Assessing The Occurrence Of Maternal Mortality And Some Related Factors At Komfo Anokye Teaching Hospital

Adjei Mensah Isaac, Agyei Wallace, Kwasi Boateng

Abstract: Maternal Mortality in Ghana continues to be a major public health problem despite many strategies devised by the international community to reduce it. The United Nations (UN, 2009) reports indicates that more than 1500 women die each day from pregnancy related causes resulting in an estimated figure of 550,000 maternal deaths annually. This paper applies logistic regression model to determine the key factors that have significant effect to predicting the occurrence or non-occurrence of maternal mortality incidence. An annual maternal mortality data from 2007 to 2012 from Komfo Anokye Teaching Hospital (KATH) was analyzed. The results showed that AGE, PARITY and GRAVIDA contributes significantly to the occurrence of maternal mortality.

Index Terms: Age, Parity, Gravida, Logistic regression, Maternal Mortality

1 INTRODUCTION

As explained by Sha and Say [1], maternal mortality is defined as the death of a woman while pregnant or 42 days after termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to the pregnancy and its management but not from accidental or incidental cause. Maternal mortality continues to be a major cause of death among women of reproductive age in many developing countries globally and remains a serious public health issue especially in developing countries (WHO [2]). In the contemporary world, maternal mortality is considered as a violation of the rights of women and its rate is perceived as a critical index of the level of development of a country. The attention of the world began to focus more on maternal mortality when in 1985, Rosenfield and Maine [3], published an article titled "Maternal Mortality- a neglected tragedy". Rosenfield and Maine alerted the world to the fact that, many developing countries were neglecting this important issue on maternal mortality rates in developing countries globally. According to Factsheet of WHO [4], 1500 women die from pregnancy related complications every day. Most of these deaths occur in developing countries of which most are avoidable. Ujah et al., [5] pointed out that, whole 25% of females of reproductive age lived developed countries and they contributed only 1% of maternal deaths worldwide. A total of 99% of all maternal deaths occur in developing countries.

According to WHO [4], fifteen (15) countries which includes Afghanistan, Angola, Burundi, Cameroon, Liberia, Chad, Congo, Guinnea-Bissau, India, Malawi, Niger, Nigeria, Rwanda, Sierra-Leon, and Somalia were having maternal mortality ration (MMR) of at least 1000 per 100,000 live births, of which all with the exception of Afghanistan and India which were not African countries. Maternal mortality is one of the most sensitive indicators of health disparity between the richer and the poorer nations. Developing countries stand the greatest risk of having obstetric complications being the leading cause of maternal death of women of reproductive age claiming lives of an estimated figure of 529, 000 each year (Freeman et al., [6]). Maternal mortality ratio in Africa remains the highest in the world with an average actually increasing from 870 per 100,000 live births 1900 to 1000 per 100,000 live births in 2001 (Turner, [7]). Despite the various policy calls to action and international networking amo3ngst development agencies on the topic, in Africa the situation is worsening. Though much has been learned during the past decade about the causes of maternal death, there is little evidence of significance progress towards the ambitious goal of halving maternal mortality. The WHO [4], reported that every year, over half a million women continue to lose their own lives to the hope of creating lives. Every minute of every day, a woman in the world dies as a result of complications arising during pregnancy and childbirth (UNICEF, [8]). In order to respond to this menace, the Millennium Development Goal 5 (MDG5), which is aimed to improve maternal health was developed. The target of the MDG5 is to reduce Maternal Mortality Rate by three-quarters from 1990-2015. The world's maternal mortality ration (MMR) as a result is declining to meet the target of the Millennium Development Goal 5 (MDG5) which has the aim of reducing the number of women who die in pregnancy and childbirth by three-quarters of the year 2015 (Mairiga et al,. [9]). The trend of maternal mortality in developing countries according to Shan and Say [1], is much worse as researches conducted in various countries of Sub-Saharan Africa gives the indication that, maternal mortality has not only continued to increase, but has instead been increasing after the laugh of the Safe Motherhood Initiative in Kenya in the year 1987. Interventions targeting the reduction of maternal mortality in Ghana have been implemented. Notable among these interventions is the user free exemption that was implemented in 2003. This policy enables pregnant women to have free access to delivery cost

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at both private and public health facilities in the country. During the year 2003 and 2006 respectively, the evaluation of these interventions showed a reduction which was very dramatic with respect to maternal mortality incidence. This as a result gives the indication that, maternal mortality in many cases is preventable but it requires a comprehensive understanding of the factors that significantly contributes maternal mortality with respect to it occurrences. Based on this gab, this paper will try to determine the factors that contributes significantly to the occurrence of maternal mortality using Logistic regression model.

2 METHODOLOGY

The occurrence of maternal mortality was assessed with respect to the factors such as age, educational status, marital status, residence status, parity, gravida, and length of stay at the hospital. Data from the research work was secondary, historical annual maternal mortality data for the years 2007 through to 2012 compiled by Komfo Anokye Teaching Hospital Ghana. A total of 1,015 maternal deaths within the age group 12-49 years were analysed using logistic regression analysis.

2.1 General Logistic Regression Model

Logistic regression model is widely used to model outcomes of categorical dependent variables. Logistic regression allows a researcher to test models to predict categorical outcomes with two or more categories. This type of regression consist of independent variables that are either categorical or continuous. On the other hand, multinomial logistic regression is applied o when the outcome of the response variable has more than two categories. The general logistic regression model is formulated as:

$$\log it(\pi_i) = \log\left(\frac{\pi_i}{1 - \pi_i}\right) = X_i^T \beta \qquad (1)$$

Where X_i is a vector of continuous measurements corresponding to covariates and dummy variables corresponding to factor levels and β is the parameter vector. The simple logistic regression model on the other hand is given as;

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha + \beta x_i \tag{2}$$

For a binary response variable *Y* and explanatory variable *X*, let $\pi(x) = P(Y = 1/X = x) = 1 - P(Y = 0/X = x)$, then the Logistic regression model is;

$$\pi(x) = \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)}$$
(3)

On the other hand, for a binary response variable *Y* with multiple explanatory variables x_1, x_2, \dots, x_p , the model becomes;

$$\pi(x) = \frac{\exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p)}{1 + \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p)}$$
(4)

2.2 Estimation of Logistic Regression using Maximum Likelihood Estimation (MLE)

The goal of Logistic regression is to estimate the K+1 unknown parameters β in the Logistic regression model that is;

$$\log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \sum_{i=0}^{k} x_{ik} \beta_k \text{ where i=1,2,3,...N}$$
(5)

This is done with the Maximum Likelihood Estimation which entails finding the set of parameters for which the probability of the observed data is greatest. The maximum likelihood equation is derived from the probability distribution of the dependent variable. Since each y_i represents a binomial count in i^{th} population, the joint probability density function of *Y* is ;

$$f(y/\beta) = \prod_{i=1}^{N} \frac{n_i!}{y_i!(n_i - y_i)!} \pi_i^{y_i} (1 - \pi_I)^{n_i - y_i}$$
(6)

For each population, there are $\binom{n_i}{y_i}$ different ways to arrange y_i successes from n_i trials. Since y_i the probability of a success for any one of the n_i trials is π_i , the probability of y_i successes is $\pi_i^{y_i}$. Likewise, the probability of $n_i - y_i$ failures is $(1 - \pi_i)^{n_i - y_i}$.

The joint probability density function in "(6)" expresses the values of *y* as a function of known and fixed values for β . The likelihood function has the same form as the probability density function, except that the parameters of the function are reversed; the likelihood function expresses the values of β in terms of know, fixed values of *y*.

Thus,

$$L(\beta / y) = \prod_{i=1}^{N} \frac{n_i!}{y_i!(n_i - y_i)!} \pi_i^{y_i} (1 - \pi_I)^{n_i - y_i}$$
(7)

The maximum likelihood estimates are the values for β that maximizes the likelihood function in "(7)". The critical points of a function (maxima and minima) occur when the first derivative equals 0. If the second derivative evaluated at that point is less than zero, then the critical point is a maximum. Thus finding the maximum likelihood estimates requires computing the first and second derivatives of the likelihood function. Attempting to take the derivatives of "(7)" with respect to β is difficult task due to the complexity of multiplicative term. Fortunately, the likelihood equation can be considerably simplified. First note that, the factorial terms in the "(7)" do not contain any of the π_i . As a result, they are essentially constants that can be ignored: maximizing the equation without the factorial terms will come to the same if they were included. Secondly note that since $b^{x-y} = \frac{b^x}{b^y}$ (from the second law of indices), and after rearranging terms, the equation to be maximized can be written as;

$$\prod_{i=1}^{N} \left(\frac{\pi_i}{1 - \pi_i} \right)^{y_i} (1 - \pi_i)$$
 (8)

Note that after taking the exponent (e) on both sides of "(5)", we obtain the relation;

$$\frac{\pi_i}{1-\pi_i} = e^{\sum_{k=0}^{k} x_{ik} \beta_k}$$
(9)

Which after solving for π_i becomes;)

$$\pi_{i} = \left(\frac{\frac{\sum\limits_{k=0}^{K} x_{ik} \rho_{k}}{\sum\limits_{k=0}^{K} x_{ik} \beta_{k}}}{\sum\limits_{k=0}^{K} x_{ik} \beta_{k}} \right)$$
(10)

Substituting "(9)" for the first term and "(10)" for the second term of "(8)", "(8)" then becomes;

$$\prod_{i=1}^{N} \left(\sum_{k=0}^{K} x_{ik} \chi_{k} \right) 1 - \frac{\sum_{k=0}^{K} x_{ik} \chi_{k}}{\sum_{k=0}^{K} x_{ik} \chi_{k}}$$
(11)

Additionally, $x_{i} ds = (b^{x_{i}})^{y} = b^{x_{i}} ds$ simplify the first and replace 1 with $\frac{1+e^{k/d}}{\sum_{k=1}^{K} x_{ik} \beta_{k}}$ to simplify the second product. Thus '(1*)^{ind} can therefore, be written as;_n

Thus ${}^{4}(4\mathfrak{P})^{**}$ can therefore be written as; $\prod \left(\sum_{k=0}^{k} x_{ik} \chi_{k} \right) \left(\sum_{1+e^{k=0}}^{k} x_{ik} \chi_{k} \right)$ (12)

The equation above therefore represents the Kernel of the Likelihood to maximize. However, it is still cumbersome to differentiate and can simplified a great deal further by taking log. Since Logarithm is a monotonic function, any maximum of the likelihood function will also be maximum of the log likelihood function and vice versa. Thus, taking the natural log of "(12)", yields the log-likelihood function:

$$\ell(\beta) = \sum_{i=1}^{N} y_i \left(\sum_{k=0}^{K} x_{ik} \beta_k \right) - n_i \log \left(1 + e^{k} e^{x_{ik} \chi_k} \right)$$
(13)

To find the critical point of the log-likelihood function, we first set derivatives with respect with respect to zero. By differentiating "(13)", note that,

$$\frac{\partial}{\partial \beta_k} \sum_{k=0}^{K} x_{ik} \beta_k = x_{ik}$$
(14)

Since the other terms in the summation from the "(14)" do not depend on β_k , they can thus be treated as constants. In differentiating the second half of "(13)", we take note of the general rule that $\frac{\partial}{\partial x} = \frac{1}{2} \cdot \frac{\partial y}{\partial x}$ Thus by differentiating "(13)" with respect to each parameter we obtain the following;

$$\frac{\partial \ell(\beta)}{\partial(\beta_{k})} = \sum_{i=1}^{N} y_{i}x_{ik} - n_{i} \cdot \frac{1}{\sum_{i=1}^{K} x_{ik}\beta_{k}} \cdot \frac{\partial}{\partial\beta_{k}} \left| 1 + e^{k=0} \right| \\ = \sum_{i=1}^{N} y_{i}x_{ik} - n_{i} \cdot \frac{1}{\sum_{i=1}^{K} x_{ik}\beta_{k}} \cdot \frac{\partial}{\partial\beta_{k}} \left| 1 + e^{k=0} \right| \\ = \sum y_{i}x_{ik} - n_{i} \cdot \frac{1}{\sum_{i=1}^{K} x_{ik}\beta_{k}} \cdot \frac{\partial}{\partial\beta_{k}} \left| \frac{\partial}{\partial\beta_{k}} \right| \\ = \sum y_{i}x_{ik} - n_{i} \cdot \frac{1}{\sum_{i=1}^{K} x_{ik}\beta_{k}} \cdot \frac{\partial}{\partial\beta_{k}} \left| \frac{\partial}{\partial\beta_{k}} \right| \\ = \sum y_{i}x_{ik} - n_{i} \cdot \frac{1}{\sum_{i=1}^{K} x_{ik}\beta_{k}} \cdot \frac{\partial}{\partial\beta_{k}} \left| \frac{\partial}{\partial\beta_{k}} \right| \\ = \sum y_{i}x_{ik} - n_{i} \cdot \frac{1}{\sum_{i=1}^{K} x_{ik}\beta_{k}} - \frac{\partial}{\partial\beta_{k}} \left| \frac{\partial}{\partial\beta_{k}} \right| \\ = \sum y_{i}x_{ik} - n_{i} \cdot \frac{\partial}{\partial\beta_{k}} \left| \frac{\partial}{\partial\beta_{k}} \right| \\ = \sum y_{i}x_{ik} - n_{i}\pi_{i}x_{ik} \quad (15)$$

The maximum likelihood estimates for β can therefore be found by setting each k+1 equations in "(15) above to zero and solve for each β_k .

2.3 Model Description

With regards to this paper, the dependent variable is maternal death which is binary (occurrence and non-occurrence of maternal death). The factors assumed to be contributing to maternal death or maternal mortality at the Komfo Anokye Teaching Hospital (KATH) are used as independent or explanatory variables. The dependent or response variable "maternal death or mortality" has two levels: 0 if the maternal

death occurs does not occur and 1 if maternal death occurs. For the explanatory variables used in the model, some were categorical and others were continuous. The explanatory variables used in the model includes age, educational level, residence status, marital status, parity, gravida and length of stay at the hospital. The logistic regression model therefore used is formulated as:

$$P(Occurrence of maternal death) = \pi(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} \quad (16)$$

And thus

$$P(Non - Occurrence) = 1 - \pi(x) = 1 - \frac{e^{g(x)}}{1 + e^{g(x)}} = \frac{1}{1 + e^{g(x)}}$$
(17)

Where g(x) represents the function of the independent variables also called the logit and given as:

$$g(x) = \beta_0 + \beta_1 AGE + \beta_2 EDULEVEL + \beta_3 RESITATUS + \beta_{41} PARITY + \beta_5 GRAVIDA + \beta_6 LENGTHSTAY + \beta_7 MARISTATUS$$
(18)

Where AGE is the age of pregnant woman, EDULEVEL is the educational level, RESISTATUS represents the residential status, PARITY is the number of times a woman have given birth to a fetus with a gestational age of 24 weeks or more, GRAVIDA represents the number of times that a woman has been pregnant and LENGTHSTAY denotes the length of stay at the hospital and MARISTATUS denotes the marital status of pregnant woman. The Logistic regression model determines the explanatory variables that makes the response variable (occurrence or non-occurrence of maternal death) most likely to be predicted using the maximum likelihood technique. Stepwise selection process of the logistic regression model is followed in this study. The goal of this process is to remove any insignificant explanatory variable or factors from the model base on the Wald statistic or the probability value procedure. The SAS 9.1 has built in routines for this procedure.

2.4 Hypothesis for assessing the statistical significance of the Logistic regression model

This paper is aimed at testing the statistical significance of the model using the hypothesis below at 0.05 level of significance.

 H_{\circ} : There exist no significant relationship between maternal death and the factors such as age, educational level, residence status, marital status, gravida, parity and length of stay at the hospital.

 H_1 : There exist significant relationship between maternal death and the factors such as age, educational level, residence status, marital status, gravida, parity and length of stay at the hospital The above hypothesis is stated mathematically as:

$$H_O: \beta_i = 0$$
 and
 $H_1: \beta_i \neq 0$ for at least one

3 RESULTS AND DISCUSSIONS

A review of the maternal mortality data revealed that, a total of 1,015 maternal deaths occurred at the Komfo Anokye Teaching Hospital during the study period (2007-2012). The table below therefore reveals the age distribution with respect

to maternal death that occurred from 2007 to 2012 at the Komfo Anokye Teaching Hospital.

 Table 1

 Age Distribution of Maternal Deaths at KATH from 2007

 2012

20,2					
Maternal Deaths	Percent				
97	9.6				
146	14.4				
191	18.8				
195	19.2				
155	15.3				
232	22.9				
1015	100.0				
	Maternal Deaths 97 146 191 195 155 232 1015				

The frequency distribution table reveals that, the age group 40 and above years recorded the highest number of maternal deaths representing 22.9% followed by 30-34 years age group which recorded 195 maternal deaths representing 19.2% whilst those within the age group 14-19 years recorded the least number of deaths (maternal deaths) representing only 9.6% of the entire population used in the study. Those within the age group 25-29 years also recorded 191 maternal deaths representing 18.8% of the total number of maternal deaths whilst 155 pregnant women died within the age group 35-39 years representing 15.3%. The remaining 146 pregnant women who died from the period 2007-2012 were also within the age group 20-24 years. This as result gives the indication that the occurrence of maternal death increases with increasing age.

3.1 Variables Eligible for entry in the Maternal Death model

Table 2
Analysis of Variables Eligible for entry into the Logistic
regression model

Variable	Degree of freedom	Score Chi- square	Pr>Chi-Square
RESISTATUS	1	0.3635	0.5466
EDULEVEL	1	0.08808	0.7763
MARISTATUS	1	9.4368	0.0021
LENGTHSTAY	1	0.2194	0.6395
PARITY	1	0.3804	0.5374
GRAVDA	1	12.3861	0.0004
AGE	1	19.7398	<0.0001

The table 2 above shows the effects (contributing factors) or explanatory variables eligible for entry into the model. This table contains the factors assumed to maternal death (occurrence or non-occurrence) at Komfo Anokye Teaching Hospital. The factors that are significant are identified based on the p-value, which reflects in the significance of the independent variables. A level of significance of 0.05 and 0.10 were required allow a variable to enter into the model. This process is called step wise selection criterion. In this process of stepwise selection, an attempt was made to remove any insignificant variable from the model before adding a significant variable to the model. Each addition or selection to or from the model was listed as a separate step. In step one of the analysis with the help of the stepwise selection, the variable AGE was selected into the model because it was observed as the most significant variable among the variables to be chosen since the p-value (<0.0001) is less than 0.05. In step two (2) the effect GRAVIDA was added to the model. Both AGE and GRAVIDA remained statistically significant at a level of significance of 0.10, hence neither AGE nor GRAVIDA was removed from the model. The variable PARITY was also added to the model in the final stage of the step selection process. The resulting model then contains AGE, GRAVIDA, and PARITY. Finally none of the remaining variables (RESISTATUS, EDULEVEL, LENGTHSTAY and MARISTATUS) met the entry criterion and stepwise selection process is terminated.

3.2 Summary of Stepwise Selection

Table 3Summary of Stepwise Selection

Effect entered	Effect removed	DF	Number In	Score Chi- square	Pr>Chi- square
AGE		1	1	0.3635	0.5466
GRAVIDA		1	2	0.0808	0.7763
PARITY		1	3	9.4368	0.0021

Table 3 shows the effects or variables that entered into the model and the effects that were removed base on the stepwise selection procedure. The table reveals that out of the seven (7) variables that were used as factors contributing to the occurrence of maternal mortality only three (3) variables including AGE, GRAVIDA and PARITY entered into the model with none of them being removed. These effects or variables remained significant at 0.10 level of significance.

3.3 Parameter Estimates

 Table 4

 Logistics Regression output for Parameter Estimates of Contributing Factors

Variable	DF	Estimat	Odds	Std.	Wald	P-
		es	Ratio	Error	Chi-	value
			Estimates		square	
Intercept	1	-0.3439	0.7080	1.4125	0.0593	0.8077
AGE	1	0.7265	2.0678	0.2946	6.0808	0.0137
GRAVIDA	1	0.9994	2.7167	0.5105	3.8324	0.0403
PARITY	1	1.7276	5.6271	0.5683	9.2407	0.0024

The table 4 above provides the output of the parameter estimates of the three (3) factors contributing significantly to the prediction of the occurrence of maternal death at KATH. From the table the odds ratio estimates for the three (3) variables, their corresponding regression coefficients, the Wald test statistic which follows the Chi-square distribution and their respective p-values were obtained. The odds ratio for the effect AGE was given from the table 4 as 2.0678 which gives

the indication that the ages of pregnant women are found to be 2.0678 times more likely to predict the occurrences of maternal death than non-occurrences. GRAVIDA on the other hand had an odds ratio estimate of 2.7167 which indicates GRAVIDA is 2.7167 times more likely to cause the occurrence of maternal death at KATH than non-occurrence. This as a result means that, the number of times a woman conceives. the number of miscarriages as a result of pregnancy and other factors contributes greatly to the various maternal deaths being recorded at the Komfo Anokye Teaching Hospital for the past five years period under study. Similarly, the variable PARITY which constitutes the number of birth was observed to be one of the most contributing factors in determining the occurrences of maternal death since it was found to be 5.6271 times more likely to cause maternal death than nonoccurrence in the research area. Generally, the table reveals that maternal mortality (maternal death) is affected by unmeasured factors (i.e. AGE, PARITY, and GRAVIDA) since their respective p-values are less than 0.05 meaning they all provide significant contribution to the estimation of the prevalence rate of maternal death. Hence the contributing factors found to have serious impact on the occurrence maternal mortality are AGE, PARITY and GRAVIDA. These variables therefore contribute significantly to the model at 0.05 level of significance. Therefore the Logistic regression model (logit) developed is given as:

$$g(x) = -0.3439 + 0.7265(AGE) + 0.994(GRAVIDA) + 1.7276(PARITY)$$
 (19)

Thus;

$$\pi(y) = \frac{e^{-0.3439 + 0.7265(AGE) + 0.994(GRAVIDA) + 1.7276(PARITY)}}{1 + e^{-0.3439 + 0.7265(AGE) + 0.994(GRAVIDA) + 1.7276(PARITY)}}$$
(20)

Which indicates the likelihood of a pregnant woman on admission at KATH dying or surviving base on the contributing factors. In summary, the table 4 indicates that, factors such as AGE (p-value0.0137), GRAVIDA (p-value=0.0403) and PARITY (p-value=0.0024) contribute significantly to the occurrence of maternal mortality at Komfo Anokye Teaching Hospital with PARITY being the most significant contributing factor, followed by AGE and then GRAVIDA.

3.4 Model Diagnostics

This section discusses the various approaches used in checking the adequacy of the logistic regression model. Both table 5 and 6 below were used in testing the overall fitness of the model under study. From table 5 below, it was deduced that the values of the various selection criterions that is AIC, SC and -2logL under the column "intercept and covariates" that is 60.614, 79.035 and 60.614 respectively are less than the respective values of the AIC, SC and -2logL under the column labelled "intercept only" that is 96.279, 98.884 and 94.279 respectively. This therefore indicates that, the model developed statistically best fit more than an empty model (model including the intercept only). This is due to the fact that, the smaller the values of the various selection criterion used (AIC, SC and -2logL) the better the model. Also from table 6. all the statistical test (Likelihood ratio test, Score and Wald test) used in testing the efficiency of the model developed in this paper proofed to be statistically significant since their respective p-values were all less than the level of significance 0.05 indicating that the model developed (Logistic regression model) as whole significantly fits well or better than an empty model which as a result leads to the rejection of the null hypothesis. This therefore brings out the implication that, there exist a statistically significant relationship between maternal death and the factors that contributes to the occurrences of maternal death.

Table 5Model Fit Statistic

Selection Criterion	Intercept only	Intercept and covariates
AIC	96.279	68.614
SC	98.884	79.035
-2logL	94.279	60.614

Table 6

Testing Global Null Hypothesis, BETA=0

Test		Degree of	Pr>Chi-
Test	Chi-square	freedom	square
Likelihood Ratio	33.6643	3	<.0001
Score	30.8952	3	<.0001
Wald	19.4268	3	0.0002

4 CONCLUSION

A logistic regression model was used to develop a model in this paper. The analysis gives a confirmation at 0.05 level of significance. The result in this research work revealed that, the model provided a reasonable statistical fit. Using the concept of p-value together with Wald-statistic, the study variables were subjected to significance testing. Only three (3) factors or variables namely, AGE, PARITY and GRAVIDA were statistically significant out of the seven (7) factors or variables assumed to be contributing to the occurrence of maternal mortality. PARITY was found to be the greatest factor that contributes significantly to the occurrence of maternal mortality (p-value=0.0024<0.05, Wald Chi-square=9.2407) followed by AGE (p-value=0.0137<0.05, Wald Chi-square=6.0808) and then GRAVIDA (p-value=0.0403<0.05, Wald Chisquare=3.8324)

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