

**APPLICATION OF LOGISTIC
REGRESSION MODEL TO DETERMINE
FACTORS CAUSING MATERNAL
MORTALITY: A CASE STUDY OF
MIGORI COUNTY REFERRAL
HOSPITAL (2007-2015)**

by

**OLWALO, MUSA OKECH
MSC/MAT/6002/2013**

A project report submitted in partial fulfilment
of the requirements for the degree of
Master of Science in Applied Statistics

in the

**School of Mathematics, Statistics and Actuarial Science
MASENO UNIVERSITY
Maseno**

December, 2017.

Copyright © 2017
Maseno University
All Rights Reserved

DECLARATION

This project report is my own work and has not been presented for a degree award in any other institution.

OLWALO, MUSA OKECH
MSC/MAT/6002/2013

This project report has been submitted for examination with my approval as the university supervisor.

Prof. Fredrick Onyango, Supervisor

Maseno University

2017

*This work is dedicated to my late parents Valentine Olwalo and Mary
Aoko Nyakaracham. ...*

.....

.....

ACKNOWLEDGMENTS

I would like to acknowledge the invaluable support from my supervisor Prof Fredrick Onyango who was very dependable; he offered direction, suggestion and encouragement during the entire period of study I would also like to give much thanks to our librarians in Homa-Bay Campus and Kisumu City campus for their assistance during my course work. I am also grateful to Mr. Keya Fredrick Okoth in charge of the Health Records Department at the Migori County Referral hospital, he availed all the available maternity registers during the collection of data. I appreciate my course mates Jacob Mageto, ReniceBunde, Samuel Ochieng Otiende and others for their constant encouragement and reminder that we must graduate this year. Lastly I would like to thank our almighty God our father who has kept us strong and has brought us this far.

ABSTRACT

Kenya is one of the major contributors to the poor maternal health status in Africa with maternal mortality ratio of 488 maternal deaths per 100,000 live births translating to 7,700 maternal deaths annually [23]. There are regional disparities in maternal mortality among the 47 counties with county with the highest maternal mortality has almost 20 times maternal deaths of that with the lowest. Migori County is one of the counties with the highest burden of maternal mortality in the country with maternal mortality ratio of 673 per 100, 000 live births [23]. In Migori County there is the problem of inability to ascertain the leading causes of these deaths in the hospital as well as increment or otherwise of recorded deaths, there is very little information available on causes of maternal mortality. There is general lack of functioning vital registration systems where births and deaths go unrecorded especially when they take place at home. Thus we are only left to get estimates from a wide variety of sources such as prior census, prior national or regional surveys. To fill this gap a study was done to determine specific causes of maternal mortality using Logistic Regression Model technique on the data from Migori County Referral Hospital from the year 2007 to the year 2015. In this study we found out that out of possible 11 causes of maternal mortality, AGE and ANC were the only significance contributors to maternal mortality in this county. ANC was found to be the most significant contributing factor to occurrence of maternal death with p value of $0.011 < 0.05$ followed by AGE of p value $0.036 < 0.05$. The study recommends that state ministry of education; county government and other partners should start sex education in our schools to avert unwanted pregnancies among the

students who are the majority in unmarried groups. The government should encourage ANC among expected mothers in Migori County.

Contents

| | | |
|----------|---|-----------|
| 1 | Introduction | 2 |
| 1.1 | Introduction | 2 |
| 1.2 | Background of the Study | 2 |
| 1.3 | Basic Concepts | 11 |
| 1.4 | Statement of the problem | 12 |
| 1.5 | Objective of the Study | 13 |
| 1.5.1 | General objective of the Study | 13 |
| 1.5.2 | Specific objective of the Study | 13 |
| 1.6 | Significance of the study | 13 |
| 2 | Literature Review | 15 |
| 2.1 | Other applications of Logistic Regression | 29 |
| 3 | Research Methodology | 36 |
| 3.1 | Introduction | 36 |
| 3.2 | Logistic Regression Model | 36 |
| 3.3 | The Model Description | 37 |
| 3.4 | Simple Logistic regression Model | 39 |
| 3.4.1 | Odds in Logistic Regression | 39 |
| 3.4.2 | Odds Ratio in Logistic Regression Model | 41 |
| 3.5 | Estimation of Logistic Regression Using Maximum Likelihood Estimation | 41 |
| 3.6 | Logistic Regression Model Evaluation | 46 |
| 3.6.1 | Likelihood Ratio Test | 46 |

| | | |
|----------|--|-----------|
| 3.6.2 | Hosmer and Lemeshow test | 48 |
| 3.6.3 | Wald Statistic | 49 |
| 4 | Results and Discussion | 50 |
| 4.1 | Introduction | 50 |
| 4.2 | Preliminary analysis | 50 |
| 4.3 | Categorical Variables | 52 |
| 4.4 | Parameter Estimates | 59 |
| 4.5 | Model Evaluation | 61 |
| 4.6 | Discussion of Results | 64 |
| 5 | Conclusions and Recommendations | 66 |
| 5.1 | Introduction | 66 |
| 5.2 | Conclusions | 66 |
| 5.3 | Recommendations | 67 |

List of Figures

Index of Notations

List of Tables

| | | |
|------|--|----|
| 4.1 | Number of Maternal deaths, Number of Live Births and the maternal mortality ratios | 51 |
| 4.2 | Case Processing Summary Table | 51 |
| 4.3 | Dependent Variable Encoding | 52 |
| 4.4 | Categorical Variable Coding | 53 |
| 4.5 | Result with only the constant included before any coefficient relating to predictor variables. | 53 |
| 4.6 | Variable not in the Equation. | 54 |
| 4.7 | Variables in the Equation | 55 |
| 4.8 | Block 1 Method : Classification table | 56 |
| 4.9 | Model Chi- Square | 57 |
| 4.10 | Model Summary | 58 |
| 4.11 | Logistics Regression output for Parameters Estimates of contributing factors | 59 |
| 4.12 | Hosmer and Lemeshow Test | 62 |
| 4.13 | Classification table | 63 |

Chapter 1

Introduction

1.1 Introduction

This study sought to determine the significant causes of maternal mortality at Migori County referral Hospital (MCRH) from the year 2007 to the year 2015 using logistic regression model. This section of the report included the background information of the study, statement of the problem, objective of the study, significance of the study and the basic concepts.

1.2 Background of the Study

The persistent high maternal mortality has for many years been a neglected tragedy, as pointed out by Rosenfield and Maine [40] in their thought provoking article titled Maternal Mortality neglected tragedy where is M in MCH[41]. Another crusade against the high maternal mortality was highlighted by WHO and other groups in 1987 when they

launched the safe motherhood initiative a global campaign to raise awareness among policymakers about maternal mortality. However, maternal mortality did not decrease significantly over the subsequent decade, a shortfall attributed to the initiatives lack of strategic focus and actionable agenda and goals [31]. Before this international conference there was WHO publication about maternal mortality titled *Maternal Mortality, helping women off the road of death* [49].

Several years later, in 1992 a landmark publication by McCarthy and Maine [25] provided a framework for examining the causes of maternal mortality and highlighted the three target events that must occur before a maternal death can result: (1) a conception; (2) a serious complication of pregnancy; (3) an adverse outcome of that complication, with or without treatment. Perhaps not surprisingly, the authors analysis found that societies with the lowest levels of maternal mortality had achieved this result "preventing pregnancies, by reducing the incidence of certain complications, and by having adequate facilities and well-trained staff to treat the complications" [31].

In 1990 there was a world summit for children who declared a goal of reducing maternal mortality of 1990 by half by the year 2000; this was followed by the 1994 Cairo International Conference on Population and Development which again heralded the need to reduce the 1990 maternal mortalities by half by the year 2000. Increasing attention has been paid to maternal mortality trends in developing countries especially in the context of United Nations Millennium Declaration in 2000 in which world leaders came together at the United Nations to establish the global Millennium Development Goals (MDGs) - eight times bound targets for

meeting the needs of the worlds poorest people, with deadline of 2015. MDG 5 is to improve maternal health with a target for each country to achieve a 75percent reduction in maternal mortality, relative to their 1990 levels and more recently, a second target to achieve universal reproductive health was added to the fifth MDG [29]. Despite the fact that 189 countries have signed the Millennium Declaration, a United Nations progress report from 2008 stated that Maternal mortality has remained unacceptably high across much of the developing world, constituting the area of least progress among all MDGs [51]. Moreover, with a few notable exceptions, little progress has been reported in the global decline of maternal mortality over the past decade [2].

In 1998 Safe Motherhood was the slogan for the World Health Day. After seven years later, the progress was still slow, and on the World Health Day 7th April 2005, in New Delhi, the topic was again the same. The World Health Report 2005, entitled Make every mother and child count [50] was then launched, and the WHO Director General Lee Jong- Wook stated: *"More than six million children could be saved if they have simple health care and thousands of women could be saved if they had access to skilled care. The millennium goals for health are attainable; our message today is that of hope"* [50]. To this end many high level stakeholders endorsed a Delhi declaration on maternal, newborn and child health. The declaration describes several concrete actions that are urgently needed for improvement of maternal and child care to take place within 2007. The declaration proposed development of national targets and plans of actions and the mobilizing of resources for necessary coverage of care, to meet the shortages of skilled personnel and for developing systems for monitoring

progress. It was however, sad to see that international initiatives were slow to produce concrete results in reducing the maternal mortality especially in low- income countries one possible reason may be that the Safe Motherhood Initiative when it was launched in 1987 was too broad [46].

Globally, the estimated number of maternal deaths worldwide in 2005 was 536,000 up from 529,000 in the year 2000 [28]. According to WHO [50], 500, 000 women die from complications of pregnancy and childbirth, and more than 99percent of these deaths occur in less developed regions. For each woman who dies of a pregnancy- related condition, it is estimated that 15-30 women suffer from serious damage and that in Sub-Saharan Africa alone, between 50,000 and 100,000 women each year develop fistulas canal that allow leakage of urine or faeces [46]. As a consequence, many of them become outcasts, rejected by their husbands and families.

Of all health statistics monitored, maternal mortality is the one showing the largest difference between developed and developing countries. Current estimates of maternal mortality ratios vary from more than 1000 per 100,000 live births in some of the African countries, to around 500 in many countries in Asia, 200-400 in several countries in South America and less than 10 per 100,000 live births in some European countries [50]. According to WHO [51] Factsheet, 1500 women die from pregnancy or pregnancy related complications every day. Most of these deaths occur in developing countries, and most are avoidable. Ujah [45] also noted that of all health statistics compiled by the World Health Organization, the largest discrepancy between developed and developing countries occurred in maternal mortality. He went further and noted that 25percent of females of reproductive age lived in developed countries; they contributed

only 1percent to maternal deaths worldwide [45]. A total of 99percent of all maternal deaths according to Ujah as quoted by Mojekwu and Ibekwe [28] occur in developing countries and more than half of these deaths occur in Sub-Saharan Africa and one third in South Asia. The maternal mortality ratio in developing countries is 500 maternal deaths per 100,000 live births versus 9 in developed countries [28].

Globally about 80 percent of maternal deaths are due to four major causes severe bleeding, infections, hypertensive disorders in pregnancy (eclampsia), prolonged labor and obstructed labor, these are direct causes of maternal mortality and indirect causes include diseases that complicate pregnancy or are aggravated by pregnancy such as malaria, anemia, hepatitis, anesthetic death, meningitis, HIV/AIDS, sickle cell anemia and acute renal failure which could be a complication of eclampsia. Women also die because of poor health at conception and a lack of adequate care needed for the healthy outcome of the pregnancy for themselves and their babies (WHO Factsheet, 2008). Omoruyi [35] estimated that more than 70 percent of maternal deaths could be attributed to five major complications: hemorrhage, infection, unsafe abortion, hypertensive disease of pregnancy and obstructed labor. He further found out that poor access to and utilization of quality reproductive health services contribute significantly to the high maternal mortality level in developing countries. In Ghana, the government showed much commitment to addressing the challenges of maternal mortality, specifically the problem of low coverage of supervised deliveries and high institutional maternal mortality rate among others. Maternal Mortality was therefore declared a national emergency in 2008, (Ghana Millennium Development Goals report, 2010) and the

programme of free health care for pregnant women, including deliveries through the national Health insurance Scheme was implemented since July 2008. Their teaching and referral hospital Okomfo Anokye experienced the nationwide increase in supervised deliveries [41].

In some areas of East Africa, Kenya being a member, the lifetime risk of a maternal death reaches 1 in 11 in contrast to around 1 in 5000 in Sweden and Norway, representing an almost 500-fold difference [22]. According to the most recent UN consensus document covering years through 2010, of the 94 countries with highest maternal mortality ratios (> 100) in 1990, 10 have already reached their 2015 mortality reduction goals, and 9 additional countries were judged to be "on track" to reach their 2015 goals. Fifty other countries, including Kenya were unlikely to achieve their respective 2015 goals, were judged to be making progress. Of the remaining 25 countries, 14 were considered to have made insufficient progress and 11 others no progress at all [52] and [31]. And knowing this progresses, the maternal mortality must be measured using indicator, that is observable variables that tells whether we are making a decrease or not and the most obvious measure of maternal mortality as [31] puts it, is the actual number of maternal deaths that occur per year (or other specified period), estimated to be 287,000 by WHO [52]. Another commonly used indicator for mortality risk of each pregnancy in a specific population is the maternal mortality ratio (MMR), which is calculated by the number of maternal deaths per 100,000 live births, it is normally sometimes cited as proportion of all deaths of women 15-49 years old that are due to pregnancy- related causes. Another indicator is the maternal mortality rate that is the number of maternal deaths per 100,000 women

15-49 years old in the population, regardless of their pregnancy status. Another country specific indicator is the adult lifetime risk of maternal death, which is the chance of a current 15- year old woman dying of a pregnancy related cause before age 49, its calculation is based on the populations total fertility rate, which indicates the average lifetime number of pregnancies for each woman in the population, and the maternal mortality ratios which indicates the mortality risk for each pregnancy [31].

Nieburg [31] further argued that no matter which of these indicators is considered, the current global toll of avoidable pregnancy related deaths is staggering. And some of the data used to create these national and global maternal mortality estimates are collected from national vital registration systems that utilize formal death and birth certificates, as in the United States and many other countries. However, the vital registration systems of 115 of the 180 countries included in the 2012 UN maternal mortality report were either incomplete (N=88) or nonexistent (N=27), meaning that some or all of their national mortality and live birth estimates could not be obtained and/ or analyzed from death /or birth certificates. This means that data have gaps hence the estimate for each mortality indicator include an extremely a wide of uncertainty and the magnitude of these uncertainty ranges is itself an indicator of the major difficulties inherent in estimating and using maternal (or infant) mortality numbers in population that lack functioning vital registration systems like Kenya where births and deaths goes unrecorded especially when they take place at home, for such large gaps in death and birth certification data, the needed numbers have to be estimated by statistical modeling of indirect data obtained from a wide variety of sources such as a prior census, prior

national or regional surveys, and/ or various health facility records [52].

The Kenya Demographic Health Survey of 2014 found out that the proportion of mothers reporting antenatal care from health professional increased from 88percent to 96percent 2003 and 2014 respectively. The percentage of births attended by skilled health provider increased from 42percent in 2003 KDHS [11], 44percent in 2008-2009 KDHS [12], and 62percent in 2014 KDHS [13]. The percentage of births occurring in health facility also increased from 40percent in 2003 KDHS [11], 43percent in 2008-2009 KDHS [12] and 61percent in 2014 KDHS [13]. Finally the post-natal care in the first two days after birth also increased from 10percent in 2003 KDHS, 42percent in 2008-2009 KDHS [12] to 51percent in 2014 KDHS [13]. In general there is a general 20percent point increment from 2003-2014. The leading causes of these deaths are obstetric complications such as severe bleeding, obstructed labor, and infections and hypertension disorders of the pregnancy such as the eclampsia and preeclampsia. There are also indirect causes such as malaria, diabetes, anemia, HIV/AIDS, Hepatitis and one striking phenomenon is that all these causes are preventable.

Efforts has been made by the Government of the day indicating that the policies and programmes are working such as abolition of maternity charges in all public health facilities by the President of the republic of Kenya on June 1st, 2013 for expectant mothers and girls of reproductive age to deliver in health facilities with skilled birth attendant. There is also the beyond zero campaign launched by her Excellency the first lady Margaret Kenyatta, which is raising the consciousness of the entire nation about the plight of women and girls in need of care. The programme has

been distributing the mobile clinics fully equipped to provide emergency obstetric care services. The county government of Migori has also purchased ambulances to Migori County Referral Hospital and Sub-County hospitals to increase accessibility for obstetric services.

Despite these progresses, maternal mortality rate is still unacceptably high in Kenya with Migori County being one of the 15 counties with high burden of maternal deaths with estimated maternal mortality ratio of 673 per 100,000 live births [23]. This high maternal mortality ratio has been contributed to insufficient political commitment, low numbers of skilled healthcare providers and the inability to retain skilled birth attendants in most priority rural areas, inaccessible and impassable roads to deal with obstetric conditions in all places in the county especially rural areas, lack of skilled birth attendants in most of the health facilities. The ambulatory services available are not effective and efficient as most of the population cannot accessed them for referral network as they only respond when called by an officer from health facility but at a slow pace, they are not swift at an emergency and there is lack of essential drugs at the health facilities. The Kenyas target according to post 2015 agenda is to reduce maternal mortality ratio to 70 per 100,000 by the year 2030 (Sustainable Development Goals (SDG), 2015). This target according health professionals, is still hard to achieve given that there are no sufficient resources allocated to health in the country and to devolve units and there is no statistical evidence to justify a community intervention to be undertaken to reduce the maternal death in Migori County and Kenya at large.

According to United Nations Population Fund Agency (UNFPA) it is noted that there are disparities in maternal mortality between the 47

counties in Kenya with the county with highest maternal mortality has almost 20 times deaths of that with the lowest [23]. The agency went further and identified 15 counties with the highest maternal deaths and mortality ratio adding up to 98percent of the total, Migori County is one of them. The other counties are: - Mandera, Turkana, Wajir, Nairobi Nakuru, Siaya, Kisumu, Homa Bay, Kakamega, Marsabit, Lamu, GarisaTaita-Taveta and Isiolo. And according to Marleen Temmerman Director of reproductive Health at the World Health Organization (WHO), the drop in maternal mortality in Kenya over the last 23 years (1990-2013) is less than 1percent annually, which is lower than the 5.5 % as per the target in the Millennium Development Goal (MDG).

1.3 Basic Concepts

Definition 1.3.1 (Maternal mortality/Maternal death)

This is the death of a woman while pregnant or within 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management (WHO-ICD 10).

Definition 1.3.2 (Binary Logistic Regression)

This is a statistical tool that allows one to test models to predict categorical outcomes with two or more categories where the outcome of the response (dependent) variable is dichotomous which is the pregnant woman once admitted in the county referral hospital , died or discharged.

Definition 1.3.3 (Parity)

This is the number of times a woman has given birth to a fetus with

gestational age of 24 weeks or more.

Definition 1.3.4 (Gravida)

This is the number of times that a woman has been pregnant

Definition 1.3.5 (Puerperal sepsis)

This is a situation whereby a temperature of the woman is $38^{\circ}C$ or higher more than 24 hours after delivery.

Definition 1.3.6 (Eclampsia)

This is diastolic blood pressure $> 110mmhg$ or proteinuria > 3 after 20 weeks gestation.

1.4 Statement of the problem

The goal of reducing maternal mortality ratio (MMR) between 1990 and 2015 by three quarters was not met in Kenya as the country still experiences high burden of maternal mortality ratio of 488 deaths per 100,000 live births. This is partly due to inaccuracy in the ascertainment of the causes of maternal deaths due to incomplete death registration system, secondly, there is lack of published studies on the causes of pregnancy-related deaths in Kenya [15], third, there is no statistical evidence to justify a community intervention to be undertaken to reduce the maternal mortality, forth, there are no studies that have been done on trends of maternal mortality over the years to predict the future causes of maternal mortality in Kenya and Migori County in particular. In our study we determined the factors causing maternal mortality in Migori County Referral Hospital (MCRH) using logistic regression model. Data from the

Migori County Referral Hospital (MCRH) from the year 2007-2015 was used in the study

1.5 Objective of the Study

1.5.1 General objective of the Study

To determine significant factors causing maternal mortality in Migori County Referral Hospital.

1.5.2 Specific objective of the Study

To determine if Age, Parity, Gravida, Residence, Marital status, Mode of Delivery and Ante- Natal Care (ANC) contributes to maternal Mortality in Migori County Referral Hospital

1.6 Significance of the study

As evidenced from different studies and reports, the Millennium development Goal (MDG) five target of reducing maternal mortality by three quarters [52]. was not achieved especially in developing countries. Now with Sustainable Development Goals (SDG) in Place, statistical modeling is a key requirement in maternal mortality intervention since it provides models which can be applied in different case scenarios and therefore this study would generate models that would be useful in predicting the

likelihood of maternal death in the Migori County Referral Hospital, secondly the study would furnish decision makers and other health practitioners with information about the pregnancy outcomes in the county referral hospital hence development of actionable plans to improve maternal health policies and implementation. Thirdly, the study would provide year to year variations in the occurrences of maternal deaths in the Migori County referral hospital so that appropriate intervention measures can be put in place. Lastly, study would contribute to the knowledge on the use of Logistic regression models and logistic binary models on maternal health and mortality in Kenya as a whole.

Chapter 2

Literature Review

Maternal death is defined as the death of a woman while pregnant or within 42 days of termination of the pregnancy, irrespective of the duration and site of the pregnancy, its management but not from accidental or incidental causes [52]. Pregnancy and child bearing offer women opportunities for personal development and fulfillment. But in different countries and to varying extents, it also has inherent risks. Maternal mortality is an important indicator of womans health and status. It shows clearly the differences between rich and poor, rural and urban, with the vast majority of deaths occurring in resource-poor settings, and most being preventable [52]. According to WHO [52], around 800 women die from maternal causes every day. In developed countries, the maternal mortality ratio (MMR) averages around 11 deaths per 100, 000 live births. Almost 300,000 maternal deaths were estimated to have occurred worldwide in 2010. More than one quarter of the words maternal mortality burden (77,000 deaths) occurred in India, Pakistan and Indonesia alone. Large numbers of maternal deaths also occurred in Sub- Saharan Africa. The countdown to 2015 for maternal, newborn, and child survival in its 2012

cycle reports indicated that only nine out of the 75 count down countries were on track to achieve the Millennium Development Goal (MDG) 5 targeted to reduce the maternal mortality ratio (MMR, maternal deaths per 100,000 live births) by three quarters between 1990 and 2015 [31] which was not met hence the Sustainable Development Goals (SDG) which is to reduce the maternal mortality by 70 percent by the year 2030. In this study we determined the factors causing maternal mortality using Logistic regression model with data from Migori County Referral Hospital.

Internationally, maternal mortality ratio is defined as the number of direct and indirect deaths per 100,000 live births (WHO-ICD-10) that is given as

$$\text{Maternal mortality ratio} = \frac{\text{Total Maternal Deaths}}{\text{Total live Births}} \times 100000 \text{ live birth} \quad (2.1)$$

In many African countries including Kenya this important indicator is difficult due to lack of death certificates since many people do not report death to authorities and the denominator data is always not available due lack of vital statistics which is also unreliable [41].

Yoko et al., [53] examined the quality of the data used for the estimates of MMR provided by the Trinidad and Tobago Central Statistical office (CSO). A retrospective reproductive age mortality survey (RAMOS) was applied for 2000-06 to evaluate national estimates. They found that, data from CSO and external data sources yield conflicting results. The CSO estimate of MMR in 2005 was 34.8 while those provided by UNICEF and the World Bank were 45.0 and 55.0 respectively. Because of the conflicting results they recommended that specific maternal death review committee

be established as the ideal maternal death review mechanism across all health jurisdictions in Trinidad and Tobago.

Fernandez et al. [17] in their report titled Increase in maternal mortality associated with change in the reproductive pattern in Spain: 1996-2005. They analyzed the age related trend in the maternal mortality ratio among mothers in Spain for the decade 1996-2005. They also described the causes of death and associated socio-demographic factors for the years with highest mortality. They applied an indirect standardization and Poisson regression model. They found out that, prevalence of live births among mothers aged 35 years and over was 15 percent higher in Spain than in Europe. The maternal mortality rate increased by 20 percent (standardized mortality ration of 1.2, 95percentCI of 0.9 to 1.4) in 2005 with respect to 1996. The related risk of maternal mortality was three times higher (relative risk of 2.90, 95percentCI 2.01 to 4.06) among mothers aged 35-44 years as compared to those aged under 35 years. The highest mortality was detected during 2003-2004. The study therefore concluded that there was a change in the maternal mortality trend characterized by an increase in the prevalence of live births among mothers aged 35 years and above.

Razum, et al. [39] examined the impact of marital status on maternal mortality in the period before and after German reunification in the area covered by the former East Germany. They calculated the maternal mortality ratio by relating the number of maternal deaths among women resident in eastern Germany in 1980-1996 to respective number of live births, using national register data. They investigated the effect of marital status, with controls on maternal age and year of death, using

a Poisson regression model. Altogether, 413 maternal deaths and 2.99 million live births were reported. The overall maternal mortality ratio was stable before, and declined after, reunification. Before reunification, unmarried women had a risk of maternal death equal to that of married women; after reunification they had 2.6 times the age adjusted risk of married women. Unmarried status thus became a significant risk factor for maternal mortality in eastern Germany after reunification.

In the rural India, Shah et al.[42] did a study where they examined changes in epidemiology of maternal mortality in rural India in the context of increasing institutional deliveries and implementation of community-based interventions that can inform policies to reach MDG-5. They analyzed the prospectively collected community-based data of every pregnancy and its outcome from 2002 to 2011 in rural, tribal area of Gujarat, India as part of safe- motherhood programme implemented by voluntary organization, SEWA Rural. They determined the incidence rates for maternal mortality according to place, cause and timing of maternal deaths in relation to pregnancy. Annual incidence rate ratios (IRR) and 95percent CI, adjusted for caste and maternal education, were estimated using Poisson regression to test for linear trend in reduction in mortality during the study period. 32,893 pregnancies, 29, 817 live births and 80 maternal deaths were recorded. They found out that maternal mortality ratio improved from 607 (19 deaths) in 2002-2003 to 161 (5 deaths) in 2010-2011. The institutional delivery rate increased from 23percent to 65percent. The trend of falling maternal deaths was significant over time, with an annual reduction of 17percent (adjusted IRR 0.83 CI 0.75-0.91, P-value ≤ 0.001). There were significant reductions in adjusted inci-

dence rate of maternal deaths due to direct causes, during intrapartum and post-partum periods, and those which occurred at home. However, reductions in incidence of maternal deaths due to indirect causes, at hospital and during ante partum period were not statistically significant and they concluded that gains in institutional deliveries and community based interventions resulting in fewer maternal deaths due to direct causes of maternal mortality during pregnancy at community and hospitals for further reduction in maternal deaths to achieve MDG-5.

A study exploring the driving forces behind large changes in risk of maternal mortality at a population level, that is they explored how Bangladesh achieved the reductions in maternal mortality and they focused on change between 1998-2001 and 2007-2010, on the basis of the reference periods of the 2001 and 2010 Bangladesh Maternal Mortality Survey (BMMS) whose data were used to measure changes in the maternal mortality ratio (MMR) and from these and six Bangladesh Demographic and Health Surveys to measure changes in factors potentially related to such change [7]. They estimated the changes in risk of maternal death between the two surveys using Poisson regression and found out that MMR fell from 322 deaths per 100,000 live births (95% CI 253-391) in 1998 -2001 to 194 deaths per 100,000 live births 149-238) in 2007-2010, which gave an annual rate of decrease of 5.6 %, which was slightly higher than that required (5.5%) to achieve the MDG target between 1990 and 2015. They concluded that key contribution to this decrease was a drop in mortality due to improved access to health facilities.

Qin [38] conducted a Hospital-Based Review of Maternal Mortality in Ghana using data from biostatistics unit as well as all maternal deaths

following admission from the period 1st January 2008 to 31st May 2010. The analyzed result revealed an estimated maternal mortality ratio of 1021.9 per 100,000 live births (95percent CI: 906.6- 1130.8) which was consistent with other institutional based studies in Ghana.

Sarpong,[41] examined the occurrence and incidence of Maternal Deaths as well as maternal mortality ratios at the Okomfo Anokye Teaching Hospital in Kumasi from 2000 to 2010. The study explored the feasibility for application of Poisson models and time series autoregressive integrated moving average (ARIMA) in the study of occurrence and incidence of maternal deaths and to predict Maternal Mortality ratios respectively. His result revealed that the mean number of occurrence of maternal death cases were high for all the years considered and established that the mean number of occurrence of maternal death cases has not significantly reduced over the period 2000 to 2010. The result further showed that there was a statistically significant in the incidence of maternal deaths difference between year 2010 (referenced year) and years 2004, 2005 and 2008. He fitted ARIMA model to predict maternal mortality ratios (MMRs) for the next eight quarters. In which he concluded that the mean number of occurrence of maternal death cases has not significantly reduced over the period 2000 to 2010 and that the ARIMA model was adequate for forecasting quarterly maternal mortality ratios at the hospital.

Abdulai [1] in his analysis of maternal mortality in Wa District, he examined the occurrence and incidence of maternal deaths in Wa District from 1998 to 2010 as well as the factors that contribute to maternal deaths at the Upper West Regional Hospital (UWRH) from 2008-2012 using Poisson and Logistic regression models. Poisson regression model

was used to examine the occurrence and incidence of maternal deaths while logistic regression was used to assess the factors that contribute to maternal death at UWRH. He found that the mean number of occurrence of maternal mortality was high in 2001 and 2009 as compared to 2010 and also established that the mean number of occurrence of maternal mortality did not significantly reduce over the study period 1998-2010. The incidence of maternal mortality was high in 2001 but low in 2002, 2004 and 2008 as compared to 2010 (reference year). He also found that the mean incidence of maternal death cases did not change. He concluded that age, parity and delivery type contributed significantly to pregnancy outcome at the UWRH.

In a study by Bassoumah, [9] he explained how socio-cultural factors mediate to influence the use of health facilities during the pregnancy postpartum period in Awutu-Senya District of the Central Region of Ghana using the delays model. The study targeted women who gave birth between September 2007 and September 2009 in the sampled areas. Proportionate stratified sampling technique was used to select 246 respondents from the chosen communities. The study observed low antenatal, delivery and postnatal care attendance from 2006 to 2008. Maternal mortality ratio increased from 115 per 100,000 live births in 2004 to 176 per 100,000 live births in 2008, whilst proportion of births outside orthodox medical facilities continues to increase in the face of National Health Insurance and other maternal health policies and programmes. Results showed that there was no association between attendance at clinics for antenatal care and residence. However, there was a significant a positive relationship between attendance at clinics for postnatal care and residence. Again, a sig-

nificant and a positive relationship between supervised delivery and level of education was also established. It was recommended that the Ghana Health Service should pay attention to the socio-cultural environment in order to encourage antenatal care attendance, supervised deliveries and postnatal care in the health facilities for achievement of the MDG 5.

Aikins [6] conducted a study to determine whether the free antenatal and delivery care provided by the Ghanaian government was encouraging pregnant women to access the health facility in order to improve maternal health and also whether it was aiding in the reduction of maternal deaths. A total of three health personnel and fifty- five pregnant women participated in the study, semi structured interviews and observations were used to collect the data. The study revealed that there was an unstable maternal death even though the pregnant women had free access to antenatal care. The skilled birth attendants at delivery as per pregnant woman ratio was quite poor, the ratio is 1:17,733 and the Nurse population ratio was 1:1,510 with disparities between urban and rural settings and dwellers. For instance in Kumasi the ratio of Midwives to Women of reproductive age was 1:427.

Obiechima et al.[32] conducted a study on maternal mortality at Nnamdi Azikiwe University Teaching Hospital (NAUTH) in Southeast Nigeria. The study assessed NAUTHs progress in achieving a 75percent reduction in the maternal mortality ratio (MMR) and to determine the major causes of maternal mortality. It was a 10 year retrospective study, conducted between January 1, 2003 and December 31, 2012. During the study there were 8,022 live births and 103 maternal deaths, giving an MMR of 1,284/100,000 live births. The MMR was 1,709 in 2003 reduc-

ing to 1,115 in 2012. There was 24.86percent reduction over 10 years, hence, in 15 years; the reduction should be 37. This extrapolated reduction over 15 years is about 38% less than the target of 75% reduction. They found out that major direct causes of maternal mortality in their study were: pre-eclampsia/eclampsia (27%) hemorrhage (22%), and sepsis (12%). Most of the maternal deaths occurred in unbooked patients (98%) and within the first 48 hours of admission (76%). They concluded that MMRs in NAUTH were still very high and the rate of reduction was very slow. At this rate, it will take NAUTH 30 years, instead of 15 years to achieve a 75percent reduction in maternal mortality.

An article by Adamu et al.,[3] published in the European Journal of Obstetrics and Gynecology and Reproductive Biology, sought to determine the incidence and causes of maternal mortality as well as its temporal distribution over the last decade (1990-1999). All maternal deaths recorded within the study period in the State of Kano, Northern Nigeria, were analyzed. Maternal mortality ratios (MMR) were computed using the Poisson assumption to derive confidence intervals around the estimates. A non-linear regression model was fitted to obtain the best temporal trajectory for MMR across the decade of study. Their study reveals that a total of 4154 maternal deaths occurred among 171,621 deliveries, yielding an MMR of 2,420 deaths per 100,000. Eclampsia, ruptured uterus and anemia were responsible for about 50percent of maternal deaths. They concluded that the area had one of the highest maternal mortality ratios in the world and suggested that maternal mortality could be reduced by half at the study site with effective interventions targeted to prevent deaths from eclampsia, ruptured uterus and anemia.

Mojekwu and Ibekwe [28] in their study published in the International Journal of Humanities and Social Sciences sought to bring together some of the risk factors mentioned in the past as responsible for high maternal mortality in Nigeria and to identify the factors that seem to have effect than the others on maternal mortality in Nigeria. Data on the 36 states of the federation and the FCT Abuja was obtained from the Nigeria Demographic and Health survey 2008, the annual Abstract of Statistics of the National Bureau of statistics and Society of obstetrics and Gynecology of Nigeria. Simultaneous multiple regressions on the fourteen variables for maternal mortality modeling in Nigeria was done, then stepwise regression was applied to identify from among the fourteen variables, the major determinants factors that appear to affect maternal mortality ratio more than the others. Narrowing down attention to a small number of the major determinants of high maternal mortality should help gain the focused attention of government since maternal mortality is just one among hundreds of issues competing for the attention of political leaders at any given time. The study found that delivery by a skilled health professional and educational attainment of women had more effect on maternal mortality ratio than the other factors. The implications of the findings was that advocates of maternal mortality reduction in Nigeria will need to focus more attention on developments in the educational sector and not just on making direct improvements to the healthcare system.

Determining the maternal mortality ratio at the Jos University Teaching Hospital was a study designed by [30], they went further to ascertain the causes of maternal death at the hospital. Their study was a prospective descriptive analysis of all maternal deaths at the Jos Uni-

versity Teaching Hospital (JUTH), Jos North Central Nigeria from 1st June, 2006 to 31st May, 2008. The study revealed that there were 56 maternal deaths and 4443 live births at the Jos University Teaching Hospital giving a maternal mortality ratio of 1260/100,000 live births. Of these, there were 15 deaths among 81 patients who were not booked giving a maternal mortality ratio of 18518/100,000 live births. Twenty-five deaths occurred among those who booked elsewhere (2969/100,000 live births) and 9 deaths among women who booked in JUTH with a maternal mortality ratio of 256/100,000 live births. Thirty nine (69.6percent) of the deaths were direct maternal deaths while 17 (30.4percent) were indirect maternal deaths. The leading causes of direct maternal deaths were eclampsia (28.6%), hemorrhage (23.1%), unsafe abortion (8.9%) and pulmonary embolism (5.4percent). Of the indirect causes of maternal mortality, HIV/AIDS accounted for 8.9%, 3.6% and 1.8% respectively. The study found that maternal mortality ratio is still high in JUTH. It was found to be lower in those that had tertiary education and booked patients. HIV/ AIDS appear to be emerging as one of the leading causes of maternal mortality in this study.

Garene et al. [19] sought to unearth the uncertainty in the levels of global maternal mortality which reflects data deficiencies, as well as differences in methods and definitions. They presented levels and trends in maternal mortality in Agincourt, a rural sub district of South Africa, under long term health and socio-demographic surveillance. All deaths of women aged 15 years -49 years occurring in the study area between 1992 and 2010 were investigated, and causes of death were assessed by verbal autopsy. Two case definitions were used: obstetrica (direct) causes,

defined as death caused by conditions listed under 000-095 in International Classification of Diseases-10; and pregnancy related deaths defined as any death occurring during the maternal risk period (pregnancy, delivery, 6 weeks postpartum), irrespective of cause. The study revealed that, case definition had a major impact on levels and trends in maternal mortality. The obstetrical mortality ratio averaged 185 per 100,000 live births over the period (60 deaths), whereas the pregnancy related mortality ratio averaged 423 per 100,000 live births (137 deaths). Results from both calculations increased over the period, with a peak around 2006, followed by a decline coincident with the national roll-out of Prevention of Mother to- Child Transmission (PMCT) of HIV and antiretroviral treatment programs. The result indicated that mortality increase from direct causes was mainly due to hypertension or sepsis. Mortality increase from other causes was primarily due to the rise in deaths from HIV/AIDS and pulmonary tuberculosis. These trends underline the major fluctuations induced by emerging infectious diseases in South Africa, a country undergoing rapid and complex health transitions. Findings also pose questions about the most appropriate case definition for maternal mortality and emphasize the need for a consistent definition in order to better monitor and compare trends over time and across settings.

Okaro et al.[33] in their comparative retrospective analysis of maternal deaths at the University of Nigeria Teaching Hospital, Enugu, Nigeria, carried out for a two ten- year periods: 1976-1985 and 1991-2000- in order to evaluate the effect of Safe Motherhood Initiative of 1985 which took place in Kenya on maternal mortality in the hospital. Variables for the two periods were compared by means of t-test at 95percent CI. Mater-

nal mortality ratio was significantly higher in period II than in Period I (1406 versus 270 per 100,000 live births, $p=0.000$). The leading causes of maternal death were uterine rupture for period I and septicemia for period II. Although from the first to the second there was more than a proportionate decrease in the number of deliveries. There was also increase in the incidence of anemia due to diminished standards of living and in the mean decision intervention interval (1.5-+ 0.5 versus 5.8-+ 1.2 =hours; $p=0.000$) as a result of worker dissatisfaction and changes in hospital policies. The researchers conclude that since the launching of the Safe Motherhood Initiative, MMR at the University of Nigeria Teaching Hospital, Enugu, Nigeria, has increased five-fold as a result of institutional delays and deterioration in the living standards of Nigerians, both consequences of a depressed economy. To halt this trend, the researchers recommend that the living standard of all Nigerians should be improved.

Mirasi [27] in his study in Kisumu Sub- County, he sought to assess the determinants of maternal mortality, maternal service utilization and in particular find out whether the use of voucher for health has had an impact in reduction of maternal deaths as well as increasing utilization of maternal services in Kisumu Sub-County. A total of 293 pregnant women from 31 health facilities selected through purposive sampling were randomly interviewed while 210 maternal delivery outcomes were reviewed using questionnaires and structured checklist respectively. COX proportion Hazard regression model and Logistic regression model were used to estimate determinants of maternal mortality while general linear regression model was performed to predict the factors influencing maternal service utilization. The result showed that overall women who attend ma-

ternal clinic and those who succumb to maternal related deaths are young. Utilization of maternal service is on the rise while maternal deaths are drastically decreasing. The factors that influence maternal service utilization in Kisumu sub-county include level of education, voucher for health, payment for service, and knowledge on maternal visits while the determinants of maternal mortality include age, marital status, wealth index, voucher for health and presence of other diseases.

Desai [16] in their study of the analysis of pregnancy-related mortality in the KEMRI/CDC health and demographic surveillance system in Western Kenya, they sought to estimate the burden of and characterize risk factors for pregnancy-related mortality. They evaluated deaths that occurred between 2003 and 2008 among women of childbearing age (15-49 years) using Health and Demographic Surveillance System data in rural western Kenya. Of the 3,223 deaths in women 15-49 years, 249 (7.7 percent) were pregnancy related. One third (34 percent) of these were due to direct obstetric causes, predominantly postpartum hemorrhage, abortion complications and puerperal sepsis. Two-thirds were indirect; three-quarters were attributable to human immunodeficiency virus (HIV/AIDS), malaria and tuberculosis. Significantly more women who died in lower socio-economic groups sought care from traditional birth attendants ($=0.034$) while less impoverished women were more likely to seek hospital care ($=0.001$). The pregnancy-related mortality ratio over the six years was 740 (95percent CI 651-838) per 100,000 live births, with no evidence of reduction over time (linear trend $=1.07;=0.3$). They concluded that these data supplement current scanty information on the relationship between infectious diseases and poor maternal outcomes

in Africa. They indicate low uptake of maternal health intervention in women dying during pregnancy and postpartum, suggesting improved access to and increased uptake of skilled obstetric care, as well as preventive measures against HIV/AIDS, malaria and tuberculosis among all women of childbearing age may help to reduce pregnancy related mortality.

2.1 Other applications of Logistic Regression

Mensah et al. [4] in their study of assessing the occurrence of maternal mortality and some related factors at Komfo Anokye Teaching Hospital. They sought to determine key factors that have significant effect to predicting the occurrence or non-occurrence of maternal mortality incidence. They used logistic regression model, they used an annual maternal mortality data from 2007 to 2012 from Komfo Anokye Teaching Hospital (KATH). They found that AGE, PARITY and GRAVIDA contribute significantly to the occurrence of maternal mortality.

Suwal [43] in his study of unraveling the complexity of maternal mortality in Nepal. He discussed the maternal mortality situation in Nepal and analyses the differentials in maternal mortality by place of residence, region, ethnic and religious groups, age at death and parity using the 1996 Nepal Family Health Survey data. The sampling unit was the ever married woman who was in the age group 15-49 years at the time of the survey. The total number of eligible women interviewed was 8, 429 of which 712 (8.45 percent) women came from urban areas and 7,717 (91.55percent)

came from rural areas (Ministry of Health 1997a). The information on maternal mortality was collected by the sibling survival method. That is, the eligible respondents in the survey were asked about the characteristics and survival of their siblings. Cross tabulation were computed between the social, demographic and geographic variables and maternal deaths. In the second section, effects of different regional, spatial, demographic ethnic and religious factors on maternal mortality were analyzed by using Logistic regression. The dependent variable was dichotomous in nature; it was ratio of women (12-49 years old) dying of maternal causes versus women dying of their causes (cut off age for Nepal in this survey was 12 years for those siblings who died of reproductive complications. He found out that almost 28percent of deaths of women in reproductive age were accountable to maternal causes. Logistic regression analysis shows, ethnicity, age of women, and number of births as strong predictors of maternal mortality.

Gauri and Ganga [20] in their work of mathematical modeling of health service utilization data using multiple logistic regressions they analyzed the use of maternal health services and delivery system in Nepal, data was extracted from individual records of a data file of the Nepal demographic health survey, 2006. The unit of analysis for the study was the ever married woman who had at least one live birth in the five years preceding the survey. The sample consisted of 4182 ever married women. Statistical model was developed to establish a linkage between utilization of maternal health services (place of delivery) and several factors. In the process of model development logistic regression was selected. They used Newton Raphason iterative method to solve the equations known as iteratively

weighted least squares algorithm and the results were interpreted in terms of odd ratios. They concluded that women with low education level, those residing in rural areas and those with low socio-economic status are less likely to use a health facility for delivery.

Chukwu and Oladeji [14] in their study of modeling the determinants of maternal Mortality: A comparative of Logistic regression and Artificial Neural Network Model they sought to predict maternal mortality using logistic regression model and Artificial Neural Network model using hospital based records ranging from 2003-2012 on mothers age, mode of delivery, parity, sex of the baby, babys weight at birth, nature of complication which they considered as independent variables vis-a vis the mothers status which was their dependent variable. They used Logistic regression model to check for the risk factor associated with maternal mortality. In order to compare the efficiency of Artificial Neural Network Model and logistic Regression model, the following measures were used: sensitivity, specificity and goodness of fit. Their work showed that Artificial Neural Network outperformed Logistic regression with sensitivity 50.6 percent versus 31.0 percent, specificity 91.6percent versus 86.6percent and the mean square error (MSE) of Artificial Neural Network is very small compared to that of the logistic regression model.

Gobopamang and Rakgoasi [18] in their study of factors associated with Non-use of maternal health services in Botswana. The study investigated individual and household factors associated with non-use of maternal health services in Botswana. They used nationally representative data from 1996 Botswana Family Health Survey. A total of weighted 19.031 women aged 15-49 years old were the sample and the unit of anal-

ysis was the women who had at least one pregnancy history in the five years prior to the survey. They used simple cross-tabulations and logistic regression analysis to analyze their data. Their study found out that teenagers were less likely to seek prenatal care, to have their babies delivered by a qualified person, and to seek post-natal check-up. Using the logistic regression analysis they observed that low-parity women were less likely to use maternal services. They further found out that women with low educational, those residing in rural areas and those with low socioeconomic status were less likely to use maternal services. They finally recommended more focused investigation for understanding the differential of the use of maternal services.

Ononokpono[36], in her study examined whether community factors moderated the association between individual factors and the use of skilled antenatal care clinic attendance. Data on 17560 women aged 15-49 years drawn from 2008 Nigeria Demographic and Health Survey was used and it was analyzed by use of multilevel logistic regression models. The study revealed variations in the use of skilled antenatal clinic attendance (ANC) across the Northern and Southern regions. Residence in communities with a high proportion of women that delivered in a health facility increased the odds of skilled antenatal clinic attendance utilization. Community education and poverty moderated the association between individual factors and the utilization of the skilled ante-natal clinic attendance. She concluded that to improve the use of antenatal clinic attendance and increase the pace towards achieving the Sustainable Development Goal (SDG) improved maternal health in the post era, increasing health facility delivery, womens education and targeting poverty alleviation programs

in disadvantaged communities should be taken into consideration.

Balogun [8] in his work aimed of the study was to obtain a logistic regression that can be used to classify the mode of delivery of pregnant women using some variables. He used data from health records of 184 pregnant women who delivered at the general hospital of Wuse. The data consist of mothers weight, height, age and babys weight, babys gender and mode of delivery (natural birth and caesarian section). The study found out that discriminant analysis cannot handle mixed data (discrete and continuous data) effectively instead logistic regression better fit the data. The model correctly classified 65.8percent original grouped cases with positive and negative predictive values 65.75percent and 68.70percent respectively, which are higher than values obtained under the discriminant analysis.

Tsawe et al., [44] sought to investigate the factors that influence the use of maternal healthcare services and childhood immunization in Swaziland. They used secondary data from Swaziland Demographic and Health Survey 2006-2007. They used pre-selected variables to study factors influencing the use of maternal and child healthcare services in Swaziland. Three types of analyses were used: Univariate, bivariate, and multivariate and the multivariate analysis, a logistic regression was run to investigate the relationship between the dependent and independent variables. The findings were that there is high use rate of antenatal care (97.3%) and delivery care (74.0%) and a low rate of postnatal care use (20.5 %). The uptake of childhood immunization is also high in the country averaging more than 80.0%. Certain factors which were found to be influencing the use of maternal healthcare and childhood immunization include: wom-

ans age, parity, media exposure, maternal education, wealth quintile and residence. The findings also revealed that these factors affect the use of maternal and child health services differently. They concluded that it is important to study factors related to maternal and child health uptake to inform relevant stakeholders about possible areas of improvement programs to educate families about the importance of maternal and child healthcare services should be implemented. In addition, interventions should focus on: (a) age differentials in use of maternal and child health services, (b) women with higher parities, (c) women in rural areas, and (d) women from the poor quintile. They recommended that possible future studies could use the qualitative approach to study issues associated with the low use of postnatal services.

Ghebrehiwet and Morrow [21] in their study which sought to determine the determinants of maternal mortality in Eritrea compared 50 women whose pregnancies led to death with 50 individually matched women that survived a severe life threatening obstetric complications in the same community also referred as near misses (controls). Their findings were that, from the comparison of maternal deaths (cases) and survivors of severe life threatening obstetric complications (controls), seeking medical care on the part of the survivors was significantly more frequent in both bivariate and multivariate analysis than was the case in those who died and was probably protective. They concluded that seeking medical care was negatively associated with maternal death and was probably protective.

Okeh and Oyeka[34] proposed a matrix approach to estimating parameters of logistic regression with a view to estimating the effects of risk factors of gestational diabetic mellitus. The odds ratio obtained from the

logistic regression were used to interpret the effects of these risk factors on gestational diabetic mellitus where obesity is a risk factor was positively associated with gestational diabetic mellitus and their proposed method was seen to compare favorably with others.

Chapter 3

Research Methodology

3.1 Introduction

This chapter discusses the logistic regression model used to determine predictive factors causing maternal mortality in Migori County Referral Hospital from the year 2007 to the year 2015. It Presents the structure of the simple logistic regression, odds in logistic regression, estimation of logistic regression model using Maximum Likelihood and logistic regression model evaluation criteria.

3.2 Logistic Regression Model

Logistic regression sometimes called the logistic model or logit model is a mathematical modeling approach that can be used to describe relationship between an independent variable or several independent variables to a dichotomous dependent variable. The model is used to estimate the probability of occurrence of an event or the probability of non-occurrence.

There are two models of logistic regression, binary logistic regression and multinomial logistic regression. Binary logistic regression is typically used when the dependent variable is dichotomous and the independent variables are either continuous or categorical. When the dependent variable is not dichotomous and is comprised of more than two categories, a multinomial logistic regression can be employed [37]. The logistic model is popular because the logistic function, on which the logistic regression model is based, provides estimates in the range 0 to 1 and an appealing S-shaped description of the combined effect of several risk factors on the risk for an event [24].

3.3 The Model Description

Maternal death or maternal mortality is the response variable or the dependent variable to be predicted. This variable is dichotomous and binary, it has two levels: - 0 if the maternal death does not occur and 1 if the maternal death does occur. There are factors assumed to be contributors to the occurrence or non occurrence of maternal death at the Migori County Referral Hospital, these are the independent variables or the explanatory variables. They include age, Parity, Gravida, residence, marital status, mode of delivery and Ante natal Care (ANC). Therefore logistic regression can be written as:-

Let p be probability of occurrence of the event and $q=1-p$ be the probability of the event not occurring

Then

$$p = \frac{e^z}{1 + e^z} \quad (3.1)$$

and

$$q = 1 - p = 1 - \frac{e^z}{1 + e^z} = \frac{1}{1 + e^z} \quad (3.2)$$

Where z represents the function of the independent variables also called the logit and is given as

$$z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 \quad (3.3)$$

Where; α is the constant

$\beta_1 \dots \beta_7$ are the parameters or coefficients of the independent variables to be estimated.

X_1 is Age which is the age of the pregnant woman

X_2 is Parity which is the number of times a woman have given birth to fetus with gestational age of 24 weeks or more

X_3 is Gravida which is the number of times the woman has been pregnant

X_4 is Residence which is the residential status of the pregnant woman

X_5 is Marital status which is the marital status of the pregnant woman

X_6 is Mode of delivery which is how the pregnant woman delivers at the MCRH

X_7 is Ante Natal Care which is the numbers of times expectant women visits the hospital before delivery.

The logistic regression model would determine the independent variables that make the dependent variable (response variable) (occurrence or non-occurrence of maternal death) most likely to be predicted.

3.4 Simple Logistic regression Model

In this case the formulas are stated in terms of the probability that an event will occur denoted by p and the probability that an event will not occur denoted by $1-p$

$$\text{logit}(y) = \ln\left(\frac{p}{1-p}\right) = \alpha + \beta X \quad (3.4)$$

Let $y = \frac{p}{1-p}$ that is the ratio of event occurring over the event not occurring. The $\ln\left\{\frac{p}{1-p}\right\}$ is called the Logit (y) and is given as:

$$\ln\left(\frac{p}{1-p}\right) = \frac{\frac{e^z}{1+e^z}}{\frac{1}{1+e^z}} = e^z \quad (3.5)$$

and

$$Z = \alpha + \beta_1 X_1 + \dots + \beta_k X_k \quad (3.6)$$

3.4.1 Odds in Logistic Regression

Odds of an event are the probability that an event will occur to the probability that it will not occur. If the probability of an event occurring is p , the probability of the event not occurring is $(1-p)$. Then the corresponding odd is a value given by $\frac{p}{1-p}$. Since logistic regression calculates the probability of an event occurring, the impact of independent variables is usually explained in terms of odds with logistic regression the mean of the response variable p in terms of an explanatory variable x is modeled relating p and x through the equation $p = \alpha + \beta x$. Unfortunately, this is not a good model because extreme values of x will give values of $\alpha + \beta x$

that does fall between 0 and 1. The logistic regression solution to this problem is to transform the odds using the natural logarithm (Peng and Ingersol, 2012). So with logistic regression, we modeled the natural log odds as a linear function of the explanatory variable.

$$\text{Logit}(y) = \ln(\text{odds}) = \ln\left(\frac{p}{1-p}\right) = \alpha + \beta x \quad (3.7)$$

That is

$$p = \frac{e^{(\alpha+\beta x)}}{1 + e^{(\alpha+\beta x)}} \quad (3.8)$$

and

$$\frac{p}{1-p} = e^{(\alpha+\beta x)} \quad (3.9)$$

Where p is the probability of interested outcome

x is the explanatory variable

α, β are the parameters of the logistic model.

Taking the anti-log of the equation above one can derive an equation for the prediction of the probability of the occurrence of interested outcome as:-

$$\begin{aligned} p &= P(y = \text{interested outcome given } X = x \text{ specific value}) \\ &= \frac{e^{(\alpha+\beta x)}}{1 + e^{(\alpha+\beta x)}} \end{aligned} \quad (3.10)$$

Extending the logic of the simple logistic regression to multiple predictors we may also construct a complex logistic regression as:-

$$\text{logit}(y) = \ln\left\{\frac{p}{1-p}\right\} = \alpha + \beta_1 X_1 + \dots + \beta_k X_k \quad (3.11)$$

Therefore;

$$\begin{aligned}
 p &= P(y = \text{interested outcome given } X_1, \dots, X_k = x_k) \\
 &= \frac{e^{\alpha + \beta_1 X_1 + \dots + \beta_k X_k}}{1 + e^{\alpha + \beta_1 X_1 + \dots + \beta_k X_k}} \\
 &= \frac{1}{1 + e^{-(\alpha + \beta_1 X_1 + \dots + \beta_k X_k)}}
 \end{aligned} \tag{3.12}$$

3.4.2 Odds Ratio in Logistic Regression Model

Odds ratio is the regression coefficient (b_i) obtained when logistic regression is calculated and it is the estimated increase in the logged odds of the outcome per unit increase in the value of the independent variable. In other words, the exponential function of the regression coefficient (e^{b_1}) is the odds ratio associated with one unit increase in the independent variable. The odds ratio can also be used to determine whether a particular exposure is a risk factor for a particular outcome, and to compare the magnitude of various risk factors for that outcome.

3.5 Estimation of Logistic Regression Using Maximum Likelihood Estimation

The goal of logistic regression is to estimate the $K+1$ unknown parameters β in the Logistic regression model.

$$\text{logit}(p_i) = \ln\left[\frac{p_i}{1 - p_i}\right] = \log\left[\frac{p_i}{1 - p_i}\right] = \sum_{i=1}^k X_i \beta_i \tag{3.13}$$

$i=1,2,\dots,k$ By Logit transformation, we have from equation (3.13) we get;

$$\frac{p_i}{1 - p_i} = e^{\sum_{i=1}^k X_i \beta_i} \quad (3.14)$$

This is done with the MLE which entails finding the set of parameters for which the probability of the observed data is greatest. The MLE is always 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

$$f(y|\beta) = \prod_{i=1}^k \frac{n_i!}{y_i!(n_i - y_i)!} p_i^{y_i} (1 - p_i)^{(n_i - y_i)} \quad (3.15)$$

For each population, there are different ways to arrange y_i successes from n_i trials. And since the probability of a success for any one of the n_i trials is p_i , the probability of y_i successes is $p_i^{y_i}$, likewise the probability of $(n_i - y_i)$ failures is $(1 - p_i)^{n_i - y_i}$

Now the joint probability density function in the above equation (3.15) 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 has the same form as the function are reversed; the likelihood function expresses the values of β in terms of the known, fixed values of y [4].

$$L(\beta|y) = \prod_{i=1}^k \frac{n_i!}{y_i!(n_i - y_i)!} p_i^{y_i} (1 - p_i)^{(n_i - y_i)} \quad (3.16)$$

The maximum likelihood estimates are the values for that maximize the likelihood function in equation (3.16). The critical points of a function (maxima and minima) occur when the first derivative equals 0. As usual

if the second derivative evaluated at that point is less than 0, then the critical point is a maximum. Thus finding the maximum likelihood estimates requires computing the first and second derivatives of the equation (3.16) with respect to β is not easy due to complexity of the multiplicative terms. Fortunately the likelihood equation can be considerably simplified. In this case we check the factorial terms in the equation (3.16) that do not contain the p_i , as a result they are essentially constants that are ignored. In fact maximizing the equation without the factorial terms will come to the same if they were included. So the above equation (3.16) can be rewritten as

$$L(\beta/y) = \prod_{i=1}^k \left(\frac{p}{1-p} \right)^{y_i} (1-p)^{n_i} \quad (3.17)$$

And if we take the exponential of the equation (3.17) on both sides we have

$$L(\beta/y) = \left(\frac{p}{1-p} \right)^{\sum_{i=1}^k X_i \beta_i} = e^{\sum_{i=1}^k X_i \beta_i} \quad (3.18)$$

On solving for p we have

$$p = \frac{e^{\sum_{i=1}^k X_i \beta_i}}{1 + e^{\sum_{i=1}^k X_i \beta_i}} \quad (3.19)$$

Substituting equation (3.18) and equation (3.19) in equation (3.17) we have

$$\begin{aligned} L(\beta/y) &= \prod_{i=1}^k \left\{ \frac{e^{\sum_{i=1}^k X_i \beta_i}}{1 + e^{\sum_{i=1}^k X_i \beta_i}} \right\}^{y_i} \left\{ \frac{1 - \frac{e^{\sum_{i=1}^k X_i \beta_i}}{1 + e^{\sum_{i=1}^k X_i \beta_i}}}{1 + e^{\sum_{i=1}^k X_i \beta_i}} \right\}^{n_i} \\ &= \prod_{i=1}^k (e^{\sum_{i=1}^k X_i \beta_i})^{y_i} (1 + e^{\sum_{i=1}^k X_i \beta_i})^{-n_i} \end{aligned} \quad (3.20)$$

Equation (3.20) is the actual likelihood function to maximize. We here simplify Equation (3.20) further by taking its log. Since the logarithm is a monotonic function, any maximum of the log likelihood function and vice versa. Thus, taking the natural log of equation (3.20) yields the log likelihood function:

$$\log L(\beta/y) = \sum_{i=1}^N y_i \left(\sum_{i=1}^k X_i \beta_i \right) - n_i \log(1 + e^{\sum_{i=1}^k X_i \beta_i}) \quad (3.21)$$

On differentiating with respect to β

$$\begin{aligned} \frac{dl(\beta)}{d\beta_i} &= \sum_{i=1}^N y_i x_i - n_i \frac{1}{1 + e^{\sum_{i=1}^k X_i \beta_i}} * \frac{d}{d\beta_k} (1 + 1 + e^{\sum_{i=1}^k X_i \beta_i}) \\ &= \sum_{i=1}^N y_i x_i - n_i * \frac{e^{\sum_{i=1}^k X_i \beta_i}}{1 + e^{\sum_{i=1}^k X_i \beta_i}} * X_i \end{aligned} \quad (3.22)$$

On substituting (3.19) in equation (3.22) we have:-

$$\sum_{i=1}^N y_i x_i - n_i p x_i = 0 \quad (3.23)$$

hence

$$\hat{p} = \frac{\sum_{i=1}^N y_i x_i}{n_i x_i} \quad (3.24)$$

The maximum likelihood estimates can be found by setting each of the $k+1$ equations in equation (3.23) to zero and solve for each β_k . Each such solution, if any exists, specifies a critical point either a maximum or a minimum. The critical point will be a maximum if the matrix of second partial derivatives (Hessian matrix) is negative definite; that is, if every element on the diagonal of the matrix is less than zero (Glub and Van, 1996). The Hessian matrix also forms the variance-covariance matrix of

the parameter estimates. The general form of the matrix of second partial derivatives (Hessian matrix is)

$$\begin{aligned}
\frac{d^2\ell(\beta)}{d\beta_k d\beta_k} &= \frac{d}{d\beta_k} \sum_{i=1}^N y_i x_{ik} - n_i x_{ik} P_i \\
&= \frac{d}{d\beta_k} \sum_{i=1}^N -n_i x_{ik} P_i \\
&= \sum_{i=1}^N n_i \cdot X_{ik} \frac{d}{d\beta_k} \left\{ \frac{e^{\sum_{i=1}^k X_i \beta_i}}{1 + e^{\sum_{i=1}^k X_i \beta_i}} \right\} \quad (3.25)
\end{aligned}$$

$$\text{Where } p_i = \frac{e^{\sum_{i=1}^k X_i \beta_i}}{1 + e^{\sum_{i=1}^k X_i \beta_i}}$$

To solve Equation (3.25) we will make use of exponential functions and the rule for quotient of two functions so as to obtain

$$\begin{aligned}
\frac{d(e^{u(x)})}{d(1 + e^{u(x)})} &= \frac{(1 + e^{u(x)})e^{u(x)} \frac{d}{dx} u(x) - e^{u(x)} \cdot e^{u(x)} \frac{d}{dx} u(x)}{(1 + e^{u(x)})^2} \\
&= \frac{e^{u(x)} \frac{d}{dx} u(x) + [e^{u(x)}]^2 \frac{d}{dx} u(x) - [e^{u(x)}]^2 \frac{d}{dx} u(x)}{(1 + e^{u(x)})^2} \quad (3.26)
\end{aligned}$$

or

$$\begin{aligned}
\frac{d(e^{u(x)})}{d(1 + e^{u(x)})} &= \frac{e^{u(x)} \frac{d}{dx} u(x) + 1 + e^{u(x)} - e^{u(x)}}{[1 + e^{u(x)}]^2} \\
&= \frac{e^{u(x)}}{[1 + e^{u(x)}]^2} \frac{d}{dx} u(x) \\
&= \frac{e^{u(x)}}{1 + e^{u(x)}} \frac{1}{1 + e^{u(x)}} \frac{d}{dx} u(x) \quad (3.27)
\end{aligned}$$

Since $\frac{du(x)}{dx} = \frac{d}{dx} \sum_{i=1}^k X_{ik} \beta_k = X_{ik}'$ While p_i and $1 - p_i$ are clearly defined.

Thus, Equation (3.25) can now be written as

$$\ell''(\beta) = - \sum_{i=1}^N n_i X_{ik} P_i (1 - P_i) X_{ik'} \quad (3.28)$$

3.6 Logistic Regression Model Evaluation

The overall model would be assessed by looking at the relationship between all the independent variables and the dependent variables. The importance of each of the independent variables would be assessed. The predictive accuracy or the discriminating ability of the model would be evaluated.

3.6.1 Likelihood Ratio Test

A logistic model with k independent variables is said to provide a better fit to the data if it demonstrates an improvement over the model with no independent variables (null model). The overall fit of the model with k coefficients can be examined via likelihood ratio test which tests the null hypothesis.

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_a : \beta_1 \neq \beta_2 \neq \dots \neq \beta_k \neq 0$$

To this the deviance with just the intercept $-2\ln L(X, \theta_0)$ is compared to the deviance when k independent variables have been added ($-2\ln L(X, \theta_k)$).

The likelihood of the null model is the likelihood of obtaining the

observation if the independent variables had no effect on the outcome. And the likelihood of the given model is the likelihood of obtaining the observation with all independent variables incorporated in the model. The difference of these two yields a goodness of fit index G, χ^2 statistic with k degree of freedom (Bemick and Ball, 2005). This is a measure of how well all of the independent variables affect the outcome or dependent variable.

$$G = \chi^2 = (-2\ln L(X, \theta_0)) - (-2\ln L(X, \theta_k)) \quad (3.29)$$

Where the ratio of the maximum likelihood is calculated before taking the natural logarithm and multiplying by -2 [47].

The term likelihood ratio test is used to describe this test. If the p -value for the overall model fit statistic is less than the conventional 0.05, then reject H_0 with the conclusion that there is evidence that at least one of the independent variables contributes to the prediction of the outcome.

The change in deviance G approximately follows the chi-square distribution with respective degree of freedom. The term deviance was designed by [26] and given by $D=2\ln(\text{likelihood})$ for the fitted model. If the deviance reduces as predictor, indicates the model fits the data well. The goodness of fit (the degree of closeness of the model-predicted value to the corresponding observed value) is useful for applying to the regression model.

3.6.2 Hosmer and Lemeshow test

The Hosmer Lemeshow test is to examine whether the observed proportions of events are similar to the predicted probabilities of occurrence in sub groups of the model population. The Hosmer-Lemeshow test is performed by dividing the predicted probabilities into deciles (10 groups based on percentile ranks) and then computing a pearson chi-square that compares the predicted to the observed frequencies in a 2-by-10 table.

The value of the test statistics is

$$H = \sum_{g=1}^{10} \frac{(O_g - E_g)^2}{E_g} \quad (3.30)$$

Where O_g and E_g denote the observed events and expected events for the g^{th} risk decile group. The test statistic asymptotically follows a χ^2 distribution with 8 (number of groups -2) degrees of freedom. Small values (with large p- value closer to 1) indicate a good fit to the data, therefore, good overall model fit. Large values (with $p < 0.05$) indicate a poor fit to the data [37].

This test is also called chi-square test. It is more reliable than the traditional chi-square test [5]. In general Hosmer Lemeshow goodness of fit test divides subject into deciles based on predicted probabilities and computes a chi-square from observed and expected frequencies. Under the null hypothesis, the distribution of the statistic is well approximated by the chi-square distribution with g-2 degree of freedom. To support the model, a significance value greater than 0.05 is needed as noted above. The large p value signifies that there is no difference between the ob-

served and predicted values, implying that the model fits the data at an acceptable level.

3.6.3 Wald Statistic

The Wald statistic can be used to assess the contribution of individual predictors or the significance of individual coefficients in a given model [10]. The Wald statistic is the ratio of the square of the regression coefficient to the square of the standard error of the coefficient. The Wald statistic is asymptotically distributed as chi-square distribution.

$$W = \left[\frac{\beta_i}{SE_{\beta_i}} \right]^2 \quad (3.31)$$

Where β is the i^{th}

Each Wald statistic is compared with Chi-square with 1 degree of freedom.

Chapter 4

Results and Discussion

4.1 Introduction

This chapter deals with the analysis of data and discussion of findings. Specifically secondary data was collected from the maternity registers from the year 2007 to the year 2015 recorded from the gynecology and obstetrics department of the Migori County Referral Hospital (MCRH). There were a total of 80 maternal deaths recorded.

4.2 Preliminary analysis

The following data represents the number of maternal deaths, number of live births and maternal mortality ratio (maternal deaths per 100,000) from the Migori County Referral Hospital (MCRH) from the year 2007 to the year 2015.

Table 4.1: Number of Maternal deaths, Number of Live Births and the maternal mortality ratios

| Year | No of Deaths | No of Live Births | Maternity Mortality Ratio (100,000) |
|-------|--------------|-------------------|-------------------------------------|
| 2007 | 2 | 504 | 397 |
| 2008 | 0 | 1437 | 0 |
| 2009 | 5 | 1162 | 430 |
| 2010 | 8 | 2006 | 390 |
| 2011 | 12 | 2029 | 591 |
| 2012 | 4 | 627 | 638 |
| 2013 | 8 | 2784 | 323 |
| 2014 | 23 | 3784 | 608 |
| 2015 | 17 | 4244 | 401 |
| Total | 80 | 18577 | 4306 |

Results from table 4.1 shows that there were 18.577 live births compared with 80 maternal deaths with various maternal mortality ratios as showed above

Table 4.2: Case Processing Summary Table

| Unweighted Cases | | No | Percent |
|---|----------------------|----|---------|
| | Included in Analysis | 80 | 100.0 |
| Selected Cases | Missing Cases | 0 | 0.0 |
| | Total | 80 | 100.0 |
| Unselected Cases | | 0 | 0.0 |
| Total | | 80 | 100.0 |
| a. if weight is in effect, see classification table for the total number of cases | | | |

From table 4.2, N=80 which is 100

Table 4.3: Dependent Variable Encoding

| Original Value | Internal Value |
|----------------|----------------|
| No Death | 0 |
| Death | 1 |

From table 4.3 SPSS gave the way it had encoded the binary variable maternal death. In this case 0 means no maternal death occurred and 1 means maternal death occurred as this will enable us to model the probability of maternal mortality occurring which was the response we require.

4.3 Categorical Variables

The study had predictor variables that are categorical are:- mode of delivery, marital status and residence and some are continuous such as:-age, ANC, parity and Gravity. For those independent variables which are categorical we used dummy variables to contrast the different categories. For each variable we chose a baseline category and then contrasting all remaining categories with the baseline. If an independent variable has K categories, we would need K-1 dummy variables to investigate all the differences in the categories with respect to the dependent variable as showed in the table below.

Table 4.4: Categorical Variable Coding

| | | Freq. | Parameter Encoding | | |
|------------|-----------|-------|--------------------|-------|-------|
| | | | (1) | (2) | (3) |
| | Normal | 38 | 0.000 | 0.000 | 0,000 |
| MDELIVERDY | Ceasarian | 24 | 1.000 | 1.000 | 0.000 |
| | Breach | 5 | 0.000 | 0.000 | 0.000 |
| | Unknown | 13 | 0.000 | 0.000 | 1.000 |
| | Single | 19 | 0.000 | 0.000 | |
| MSTATUS | Married | 51 | 1.000 | 0.000 | |
| | Unknown | 10 | 0.000 | 1.000 | |
| | Rural | 51 | 0.000 | 0.000 | |
| RESIDENCE | Urban | 18 | 1.000 | 0.000 | |
| | Not Known | 4 | 0.000 | 1.000 | |

Table 4.5: Result with only the constant included before any coefficient relating to predictor variables.

| | | Predicted | | |
|--------|--------------------------|-----------|-------|-------------------|
| | | MDEATH | | |
| | Observed | No Death | Death | percentage Corect |
| Step 0 | No Death | 0 | 31 | 0.0 |
| | Death | 0 | 49 | 100.0 |
| | Overall Percentage Overa | | | 61.3 |

a. Constant is included in the model. b. The cut value is .500

From the (2×2) classification table above the logistic regression compares this model with a model including all the predictors (Age, parity,

Gravid, residence, Marital status, mode of delivery and ANC) to determine whether the latter model is more appropriate. The table suggests that if we knew nothing about our variables and guessed that maternal death would occur we would be $(\frac{49}{80} \times 100) = 61.3\%$ of the time.

Table 4.6: Variable not in the Equation.

| | | | Score | df | Sig. |
|--------|-----------|--------------------|--------|----|-------|
| | | Age | 1.151 | 1 | 0.283 |
| | | Parity | 0.018 | 1 | 0.893 |
| | | Gravida | 0.176 | 1 | 0.675 |
| | | Residence | 2.748 | 2 | 0.253 |
| | | Residence(1) | 2.673 | 1 | 0.102 |
| Step 0 | Variables | Residence(2) | 0.225 | 1 | 0.636 |
| | | MSTATUS | 6.881 | 2 | 0.032 |
| | | MSTATUS(1) | 1.739 | 1 | 0.187 |
| | | MSTATUS(2) | 1.693 | 1 | 0.193 |
| | | MDELIVERY | 9.758 | 3 | 0.021 |
| | | MDELIVERY(1) | 0.023 | 1 | 0.881 |
| | | MDELIVERY(2) | 8.430 | 1 | 0.004 |
| | | MDELIVERY(3) | 0.539 | 1 | 0.549 |
| | | ANC | 3.813 | 1 | 0.051 |
| | | Overall Statistics | 23.182 | 11 | 0.017 |

The variables not in the table tell us whether each independent variable improves the model. The answer is yes because for the predictor variables marital status which had statistical significance of 0.032 and MDELIVERY (2) which had statistical significance of 0.004 if included

would add the predictive power of the model. If they had not been significant and able to contribute to the prediction, then termination of the analysis would obviously occur at this point.

Table 4.7: Variables in the Equation

| | B | S.E | Wald | df | Sig. | Exp(B) |
|-----------------|-------|-------|-------|----|-------|--------|
| Step 0 Constant | 0.458 | 0.229 | 3.980 | 1 | 0.046 | 1.581 |

The output assessed the usefulness of having a null model which was a model with no predictor variables. The Variable in the equation table 4.7 above only included a constant so each pregnant mother going to Migori County Referral Hospital had the same chance of dying. So the null model calculated as:- $\ln\left(\frac{p}{1-p}\right) = \alpha = 0.458$, $p = \text{probability of dying} = \frac{e^{0.458}}{1+e^{0.458}} = 0.613$

If the probability of pregnant woman dying at MCRH is 0.5 or more we would predict maternal death (maternal death=1) and no maternal death if the probability was less than 0.5. Therefore from the foregoing more expecting women at the MCRH died since the probability of dying is 0.613 and therefore everyone was predicted as succumbing to maternal death (coded 1). As 61.3% of women were correctly classified, classification from the null model was 61.3% accurate as showed in table 4.7 above. The addition of predictor variables should increase the percentage of correct classification if the model is good as we would observe later in table 4.8 below.

Table 4.8: Block 1 Method : Classification table

| | | Predicted | | |
|--------------------------|----------|-----------|-------|-------------------|
| | | MDEATH | | |
| Observed | | No Death | Death | percentage Corect |
| Step 0 | No Death | 19 | 12 | 61.3 |
| | Death | 5 | 44 | 89.8 |
| Overall Percentage Overa | | | | 78.8 |

a. The cut value is .500

Table 4.8 above showed that $\frac{44}{49} = 89.8\%$ were correctly classified as predicted events (maternal death occurring) this was the sensitivity of the prediction, the percentage of occurrences correctly predicted. Again $\frac{19}{31} = 61.3\%$ were classified where the predicted event of maternal death was not observed. This was specificity, the percentage of non-occurrences correctly predicted. Overall our predictions were correct 63 out of 80 times, for an overall success rate of 78.8%. Initially it was only 61.3% for the model with intercept only as showed in table 4.7 above.

On error rates classification, a false positive predicted that the event would occur when in fact it did not. Our decision rule predicted maternal death occurring 56 times. This prediction was wrong 12 times for a false positive rate of $\frac{12}{56} = 21.43\%$. A false negative predicted that the event would not occur when in fact it did occur. The decision rule predicted non-occurrence of maternal death 24 times. That prediction was wrong 5 times, for a false negative rate of $\frac{5}{24} = 20.83\%$.

Table 4.9: Model Chi- Square

| | | Chi-Square | df | Sig. |
|--------|-------|------------|----|------|
| | Step | 29.723 | 11 | .002 |
| Step 1 | Block | 29.723 | 11 | .002 |
| | Model | 29.723 | 11 | .002 |

Table 4.9 above is used to test the overall significance of the model. It is derived from the likelihood of observing the actual data under the assumption that the model that has been fitted is accurate. Hence there are two hypotheses to test in relation to the overall fit of the model. In our case of model chi square has 11 degree of freedom, a value of 29.723 and a probability of $p < 0.002$. Thus the indication is that the model has a good fit, with the model containing only the constant indicating that the predictors do have significant effect and create essentially a different model.

Table 4.9 has step 1 this is because we are entering both variables and at the same time providing only one model to compare with the constant model. The step is a measure of the improvement in the predictive power of the model since the previous step.

The difference between $-2\loglikelihood$ for the best- fitting model and $-2\loglikelihood$ for the null hypothesis model (in which all the b values are set to zero in block 0) is distributed like chi squared, with degree of freedom equal to the number of predictors; this difference is the Model chi square that SPSS refers to. Very conveniently, the difference between $-2\loglikelihood$ values for models with successive terms added also has

a chi squared distribution, so when we use a stepwise procedure, we can use chi-squared tests to find out if adding one or more extra predictors significantly improves the fit of our model.

Table 4.10: Model Summary

| Step | -2 Log likelihood | Cox and Snell R Square | Nagelkerke R Square |
|------|-------------------|------------------------|---------------------|
| 1 | 77.096 | .301 | .421 |

Although there is no close analogous statistic in logistic regression to the coefficient of determination R^2 the Model summary table 4.10 above provides some approximations. Cox and Snell's R^2 attempts to imitate multiple R-Square based on "likelihood", but its maximum can be (and usually is) less than 1.0, making it difficult to interpret. Here it is indicating that 31.0% of the variation in the dependent variable is explained by the logistic model. The Nagelkerke's R^2 will normally be higher than the Cox and Snell measure. Nagelkerke's R^2 is part of SPSS output in the "Model Summary" table and is the most reported of the R^2 estimates. In our case it is 0.421 indicating a moderately strong relationship between the predictors and the prediction.

4.4 Parameter Estimates

Table 4.11: Logistics Regression output for Parameters Estimates of contributing factors

| | Estimates | SE | Wald χ^2 | df | p-value | Odds Ratios |
|--------------|-----------|-----------|---------------|----|---------|-------------|
| AGE | .141 | .067 | 4.402 | 1 | .036 | 1.152 |
| PARIRY | -.405 | .273 | 2.209 | 1 | .137 | .667 |
| GRAVIDA | .237 | .268 | .781 | 1 | .377 | 1.267 |
| RESIDENCE | | | 2.752 | 2 | .253 | |
| RESIDENCE(1) | 1.321 | .797 | 2.745 | 1 | .098 | 3.747 |
| RESIDENCE(2) | .286 | 1.316 | .047 | 1 | .828 | 1.331 |
| MSTATUS | | | 4.752 | 2 | .093 | |
| MSTATUS(1) | .876 | .793 | 1.221 | 1 | .269 | 2.401 |
| MSTATUS(2) | 2.478 | 1.138 | 4.740 | 1 | .029 | 11.918 |
| MDELIVERY | | | 1.730 | 3 | .630 | |
| MDELIVERY(1) | -.605 | .694 | .760 | 1 | .383 | .546 |
| MDELIVERY(2) | -22.858 | 15427.288 | .000 | 1 | .999 | .000 |
| MDELIVERY(3) | -1.037 | .831 | 1.558 | 1 | .212 | .355 |
| ANC | .467 | .183 | 6.512 | 1 | .011 | 1.595 |
| CONSTANT | -4.092 | 1.756 | 5.430 | 1 | .020 | .017 |

Table 4.11 above shows the output of the parameter estimates of the 11 factors contributing to the occurrence of maternal death or non occurrence of maternal death at the Migori County Referral Hospital. From the table the odds ratio estimates for the predictor variables, their corresponding regression coefficients, and the Wald test statistic which follows the chi

squared distribution and their respective p values are obtained. The full model in general given as:-

$$\begin{aligned} \text{Logit}(MDEATH) = & -4.092 + 0.141X_1 - 0.405X_2 + 0.237X_3 + 1.321X_{4(1)} \\ & + 0.286X_{4(2)} + 0.876X_{5(1)} + 2.478X_{5(2)} - 0.605X_{6(1)} \\ & - 22.858X_{6(2)} - 1.037X_{6(3)} + 0.467X_7 \end{aligned} \quad (4.1)$$

The coefficients were contained in the column headed Estimates. A negative value means that the odds of occurrence of maternal death decreases. From the table 4.11 the odds ratio estimates for the predictor variables, their corresponding regression coefficients, and the Wald test statistic which followed the chi-squared distribution and their respective p values were obtained.

From table 4.11 the variable with p values less than 0.05 are significant since our confidence interval was measured at 95%. Therefore from the table three factors that were significantly contributing to the prediction of the occurrence of maternal death at Migori County Referral Hospital were AGE, and ANC with p values 0.036, and 0.011 respectively. The odds ratio for the effect AGE was given as 1.152 which gave the indication that the ages of pregnant women were found to be 1.152 times more likely to predict the occurrences of maternal death than the non-occurrences. Similarly ANC which constitutes the number of times a pregnant woman goes for ante- natal care had odds ratio of 1.595 which means that it is 1.595 times more likely to cause the occurrence of maternal death. Therefore the logistic regression model (Logit) developed was given by:-

$$z = -4.092 + 0.141X_1 + 0.467X_7 \quad (4.2)$$

thus

$$p = \frac{e^{(-4.092+0.141X_1+0.467X_7)}}{1 + e^{(-4.092+0.141X_1+0.467X_7)}} \quad (4.3)$$

The equation above is the predictive equation, it indicated the likelihood of a pregnant woman on admission to Migori County Referral Hospital dying or surviving depending on the contributing factors. In summary factors such as AGE (P value 0.036) and ANC (P value 0.011) contributed significantly to the occurrence of maternal deaths at Migori County Referral Hospital with ANC being the most significant contributing factor followed by AGE. For example if a pregnant woman at the MCRH aged 23 years old attended ANC one times, the probability of occurrence of maternal death would be 0.405 given as:-

$$p = \frac{e^{(-4.092+0.141 \times 23+0.467 \times 1)}}{1 + e^{(-4.092+0.141 \times 23+0.467 \times 1)}} = 0.405 \quad (4.4)$$

A gain if a woman of age 35 who had attended ante-natal 2 times the probability of maternal death occurring would be 0.64 given as:-

$$p = \frac{e^{(-4.092+0.141 \times 35+0.467 \times 1)}}{1 + e^{(-4.092+0.141 \times 35+0.467 \times 1)}} = 0.640 \quad (4.5)$$

4.5 Model Evaluation

Here we checked the adequacy of the logistic regression model. First we looked at those statistical tests (likelihood ratio test, score and the wald

statistics) which test the efficiency of the logistic regression model to be statistically significant since their respective p values were all less than the level of significance 0.05 indicating that the model developed significantly fits well hence this leads to the rejection of the null hypothesis that there did not exist a relationship between the predictors variables age, parity gravida, residence, marital status, mode of delivery and the ANC and maternal deaths at Migori County Referral Hospital and we accepted the alternative hypothesis.

Table 4.12: Hosmer and Lemeshow Test

| Step | Chi-Square | df | p-value |
|------|------------|----|---------|
| 1 | 4.469 | 8 | .813 |

A probability (p value computed above in table 4.12) is computed from the chi-square distribution with 8 degrees of freedom to test the fit of the logistic model. If the H-L goodness-of-fit test statistic is greater than 0.05, as we want for well fitting models, we fail to reject the null hypothesis that there is no difference between observed and model-predicted values, implying that the model's estimates fit the data at an acceptable level. That is well fitting models show non-significance on the H-L goodness of fit test. This desirable outcome of non significance indicates that the model prediction does not significantly differ from the observed. Our H-L statistic has a significance of 0.813 (p-value) which means that it is not statistically significant and therefore our model is quite a good fit.

Table 4.13: Classification table

| | | Predicted | | |
|--------------------------|----------|-----------|-------|-------------------|
| | | MDEATH | | |
| Observed | | No Death | Death | percentage Corect |
| Step 0 | No Death | 19 | 12 | 61.3 |
| | Death | 5 | 44 | 89.8 |
| Overall Percentage Overa | | | | 78.8 |

a. The cut value is .500

Here we want look at the cases we have managed to classify correctly, so from the table above we are told of how many of the cases where the observed values of the dependent variable were 1 or 0 respectively have been correctly predicted. So from table 5.2 the columns are the two predicted values of the dependent, while the rows are the two observed (actual) values of the dependent. In a perfect model, all cases will be on the diagonal and the overall percent correct will be 100%. In our study 89.8% were correctly classified, for the "death" and 61.3% for the "no death" group. Overall 78.8% were correctly classified. This is a considerable improvement on the 61.3% correct classification with the constant model so we know that the model with predictors is a significantly better model.

4.6 Discussion of Results

This study showed that there were 80 maternal deaths and about 18577 live birth deliveries. This translated to a total maternal mortality ratio of 431 per 100,000 live births, within the study period of the year 2007 to the year 2015. The average annual MMR recorded for the study period was 468 per 100,000 live births which was lower than the country average annual of 488 maternal deaths per 100,000 and the Migori County average annual of 673 maternal deaths per 100,000. These averages were more than the estimate of this study. The study found out that ANC was the most significant predictor variable which was 1.595 times likely to cause the occurrence of the maternal death at the hospital and then AGE which was 1.152 more likely to cause the occurrence at the hospital during the study period. These findings were similar to the findings of Sailifu (2014), who found out that pregnant women who delivered through caesarian section were 2 times more likely to die than those who delivered through spontaneous vaginal delivery (SVD) or normal (mode of delivery). Parity on the other hand reduces the risk of dying, that is pregnant women with parity are 0.727 times less likely of dying than those with no parity controlling other factors in the model. He also found out that age had effect on pregnancy outcome at the Upper West Regional Hospital (UWRH) in Ghana. This study was also in tandem with the study of Mensah et al. [4] in their study where they were assessing the occurrence of maternal mortality and other related factors at Komfo Anokye Teaching Hospital (KATH) in Ghana. They found out that AGE, Parity and Gravida were the only three factors that were statistically significant out of the seven variables with parity found to be the most contributing factor

to the occurrence of maternal mortality at the hospital followed by Age the Gravida.

Chapter 5

Conclusions and Recommendations

5.1 Introduction

This chapter looks at the outcome of the analysis and considers the extent to which the objectives of the study have been achieved. It also considers the recommendations the researcher wishes to put a cross for the hospital administrators, the partners in health and other stakeholders.

5.2 Conclusions

The study was aimed to determine factors affecting the prediction of occurrence or non occurrence of maternal mortality at Migori County Referral hospital from the year 2007 to 2015. In this study a logistic regression model was used to develop a model. The result in the study revealed that only two predictor variables were the most significant ANC and AGE

among the 11 predictor variables based on the confirmation at 0.05 level of significance. The two predictor variables were the ones contributing to the occurrence of maternal mortality at the Migori County Referral Hospital using the concept of p value; the variables were subjected to significance testing. ANC was found to be the most significance factor that contribute to the occurrence of maternal mortality with a p value of $0.011 < 0.05$, followed by the AGE of p value $0.036 < 0.05$. However, the literature reviewed revealed that length of stay at the hospital, educational level of the pregnant woman, the educational level of the husband and occupation of the husband for those women who were married, the birth plans and the three delay models which were proposed by Maine and Thadeus in 1994 as the major causes of maternal mortality in Asia and Sub Saharan Africa. But the maternity register at the Migori County Referral Hospital (MCRH) had no data related to this variables, some of the variables were not even recorded though they were suppose to be recorded like the length of stay at the hospital.

5.3 Recommendations

In this section we made recommendations based on the findings of this study.

The study found out that ANC was the most significant followed by AGE; It was recommended that the government and the hospital management of the County Referral hospital should make every effort to liaise with schools to provide the sex education to prevent unplanned pregnancies among teenagers which is at alarming rate currently at country at

large. This was reflected in the landmark publication of McCarthy and Maine in 1992 as depicted from our literature. These two gentlemen provided a framework for examining the causes of maternal mortality and highlighted three events that must occur before maternal death occur that is, conception, serious complication of pregnancy and adverse outcome of the pregnancy. And the authors analysis found that societies with low level of maternal mortality were due to prevention of pregnancies. There should be intense provision of family planning to both married and unmarried women and sex education in our schools and ante-natal visits to expecting women before delivery

References

- [1] Abdulai,S. (2014). *Analysis of maternal Mortality in Wa district*. Master thesis, Mphil thesis, Department of Mathematics, Kwame Nkrumah University of Science and Technology, 2014.
- [2] AbouZahr, C. (2011). *New Estimates of Maternal Mortality and how to interpret them: choice or confusion?*. Journal of Reproductive health Matters, 2011.
- [3] Adamu, Y. M. (2002). *"Maternal Mortality in Northern Nigeria: a population based study"* European Journal of Obstetrics and Gynecology and Reproductive Biology, 2003.
- [4] Adjei M., Agyei W., and Kwasi B., (2015). *Assessing the occurrence of maternal mortality and some related factors at KomfeAnokye Teaching Hospital in Ghana*. International Journal of Scientific and Technology Research Vol. 4 Issue 12, 2015
- [5] Agresti, A.(1990). *Categorical Data Analysis*, 1990. New York Willey.
- [6] Aikins, L. (2010). *Femal Health and Development; a case study regarding maternal health scheme in Ghana*. University of Agder, Faculty of Economics and Social Science, 2010

- [7] Arifeen, S., Hill K., Hassan A., Jameel K.,Nahrar Q.and Streatfield, p. (2010). *Maternal Mortality in Bangladesh. A count to 2015 country case study*. Lancert, 2014.
- [8] Balogun, O. (2015). *Evaluation of Logistic Regression on Mode of the Delivery of Expectant Mothers*. International Journal of Bioassays, 2015.
- [9] Bassoumah, B. (2010). *Maternal Health in Awatu-Senya District*. Masters Thesis, Department of Population and Health, University of Cape Coast, 2010
- [10] Bewickh, V., Cheek L and Boll J (2005). *Statistics review 14: Logistic regression..* Critical Care: 9(1), pp 11-118
- [11] Central Bureau of Statistics. (2004). *Kenya demographic health survey 2003*. Ministry of Planning and National development, Nairobi, Kenya
- [12] Central Bureau of Statistics. (2010). *Kenya demographic health survey 2008-2009*. Ministry of Planning and National development, Nairobi, Kenya.
- [13] Central Bureau of Statistics. (2015). *Kenya demographic health survey 2014*. Ministry of Planning and National development, Nairobi, Kenya.
- [14] Chukwu, A. and Oladeji R. (2015). *Modelling the determinants of maternal mortality: A comparative study of Logistic regression and artificial neural network model*.IOSR Journal of mathematics (IOSR-JM) Vol. 11, Issue 4 Ver. 1 (Jul-Aug. 2015), Pp 47-52.

- [15] Desai, M. (2013a). *An analysis of pregnancy-related mortality in the KEMRI/CDC health and demographic surveillance system in Western Kenya*. PLOS ONE, Vol.8, No.7, pp 1-11.
- [16] Desai, M. Philips-Howard, P., Odhiambo, F., Katana, A., Ouma, P., Hamel, J. Slutsker, K. and Laserson, K. (2013a). *An analysis of pregnancy-related mortality in the KEMRI/CDC health and demographic surveillance system in Western Kenya*. PLOS ONE, Vol.8, No.7, pp 1-11.
- [17] Fernandez, M., Garitan, I and Cavanillas, A. (2012) *An Increase in Maternal mortality associated with change in the reproductive Pattern in Spain 1996-2005*. Journal of Epidemiology Community Health, 2008.
- [18] Gabopamang, L. and Serai, D.(2003). *Factors Associated with non-use of maternal health services in bostwana*. Journal of health and PopulNutr 2003 Mar; 21 (1): 40-47.
- [19] Garene, M. Khan, K., Collinson, M. Gomez-Olive, F. and Tollman, S. (2013). *Maternal Mortality in JRural South Africa: the impact of case definition on levels and trends*. International Journal of Women's Health Vol. 5: pp 457-463
- [20] Gauri, S. and Ganga, S. (2011). *Mathematical modeling of health service utilization data using multiple logistic regressions*. BRAC University journal, vol. VIII. No. 1 and 2, 2011, pp 47-54.
- [21] Ghebrehiwet and Morrow(2003). *Determinants of Martenal Mortality in Eritrea*. Journal of Eritrean Medical association (JEMA)

- [22] Gunner, K.(2005). *Maternal deaths in developing countries: A preventable tragedy*. NorskEpidemiologi 2005: 15 (2), 141-149
- [23] KDHS(2014). *Kenya Demographic Health Survey 2014*. Calverton Maryland: CBS, Kenya [MOH] and [ORC Marco], 2014.
- [24] Kleinbaum, d., G. and Klein, M.(2010). *Introduction to logistic regression, Statistics for Biology and health*. Springer Science and Business Media LLC, 2010.
- [25] McCarthy and Maine(1992). *Safe Motherhood Programs: Options and Issues*.Center for Population and FamilyHealth, Faculty of Medicine, Columbia University, New York.
- [26] McCullagh and Nelder (1989). *Generalized Linear Model*. 2nd ed., Chapman and Hall, New York.
- [27] Mirasi,T., B., M.(2014). *Statistical Analysis of the Determinants of Maternal Mortality and Impact of voucher for Health in Kisumu sub- county, Kenya*.Masters thesis, Biostatistics in the school of pure and applied sciences, Kenyatta University, 2014.
- [28] Mojekwu, N. and Uche, I. (2012). *Maternal Mortality in Nigeria: Examination of Intervention Methods*. International Journal of Humanities and Social Sciences Vol. 2 No. 20 (Special issue October 2012)
- [29] Ndola, P. (2010). *Maternal Mortality in developing countries: Challenges in Scaling-up priority interventions*. University of California, Berkeley School of Public Health, The Bixby Centre for population health and Sustainability, 2010.

- [30] Ngwan, S. and Swede, T. (2011). *Maternal Mortality in Jos Nigeria. A facility based prospective review*. International Journal of Biological and Medical Research, Vol. 2(2): pp 565-568.
- [31] Nieburg, P. (2012). *Improving Maternal Mortality and other Aspects of Womens Health, The United States Global role*. A report of the Center for Strategic and International Studies, Global health policy center, 2012.
- [32] . Obiechima, N., Okolie, V., Okechukwu,Z., Oguejiofor, C., Nwajiaku, I., Ogbuokiri, C and Egeonu, R. (2013). *maternal mortality at nnandi azikiwe teaching hospital, South East Nigeria: a 10 year review (2003-2012)*. International Journal of women'sHealth. Vol. 5 pp 431-436
- [33] . Okaro, J., Umezulike, A, Ona, H. Chukwuali, L., Ezugwu, O. and Nweke, P. (2011). *Maternal Mortality at the University of Nigerai Teaching Hospital in Enugu*. African Journal of Productive Health. Vol. 5(2). PP 290-97
- [34] Okeh U., M. and Oyeka I., C., A.(2013). *Estimating the Fishers Scoring Matrix Formula from Logistic Model*. American Journal of Theoretical and Applied Statistics. Vol 2, No. 6, 2013, pp. 221-227.
- [35] Omoruyi G. (2008). *Causes of Maternal mortality in Nigeria*. Sunday Observer, Benin.
- [36] Ononokpono, D.(2015). *Maternal Health Care in Nigeria: Do Community factors moderate the effects of individual-level educa-*

- tion and ethnic origin.*Journal of African Population Studies, Vol. 29, No. 1, 2015
- [37] Park, H. (2013). *An introduction to logistic regression: From basic concepts to interpretation with particular attention to nursing domain.* J Korean AcadNurs Vol. 43. No. 2 April 2013.
- [38] . Qin, Y,. L. (2010) *Maternal mortality: in Ghana, Hospital Based Review in Ghana* University of Leicester.
- [39] Razum, O., Jahn, R and Snow, R. (1998) *maternal mortality in the former East Germany before and after re-unification: Changes in Risk by maritalstatus.* British Medical Journal, 319(72-17); pp 1104-1105.
- [40] Rosenfield A. and Maine, D. (1985). *Martenal Mortality- A neglected tragedy: Where is the M in MCH?*. Lancert, 1985.
- [41] Sarpong , S.(2012) *Analysis of Maternal Mortality with time; A case study of the OkomfoAnokye Teaching Hospital-Kumasi (2000-2010).* Mphil Thesis, Department of Mathematics, Kwame Nkrumah University of science and Technology, 2012.
- [42] Shah (2014). *Changing epidemiology of Martenal Mortality in Rural India. Time to reset Strategies for MDG..* Journal of Tropical Medicine and International Health. 2014
- [43] Suwal(2008). *Maternal Mortality in Nepal:Unravelling the complexity.*University of Alberta, Dept of Family Medicine. Journalof Canadian Studies in Population, Vol.35, pp 1-26.

- [44] Tsawe, M., Moto, A., Netshivhera, T., Ralesego, L., Nyathi, C., and Susuman, S.(2015). *Factors influencing the use of maternal healthcare services and childhood immunization in Swaziland*. International Journal for Equity in Health, 2015. 14:32.
- [45] Ujah I, A., Aisen O., Mutihir J., Vanderagt D., Glew R. and Oguru V. (2005). *Factors Contributing to Maternal mortality in North-Central Nigeria: A seven teen-year Review*. African Journal of Reproduction Health, Vol. 9, No. 3 pp 27-40.
- [46] Waldijk K. (1994). *Surgeons show success in early fistula repairs*. Safer Motherhood Newsletter, Issue 14, March-June, 1994
- [47] Nelder, J. and Wedderburn, R.W.M. (1972) *Generalized Linear Models*. journal of Royal statistical association, series A, 1972. 135: p. 370-384.
- [48] WHO, (1986). *Maternal mortality: Helping women off the road to death* WHO Chronicle 40, pp 175-183
- [49] WHO, (1986). *Maternal mortality: Helping women off the road to death* WHO Chronicle 40, pp 175-183
- [50] WHO (2005). *Make Every Mother and Child count, the world health report*. Geneva.
- [51] WHO (2008). *Millenium Development Goals*. www.un.org/millenniumgoals
- [52] WHO (2012). *Trends in maternal mortality: 1990 2010, WHO, UNICEF and the World Bank estimate in Geneva*. World Health Organization.

- [53] Yoko, L. and Edwin, V., C., B. (2011). *Make it happen 2015: validation of the maternal mortality ratio in Trinidad and Tobago for 2000-2006.*