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Statistical modeling of health system causes of maternal mortality among pregnant women

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Abstract
The problem of maternal death remains a serious universal concern, with nearly 295,000 women dying annually from pregnancy-related complications, the majority of which happen in countries that are not financially balanced. Many African countries accounts for about 60% of these deaths, where the incident of maternal loss proportions exceed 500 of 100,000 living childbirths in many countries. This study examines the influence of health system causes of motherly losses at Mulago Specialized Women and Neonatal Hospital in Kampala, Uganda, using statistical modeling techniques. Adopting logistic regression model, the effect of antenatal care, parity, gravidity, and age conditions on pregnant women death was assessed. Outcome of the model revealed that the significant factors identified in this model, parity (p=0.001) and antenatal care attendance (p=0.018), form a robust predictive model of maternal mortality. The findings confirm that advanced maternal age and high parity, further exacerbate risks, particularly among older women with multiple previous pregnancies. The study's predictive model combines health system factors, providing a valuable tool for early identification of high-risk cases. By incorporating regular ANC services and targeted support for high-risk groups, MSWNH can improve maternal care and reduce mortality.

Keywords: logistic regression, anemia, health conditions, mortality, live births

1. Introduction

Nearly 800 women die every day due to pregnancy difficulties and delivery according to the WHO (2019) report regardless of a universal decline of 169 deaths per 100,000 live deliveries between 2000 and 2015. In addition to this, for each pregnant woman who dies, a predictable 20 women suffer long term infirmities, damages and contagions (UNICEF, 2020). A woman dies every minute in giving birth around the world and nearly half of these deaths happen in Sub-Saharan Africa (SSA) (Olungah et al., 2019). Maternal losses are connected to obstetric difficulties during prenatal period, labour, or the postpartum period such as antenatal care, parity, gravidity and age (UNICEF, 2019).

The antenatal care (ANC) period represent a vital chance for identifying dangers to the pregnant mother as well as the unborn baby's healthiness, advising on sustenance, threat signs of unpleasant health such as underweight, anemia, hypertension or infection – and household arrangement choices after the birth (Geltore et al., 2022). Similarly, if a pregnant woman is deficient ANC, slight obstetric circumstances are not identified and managed timely it may lead to grave difficulties and maternal near-miss events will likely advance (Habte et al., 2021). Maternal near-miss (MNM) is a situation where pregnant mothers pass through and endure a severe health disorder during gravidity, delivery or within 42 days of end of the pregnancy (WHO, 2022). In a study that directed at detecting factors of MNMs among pregnant mothers admitted to tertiary hospitals in southern Ethiopia, pregnant women who were not healthily ready for delivery and its difficulties were further likely to meet MNM happenings (Habte et al., 2021). Truncated or partial ANC appointments by pregnant women have been connected with home-based childbirths and deaths (Zone et al., 2020). In a Southern Ethiopian community-based cross-sectional study, Zone et al. (2020) observed that 73.6% childbirths at home among pregnant mothers with truncated or partial ANC visits (1-3) had given delivery in the past 12 months. The reasons connected with home-based childbirths were nonexistence of an engraved delivery strategy for preparation and willingness and partial number of ANC visits.

Complex threats of difficulties and loss are connected with first gravidities and more than three to five gravidities. Mothers in their first gravidities have extended period of labor while mothers with several gravidities are more likely to agonize postnatal hemorrhage (Black et al., 2016). In an Indian study carried out to analyze 204 motherly losses, Garg (2016) establish that most of the losses happened in primi (29%) and 71% in multi pregnancy. In a study carried out at a key referral hospital in Northern Uganda, outcomes disclosed that grand multiparous mothers were at a bigger threat of not surviving (Alobo et al., 2022). Furthermore, on multivariate investigation, high parity was connected with truncated ANC turnout, which was further connected with reduced awareness of risk signs in gravidity and absence of screening for hazard reasons, all of which surge the hazard of motherly loss (Alobo et al., 2022). Home base childbirths that position high death hazard have been connected with multiparous pregnancy (Atahigwa et al., 2020). In a study carried out in Kenyan, results shown that multifarious pregnant women were less expected to give birth at the health facility when equated to primiparous pregnant women. In fact, as the number of pregnancy (parity) rises, the probability to give birth from a health facility declines, with pregnant women whose number of pregnancy was five and above having over a 50% chance of not give birth at the health facility when equated to first-time mothers (Atahigwa et al., 2020).

Young girls (aged 10–19 years) face significantly complex hazards of eclampsia, universal contagions, and difficulties during delivery equated to pregnant mothers aged 20–24 years (WHO, 2019). There is a noted contrary relationship among young delivery rates and the percentage of pregnant mothers getting the required care from an expert health qualified (WHO, 2019). Consequently, adolescent mothers often have less access to methods for preventing high-risk births, and their high-risk deliveries are less likely to be attended by a skilled birth attendant (SBA) (WHO, 2019). Furthermore, youthful deliveries are typically common among the poor, less educated mothers, compounding their deprived condition (Nik-Hazlina et al., 2022). In disparity, mature motherly age has been connected to a better probability of pre-existing health situations, amplified threat of obstetric difficulties, motherly disease, and a complex threat of development from severe motherly disease to loss (Nik-Hazlina et al., 2022). Epidemiological tendencies from universal data show that the danger of pre-eclampsia upsurges in an about linear method with motherly period, an arrangement detected in both nulliparous and multiparous pregnant mothers (Wang et al., 2021).

The heightened danger of hypertensive disorders of pregnancy (HDP) in adult women pregnancy could be associated with an unusually increase fat outline, increase-concentration fatty acid lipid, and a greater threat of vascular injury compared to younger women.
Aziz et al. (2021) discovered the part of health maintenance expenses on maternal death by means of penal data for eight South Asian countries together with Pakistan, Bangladesh, Bhutan, Nepal, Sri Lanka, India, Maldives and Afghanistan for the years 2000–2017. The study adopted a completely adapted ordinary least square (FMOLS) and dynamic ordinary least squares (DOLS) models for the experimental analysis. They observe that a one proportion point rise in health expenses was connected with a rise of 1.95 percentages in the maternal death ratio in the instance of FMOLS estimator and 0.16 percentages in the instance of DOLS estimator. Alobo et al. (2022) employed multivariate logistic regression model to evaluate the danger of maternal loss at admission in Northern Uganda. Increasing threat total for every mother centered on the unstandardized canonical factors was achieved by the discriminant equality. They discovered that the usual maternal death proportion stood 328 per 100,000 live deliveries. Nyoni (2019) employed yearly time series data on maternal losses and MMR in Zimbabwe from 1990-2015, to model and predict both maternal losses and MMR by means of ARIMA models and discovered that ARIMA (0, 2, 2) model as well as ARIMA (2, 2, 0) model are the parsimonious models for forecasting maternal losses and MMR respectively. Mustafa (2020) adopt Artificial Neural Network model in so as to investigate the tendencies of maternal losses at Chitungwiza Central Hospital (CCH) in Zimbabwe using the out-of-sample predictions range over the period January 2020 to December 2021.

Togunwa et al., (2023), engaged a strong hybrid model for motherly health danger arrangement in gravidity, which employs the strong point of artificial neural networks (ANN) and random forest (RF) procedures. A simulated neural network-built structure for forecasting motherly health threats as well as maternal death by means of health statistics records was established. Approaches which consist of original strong neural network design, DT-BiLTCN, which adopts decision trees, a bidirectional long short-term memory network, and a sequential convolutional network, were suggested. Bala et al. (2023), engaged artificial neural networks (ANNs), adaptive Neuro-fuzzy inference systems (ANFISs) and support vector machines (SVMs) and a traditional linear regression model of multiple linear regressions (MLR) to forecast and picture the improvement of Antiretroviral therapy (ART) Hospital Unit of Federal Teaching Hospital in Gombe. Raja et al. (2021) offered a machine learning ideal as threat likelihood theoretical model for the expectation of Preterm birth (PTB) Maternal death and applied by means of three diverse classifiers, specifically, decision tree (DT), logistic regression (LR), and Support Vector Machine (SVM) for the expectation. Bolanle and Oladejo (2020) discovered a machine learning-based decision support system for motherly health care where a multi-class Support Vector Machine (SVM) was established a Web-based Decision Support System for Maternity Health Care (DSSMC) to expedite automatic finding of patient and to resolve the difficult of human mistake and bias upon the occurrence of maternal losses.

These alarming statistics highlight the urgent need to examine the health system causes (such as antenatal care attendance, parity, gravidity and age) of maternal mortality among pregnant mothers. In the direction to reducing this problem, this research goal is to create a statistical model for maternal mortality using the data obtained from Mulago Specialized Women and Neonatal Hospital, Kampala. Adopting a logistic regression approach, the study will examine the relationships and interactions between health system factors such as antenatal care attendance, parity and gravidity. The logistic regression model with interaction terms will provide insights into the combined effects of these variables, allowing for the identification of key predictors and high-risk groups

2.Methodology and Model Specification

Logistic regression remains one statistical tool which handles the log-odds of any occurrence by means of a linear arrangement of simple or multiple variables that are independent. Logistic or logit regression analysis is estimating the parameters of a logistic model; the coefficients in the linear combination (Hosmer Jr et al., 2013). It is a controlled mechanism form of education procedure which does twofold arrangement responsibilities through forecasting the likelihood of a result, occurrence, or surveillance. In this work, the predictors of maternal mortality are measured by health system and socio-demographic predictors. However, logistic regression can be either simple or odds ratio model. The Simple Logistic Regression Model is formulated in relations of the likelihood that an occurrence will happen represented by p and the likelihood that an occurrence will not happen represented by $1-p$, as denoted by:

$$logit(y) = In\left(\frac{p}{1-p}\right) = \alpha + \beta x \qquad (1)$$

If $y = \frac{p}{1-p}$ denote the proportion of incident happening over the incident not happening. $In\left(\frac{p}{1-p}\right)$ is called Logit(y) and is given as:

$$logit(y) = In\left(\frac{p}{1-p}\right) = In\left(\frac{e^z}{1+e^z} \div \frac{1}{1+e^z}\right) =$$

$$In\left(\frac{e^z}{1+e^z} \times 1 + e^z\right) = In(e^z) = z$$

$$logit(y) = In\left(\frac{p}{1-p}\right) = z \qquad 2)$$

Extending the logic of the simple logistic regression to multiple predictors and their interactions will leads to constructing a complex logistic regression as:

$$logit(y) = In\left(\frac{p}{1-p}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q \qquad (3)$$

since $Z = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q$.

The Odds Ratio in Logistic Regression Model is the probabilities of an incident happening remain distinct by means of the proportion of the chance of the incident happening in respect to the possibility of it not happening. Since p is the likelihood of an incident happening and (1-p) the likelihood of an incident not happening then the consistent probability is $\frac{p}{1-p}$. The logistic regression model formulates the likelihood of an incident happening, so the impacts of explanatory variables are described in relations of probabilities. And to find the corresponding probability of an event occurring, take the anti-log of (3).

$$logit(y) = In\left(\frac{p}{1-p}\right)$$

$$= \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q \qquad (4)$$

Where

$$\frac{p}{1-p} = e^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q)} \qquad (4)$$

$$p = P(y = 1|X) = \frac{e^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q)}}{1 + e^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q)}} \qquad (5)$$

and

$$p = \frac{1}{1 + e^{-(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \cdots + \beta_{pq} x_p x_q)}} \qquad (6)$$

Therefore, the statistical model formulated for Healthcare System Factors (HSF) causing maternal mortality is given by:

$$logit(MDEATH) = \alpha + \sum_{i=1}^{3} \beta_i X_i + \varepsilon \qquad (7)$$

where MDEATH is maternal mortality, α is a constant, β_i = Coefficients of the independent variables, X_1= antenatal care attendance, X_2= parity, X_3= gravidity, ε = error term

2.4 Model Evaluation

The predictive accuracy of the model would be evaluated using the Likelihood ratio test, Wald statistic, Hosmer and Lemeshow test. In the Likelihood Ratio Test, **t**he deviance with n independent variables $-2InL(X,\theta_n)$ is equated to the nonconformity when the interaction terms require remained included. The probability ratio test is formulated as:

$$\lambda = -2\log\left(\frac{L_{reduced}}{L_{full}}\right) = (-2\log L(X,\theta_n)) - \left(-2logL(X,\theta_{n,ij})\right) \quad (8)$$

where $L_{reduced}$ is the maximum likelihood of the reduced model and L_{full} is the maximum likelihood of the full model.

$$L_{reduced} = \prod_{i=1}^{n} P_i^{Y_i}(1-P_i)^{1-Y_i} \ and \ P_i = \frac{1}{1+e^{-(\alpha+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n)}} \quad (9)$$

and

$$L_{full} = \prod_{i=1}^{n} P_i^{Y_i}(1-P_i)^{1-Y_i} \ and \ P_i = \frac{1}{1+e^{-(\alpha+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n+\ \beta_{12}x_1x_2+\cdots+\ \beta_{pq}x_px_q)}} \quad (10)$$

The difference yields a goodness of fit index G, χ^2 with the degree of freedom df = (number of parameter in the full model) - (number of parameter in the reduced model). If λ exceeds the value obtained from distribution of the χ^2 having $\alpha =$ 0.05 significant, then the null hypothesis should be rejected, indicating that the interaction terms significantly improve the model fit (Hosmer Jr et al., 2013). However, the Wald Statistic (W) is a test indicator employed in determining the significance of distinct forecasters with a situation of generalized linear models, including logistic regression. It tests the null hypothesis that a particular coefficient β_j is equal to zero (or some other specified value), indicating no effect of the corresponding predictor variable (Hosmer Jr et al., 2013). For a given predictor X_j with coefficient estimate $\hat{\beta}_j$ and its standard error $SE(\hat{\beta}_j)$ the Wald statistic is computed as:

$$W = \left(\frac{\hat{\beta}_j}{SE(\hat{\beta}_j)}\right)^2 \quad (11)$$

The Wald statistic trails the distribution of the chi-square having 1 degree of freedom (X_1^2) under the test hypothesis H_0 such that $\beta_j = 0$. While Hosmer and Lemeshow Test examines whether or not the experimental probabilities of happenings remain alike to the expected likelihoods of incidence in subcategories of the ideal population. To perform Hosmer-Lemeshow statistic, the predicted probabilities of the outcome are grouped into deciles (ten groups). Within each group, the experimental and estimated statistics of happenings are compared. The test statistic is calculated using the model is:

$$H = \sum_{g=1}^{10} \frac{(O_g - E_g)^2}{E_g} \quad (12)$$

where O_g and E_g are the experimental and estimated number of happenings in the g^{th} cluster, respectively. Also, the test statistic under this distribution is associated with the χ^2. A non-substantial assessment when p > 0.05 suggests a better fits, whereas a significant test indicates a lack of fit. (Agresti, 2012)

3. Empirical Results

This part of the study deals with the analysis of data collected from Mulago Specialized Women and Neonatal Hospital, Ugandan. It includes descriptive analysis, parameter estimates and model evaluation. The data in Table 1 shows the descriptive statistics for various health-related variables across a sample of 130 cases and Figures 1 – 4 present the visual distribution of each variable

Table 1: Descriptive Statistics of the Variables

	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Age	16	42	29.66	5.250	-.433	.006
Antenatal_care_attendance	0	11	4.05	2.463	.468	-.465
Gravidity	1	8	3.92	1.645	.003	-.390
Parity	0	7	3.18	1.517	.087	-.328

The mean age is 29.66 years, with a standard deviation of 5.250 years. The negative skewness of -0.433 indicates a slight left skew, meaning there might be a few younger individuals in the sample. The kurtosis value of 0.006 suggests a shape similar to a normal distribution. The mean number of antenatal visits is 4.05, with a standard deviation of 2.463. The skewness of 0.468 indicates a slight positive skew, meaning a few individuals might have attended more antenatal visits than the average. The kurtosis of -0.465 suggests a relatively flat distribution compared to a normal distribution. The

mean of gravidity (number of pregnancies) is 3.92 with a standard deviation of 1.645. A skewness of 0.003 indicates a nearly symmetrical distribution, while the kurtosis of -0.390 suggests a relatively flat distribution. The mean of parity (number of live births) is 3.18, with a standard deviation of 1.517. The skewness of 0.087 indicates a very slight positive skew, implying a nearly symmetric distribution. The kurtosis of -0.328 indicates a very slightly flat distribution.

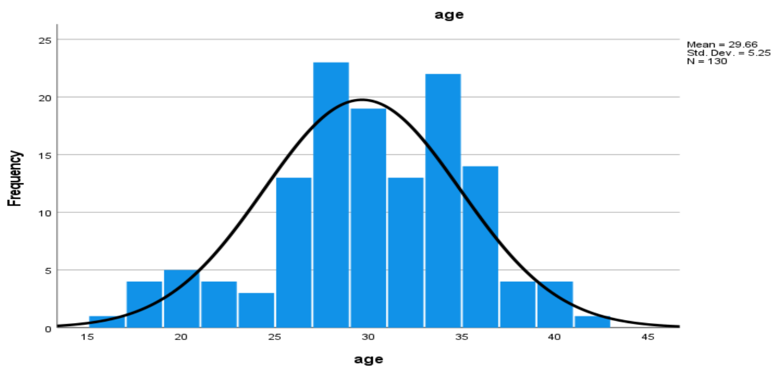

Figure 1: Age Distribution

The histogram displays the age distribution of a sample with 130 individuals, with a mean age of 29.66 years and a standard deviation of 5.25 years. The distribution appears roughly normal, peaking around ages 27 to 35, which suggest that most individuals in this sample are within this age range. There is a noticeable decline in frequency as age moves beyond 35 years.

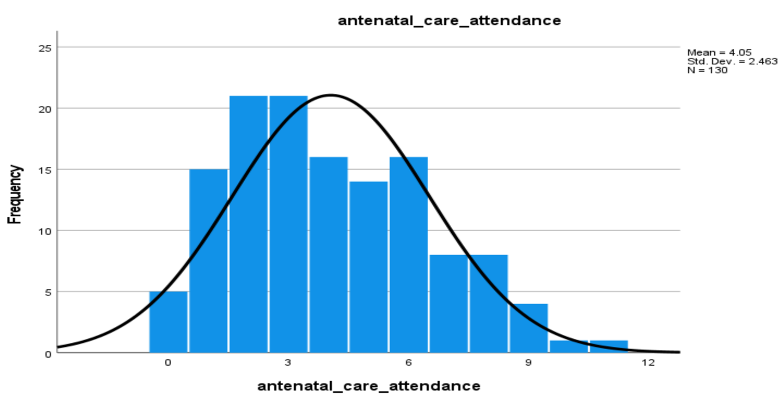

Figure 2: Antenatal Care Attendance Distribution

The histogram shows that the average number of antenatal care visits is 4.05, with most women attending between 2 to 6 visits. The right-skewed distribution suggests that while a few women had many visits, most had limited engagement, potentially increasing maternal health risks.

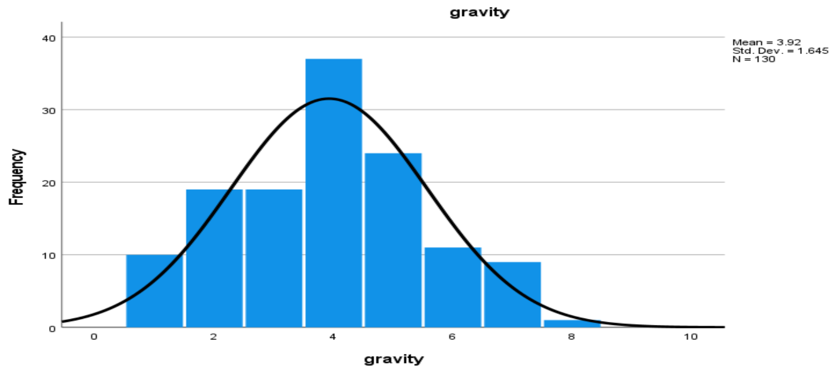

Figure 3: Gravidity Distribution

The histogram indicates that the average gravity, or total number of pregnancies, is 3.92, with the majority of women having between 3 to 5 pregnancies. The distribution is slightly right-skewed, suggesting that while many women had a moderate number of pregnancies, a smaller number had higher gravidity levels. This pattern may highlight variations in reproductive history among the participants, potentially reflecting differences in health access or family planning practices.

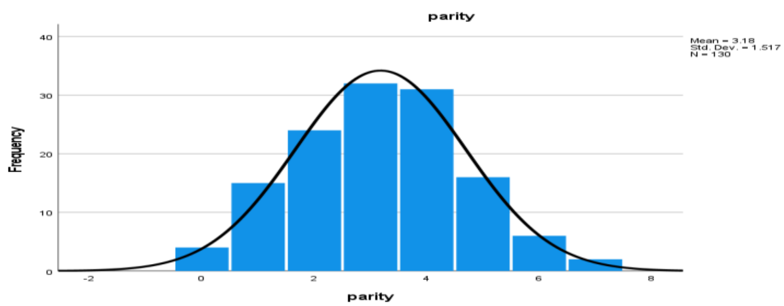

Figure 4: Parity Distribution

The histogram shows that the parity distribution among the 130 individuals is roughly normal, with an average parity of 3.14 and a standard deviation of 1.517, suggesting that most individuals have around 3 to 4 children. This indicates a balanced distribution of parity levels, with a typical family size of 3 to 4 children in the sample population.

3.1 Linearity of the logits.

Since the dependent variable maternal mortality has only 2 categories "no" when death did not occur and yes" if it did, therefore, it is considered as categorical variable measured on dichotomous scale. Table 2 provides the linearity test between the logit function and the entire continuous variable. To test the linear relationships between the logits of dependent variable and the continuous independent variables, a logistic regression model was fitted with the interactions of each continuous variable with its natural log.

Table 2: Linearity Test for the Logit Function

	B	S.E.	Wald	Df	Sig.
Ln_Antenatal_care_attendance by Antenatal_care_attendance	-.539	.662	.661	1	.416
Ln_Age by Age	3.548	1.407	6.363	1	.082
Ln_Gravity by Gravity	-7.349	4.765	2.379	1	.123
Ln_Parity by Parity	9.560	5.110	3.500	1	.061

As shown in Table 2 that all the p-values are greater than 0.05, meaning there is a linear relationship between the logit and the continuous variable in the dataset. Table 3 provides the independence test between the variables.

Table 3: Durbin Watson statistics

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
	0.698	0.488	0.430	0.378	2.08

Table 3 gives Durbin Watson statistics which is known as a measure of independency of observations. The acceptable range for the measure is 1.5 to 2.5 meaning that any figure out this range represents dependence of observations. Since the Durbin Watson calculated value 2.08 falls between the acceptable range, it implies that there no problem of autocorrelation in the dataset. To ensure the effect of each variable, a multicollinearity test was carried out. The Pearson correlation coefficient (r) is used to measure the nature of the relationship between 2 pairs of variables, and an $r > 0.7$ says that the relationship is strong. Table 4 shows that coefficient of age is not statistically significant and those which are significant are less than 0.7, therefore the dataset is free of multicollinearity.

Table 4: Correlation Test for the Dataset

		ANC	Age	Gravity	Parity
ANC	Pearson Correlation	1	-0.003	-.251**	-.283**
	Sig. (2-tailed)		0.97	0.004	0.001
Age	Pearson Correlation	-0.003	1	0.138	0.118
	Sig. (2-tailed)	0.97		0.117	0.183
Gravity	Pearson Correlation	-.251**	0.138	1	.417**
	Sig. (2-tailed)	0.004	0.117		0
Parity	Pearson Correlation	-.283**	0.118	.417**	1
	Sig. (2-tailed)	0.001	0.183	0	

**. Correlation is significant at the 0.01 level (2-tailed).

3.2 Model with Health System Causes

Finding out health system causes that influence maternal mortality in MSWNH is the specific objective of this study. Variables such as antenatal care attendance, age, parity and gravity were used to fit the logistic and check whether it has influence on the occurrence of maternal death or not, as presented in Table 5 – 8

Table 5: Model Summary for the Model with Health System Causes

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
176.342	0.304	0.358

From Table 5, it shows that 30.4% of the variation in the dependent variable is explained by the logistic model. Nagelkerke's R^2 is 0.358, indicating a quite moderate relationship between the predictors and the outcome. Table 6 displays how parameter estimates associated with the health system factors influencing the incidence or non- incidence of motherly loss at MSWNH. The table provides the likelihoods proportion evaluations ($Exp(\beta)$) in line with the forecaster variables, the equivalent regression constants, their Wald assessment indicator (that follows the pattern of the chi-squared), as well as the corresponding probability outcomes (p-values). The coefficients are listed in the space labeled **β**. Any result associated with negative value indicates that the probabilities of pregnant women loss decrease. However, any variable having p-value smaller than 0.05 are significant because the assured interval are restrained at 95%.

Table 6: Comparison of Health System Causes in the Model

	B	S.E.	Wald	Df	Sig.	Exp(B)
Antenatal_care_attendance	-0.964	0.084	132.524	1	0.018	0.381
Parity	0.172	0.097	34.119	1	0.001	1.188
Gravidity	0.913	0.135	46.002	1	0.201	2.493
Constant	-0.208	0.629	0.072	1	0.041	0.812

From Table 6 only Antenatal_care_attence and parity are statistically significant because they have a p-value (0.018 and 0.001) less than 0.05. The coefficient of Antenatal_care_attendance is negative meaning it decreases the odds of maternal death and parity on the other hand increases the odds of maternal death due to its positive coefficient. The logit equation is expressed as:

$$logit(MDEATH) = -0.208 - 0.964X_1 + 0.172X_2 + 0.913X_3 \quad (13)$$

The equation with only significant health system causes is therefore given as:

$$logit(MDEATH) = -0.208 - 0.964X_1 + 0.172X_2 \quad (14)$$

where X_1 is antenatal care attendance, X_2 is parity

Table 7: Classification Table of the Model with Health System Causes

		MDEATH		Percentage Correct
		No	Yes	
MDEATH	No	35	27	56.5
	Yes	36	22	32.4
Overall Percentage				**43.8**

The model with health system causes has improved the classification with an overall accuracy of 43.8% as shown in Table 7. The sensitivity is 32.4% and the specificity is 56.5%. The Hosmer and Lemeshow assessment evaluates the fitness for a logistic regression model using relating experimental as well as predicted probabilities and the result is shown in Table 8.

Table 8: Hosmer and Lemeshow Test for the Model with Health System Causes

Chi-square	Df	Sig.
17.419	8	0.512

It is observed from the results in Table 14 that Chi-square value is obtained as 17.419 with a p-value of 0.512, signifying that the estimated model is appropriate for the given data.

4. Conclusion

The study showed that regular antenatal care (ANC) attendance had a protective effect against maternal mortality (Exp(**β**) = 0.381, Table 5). It reduced risk due to its negative coefficient of -0.964 which emphasized the role of antenatal care in early identification of complications and management of high-risk pregnancies. Parity, or the number of previous births, also showed a slight increase in risk (Exp(**β**) = 1.188, Table 5), with a coefficient of 0.172 which indicates higher maternal mortality rates among multiparous women, likely due to cumulative health effects and weakened physical resilience over multiple pregnancies. The significant factors identified in this model, parity (p=0.001) and antenatal care attendance (p=0.018), form a robust predictive model of maternal mortality. The findings confirm that advanced maternal age and high parity, further exacerbate risks, particularly among older women with multiple previous pregnancies. Additionally, the protective effect of antenatal care (ANC) attendance emphasizes the critical role that routine prenatal visits play in managing and reducing complications associated with childbirth. The study's predictive model combines health system factors, providing a valuable tool for early identification of high-risk cases. By incorporating regular ANC services and targeted support for high-risk groups, MSWNH can improve maternal care and reduce mortality.

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