ESTIMATION OF BABY BIRTH WEIGHTS USING GENERALISED INVERSE REGRESSION MODEL WITH APPLICATION TO PRENATAL CARE DATA

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TITLE PAGE

DECLARATION

This thesis is my original work prepared with no other than the indicated sources and support and has not been presented elsewhere for a degree or any other award.

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CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance of Masinde Muliro University of Science and Technology a thesis entitled "**Estimation of Baby Birth Weights Using Generalised Inverse Regression Model With Its Applications to Prenatal Care Data .**"

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DEDICATION

This work is dedicated to my family. They are the motivation behind this academic journey.

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ABSTRACT

The global range of birth weight varies significantly across countries and regions with some countries having an average of 3.5kgs for babies of European descent,but for most African babies the birth weight ranges between 2.8kgs to over 3.5kgs. Estimation of fetal weight is of paramount importance in the management of maternal labour and reduction of baby and maternal death. Various models and techniques used in the past such as clinical method, ultra sound technique and multiple regression models that tries to estimate fetal weight before and at birth. The problem has been accuracy in estimation of fetal weight before and at birth to guarantee safe delivery since the methods are associated with measurement errors caused by position of the foetus,damage on tissues caused by the apparatus during scan and also by formulae limitations based on averages and individual variations in growth and development especially when estimated by regression models based on baby characteristics like head size and recumbent length. The study was conducted to establish the relationship between mothers weight, waist size and babies birth weight at full term delivery at Webuye Sub county hospital maternity ward in Bungoma county. Historical data on mothers weights,waist size and baby weights at birth were collected during prenatal visits and data collected were used to generate model parameters using the ordinary least squares method. The parameters were then fitted in the generalised inverse regression model. The model was then applied on data to estimate and predict birth weight. The generalised inverse regression method showed that birth weight can be estimated using information from the the mothers characteristics such as weight,and waist size. The study findings concluded that mothers pregnancy weight and waist size can be used to estimate birth weight and can also be used to prediction before the baby is born hence useful when used by medical practitioners during prenatal care assessment and also take mitigation measures against any arising emergency during birth.

TABLE OF CONTENTS

ABBREVIATIONS AND ACRONYMS

BMI	:	Body Mass Index.
EDD	:	Expected Date of Delivery.
LGA	:	Large for Gestation Age.
LBW	:	Low birth weight.
SGA	:	Small for Gestation Age.
WHR	:	Waist Hip Ratio.
WHO	:	World Health Organisation.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The general normal birth weight for full term babies globally is 3.5kg for european descent but babies for african descent vary between 2.5 to 4.0 kgs normally, but can sometimes vary across regions. The World Health Organization (2013) estimates that 16 percent of live born infants have low birth weight, which is associated with high prenatal morbidity and mortality. Fetal macrosomia is also associated with maternal morbidity, shoulder dystocia, birth asphyxia and birth trauma. High rate of prenatal mortality 39-130 per 1, 000 total births is still a major concern in developing countries and according to (WHO,2013) a large portion of this problem is related to birth weight which remains a single parameter determining maternal and fetal survival.

A study by Judith(1996) concludes that location of body fat stores as indicated by waist hip ratio (WHR) circumference affects a variety of processes in women and some of the changes affect fetal growth during pregnancy period. Therefore,variables such as waist size and weight of the mother can be of importance in prediction of birth weight at birth by fitting them in a suitable regression model. The main method of estimating birth weight in current obstetrics are clinical techniques based on abdominal palpation of fetal parts and sonographic measures of skeletal fetal parts. Steven (1998) agrees that for accuracy estimation pre-pregnancy body mass index (BMI)and gestational age respectively of the mother during pregnancy are important predictors of babies birth weight. Pregnancy body mass index (BMI) of the mother also varies from conception to delivery hence the need to consider this important variable in the model.

Accurate estimation of birth weight would help in successful management of labour and care of the newborn and help in avoidance of complications associated with fetal macrosomia and low birth weight. Godfrey (2000) notes that healthy mothers give birth to healthy babies. Kinira (2005)for instance in his study noted that overweight women with (BMI) greater than 25 are more likely to give birth to babies deemed large for gestational age and the risk is greater for women who gain excessive weight during pregnancy period. Eghbalian(2007)says underweight women with (BMI) less than 18.5, who smoke or unhealthy during pregnancy are likely to give birth to babies deemed small for gestational age (SGA).

Determining gestational age depends heavily on weight measurements which are used to predict accurately the expected date of delivery (EDD) of the baby. Upadhay(2011) noted that increase in fetal weight corresponds to increase in maternal weight. Therefore,variables such as weight and waist size of the mother can be of importance in prediction of birth weight by fitting them in a regression model.

Accurate estimation of birth weight is of paramount importance. High risk pregnancies and deliveries need to be evaluated regularly by medical practitioners through standard routine, antenatal and prenatal checks. Accurate estimation of fetal weight during pregnancy and at births presents counseling on the likelihood of survival. According to Ekele (2006) the intervention undertaken to postpone pre-term delivery, optimal route of delivery or the level of hospital where delivery should occur may be based wholly or on part of the estimation of the expected birth weight. Categorization of fetal weight into either small or large for the gestational age may lead to timed obstetric interventions that collectively represent a significant departure from routine antenatal care.

Weighing a baby at birth using a scale is considered gold standard however calibrated weight scales are not easily available in certain situations or settings where emergency situations like resuscitation, medical dosage and fluid replacement is required. It is impractical to delay resuscitation to take weight and often estimated weight is erroneous. With limited resources in rural health centres there is lack of functioning calibrated scales and funds to maintain them in good condition. Therefore use of visual assessment of birth weight is common. Visual assessment of birth weight by medical practitioners is inaccurate and therefore a fast and reliable weight estimation method at birth is necessary. Bajracharya (2012) notes that birth weight is one of the crucial first steps medical practitioners need to examine in order to proceed with management of labour and delivery.

. The problem of research is discussed in 1.2 where as the main objective and specific objective are in 1.3.1 and 1.3.2.

1.2 Statement of the Problem

During prenatal care assessment, the average normal birth weight varies from 2.5 kgs to 4.0 kgs,therefore medical practitioners need to estimate birth weight of the unborn so that they can be able to plan for future possible emergencies arising from macrosomia and low birth weights. The methods currently used such as clinical,ultra sound use of regression models based on babies characteristics to estimate birth weight have shortcomings in the sense that measurement errors are realised because of position of the foetus, maternal factors like gestational age,health and genetics. The effect of using scan equipments damage tissues of mother and baby when equipments are being used by medical practitioners. Therefore safer method is necessary for estimation of baby weight. The information about waist size and weight gathered from mothers visits can be used therefore to predict baby weight without complexity. This is crucial in determining the health of the mother as well as the development of the baby in the womb.

Further more,there is no evidence of estimation of fetal weights and birth weights using vital information such as weight and waist size from the mother visits in hospitals. Methods currently used such as ultrasound and clinical and regression models based on baby characteristics can estimate weights of unborn babies but require trained and the complex procedure. Therefore alternative simple method is necessary for estimation and prediction where such equipments are unavailable to plan for future emergencies therefore generalised inverse regression model can be used to estimate and predict birth weight as it will be demonstrated in this study.

1.3 Objectives of the Study

1.3.1 Main Objective

The main objective of the study is to use a generalised inverse regression model for estimating birth weights of babies before birth and apply on prenatal care data.

1.3.2 Specific Objectives

The specific objectives of this research are to;

(i) To use generalised inverse regression model for estimating weights before birth.

(ii) To use the generalised inverse regression model to predict future birth weights.

1.4 Significance of the Study

Medical practitioners have a challenge of identifying fetal weight before birth and risks that may arise due to complications associated with it.The complications can be averted to guarantee safety and a normal healthy birth weight if a suitable model can be applied early enough to estimate fetal and birth weight.This study came up with a simple non complex method able to estimate and predict birth weight long before the baby is born. This helps put in place mitigation measures incases where low birth weights or macrosomia are predicted.It can also be used to predict and advise future mothers on pre-natal and post-natal care requirements.

1.5 Methods of Study

1.5.1 Source of Data

Secondary data collected and stored by records department was used for the study since its cost effective easily extracted and reliable.The data was extracted in Webuye subcounty hospital maternal records department. Webuye subcounty was chosen because of familiarity with the hospital.Financial constraints also made the study to be confined to the county.

1.5.2 Source and Study Population

The target population in this study was pregnant women attending prenatal care clinic at Webuye subcounty hospital. Historical information of women who attended prenatal clinic were considered regardless of gravidity, age and residence. Those who attend prenatal care visit from 12 to 36 weeks of pregnancy were also considered since first 11 weeks are not significant in determination of birth weight.

1.5.3 General Least Squares

The general least square method was used to solve the problem of OLS estimation since it minimises the sum of residuals.The relationship between weight of the baby, mothers weight and waist size at 36 weeks of pregnancy were established. The section also states the underlying assumptions, defines the associated variables and parameters and the model application and prediction.

1.5.4 Use of R Language statistical Software

The statistical package was used to analyse collected data establish the unknown parameters and use it for inference and prediction by fitting the parameters in the model. Parameters of the model were estimated fitted in the model and the model used for estimation through description of the relationship between birth weight,mothers weight and waist size .

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter discusses the literature that exists in estimation of birth weights, developed regression models and their shortcomings in relation to the proposed study.The chapter is outlined as follows;Dares formula of estimating birth weight,current and clinical mehods,regression models,and knowledge gaps.

2.2 Dares Formula of Estimating Birth Weight

Dare.*et al.*(1990) used tactile assessment of fetal size,it was the oldest technique for assessing fetal weight through manual assessment by obstetrician by external palpation of the uterus and fetal parts. It was was commonly used because it was convenient and costless. However it has long been known as a subjective method associated with predictive errors less accurate for obese gravidas and non obese and had higher variation in prediction of birth weight even among experienced personell. Later proposed a formula for clinical fetal weight estimation which consisted of multiplying syphixial fundal height by abdominal girth it was tested on 498 full term pregnant women and obtained a correlation between clinical estimate and actual birth weight r = 0.742)which currently is slightly less accurate than clinical estimate. Chang.*et al.* (1992) used the regression analysis model including data from all routine investigation to explain the variance in newborn weights, suggesting that routine ante natal measurements had a power to predict the size of live born babies. Using the observed data and fitting in the multi-regression model developed, the variation in the weight of babies was explained by the mother's BMI and other characteristics of the baby. However the study focused on low birth weights only. The proposed model was then used to estimate the recorded weights. Analysis of prediction errors showed that the mean prediction error for data was one gram and concluded that the multi regression model is capable of predicting low birth weight based on the characteristics of mother and baby.

Vourhorst (1993) used multiple regression where the relationship between birth weight(dependent variable) and gestational age, fetal gender and parity as (independent) was studied in the model. They found out that in addition to gestation age, parity and fetal gender, the maternal age, maternal height and mid-pregnancy weight are statistically significant determinants of birth weight.

2.3 Current Clinical and Ultrasound Methods of Estimating of Birth Weights

The current techniques for predicting birth weight are clinical and ultrasonographic methods but increasing attention is being paid to using various ultrasound measurements in estimating fetal weight. Bajracharya.et.al.(2012), used multiple fetal parameters for prediction of birth weight such as biparietal head circumference, girth and recumbent length however ultrasound estimation of fetal weight is associated with errors ranging from +6 to +11 depending on parameters measured. Gultekin(2015) compared waist circumference versus sonographic estimation of fetal weight and concluded that waist circumference was a predictor superior to sonograhic estimate. The accuracy of each was determined by percentage error and proportion of estimation within 10 percent of actual birth weight. Statistical analysis by wilcoxon signed rank test had actual birth weight. The technique is also challenging in developing countries where ultrasound requires expensive equipment and trained personnel to use the equipment. The used ultra sound estimates at 28-34 weeks of gestation in predicting small and large for gestational age infants at term. The sonograhic estimated fetal weight and birth weight were converted to percentiles and compared. Multivariate linear stepwise regression analysis was then used to predict birth weight and the value compared with actual weight. In the study however sonographic estimation at the early trimester poorly predicts the birth weight at term hence not the best method.

2.4 Regression Models

Growth monitoring of a baby up to one year of age is dependent on recumbent length at birth. Rouche.*et al.* (1989) developed a regression model of estimating birth weight; the recumbent lengths fitted well in the model for first year of life and were used for prediction purposes. The main shortcoming of the model was that the model depended on time hence if time is zero then recumbent length becomes constant for all babies this implied birth weight also constant for babies. Etikan(2005)used linear and non linear models for prediction of birth weight among maternal demographic characteristics. The study focused on blood glucose load,age,body mass index,change in weight during pregnancy,height,gestational age,parity and fetal gender as independent variables and baby birth weight as dependent variable.Least square estimation method was used to estimate parameters. The non linear regression model he used a neural network with multilayer perceptions. The results showed that one method was not significantly better than the other.However when accuracy is required its better to use the two method then decide on the more accurate method.

Rao.*et al.* (2001) used regression methods including categorical variables for weight change during the first trimester and other covariates. The results of the study showed that maternal weight gain occurring primarily in the second and third trimesters of pregnancy predicted new born weight but maternal weight gain in the first trimester was found to be unrelated to new born weight.

Fawzia (2002) used ultrasonographic measurements on singleton pregnancies to predict low birth weight by evaluating the placental diameter and thickness at 36 weeks gestation. The measurements were fitted in logistical model as valuable parameters of prediction of low birth weight. But at 36 weeks the placenta diameter failed to reach the 5 percent level of significance, neither the sex of the baby was statistically related to birth weight. The model showed that the probability of a normal birth weight increases with increase in placental thickness and diameter; but for low birth weight prediction, this method proves unsatisfactory.

Pervin (2004) collected data on 296 babies in different clinics and hospitals in Bangladesh and monitored their growth from 0-48 months. The regression model developed used recumbent length at birth and found good fit for each and every baby separately. The growth curve then was extended backwards to zero point freehand which intercepted the y axis at some point above the origin. The point was considered as the recumbent length at birth. The major criticism was that since the measures are based on graph,they cannot be used for further statistical treatment; also ordinary least squares fitted errors shows significant correlation with estimated recumbent length indicating the presence of measurement errors in the estimated values.

Shrestha.*et al.* (2010) developed multiple linear regression models after studying the history of pregnant and details of delivered full term babies at Patan hospital. The total weight gained by the pregnant women and the correlation between the weights gained by them with the birth weight of their infants. The mean weight gain of the mothers was 9.48 (SD=3.41) kilograms and the mean birth weight of the infants was found to be 2965.66(SD=364.37) gram. Stepwise multiple regression gave rise to models that showed effect of (GWG) and age on birth weight of infants.

According to Susuki(2008) there is a relationship between birth weight, gestational period and smoking status of the mother. The regression equation for non smokers and smokers were illustrated using the equation

$$Babyweight(kgs) = -2330 + 143Gest \tag{2.1}$$

for smokers and

$$Babyweight(kgs) = -2635 + 143Gest \tag{2.2}$$

for non smokers respectively. The analysis of the regression equation was found out that 89.64 percent of the variation in birth weight of were explained by length of gestation and smoking status of the mother. Tirunesh predicted birth weight from neonatal anthropometric parameters at birth basing on crown heel length,mid upper arm circumference,umbilical nipple distance and head circumference. The parameters were measured within 24 hours of birth. The relationship between birth weight and neonatal anthropometric parameters were evaluated using correlation analysis.Birth weight regression models were developed using simple and multiple regression analysis. All neonatal anthropometric parameters had positive significance correlation with birth weight as

$$Babyweight(kgs) = 0.117 + 0.284MUAC \tag{2.3}$$

and among all the highest significance correlation was observed on mid upper arm circumference (MUAC) followed by foot length(FL)each being

$$R = 0.461 \tag{2.4}$$

and

$$r = 0.474 \tag{2.5}$$

respectively. The predictive regression model was then formulated at birth as

$$Babyweight(kgs) = 0.117 + 0.284MUAC \tag{2.6}$$

and birth weight

$$Babyweight(kgs) = 1.137 + 0.254FL \tag{2.7}$$

as compared to individual neonatal anthropometric parameters,a combination of MUAC,HL,FL, and CHL had the highest significance correlation

$$r = 0.661 \tag{2.8}$$

and multiple regression equation used to estimate birth weight was formulated as

$$Babyweight(kgs) = -2.489 + 0.254MUAC + 0.078HL + 0.11FL + 0.036 + CHL \quad (2.9)$$

.Neonatal anthropometric parameters had higher significance to identify low birth weight and therefore crucial to minimise deaths of neonates due to low birth weight.Donkor (2016) predicted birth weight by use of vital information from pregnant mothers such as fundal height(FH) ,maturity of pregnancy(M), weight of the mother and blood pressure of the mother(W).The maternal information after analysis were used to develop the inverse regression model which was used to predict birth weight.The model was formulated as

$$Baby's \ \ weight(kgs) = \frac{mothersweight - 55.1293 + 1.01558 + FH - 0.4504BP - 0.3125M}{2.236} \quad (2.10)$$

2.5 Knowledge Gaps in the Reviewed Literature

There have been various concerns among researchers for the best method of estimating birth weight and there have been considerable researches using various methods.The literature review reveals various methods among them are clinical method,ultra sonographic methods and regression models models. The clinical method over estimated birth weight while ultra sonographic method underestimated birth weight because of measurement errors caused by positioning of the foetus and difference in growth and development. Regression models mostly estimated birth weight based on baby characteristics like recumbent length,head size,and arm length. Information obtained from mothers during prenatal visits such as weight and waist size is never used to plan for future birth as per the researchers knowledge. Hence the information is no longer useful. Therefore this study will attempt to use these data from maternal visits in modelling the nature of births by using generalised inverse regression model. The method is crucial especially in developing countries where equipment is expensive and trained personnel are inadequate.

CHAPTER THREE

GENERALISED INVERSE REGRESSION

3.1 Introduction

In this chapter,we use the generalised inverse regression,apply the generalised regression on data to estimate the parameters of the model and use the model for estimation and prediction of birth weight.

3.2 The Data Matrix

The general regression equation

$$Y = X\beta + \epsilon_i \tag{3.1}$$

where Y is the dependent variable, X is independent variable β is the vector parameters,and ε is the white noise with the assumption that $Var(\epsilon_i) = \Sigma$. In ordinary least squares theory its assumed that $Var\sum = \sigma^2 I$ implying that errors are uncorrelated i.e $cov(\epsilon_i, \epsilon_j) = 0 \; i \neq j$. Mette(2011) noted that every increase in one kilogramme of pre pregnancy weight increased birth weight by 22.4 grams. therefore ,unborn babies birth weight and mothers weght depend on one another therefore the association between maternal weight and birth weight cannot be separated. Therefore the assumption that $cov(\epsilon_i, \epsilon_j) = 0 \; i \neq j$ in this study is not true. Therefore we shall assume that $cov(\epsilon_i, \epsilon_j) \neq 0$ $i \neq j$ for the dependence in the model. To achieve this we modify (1) by premultiplying by a matrix P. The matrix P is a matrix of eigen vectors obtained by decomposing $\hat{\sum}$ and has the properties of revealing dependence among variables removing autocorrelatin.

$$P'Y = P'X\beta + P'\epsilon \tag{3.2}$$

simply written as

$$Y^* = X^*\beta + \epsilon^* \tag{3.3}$$

where

$$X^* = P'X \tag{3.4}$$

,

$$Y^* = P'Y \tag{3.5}$$

and

$$\epsilon^* = P'\epsilon \tag{3.6}$$

Next we estimate the parameters in (3.3)by method of least squares to minimise errors which leads to

$$arg \min_{\beta} \hat{\epsilon}^* \hat{\epsilon}^* = arg \min_{\beta} \|Y^* - X^{'*}\hat{\beta}^*\| \tag{3.7}$$

which can be simplified to by squaring both sides and differentiating with respect to beta

$$arg \min_{\beta} \hat{\epsilon}^* \hat{\epsilon}^* \;\; = \;\; arg \min_{\beta}(X^{'*}X^* - Y^*X^*\hat{\beta}^* - X^{'*}\hat{\beta}^{'*}Y^* + X^{'*}\hat{\beta}^{'*}X^*\hat{\beta}^*) \tag{3.8}$$

Hence,

$$0 - 2X^{'*}Y^* + 2X^{'*}X^*\hat{\beta}^* = 0 \tag{3.9}$$

The solution is

$$X^{'*}X^*\hat{\beta}^* = X^{'*}Y^* \tag{3.10}$$

Thus,

$$\hat{\beta}^* = (X^{'*}X^*)^{-1}X^{'*}Y^* \tag{3.11}$$

Hence equating to zero to find beta.

$$\hat{\beta}^*_{GLS} = (X^{'*}X^*)^{-1}X^{'*}Y^* \tag{3.12}$$

Notice that(3.11)has been derived based on $\sum$ but we don't know $\hat{\sum}$. Therefore we estimate $\hat{\sum}$ based on data as follows; Let the entries of the matrix X be

$$X = \begin{pmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ \vdots & \vdots & \vdots \\ X_{p1} & X_{p2} & X_{p3} \end{pmatrix} \tag{3.13}$$

$$X_{i1} = \text{Baby weight observations}$$

$$X_{i2} = \text{Mothers weight observations}$$

$$X_{i3} = \text{Waist size observations}$$

The estimate of $\sum$ here is denoted by $\hat{\sum}$ which is equivalent to

$$\begin{aligned} \hat{\sum} &= \frac{1}{(n-1)(k-1)} \sum (\bar{X}_{ii} - X_i)(X_{ii} - X_i) \\ &= \begin{pmatrix} Var(X_{ii}) & Cov(X_i X_i) \\ Cov(X_i X_i) & Var(X_{ii}) \end{pmatrix} \end{aligned} \tag{3.14}$$

where n and k are degrees of freedom. Therefore the P used in (4.2) is now based on $\hat{\sum}$ and is obtained from decomposing $\hat{\sum}$ to

$$\hat{\sum} = P \Lambda P \tag{3.15}$$

where P is a matrix of eigen vectors, hence forth we utilise(3.3)and is vital to this study since it brings about dependence. From (3.1)we shall get our generalised inverse equation.

$$Y = B_0 + B_1 X_{1i} + B_2 X_{2i} \tag{3.16}$$

In the next section we apply the model on the data obtained from Webuye sub county hospital.

3.3 Model Application

We use data provided in Appendix A from a sample of 126 women to estimate the parameters as follows. Let the matrix X be given as to represent data points

$$X = \begin{pmatrix} 2.5 & 58 & 32 \\ 3.0 & 68 & 37 \\ 3.1 & 70 & 36 \\ 3.4 & 74 & 43 \\ 3.6 & 78 & 43 \\ 3.9 & 80 & 49 \\ \vdots & \vdots & \vdots \end{pmatrix} \tag{3.17}$$

. First,we estimate $\hat{\sum}$ from the data and here we require $\bar{X}_{1i}, \bar{X}_{2i}$ and $\bar{X}_{3i}$,they are$\bar{X}_{1i} = 3.3, \bar{X}_{2i} = 70$, and $\bar{X}_{3i} = 40$,which are the means for baby weights,mothers weights and waist sizes respectively.The deviations from their means is given by matrix d as

$$d = X_{1i} - X_i = \begin{pmatrix} -0.8 & -13 & -8 \\ -0.8 & -3 & -3 \\ -0.1 & -1 & -2 \\ -0.1 & 3 & 0 \\ \vdots & \vdots & \vdots \end{pmatrix} \tag{3.18}$$

finally

$$\hat{\sum} = \frac{d'd}{n-1} = \begin{pmatrix} 0.2 & 3.2 & 2.3 \\ 3.2 & 53 & 36 \\ 2.3 & 36 & 27 \end{pmatrix} \tag{3.19}$$

and P'P=I. Then we decompose $\hat{\sum}$ to $\hat{\sum} = P\Lambda P$ Therefore

$$\begin{aligned} Det(\sum -\lambda I) &= \begin{pmatrix} 0.2-\lambda & 3.2 & 2.3 \\ 3.2 & 53-\lambda & 36 \\ 2.3 & 36 & 27-\lambda \end{pmatrix} \\ &= (0.2-\lambda)(53-\lambda)(27-\lambda) = 0 \end{aligned} \tag{3.20}$$

with eigenvalues

$$(0.0005, 0.0017, 0.7704)$$

and corresponding eigenvectors in matrix form given as

$$P = \begin{pmatrix} 0.9984 & -0.0252 & 0.0503 \\ 0.0266 & 0.5755 & 0.08174 \\ 0.0496 & -0.8174 & 0.5739 \end{pmatrix} \tag{3.21}$$

from (3.17) and (3.18) we have

$$\begin{pmatrix} 0.9984 & -0.0252 & 0.503 \\ -0.0267 & 0.5735 & 0.0817 \\ -0.0095 & 0.8174 & 0.5787 \end{pmatrix} \begin{pmatrix} 0.9984 & 0.0267 & -0.0495 \\ -0.0252 & 0.5755 & 0.08174 \\ 0.0503 & 0.8174 & 0.5739 \end{pmatrix}$$
$$= \begin{pmatrix} 1.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 1.000 \end{pmatrix} \tag{3.22}$$

$$P'\Lambda P = \begin{pmatrix} 0.9984 & -0.0252 & 0.503 \\ -0.0267 & 0.5735 & 0.0817 \\ -0.0095 & 0.8174 & 0.5787 \end{pmatrix} \begin{pmatrix} 0.0005 & 0 & 0 \\ 0 & 0.0017 & 0 \\ 0 & 0 & 0.7704 \end{pmatrix} \tag{3.23}$$
$$= \begin{pmatrix} 0.984 & -0.0267 & 0.0495 \\ -0.0252 & 0.5755 & -0.2174 \\ 0.503 & 0.8174 & 0.5737 \end{pmatrix} \tag{3.24}$$

Therefore

$$X^* = \begin{pmatrix} 0.9984 & 0.0267 & -0.0495 \\ -0.0252 & 0.5755 & 0.08174 \\ 0.0503 & 0.8174 & 0.5739 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & .... \\ 2.5 & 3.0 & 3.2 & .... \\ 32 & 37 & 38 & .... \end{pmatrix}$$

$$= \begin{pmatrix} 0.47 & 0.83 & 0.87 & .... \\ 3.7 & 4.4 & 4.51 & .... \\ 17.55 & 21 & 21.6 & .... \end{pmatrix} \tag{3.25}$$

By OLS theory

$$\beta = \begin{pmatrix} 1 & 1 & 1.... \\ 2.5 & 3.0 & 3.2.... \\ 32 & 37 & 38..... \end{pmatrix} \begin{pmatrix} 1 & 2.5 & 32 \\ 1 & 3.0 & 37 \\ 1 & 3.2 & 38 \\ \vdots & \vdots & \vdots \end{pmatrix}^{-1}$$

$$\begin{pmatrix} 1 & 1 & 1.... \\ 2.5 & 3.0 & 3.2.... \\ 32 & 37 & 38.... \end{pmatrix} \begin{pmatrix} 58 \\ 68 \\ 70 \\ \vdots \end{pmatrix}$$

$$= \begin{pmatrix} 48.64 & 1.604 & 1.3015 \end{pmatrix} \tag{3.26}$$

and

$$Y^* = \begin{pmatrix} 48.64 & 1.604 & 1.3015 \end{pmatrix} \begin{pmatrix} 0.47 & 0.83 & 0.87 & .... \\ 3.7 & 4.4 & 4.51 & .... \\ 17.55 & 21 & 21.6 & .... \end{pmatrix}$$

$$= \begin{pmatrix} 51.6 & 74.7 & 76.8 & ... \end{pmatrix} \tag{3.27}$$

Then from (3.11) we have

$$\hat{\beta}^* = \begin{pmatrix} 0.47 & 3.7 & 17.5.... \\ 0.83 & 4.4 & 21.... \\ 0.87 & 4.51 & 21.6..... \end{pmatrix} \begin{pmatrix} 0.47 & 0.83 & 0.87 \\ 4.4 & 3.0 & 4.51 \\ 17.55 & 21 & 21.6 \\ \vdots & \vdots & \vdots \end{pmatrix}^{-1}$$

$$\begin{pmatrix} 0.47 & 3.7 & 17.55.... \\ 0.83 & 4.4 & 21.... \\ 0.87 & 4.51 & 21.6.... \end{pmatrix} \begin{pmatrix} 51.6 \\ 74.7 \\ 76.8 \\ \vdots \end{pmatrix}$$

$$= \begin{pmatrix} 21.04 & 1.29 & 1.249 \end{pmatrix} \tag{3.28}$$

$$\beta^* = \begin{pmatrix} 21.04 \\ 1.29 \\ 1.249 \end{pmatrix} \tag{3.29}$$

Then the generalised model is

$$Y^* = 21.04 + 1.29X_{1i} + 1.249X_{2i} \tag{3.30}$$

The coefficient of baby weight is 1.29 so every unit increase in baby weight a 1.249 unit increase in waist size of the mother is predicted holding other values constant.The coefficient of mothers waist size is 1.249 so every unit increase in mothers waist size a 1.29 unit increase in baby weight is predicted holding other values constant.

3.3.1 Prediction of the Baby's Birth Weight

The main objective of the study was to use inverse regression method to' estimate the baby's weight before birth so that interventions can be put in place before delivery of the baby. Hence calling for prediction of baby's weight which is the subject of the section. From the above model, baby's weight can be predicted using the following generalised inverse model.

$$Baby's\ \ weight(X_{1i}) = \frac{Y_{1i} - 21.04 - 1.249X_{2i}}{1.29} \tag{3.31}$$

where

Y_{1i} = mother's weight.

X_{1i}= Baby's weight

X_{2i}=Waist size.

Example

A prenatal information from one of the mother's records in the data collected had the following values;

Waist size=36.0cm

Mother's weight=70Kg

Fitting the information into the model gives baby weight=(70-21.04-1.249*36)/1.29=3.09kgs from data given, the calculated is 3.09 which shows a slight variation from true value(3.10).This shows that in a given situation where the mothers prenatal information(weight and waist size) are known the weight of the baby can be predicted with or determined with small error.

CHAPTER FOUR

CONCLUSION AND RECOMMENDATION

4.1 Introduction

This chapter is divided in subsections 4.1 and 4.2; that is conclusion and recommendation respectively.

4.2 Conclusion

In this study, generalised inverse method was applied on a data set from a Webuye sub-county hospital of Bungoma County (Western Kenya). The study investigated the relation between mothers weight, waist size and birth weight. The method used enabled us to predict birth weight which occurred at full term before delivery . The study results and model could be used in prediction and estimation of birth weights before birth so that necessary interventions can be put in place by medical practitioners to avoid complications associated with low and high birth weights.

4.3 Recommendation

The study concentrated on estimation of singleton birth at full term and it could be interesting for further investigations to be carried out on birth resulting in twins triplets or more then results compared for efficiency. We also recommend a suitable model that includes other maternal characteristics such as height of the mother and fundal height. The model model used is simple to use and therefore cost effective therefore can be used in developing countries where medical equipments are not available for therefore an application software can bne developed for medical practitioners in rural settings to use for prediction.

4.4 Limitation of the Study

The method can only estimate birth weight resulting in singleton birth but not twins or more births. Family and other maternal factors like heredity, health status of the mother also affect birth weight, therefore this method may yield different results when applied.

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APPENDIX A

Prenatal Information of Pregnant Women at birth

Baby's weight	Weight of the mother	Waist size
2.50	58.0000	32.00
3.00	68.0000	37.00
3.10	70.0000	36.00
3.40	74.0000	43.00
3.60	78.0000	43.00
3.90	80.0000	49.00
2.60	58.0000	34.00
3.20	61.0000	34.00
2.80	85.0000	44.00
3.20	75.0000	36.00
1.70	75.0000	37.00
3.00	72.0000	36.00
3.90	62.0000	37.00
3.70	80.0000	42.00
3.60	88.0000	44.00
3.90	68.0000	37.00
3.00	58.0000	32.00
3.00	63.0000	36.00
2.00	78.0000	37.00
2.80	60.0000	34.00
2.80	80.0000	39.00
2.50	74.0000	36.00
3.60	64.0000	35.00
2.50	75.0000	36.00
2.50	63.0000	35.00
3.60	68.0000	35.00
3.60	64.0000	31.00
3.60	72.0000	42.00
3.40	92.0000	42.00
3.40	70.0000	36.00
2.20	62.0000	36.00
1.90	70.0000	39.00
3.00	64.0000	36.00
3.80	66.0000	37.00
3.60	62.0000	36.00
3.20	71.0000	36.00
3.00	70.0000	36.00
3.30	59.0000	32.00
3.60	61.0000	36.00
3.20	66.0000	36.00
1.70	66.0000	38.00
3.40	58.0000	35.00
3.90	73.0000	37.00

Baby's weight	Weight of the mother	Waist size
3.60	79.0000	39.00
2.50	58.0000	32.00
3.90	69.0000	34.00
3.60	73.0000	34.00
3.20	58.0000	35.00
3.90	58.0000	32.00
2.80	69.0000	37.00
3.60	88.0000	41.00
3.30	58.0000	32.00
3.80	58.0000	30.00
3.40	68.0000	36.00
2.50	60.0000	35.00
2.80	72.0000	35.00
3.60	68.0000	34.00
3.60	62.0000	36.00
3.40	68.0000	34.00
3.40	50.0000	30.00
2.20	55.0000	32.00
3.80	57.0000	32.00
3.30	78.0000	38.00
3.60	68.0000	34.00
3.60	92.0000	43.00
3.20	53.0000	30.00
3.00	59.0000	32.00
3.60	67.0000	37.00
3.80	109.0000	48.00
3.40	61.0000	37.00
3.60	68.0000	34.00
3.40	62.0000	37.00
3.60	67.0000	37.00
3.80	92.0000	40.00
3.60	109.0000	50.00
3.30	59.0000	34.00
3.80	65.0000	35.00
3.90	68.0000	36.00
3.20	73.0000	37.00
3.90	69.0000	34.00

Baby's weight	**Weight of the mother**	**Waist size**
3.00	68.00	37.00
3.20	109.0000	49.00
3.30	60.0000	37.00
3.90	72.0000	35.00
3.40	78.0000	36.00
3.60	65.0000	34.00
3.60	68.0000	34.00
3.80	73.0000	36.00
3.30	72.0000	35.00
3.60	60.0000	35.00
3.40	66.0000	37.00
3.90	80.0000	40.00
3.60	66.0000	34.00
3.60	63.0000	37.00
3.90	80.0000	36.00
3.60	73.0000	35.00
3.60	78.0000	36.00
3.00	80.0000	40.00
3.30	58.0000	34.00
3.20	69.0000	34.00
3.60	60.0000	32.00
3.90	72.0000	35.00
3.40	68.0000	36.00
3.60	65.0000	37.00
3.60	69.0000	35.00
2.20	73.0000	34.00
3.80	80.0000	38.00
3.90	66.0000	37.00
3.30	52.0000	34.00
3.60	68.0000	34.00
3.40	78.0000	35.00
3.90	65.0000	35.00
3.20	68.0000	36.00
3.60	72.0000	35.00
3.00	60.0000	32.00
3.60	55.0000	33.00
3.60	65.0000	37.00
3.20	78.0000	39.00
3.30	59.0000	32.00
3.90	109.0000	47.00
3.20	61.0000	35.00
3.60	68.0000	32.00
3.90	72.0000	35.00
3.40	65.0000	36.00
2.80	78.0000	39.00
3.30	109.0000	48.00