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Application of Survival Analysis of Pregnancy women and related post-delivery using Logistic Model Approach.

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ABSTACT

Maternal mortality has been described as one of the foremost and most neglected health problems and human rights abused in the world. It is defined as the probability or percentage of mothers dying as a result of pregnancy related complications or post-delivery complications every year. About 830 women die from pregnancy or child related complications around the world. This research project is aimed at monitoring the delivery process performance and studying the factors that influence its outcome. A total number of two thousand nine hundred and ninety six (2,996) cases out of which eleven thousand and eighty two (11,082) cases were delivered at Caesarean and Spontaneous Vaginal Delivery sections were used in this research. The Cumulative Sum (CUSUM) control chart scheme is used for monitoring while the logistic regression model is fitted to determine the factors contributing to maternal death using Mother Child Hospital, Akure as a case study. Backward variable elimination procedure was used to generate a reduced form of the model that contains only the significant variables at a respectable alpha-value, 0.05. The result from the CUSUM chart shows that all the plotted points are within the control limit and this suggests that the delivery processes have improved over time. The result from the binary logistic regression shows that out of nine factors that were investigated in this research, parity, period of labour (measured in hours), previous caesarean section and length of baby are statistically significant and might influence the delivery process of a pregnant woman. The relationship between the selected risk factors and maternal survival status was then carried out through interpretation of odds ratios from logistic regression. The result of Hosmer-Lemeshow goodness of fit also suggested that the fitted model can be used to predict the outcome of a delivery process of a pregnant woman.

Keywords: CUSUM Chart, Logistic regression model, Post-delivery, Pregnancy women, Survival status

1.0 INTRODUCTION

Pregnancy and childbirth are physiological events that should bring joy to the woman, the family and the society at large, but sometimes it turns out to be a source of sorrow. For some women in certain parts of the globe, particularly in developing countries, the reality of motherhood is often grim. This is due to the fact that motherhood may be marred by unforeseen complications or even loss of lives. Some women lose the fetus even before being born or shortly after birth; whiles some others lose both their lives and the lives of their babies. Maternal processes in Africa are prone to crises as a result of multiple socio-economic and religious factors which interact with biological factors. A combination of cultural beliefs and practices, male-dominance, low status of women and high fertility affect pregnancy outcomes in the continent, especially in sub-Saharan Africa (Senah, 2003; AbouZahr, 2007; Nwokocha 2007).
Maternal mortality refers to the death of a woman from any cause related to or aggravated by pregnancy or its management (excluding accidental or incidental causes) during pregnancy and childbirth or within 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy (WHO). According to the recent global estimates by World Health Organization (WHO), the United Nation Children's Fund (UNICEF) and the World Bank, close to six hundred thousand women die annually from pregnancy-related complications, ninety-nine percent of which occur in less developed world. This situation makes maternal mortality the health indicator that shows the largest disparity between the developed and developing countries. In sub-Saharan Africa, one out of every 13 women dies of pregnancy-related causes during their lifetime as with one in 4,085 women in industrialized countries (McAlister *et al;* 2006). In Ghana one in 45 women has a risk of dying from pregnancy-related causes in her lifetime (WHO, UNICEF and World Bank, 2008). It is therefore evident that developing countries continue to bear the larger portion of pregnancy-related deaths. It is also recognized that access to skilled delivery care of good quality will contribute to reducing maternal and prenatal mortality and morbidity. The importance of this situation is reflected in the Sustainability Development Goal (SDG) 3 aimed at reducing maternal mortality ratios to 75 per 100,000 by the year 2030. In Nigeria, maternal mortality ratio is estimated to range from 214 to 700 per 100,000 live births. These figures have persisted for some time despite various policies and initiatives including an Antenatal Care policy and the Safe Motherhood initiative African (2006).

The main objective of this research paper is to monitor the performance of maternal delivery process and also fit the appropriate logistic regression model on factors that influence the outcome of deliveries

2.0 LITERATURE REVIEW

The literature deals with the collection of other relevant research works that will provide bases for present research the collection, collation and coordination of related literature are of paramount importance in every study. Review of related literatures in statistical research is sometimes very elaborate and very necessary due to its vast areas of applications.

Maternal mortality is defined as the death of a woman while pregnant or within 42 days of termination of pregnancy, irrespective of the duration of the pregnancy, from any cause related to or aggravated by the pregnancy or its management WHO (1986).

Olanrewaju (2013), he stated that Nigeria high maternal mortality rate is second only to that of China adding that the country held the record as Africa's highest contributor to MMR; also the CIA World Fact Book (2013) puts MMR in the country at 630 per 100,000 live births.

Agan et al. (2010) did a study titled "Trends in maternal mortality at the University Teaching Hospital, Nigeria 1999 - 2009". They sought to assess trends in maternal mortality in a tertiary health facility, the maternal mortality ratio, the impact of socio-demographic factors in the deaths, and common medical and social causes of these deaths at the hospital. The study was a retrospective review of obstetric service delivery records of all maternal deaths over an 11-yearperiod (01 January 1999 to 31 December 2009).

Fern´andez et al. (2008), published a research report titled ”Increase in maternal mortality associated with change in the reproductive pattern in Spain: 1996-2005”. Their study aimed at analyzing the age-related trend in the maternal mortality ratio among mothers in Spain for the decade 1996-2005, and to describe the causes of death and associated socio-demographic factors for the years with highest mortality.

Sullivan et al. (2003), published the report of their study titled “Maternal-fetal medicine specialist density is inversely associated with maternal mortality ratios” in the American Journal of obstetric and Gynecol. Their objective was to determine the relationship between state-specific maternal mortality ratios and the density of maternal-fetal medicine specialists. State maternal mortality ratios from 1994 to 2001 were calculated from the Centers for Disease Control and Prevention WONDER database.

3.0 Research Methodology

This section describes the statistical tools used to meet the study objectives. The principles of the cumulative Sum (CUSUM) Chart and Logistic regression model techniques are discussed

3.1 The Cumulative Sum (CUSUM) Chart

CUSUM chart is a time-weighted control chart that displays the cumulative sums (CUSUMs) of the deviations of each sample value from the target value. In view of the fact that it is cumulative, minor drifting in the process mean lead to steadily increasing or decreasing cumulative deviation values. This chart is especially useful in detecting small shifts away from the target. CUSUM chart is based on sequential monitoring of a cumulative performance measure over time. With several developments and adaptations, it has emerged as a suitable method for monitoring healthcare outcomes value, Wohl(1977). If a trend develops upward or downward, it indicates that the process mean has shifted, and special causes should be looked for the plot points can either be subgroups or individual observations. When data are in subgroups, the mean of all the observations in each subgroup is calculated and used. CUSUM statistics for individual are calculated using the individual observations.

CUSUM chart is used to monitor the mean of a process based on samples taken from the process at given times (hours, shifts, days, weeks, months, etc.). For subgroups, the measurements of the samples at a given times constitute a subgroups. Rather than examining the mean of each subgroup independently, the CUSUM chart shows the accumulation of information of current and previous samples. For this reason CUSUM chart is generally better than the X-bar chart for detecting small shifts in the mean of a process.

3.1.1 Design Method

For counted data CUSUM, the parameters to be determined are the target value for the process, denoted by *k*, and the decision interval, denoted by *h*. The value of *k* can be described as the goal value of the process which is usually chosen between the acceptable process mean values, μa and the mean that the CUSUM scheme should detect quickly, μd, otherwise known as the barely tolerable mean value.

Kemp (1962) gave the expression for determining k as

$$k = \mu_a + \frac{1}{2}\Delta \qquad 3.1$$

Where Δ is the deviation from the acceptable process. Lucas *et al*, (1982) also recommended that the value of k be $\frac{1}{2}\Delta$ for a scheme designed to detect a specific mean shift of Δ, and it should also be chosen close to

$$k = \frac{\mu_d - \mu_a}{ln\mu_d - ln\mu_a} \qquad 3.2$$

Montgomery (2005) recommended that a reasonable value for h is five times the process standard deviation σ, which gives a good in-control ARL value for the data, and so $h = 5\sigma$

3.2 Logistic Regression Model

Logistic regression measures the relationship between a categorical dependent variable and one or more independent variables which are usually continuous (but not necessarily), by converting the dependent variable to probability scores. Logistic regression model is mainly used to identify the relationship between two or more explanatory variables (Cox and Snell, 1994). Logistic regression model can be binomial or multinomial. Binomial or binary regression refer to the instance in which the observed outcome can have only two possible outcomes (e.g., "dead" vs "alive", "success" vs "failure", or "yes" vs "no"). Generally, the outcome is coded "0" and "1" as it leads to the most straight forward interpretation. Logistic regression is used to predict the odds of being a success based on the predictor(s). Like other forms of regression analysis, logistic regression makes use of one or more predictor variables that may be either continuous or categorical.

3.2.1 The Logistic Regression Equation

The Logistic regression model for the dependence of pi (response probability) on the values of k explanatory variables is given below,

$$P_i = \frac{\exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k)}{1 + \exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k)} \qquad 3.3$$

Where P_i is the expected probability that the outcome is present; X_i through X_k are distinct independent variables and β0throughβk are the regression coefficients?

$\left(\frac{P}{1-P}\right)$ is the ratio of the probability of a failure and is called odds,

The odds in favour of success is written as

$$\left(\frac{P}{1-P}\right) = \frac{\exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k) \Big/ 1 + \exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k)}{1 \Big/ \exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k)}$$

$$\frac{P}{1-P} = \exp\left(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k\right) \qquad 3.4$$

Taking the natural logarithms of each side of this equation;

$$ln\left(\frac{P}{1-P}\right) = ln\left(\exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k)\right) = (\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k)$$

Hence

$$Logit(P_i) = Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_k \qquad 3.5$$

4.0 Result and Discussion

4.1 Monitoring the Performance of the Maternal Delivery Process Using CUSUM Chart
4.1.1 Determination of the CUSUM Parameters (h, k)
The acceptance mean level μ_a is chosen nearer to the current mean level, following Lucas(1985). Thus the mean level = 6.2778, and $\mu_a \approx 6$. From the data, the standard deviation, $\sigma = 3.32904$ Suppose a shift of 1σ is chosen from μ_a to be a reject able level, then a shift of 1 σ in the positive direction gives
$\mu_d \approx 9$.
$k = \mu_d - \mu_a ln\mu_a - ln\mu_a = 9 - 6ln9 - ln6 = 7.3989 \approx 7$
$h = 5\sigma, Montgometry$ (2005)
$h = 5 * 3.32904 = 16.64525 \approx 17$

Fig. 1: CUSUM chart for patient that died during child birth (2014 to 2016) **Fig. 1: CUSUM chart for patient that died during child birth (2014 to 2016)**
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Fig. 1 above shows the CUSUM chart for the women that died during child birth between 2014 and
2016 in order to monitor the delivery process performance. The result shows that all the plotted points are within the control limit and this suggest that the delivery processes have improved over
time.
4.2 Modeling the outcome of the mother during child birth
A direct binary logistic regression modeling was carried out to assess the impact of the independent variables on the likelihood of a pregnant woman at Mother and Child Hospital dying during child birth. The response variable is the outcome of pregnancy, the outcome and delivery types are categorical variables and their categories are as follows;

$$outcome = \begin{cases} 1, & if\ patient\ dies \\ 0, & if\ otherwise \end{cases}$$

$$Delivery\ type = \begin{cases} 1, & if\ caesarean\ surgery \\ 0, & if\ spontaneous\ vaginal\ delivery \end{cases}$$

Model to be fitted

$$Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9$$

$X_1 = Age,\quad X_2 = Parity,\quad X_3 = Period\ of\ labour,\quad X_4 = Prevous\ CS,$
$X_5 = Estimated\ blood\ labour,$
$X_6 = Weight\ of\ body,\quad X_7 = Head\ circumference\ of\ the\ baby,$
$X_8 = length\ of\ baby,\quad X_9 = mode\ of\ delivery$

4.2.1 Fitting the Logistic Model

In this study, predictions and evaluation of models are mainly based only on the function of the significant predictor variables. The backward elimination selection procedure was applied at 5%level of significance, to arrive at the final risk model. After six backward elimination processes, four statistically significant ratios were retained in the model. The result in table 1 below indicates that parity, period of labour (measured in hours), previous caesarean section and length of baby are statistically significant and were retained in the model. The result is presented in the table below**.**

Table 1: Table showing the parameter estimates for delivery processes

Variables	B	S.E	Df	Sig.	Exp (B)
X_2	**0.142**	**0.039**	**1**	**0.000**	**0.753**
X_3	**0.002**	**0.001**	**1**	**0.003**	**1.002**
X_4	**0.002**	**0.000**	**1**	**0.000**	**1.002**
X_8	**-0.214**	**0.098**	**1**	**0.028**	**1.807**
constant	**-5.424**	**0.253**	**1**	**0.000**	**0.004**

The coefficient estimate of the logit model is traditionally interpreted using the odds ratio, and is provided in the exp(β) column. The odd ratio of 0.753 of parity is an indication that women with high parity are 0.753 less like to experience the event than those with low parity. Also women who spend more time laboring are 1.003 times more likely to experience the event than those who spend lesser time. An odd ratio of 1.002 is an indication that women who have had one or more previous caesarean sections are

1.002 times more likely to experience the event than those who have no record of previous caesarean section. Also the length of the baby is 1.807 times more likely to experience the event when all other variables are kept constant.

The logistic regression model is obtained as follows:

$$P = \frac{exp(\beta_0 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_8 X_8)}{1 + exp(\beta_0 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_8 X_8)}$$

Where, $\hat{\beta} = -5.424, \quad \hat{\beta}_2 = 0.142, \ \hat{\beta}_3 = 0.002, \ \hat{\beta}_4 = 0.002, \ \hat{\beta}_8 = -0.214$

$$\hat{p} = \frac{exp(-5.424 + 0.142 * X_2 + 0.002 * X_3 + 0.002 * X_4 - 0.214 * X_8}{1 + exp(-5.424 + 0.142 * X_2 + 0.002 * X_3 + 0.002 * X_4 - 0.214 * X_8}$$

Alternatively:

$$ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{\beta}_0 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \hat{\beta}_4 X_4 + \hat{\beta}_8 X_8$$

$$ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = -5.424 + 0.142 * X_2 + 0.002 * X_3 + 0.002 * X_4 - 0.214 * X_8$$

4.2.2 Testing the appropriateness of the Fitted Model

The Hosmer-Lemeshow's goodness of fit test is used to test the significance of the fitted model

Table 2: Table showing the result of Hosmer-Lemeshow Test

	Chi-square	Df	Sig.
	32.118	8	0.374

Table 2 above gives the result of Hosmer-Lemeshow (H-L) test. The statistic under consideration has a significance value of 0.374 which is greater than 0.05. This means that it is not statistically significant and we conclude that the model is a good fit.

5.0 Summary of findings and Conclusion

5.1 Summary of findings

The CUSUM chart was plotted on the number of women that died to monitor the performance of delivery process. The result shows that all the plotted points are within the control limit and this suggests that the delivery processes have improved over time.

The result from the binary logistic regression shows that out of nine factors (age, parity, period of labour, previous caesarean section, estimated blood loss, weight of baby, head circumference of the baby, length of baby and mode of delivery) that were investigated in this research that might have influence on the outcome of a mother during delivery process, parity, period of labour (measured in hours), previous caesarean section and length of baby are statistically significant.

The result of Hosmer-Lemeshow goodness of fit suggests that the fitted model can be used to predict the outcome of a delivery process of a pregnant woman.

5.2 Conclusion

The result from the CUSUM chart shows that all the plotted points are within the control limit and this suggests that the delivery processes have improved over time.

The result from the analysis shows parity, period of labour (measured in hours), previous caesarean section, and length of baby are statistically significant variables that influence the death of patients during delivery.

5.3 Recommendations
In the light of the above result,
(i) Unnecessary delay of attention from the side of the medical personnel to patients in labour should be highly discouraged.
(ii) Women who have had up to three prior caesarean deliveries should be offered proper counseling by a senior obstetrician to be aware of serious maternal complications which is as a result of increased number of CSs. (iii) Vaginal Birth after Caesarean Section (VBAC) is an option that should be recommended to patients.
(iv) Hospital management should ensure that records on the level of pre-operative risk of each patent are properly documented for proper evaluation of performance.
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