald Statistic

The Wald statistic can be used to evaluate the importance of individual coefficients or the contribution of individual predictors in a particular model (Bewick *et al.,* 2005). The Wald statistic is the square of the regression coefficient divided by the square of the coefficient's standard error. As a Chi-square distribution, the Wald statistic is asymptotically distributed.

$$W = \frac{\beta_j^2}{SE_{\beta_j^2}} \qquad (18)$$

A Chi-square with one degree of freedom is used to compare each Wald statistic. Wald statistics are simple to calculate, but their accuracy is debatable.

Odds Ratios With 95% CI.

Individual predictors can be evaluated using an odds ratio with a 95 percent confidence interval (CI**)** (Peng & So, 2002). The 95 percent confidence interval, unlike the p value, does not convey the statistical significance of a metric. If it does not overlap the null value (e.g. OR=1), it is used as a proxy for the presence of statistical significance. The OR accuracy is estimated using the 95 percent confidence interval. A big CI implies that the OR has a low level of precision, whereas a small CI suggests that the OR has a better level of precision. The population log odds ratio has an approximate confidence interval of

$$95\%\ CI for the In\ (OR) = In\ (OR) \pm 1.96 \times \{SEIn\ (OR)\} \qquad (19)$$

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Where ln(OR) is the sample log odds ratio and SE ln(OR) is the log odds ratio's standard error (Morris & Gardner, 1988). We derive the 95 percent confidence interval for the odds ratio by taking the antilog:

$$95\% CI for OR = e^{In\,(OR) \pm 1.96 \times \{SEIn\,(OR)\}} \quad (20)$$

Classification Table

A classification table is a tool for assessing the logistic regression model's predictive accuracy (Peng & So, 2002). The observed values for the dependent outcome are cross-classified in this table, as are the predicted values (at a user-defined cut-off value). If a cutoff value is 0.5, all predicted values over 0.5 may be characterized as forecasting an event, while all forecasted values below 0.5 can be classified as not predicting an event. Then a two-by-two data table with binary observed outcomes and dichotomous predicted outcomes can be created. The table is structured as follows:

Table 1. Sample Classification

Observed	Predicted	
	1	0
1	a	b
0	c	d

a, b, c and d are the number of observations in the corresponding cells

It is expected that a lot of numbers will be contained in a and d cells and very few in b and c cells if the logistic regression model fits well.

The Model Predictive Accuracy Metrics

The assessment of the predictive accuracy of a logistic model using classification table is achieved by employing a number of metrics, computed using the cell entries of the classification table. These metrics include accuracy (A), precision (P), sensitivity (SE), specificity (SP) and F1-score (Peng *et al.,* 2002). However, sensitivity and specificity are commonly used in the literature.

F1-Score combines precision and sensitivity into a single metric. It provides a balance when there is need for both precision and sensitivity. Specificity measures how many of the actual negatives were correctly identified by the model and it is used when the cost of false positive is high. Sensitivity measures how many of the actual positives were correctly identified by the model and is used when the cost of false negative is high. Precision measures how many of the predicted positive outcome are actually positive and it is also used when the cost of false positive is high. Accuracy measures the proportion of all correct predictions out of the total predictions and it is used when the dataset is balanced (similar number of positive and negative classes) or when both false positives and false negatives carry similar consequences. Reference to table 1, the formulae for these metrics are given as:

$$SE = a/(a+b) \quad (21)$$

$$SP = d/(c+d) \quad (22)$$

$$A = a + d/(a+d+b+c) \quad (23)$$

$$F1 - Score = 2\frac{P \times SE}{P + SE} \quad (24)$$

$$P = a/(a+c) \quad (25)$$

Higher SE indicates that the model identifies most positive cases but might misclassify some negatives as positives. High P value on one hand means that when the model predicts “positive”, it is usually correct. The value of A shows that the model correctly predicts both positives and negatives out of the total predictions. High SP means that the model avoids false positives. Finally, high F1-Score indicates that the model performs well in handling both false positives and false negatives.

Discrimination with ROC Curves

Using the same two-by-two table concept, instead of selecting a single cutoff value, the entire range of cutoff values from 0 to 1 can be investigated. A two-by-two table can be created for each feasible cutoff value. The ROC (Receiver Operating Characteristic) curve is created by plotting the pairings of sensitivity and one minus specificity on a scatter plot. The area under this curve (AUC) is a measure of the model's overall fit. The AUC ranges from 0.5 (no prediction capacity) to 1.0 (high predictive ability) (perfect predictive ability). A higher AUC shows that the model is more predictive. Good classification results (better than random) are represented by points above the diagonal separating the ROC space, whereas bad classification results are represented by points below (worse than random) (Grigoryev *et al*., 2016, Bewick *et al*., 2004, Seshan *et al*., 2013 and Takahashi *et al.,* 2006)

Omnibus test

Omnibus test uses the likelihood ratio chi-square test to compare the log-likelihoods of the null model (L_0) and the full model (L_M): The test tests the null hypothesis that the full model is not significantly better than the null model (Liu *et al*., 2012, and Al Bairmani *et al*., 2021). The test statistic for the test is given as:

$$X^2 = -2 \times (log - likelihoodofnullmodel - log - likelihoodoffullmodel) \quad (26)$$

where a higher value of X^2 indicates that the model with predictors explains more variation than the null model. The degree of freedoms is equal to the number of predictors in the model.

Negelkerke R^2

Negelkerke R^2 is a pseudo R-squared statistic used to assess the goodness-of-fit of a logistic regression model. Pseudo R^2 values measure how well the logistic model explains the variation in the binary outcome variable. The statistic adjusts Cox and Snell's R^2 to scale it between 0 and 1, making it easier to interpret. Negelkerke R^2 value of 0 indicates that the model explains none of the variance in the dependent variable, while Negelkerke R^2 value of 1 indicates that the model perfectly explains the variance (Smith & McKenna, 2013 and Allison, 2013 and Mbachu *et al*., 2012). Given the formula for Cox and Snell's R^2 expressed as in equation (27):

$$R^2_{CoxSnell} = 1 - \left(\frac{L_0}{L_M}\right)^{\frac{2}{N}} \quad (27)$$

where L_0 is the likelihood of the null model, L_M is the likelihood of the fitted model and N is the sample size, the formula for Negelkerke R^2 is given as:

$$R^2_{Nagelkerke} = \frac{R^2_{CoxSnell}}{1 - L_0^{\frac{2}{N}}} \quad (28)$$

III. RESULTS AND DISCUSSION

RESULTS

Descriptive Statistics

The study included 1000 women of reproductive age, with mean age of 29 years, the average income level of N2888.06 and their husbands mean income level of N4239.07. Approximately, 61.70% of the participants reside in Urban areas while 38.30% reside in rural areas. Civil servants were 48.80%, business women 35.70% while 15.5% were just house wives with no specific businesses. The households in the study comprises 41.40% farmers, 47.50% civil servants and 11.10% business men. The maternal level of education was 2% for women with informal education, 31.70% for women with primary education, 32.90% for women with secondary education and 33.40% for women with post-secondary education. Similarly, the households' level of education was 3.5% traditional school certificated holders, 1.7% primary certificate holders, 46% secondary school certificate holders and 48.80% post-secondary school certificate holders. 4.30% of the mothers never attend clinic for ANC, 47.50% attend irregularly and 48.20% attend very regularly. About 97.60% of the women had normal protein level while just 2.40% had abnormal protein level examined. More so, 96.50% had normal glucose level while 3.50% were diabetic. Equally, 59.60% of the women experienced bleeding while 40.40% did not. 4.60% experienced prolonged labor while 95.40% did not. Similarly, 11% were anemic while 89% were not. 4.50% received care from an unskilled health practitioner while 95.50% received care from skilled

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health practitioner. 4.8% had socio-cultural beliefs while 95.20% had no socio-cultural beliefs. 3.80% of the mothers delivered at home while 96.20% delivered at hospitals.

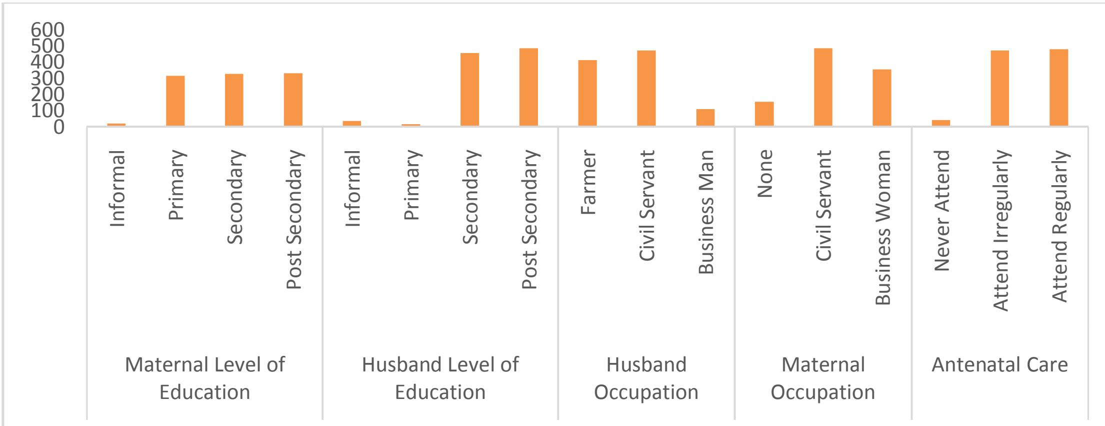

Fig 2. Distribution of Maternal Mortality based on MLE, HLE, MO, HO and ANC

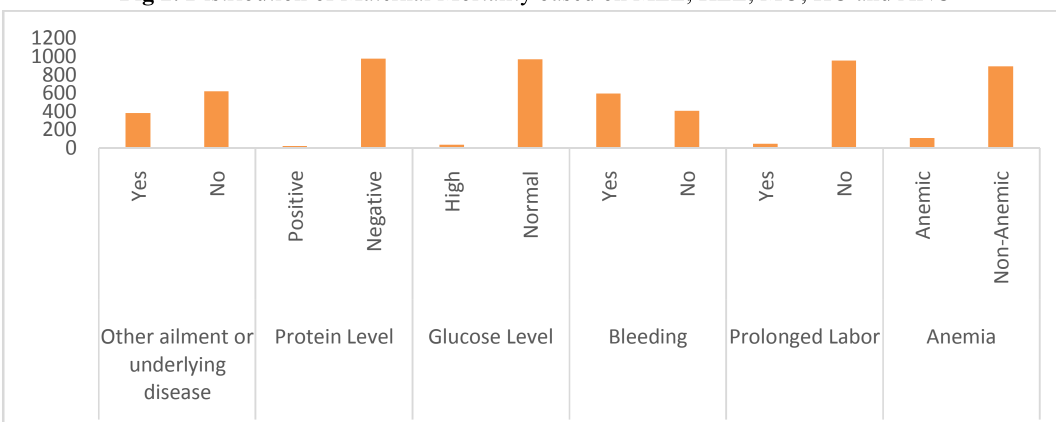

Fig 3. Distribution of Maternal Mortality based on OA, PL, GL, Bleeding and PLB

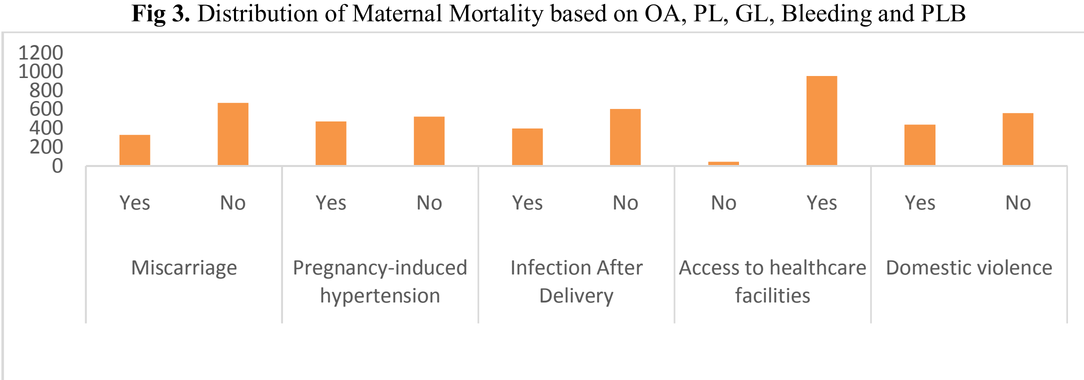

Fig 4. Distribution of Maternal Mortality based on Miscarriage, PIH, IAD, AHF and DV

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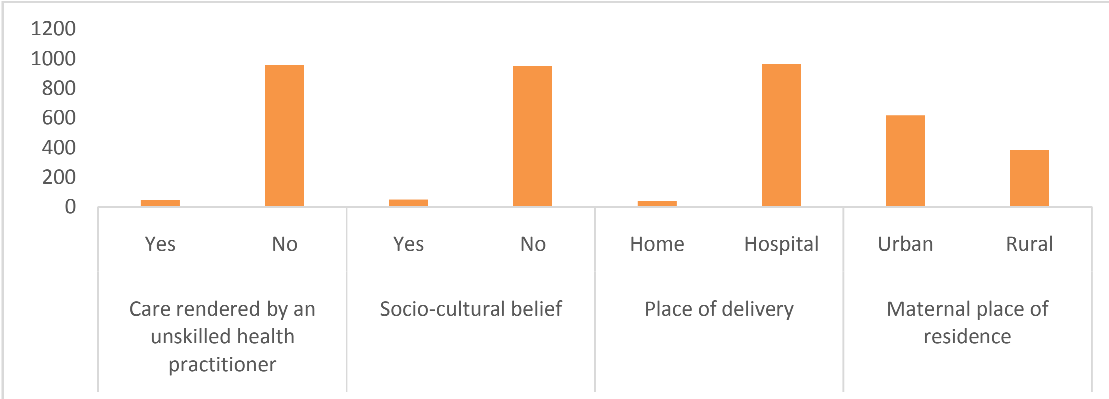

Fig 5. Distribution of Maternal Mortality based on CRUSP, SCB, PD and MPR

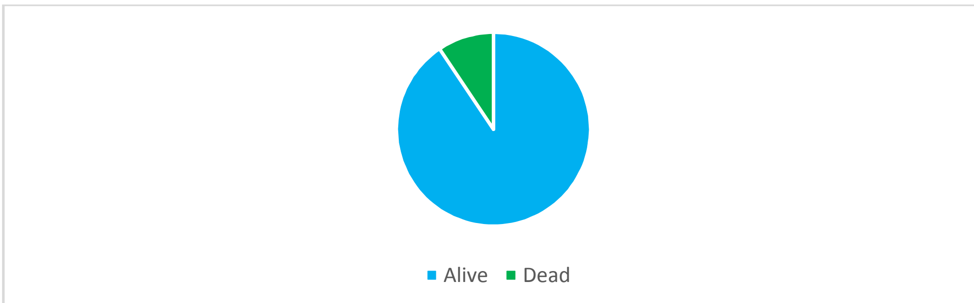

Fig- 6. Prevalence of Maternal Mortality in Kazaure Emirate

Table 2. Distribution of Respondents based on the Risk Factors

Rsik Factors	Frequency Dead	Alive	Percentage	Chi-square	P-value
Maternal place of residence				41.783	0.00
Urban	29	588	61.70		
Rural	65	318	38.30		
Husband Occupation				2.43	0.30
Farmer	46	368	41.40		
Civil Servant	39	436	47.50		
Business Man	9	102	11.10		
Maternal Occupation				46.482	0.00
None	37	118	15.50		
Civil Servant	28	460	48.80		
Business Woman	29	328	35.70		
Maternal Level of education				157.692	0.00
Traditional	18	2	2.00		
Primary	26	291	31.70		
Secondary	30	299	32.90		
Post-Secondary	20	314	33.40		
Husband Level of Education				406.689	0.00
Traditional	29	6	3.50		
Primary	17	0	1.70		
Secondary	25	435	46.00		
Post-Secondary	23	465	48.80		
Antenatal Care				256.33	0.00

Never Attend	34	9	4.30		
Attend Irregularly	32	443	47.50		
Attend regularly	28	454	48.20		
Protein Level				157.829	0.00
Normal	74	902	97.60		
High	20	4	2.40		
Glucose Level				121.702	0.00
Normal	72	893	96.50		
High	22	13	3.50		

Also, 44% of the mothers experienced domestic violence while 56% did not. 95.4% of the mothers had access to health care facilities while 4.60% did not. 39.60% had infection after delivery while 60.40 had no infection after delivery. 33% of the mothers had miscarriage while 67% had no miscarriage. Finally, 38.20% had other other ailment while 61.80% had at least one of the ailments earlier mentioned (Tables 2 and 3 and Fig 2, 3, 4, 5 and 6).

Table 3. Distribution of Respondents based on the Risk Factors Continued

Rsik Factors	Frequency		Percentage	Chi-square	P-value
	Dead	Alive			
Bleeding				12.447	0.00
Yes	72	524	59.60		
No	22	382	40.40		
Prolonged Labor				303.444	0.00
Yes	38	8	4.60		
No	56	898	95.40		
Anemia				37.406	0.00
Anaemic	28	82	11.00		
Non-Anaemic	66	824	89.00		
Care rendered by an unskilled health practitioner				258.692	0.00
Yes	35	10	4.50		
No	59	896	95.50		
Socio-cultural belief				421.229	0.00
Yes	45	3	4.80		
No	49	903	95.20		
Place of delivery				297.394	0.00
Home	34	4	3.80		
Hospital	60	902	96.20		
Domestic violence				17.861	0.00
Yes	22	418	44.00		
No	72	488	56.00		
Access to healthcare facilities				359.916	0.00
Yes	53	901	95.40		
No	41	5	4.60		
Infection After Delivery				20.079	0.00
Yes	17	379	39.60		
No	77	527	60.40		
Pregnancy-induced hypertension					
Yes	18	456	47.40		
No	76	450	52.60		
Miscarriage				33.245	0.00
Yes	6	324	33.00		

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No	88	582	67.00		
Other Ailment				38.739	0.00
Yes	8	374	38.20		
No	86	532	61.80		

Logit Model Results

The logit model revealed that the higher the reproductive age of the women, the less likely they are to die of pregnancy complications (Odds Ratio = 1.22; 95% C.I = 1.580– 2.569). It also revealed that those women who reside in rural areas were more likely to die of pregnancy complications than those in urban areas (Odds Ratio = 2.26; 95% C.I = 1.209–4.202).

The logit model revealed interesting results about the effect of socioeconomic factors on the prevalence of maternal mortality in Kazaure Emirate (see Tables 2 and 3). The model revealed that women who had secondary education were more likely to die of pregnancy complications than those with post-secondary education (Odds Ratio = 1.963; 95% C.I = 1.263–3.232), those who had primary education were also more likely to die of pregnancy complications than those who had post-secondary education (Odds Ratio = 3.467; 95% C.I = 2.344–4.356) and those who had informal education were also more likely to die of pregnancy complications than those who had post-secondary education (Odds Ratio = 5.564; 95% C.I = 3.456–8.345). Similarly, wives of the households who had secondary education were more likely to die of pregnancy complications than those with post-secondary education (Odds Ratio = 1.790; 95% C.I = 1.280–2.691), those who had primary education were also more likely to die of pregnancy complications than those who had post-secondary education (Odds Ratio = 2.950; 95% C.I = 1.354–4.875) and those who had informal education were also more likely to die of pregnancy complications than those who had post-secondary education (Odds Ratio = 4.987; 95% C.I = 3.983–7.268). The effect of income of women and their husbands on maternal mortality in Kazaure Emirate was investigated. The investigation revealed that women with good income were less likely to die than those with poor income (Odds Ratio = 1.897; 95% C.I = 1.005–2.543). Similarly, the investigation revealed that wives of the households who had good income were as well less likely to die than those with poor income (Odds Ratio = 3.00; 95% C.I = 1,999–4.000). Perceived to influence maternal mortality, place of delivery was as well studied for possible maternal mortality prediction ability in Kazaure Emirate. The results revealed that women who delivered at the clinic were less likely to die of pregnancy complications than women who delivered at home (Odds Ratio = 6.639; 95% C.I = 5.870–7.856). Antenatal care (ANC), a program that checks up pregnant women, was also revealed to have significant effect on maternal mortality in the study area. The logit model showed that women who attended ANC regularly were less likely to die of pregnancy complications than those who attended ANC irregularly (Odds Ratio = 0.68; 95% C.I = 0.282–0.890) and those who attended ANC irregularly were equally likely to die of pregnancy complications (Odds Ratio = 0.68; 95% C.I = 0.282–0.890). Someone's nature of business might have some form of association with maternal mortality and thus examined for confirmation by this study. The examination surprisingly revealed that women whose husbands were engaged in farming were equally likely to die of pregnancy complications as those whose husbands were engaged in business (Odds Ratio = 0.050; 95% C.I = 0.478–1.854). The examination also revealed that women whose husbands were engaged in farming were equally likely to die of pregnancy complications as those whose husbands were engaged in business (Odds Ratio = 0.069; 95% C.I = 0.357–1.462). In rural or urban areas, expertise of medical practioners receiving child delivery is crucial to well being of not just the child but also the mother. This study thus investigated the effect of deliver under the care of unskilled medical practioner on maternal mortality. The investigation established that women whose maternal care were rendered by an unskilled health practitioner were more likely to die of pregnancy complications than those whose maternal care were rendered by skilled health practitioner (Odds Ratio = 4.443; 95% C.I = 2.453–5.295). Some women in some regions in Nigeria have different socio-cultural beliefs about life and therefore participate differently in pregnancy management. An investigation about how socio-cultural belief associate with maternal mortality in Kazaure Emirate revealed that women who had socio-cultural belief were equally likely to die of pregnancy complications as those who had no socio-cultural belief (Odds Ratio = 1.577; 95% C.I = 0.914–1.852). Similar to how socio-cultural belief associate maternal mortality in Kazaure Emirate, domestic violence was revealed by the logit model to have no significant effect on maternal mortality. Specifically, the model revealed that women who experienced domestic violence were equally likely to die of pregnancy complications

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as those who did not experienced domestic violence (Odds Ratio = 0.404; 95% C.I = 0.046–1.001). However, the model revealed that women who did not have access to healthcare facilities were more likely to die of pregnancy complications as those who had access to healthcare facilities (Odds Ratio = 2.357; 95% C.I = 1.200–4.243).

The logit model showed that some medical factors significantly predict maternal mortality in Kazaure Emirate while some do not. In particular, the model revealed that women who had pregnancy-induced hypertension were more likely to die of pregnancy complications than women without pregnancy-induced hypertension (Odds Ratio = 4.879; 95% C.I = 3.157–6.465). It also showed that women whose protein level was normal were equally likely to die of pregnancy complications as those whose protein level was not normal (Odds Ratio = 0.930; 95% C.I = 0.391–2.193).

Table 4. Effect of Socio-economic, Environmental and Medical Factors on Maternal Mortality in Kazaure Emirate

	B	S.E.	Wald	df	P-Value	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
MAB	5.031	0.021	2.110	1.000	0.014	1.220	1.580	2.569
HLI	5.000	0.000	3.456	1.000	0.003	3.000	1.999	4.000
MLI	6.668	0.000	0.446	1.000	0.004	1.897	1.005	2.543
MPR								
Urban								
Rural	-4.650	0.323	4.062	1.000	0.044	0.522	0.277	0.982
HO			0.968	2	0.616			
Business Man								
Farmer	-2.998	4951.507	0.000	1.000	1.000	0.050	0.478	1.854
Civil Servant	-2.676	4951.507	0.000	1.000	1.000	0.069	0.357	1.462
MO			0.794	2.000	0.672			
Business Woman								
None	-0.914	4137.840	0.000	1.000	1.000	0.401	0.567	1.986
Civil Servant	-0.289	0.324	0.794	1.000	0.373	0.749	0.397	1.414
MLE			1.874	3.000	0.000			
Post Secondary								
Traditional	8.489	91241.717	0.000	1.000	0.000	5.564	3.456	8.345
Primary	0.047	0.417	2.013	1.000	0.010	3.467	2.344	4.356
Secondary	0.477	0.385	3.536	1.000	0.015	1.963	1.263	3.232
HLE			5.223	3.000	0.000			
Post Secondary								
Traditional	69.254	45139.395	4.000	1.000	0.000	4.987	3.983	7.268
Primary	2.119	19329.545	4.900	1.000	0.000	2.950	1.354	4.875
Secondary	0.587	0.327	6.223	1.000	0.003	1.790	1.280	2.691
ANC			7.446	2.000	0.000			
Attend Regularly								
Never Attend	-38.643	784129679.419	5.000	1.000	1.000	0.000	0.297	1.024
Attend Irregularly	0.217	0.325	4.446	1.000	0.504	1.242	0.657	2.348
PL								.
Negative								
Positive	-26.092	91653.247	0.000	1.000	1.000	0.930	0.391	2.193

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The model further revealed that women whose glucose level was normal were less likely to die of pregnancy complications than those whose glucose level was not normal (Odds Ratio = 4.342; 95% C.I = 3.234–5.534). Also, women who had bleeding were more likely to die of pregnancy complications than those who had no bleeding (Odds Ratio = 2.321; 95% C.I = 1.294–4.321). Similarly, women who were anaemic were more likely to die of pregnancy complications than those who were not (Odds Ratio = 3.782; 95% C.I = 2.392–5.295). Similarly, women who experienced prolonged labor were more likely to die of pregnancy complications than those whose did not (Odds Ratio = 3.271; 95% C.I = 1.012–3.593). Additionally, the model also revealed that women who had infection after delivery were equally likely to die of pregnancy complications as those who did not have infection after delivery (Odds Ratio = 0.203; 95% C.I = 0.021–1.142). On the miscarriage, the model revealed that women who had miscarriage were equally likely to die of pregnancy complications than those who did not have miscarriage (Odds Ratio = 0.380; 95% C.I = 0.090–1.001). Finally, women who experienced other ailments were less likely to die of pregnancy complications than those who experienced the specified ailments (Odds Ratio = 0.317; 95% C.I = 0.080–0.973) (see Tables 4 and 6).

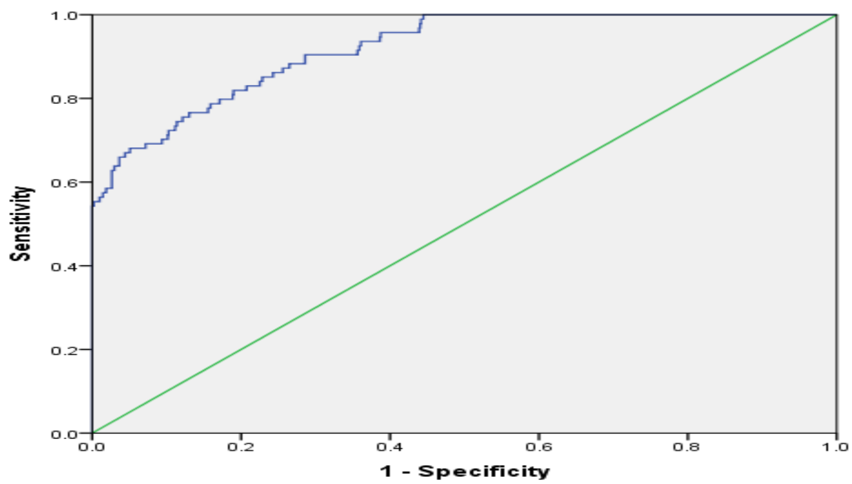

Fig 7. Receiver Operating Characteristic (ROC)

Table 5. Model Evaluation Statistics

Test	Test Statistic	Degrees of Freedom	P-Value
AUC	0.918	-	0.000
Hosmer and Lemeshow Test	6.341	8	0.609
Nagelkerke R Square	0.621	-	-
Omnibus Tests	339.474	30	0.000
Sensitivity	53.20%	-	-
Specificity	100%	-	-
Accuracy	95.60%	-	-
Precision	100.00%	-	-
F1-Score	69%	-	0.000

The area (AU) (0.918), the area under the curve (AUC) and the negelkerke R-squared (0.621) suggest that the model is a good fit to the empirical dataset, indicating a strong discrimination power. Hosmer and Lemeshow test (p-value >0.05) and the Omnibus tests (P-value < 0.05) indicate that the model fits the empirical dataset well. The sensitivity (53.20%), specificity (100%), accuracy (95.60%), precision (100%) and F1-score (69%) further indicates predictive power of the model (see Table 5 and Fig 7). Hence the model suitable for further inferences.

Table 6. Effect of Socio-economic, Environmental and Medical Factors on Maternal Mortality in Kazaure

	B	S.E.	Wald	df	P-Value	Exp(B)	95% Lower	C.I.for Upper
GL								.
Normal								
High	53.105	7879.355	0.000	1.000	0.000	4.342	3.234	5.534
Bleeding								.
No								
Yes	-17.738	5782.111	0.000	1.000	0.001	2.321	1.294	4.321
PLB								.
No								
Yes	1.185	21739.038	0.000	1.000	0.000	3.271	1.012	3.593
Anaemia								.
Non-anaemic								
Anaemic	-51.462	8264.735	0.000	1.000	0.005	3.782	2.392	5.295
CRUSP								.
No								
Yes	21.252	784129677.617	0.000	1.000	0.000	4.443	2.453	6.872
SCB								.
No								
Yes	3.353	38713.378	0.000	1.000	1.000	1.577	0.914	1.852
PD								.
Hospital								
Home	20.314	40300.625	0.000	1.000	0.000	6.639	5.870	7.856
DV								.
No								
Yes	-15.049	10038.318	0.000	1.000	0.999	0.404	0.046	1.001
AHF								.
Yes								
No	11.030	33745.670	0.000	1.000	0.000	2.357	1.200	4.243
IAD								.
No								
Yes	-1.596	8962.843	0.000	1.000	1.000	0.203	0.021	1.142
PIH								.
No								
Yes	18.590	5782.180	0.000	1.000	0.010	4.879	3.157	6.465
Miscarriage								.
No								
Yes	-0.967	5770.285	0.000	1.000	1.000	0.380	0.090	1.001
OA								.
No								
Yes	-1.177	7987.428	0.000	1.000	1.000	0.317	0.080	0.973

Discussion

The aim of this study was to identify the factors associated with maternal mortality in Kazaure emirate. The study revealed that maternal place of residence, maternal age at birth, husband occupation, maternal occupation, husband

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level of Income, maternal level of income, maternal level of education, husband level of education, antenatal care, protein level, glucose level, bleeding, prolonged labor, anemia, care rendered by an unskilled health practitioner, socio-cultural belief, place of delivery, domestic violence, access to healthcare facilities, infection after delivery, pregnancy-induced hypertension, miscarriage and other ailment or underlying diseases are significantly associated with maternal mortality in Kazaure Emirate**.**

The findings of this study indicated that the higher the reproductive age of a woman in the study area, the less likely she is to die of pregnancy complications.Studies had revealed similar results in the past. For instance, the odds of maternal death were lower in older mothers compared to younger mothers in some studies (Chowdhury *et al*., 2007**;** Karlsen *et al*., 2011**;** Illah *et al.,* 2013**;** Kassebaum *et al.,* 2016**)**. Contrary to this,other studies by Adamu *et al*., 2003and Meh *et al*., 2019 showed lower maternal deaths in younger mothers than older mothers. The disagreement may be attributed to religious and cultural practices, depending on the area of study (Meh *et al*., 2019).

The findings herein showed that women with good income were less likely to die than those with poor income in Kazaure Emirate. Similarly, wives of the households who had good income were less likely to die than those with poor income. These findings are supported by some studies in the past such as Salisu & Hamza, (2024) and Boundioa & Thiombiano, (2024). Investigating the effect of home delivery on maternal mortality as compared to hospital delivery in the study area, the study found out that women who delivered at the clinic were less likely to die of pregnancy complications than women who delivered at home. This is also supported by Molomo *et al*., (2024).

The type of business engaged in by women or their husbands does not significantly predict maternal mortality in Kazaure Emirate. Put differently, women whose husbands were engaged in farming were equally likely to die of pregnancy complications as those whose husbands were engaged in trading or other businesses, including being just a house wife. Also, women whose husbands were engaged in farming were equally likely to die of pregnancy complications as those whose husbands were engaged in business or civil service. The same was revealed about the women's husbands by the findings of this study and was empirically supported by Salisu & Hamza, (2024).

Lack of access to healthcare facilities increases risk of complications as per the findings herein, even leading to death. This aligns with other studies in Nigeria and abroad such as Olonade *et al.,* (2019) and Meh *et al*., (2019). A possible explanation to which is that access to health care is usually better in urban than rural areas.

Residence in the rural area was revealed to significantly increase the risk of maternal mortality in Kazaure emirate. This is also in agreement with Ward *et al.,* (2024). Also, agreeing with the findings of this research that revealed women with better education were identified as protected from maternal mortality compared to those that were less educated, Ward *et al.,* (2024) opine that low educational attainment of both the women and their husbands are associated with maternal mortality.

On the contribution of ANC non-attendance to the problem of maternal mortality, the study showed that women who attended ANC regularly were less likely to die of pregnancy complications than those who attended ANC irregularly and those who attended ANC irregularly were equally likely to die of pregnancy complications. To put it madly, regular ANC attendance was seen to have less likelihood of causing maternal death among woman than seldom attendance for ANC or even complete non-attendance for ANC by pregnant women in Kazaure emirate. The finding was consistent with previous studies such as Karlsen *et al*. (2011),Mbassi *et al.,* (2011),Hoj *et al*. (2002),Nafiu *et al*. (2016),Ntoimo *et al*. (2022), Mgawadere*et al*., (2014) and Njoku *et al.,* (2024) andAmoo&Ajayi(2019). Women whose maternal care were rendered by an unskilled health practitioner were more likely to die of pregnancy complications than those whose maternal care were rendered by skilled health practitioner. However, women who had socio-cultural belief were equally likely to die of pregnancy complications as those who had no socio-cultural belief. This aligns with a study by Odekunle, (2016). Women who experienced domestic violence were equally likely to die of pregnancy complications as those who did not experienced domestic violence. Some studies in these directions confirm the stand of this study (Abbey, 2018, Ijadunola *et al*., 2010, Badamasi, 2021 and Azuh *et al*., 2017).

The study observed that women whose glucose level was normal were less likely to die of pregnancy complications than those whose glucose level was not normal. Also, women who had bleeding were more likely to die of pregnancy complications than those who had no bleeding. Similarly, women who were anemic were more likely to die of pregnancy complications than those who were not. Moreover, women who experienced prolonged labor were more likely to die of pregnancy complications than those whose did not. These agreed with some studies by Aderanti *et al., (*2024), Oguejiofor *et al*., (2024), Adefala *et al.,* (2024) and Folarin *et al.,* (2024).

Just as Edene *et al*., (2024) identified hypertension in pregnant woman as significant cause of maternal death in their study, the findings of this research also revealed that women who had pregnancy-induced hypertension were more likely to die of pregnancy complications than women without pregnancy-induced hypertension. Nevertheless, this study revealed that women whose protein level was normal were equally likely to die of pregnancy complications as those whose protein level was not normal, indicating that abnormality in protein level of pregnant women of Kazaure Emirate does not pose big risk of maternal deaths. However, Waziri *et al*., (2024) negates this finding by reiterating that abnormal protein in the blood sample of pregnant women significantly contributes to the menace of maternal mortality.

Women who had infection after delivery were equally likely to die of pregnancy complications as those who did not have infection after delivery. Women who had pregnancy-induced hypertension were more likely to die of pregnancy complications than those who did not have pregnancy-induced hypertension. Women who had miscarriage were equally likely to die of pregnancy complications than those who did not have miscarriage. Finally, women who experienced other ailments were less likely to die of pregnancy complications than those who experienced the specified ailments. These findings also agreed with (Sageer *et al*., 2019, Chidinma, 2024, Etuk *et al.,* 2024 and Adinma *et al*., 2024).

IV. CONCLUSION

Maternal mortality in Kazaure Emirate remains a critical public health issue, requiring evidence-based strategies to identify and mitigate its underlying causes. This study applied a logit model to analyze determinants of maternal mortality, revealing that low reproductive age, low education attainment by women or their households, rural residence, low level of income of women or their households, husband occupation, non-business mindset of women or their households, abnormal glucose level in women, bleeding, prolonged labor, anemia, care rendered by unskilled personnel, home delivery, access to healthcare facilities, pregnancy-induced hypertension, miscarriage and other ailments are significant predictors of maternal deaths. The logit model demonstrated strong predictive accuracy, underscoring its utility in understanding and addressing maternal health challenges in the region.

The findings highlight the urgent for targeted interventions to improve healthcare access, enhance maternal education and strengthen antenatal care services. Expanding healthcare infrastructure, particularly in rural areas and implementing community-based health education programs are essential steps toward reducing maternal mortality. Additionally, increasing investment in maternal health services and promoting policy reforms can significantly improve health outcomes for women in Kazaure Emirate.

This study contributes to the growing body of literature on maternal health by providing a data-driven framework for managing maternal mortality. The application of logit model offers valuable insights for policy makers, healthcare providers and stakeholders, enabling them to design and implement effective interventions. Future research should explore longitudinal data and incorporate additional variables to further refine the model and enhance its predictive capabilities. By addressing the identified determinants, Kazaure Emirate can make significant progress toward achieving sustainable reductions in maternal mortality and improving the overall well-being of its population.

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