RISK-ADJUSTED MULTI-STAGE BAYESIAN PERFORMANCE MONITORING MODEL FOR MATERNAL HEALTHCARE

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BY
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A thesis submitted to the Department of Industrial & Production Engineering, Bangladesh University of Engineering & technology, in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering

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CERTIFICATE OF APPROVAL

The thesis titled **"Risk-adjusted Multi-stage Bayesian Performance Monitoring Model for Maternal Healthcare"** submitted by Ridwan Al Aziz, Student no: 1014082001 P has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering on August 1, 2017.

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It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

_____

Ridwan Al Aziz

To the Almighty

To my family

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All credits go to the Almighty, for his boundless grace in successful completion of this thesis.

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ABSTRACT

Most statistical process control programs in healthcare focus on surveillance of outcomes at the final stage of a procedure, such as mortality or failure rates. Such an approach ignores the multi-stage nature of these procedures, in which a patient progresses through several stages prior to the final stage. In this study, a Bayesian network and a multivariate binary logistic regression predictive model have been formulated considering different aspects of antepartum period and some new outcome variables and risk factors. The model formulation is based on the combination of an extensive study of previous researches, expert opinions and empirical evidences. Based on the model, data have been simulated for monitoring by the multi-stage exponentially weighted moving average control charts. The formulated models and control charts demonstrate that different variables of antepartum period and other new variables incorporated in this study are crucial in evaluating the risk of the pregnant mothers and infants. The predictive model with control charts not only benefits the patients, but also gives the healthcare management a vital competitive edge by enhancing efficiency and accuracy of performance and better utilization of different resources.

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LIST OF ABBREVIATIONS

APH	Antepartum Hemorrhage
BOH	Bad Obstetric History
CL	Center Line
CS	Cesarean Section
CUSUM	Cumulative Sum
DAG	Directed Acyclic Graph
DMCH	Dhaka Medical College Hospital
EAS	External Anal Sphincter
EWMA	Exponentially Weighted Moving Average
FGR	Fetal Growth Restriction
GDM	Gestational Diabetes Mellitus
IAS	Internal Anal Sphincter
icddr,b	International Center for Diarrhoeal Disease Research, Bangladesh
IUGR	Intrauterine Growth Restriction /Retardation
LBW	Low Birth Weight
LCL	Lower Control Limit
MDG	Millennium Development Goal
MLE	Maximum Likelihood Estimation
OMCH	Osmani Medical College and Hospital
PPH	Postpartum Hemorrhage
PROM	Pre-mature Rupture of Membrane
RDS	Respiratory Distress Syndrome
SDG	Sustainable Development Goal
SGA	Small for Gestational Age
UCL	Upper Control Limit
UCP	Umbilical Cord Prolapse
VIF	Variance Inflation Factor
VLAD	Variable Life-adjusted Display
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

Maternal health refers to the health of women during pregnancy, childbirth and the postpartum period. While motherhood is often a positive and fulfilling experience, for too many women it is associated with suffering, ill-health and even death. In an effort to reduce worldwide maternal mortality, all the countries that gathered at the United Nation Millennium Summit in 2000, agreed to put maternal mortality as one of the eight Millennium Development Goals (MDGs). On 25th September, 2015, these MDGs were replaced by a set of even more ambitious goals known as the 17 Sustainable Development Goals (SDGs) to be achieved by 2030, among which improving maternal health still remains one of the major concerns [1]. This shows that although the overall scenario of maternal healthcare is improving worldwide, there still remains a huge scope for improvement and a stream of focused research is of absolute significance to achieve the daunting targets by 2030.

In the landmark report "To Err Is Human: Building a Safer Health System" by Kohn et al. [2], it was estimated that up to 98,000 preventable deaths are caused by errors in the health system in the United States each year. Baker et al. [3] estimated that each year between 9000 and 24,000 deaths in Canadian hospitals are due to mistakes that could have been prevented. Rothschild et al. [4] concluded that in the intensive care unit, the rates for preventable adverse events and serious errors were 36.2 and 149.7 per 1000 patient-days, respectively. On February 10, 2015, 32 people, including 10 babies, died at MAG Osmani Medical College and Hospital (OMCH) in Sylhet, Bangladesh within 24 hours. And the doctors could only came up with a vague response for all – "various complications". However, the relatives claimed that the patients died mostly due to negligence and wrong treatment of doctors [5]. Dhaka University students vandalized the Central Hospital due to the death of a fellow student named Afia Jahin Chaity on 18th May, 2017, as the doctors could not justify the reason for the death [6]. After that, Gonoshasthya Kendra founder Dr. Zafrullah Chowdhury rightly suggested that confusion over a patient's death can be avoided if all hospitals audit the deaths and maintain a detailed record of every death [7].

These issues become more heart-breaking, when now-a-days, they are turning a joyous occasion of a birth of a new baby into a nightmare for the parents and others. "83,100 babies are stillborn and there are 76,000 neonatal deaths every year. Skilled birth attendance at

delivery is 42%, institutional delivery is 38%," said Argentina Matavel Piccin, UNFPA representative in Bangladesh. Around 5,200 women in Bangladesh die each year due to pregnancy and childbirth related problems, making up eight percent of the total deaths among women of reproductive age [8]. All these alarming and horrific statistics call for a more precise and sound method for monitoring maternal healthcare.

Monitoring maternal healthcare can be a tricky business as like many healthcare and medical procedures, it comprises multiple stages. For example, in a major surgical procedure, the patient is prepared for the operation, anaesthetized and the surgery is then carried out. A poor outcome at an upstream stage is likely due to the poor outcomes at downstream stages. Most studies on healthcare performance monitoring focus on monitoring end-stage clinical outcomes, ignoring what occurs in the earlier stages of the procedure and which may can lead to wrong inference about healthcare procedure [9]. So, multistage decomposition of healthcare procedure and monitoring multistage process outcome including specially the earlier stages can provide more accurate detection and diagnosis of the presence of any human or process error.

1.1 Rationale of the Study

In maternal healthcare, patients with different clinical presentations and physiology pose different pre-operative risks [10]. These prior risks should be monitored carefully as a death of relatively low-risk patient calls for more significant adjustment than that of a high-risk patient. That's why, various risk-adjusted control charts, e.g., "Risk-adjusted Cumulative Sum" (CUSUM) chart [11] and "Risk-adjusted Exponentially Weighted Moving Average" (EWMA) chart [12] have become very popular. While previously researchers focused on surveillance of outcomes at the final stage (e.g., mortality rate), very recently Sibanda [9] has formulated the maternal delivery process as a 3-stage (namely – dilation, birth and postpartum period) process and proposed a "Risk-adjusted Multi-stage" chart which enables explicit monitoring of upstream stage (prior to the final stage) outcomes also. Moreover, it facilitates better understanding of inter-relationship and the most effective allocation of resources among different stages. However, the swiftness and accuracy of this monitoring system not only depend on control chart selection, but also on incorporating the effects of significant factors for evaluating the pre-operative risks of the pregnant mothers. Ramesh et al. [13] presented a comprehensive review on the complications associated with the

pregnancy period before the delivery process (termed as antepartum period) and suggested that maternal mortality can be reduced to a great extent by monitoring these complications. Numerous researchers like Nair et al. [14], Bauserman et al. [15], Yego et al. [16], Savadogo et al. [17], Gabrysch and Campbell [18], Kuo et al. [19], Harper et al. [20], etc. suggested through their research that risk factors of antepartum period along with age during first pregnancy, Eclampsia (convulsions with high blood pressure), multiple gestations (twin or more fetuses), etc. are extremely significant in evaluating prior risk profile of pregnant mothers.

However, the effect of the abovementioned factors on evaluating the prior risks of the pregnant mothers has not been considered for a multi-stage monitoring system in any previous work. So formulating a comprehensive model by including the antepartum period as an additional upstream stage and the significant factors of the delivery period for a more realistic and accurate risk-adjusted multi-stage monitoring system, is still an open problem and yields the scope of the proposed thesis.

1.2 Objectives of the Study

The specific objectives of this research are:

- To formulate a Bayesian network model that predicts the outcomes of different stages of antepartum and delivery period considering the complex inter-relationship of significant factors.
- To develop risk-adjusted multi-stage control charts which help the healthcare facilities to monitor each stage simultaneously.

So, this research has developed risk-adjusted multi-stage control charts based on the output of a predictive model which will incorporate the effects of the significant factors of both the antepartum and the delivery period, leading to a more realistic and accurate monitoring system for maternal healthcare facilities.

1.3 Outline of the Methodology

The outline of the research methodology is as follows –

- Different process variables and risk factors affecting the outcome of a maternal delivery process are identified with the help of previous research works and expert knowledge.

- Antepartum period is modeled as the most upstream stage with relevant outcome variables.
- The maternal delivery process after the antepartum period is modeled as a 3-stage process with relevant outcome variables.
- After defining different variables and factors, a datasheet is developed and data are collected from the Dhaka Medical College Hospital (DMCH).
- Logistic regression analysis is performed in Minitab software to identify the statistically significant variables, factors and their relationships.
- A Bayesian network and a mathematical model are formulated for predicting outcomes of each stage from a combination of empirical evidence, literature review and expert opinions.
- Data are simulated with the help of MATLAB software.
- Multi-stage EWMA control charts are developed to monitor different outcome deviations of each stage for the simulated data.

1.4 Organization of the Report

This research work has been organized in seven chapters, along with a list of references and appendices. Chapter 1 is entitled as "Introduction", which describes the motivation, background and justification of the research on maternal healthcare. The research objectives and the outline of methodology followed in this thesis are also depicted there.

The theoretical background of different stages of maternal care along with their corresponding process variables, outcome variables and risk factors are discussed in the following Chapter 2, termed as "Theoretical Foundation". Basic concepts on Bayesian network, multivariate binary logistic regression and multi-stage EWMA control charts are also discussed in this chapter.

Evolution of researches on different monitoring systems for healthcare, specially for maternal healthcare by international researchers is summarized in the following Chapter 3, termed as "Literature Review".

The latter portion of this paper deals with the target problem and its detailed formulation, which is illustrated in Chapter 4, named as "Model Formulation". This chapter also includes the detailed data analysis along with the formulations.

In Chapter 5, which is called “Multi-stage Control Chart Development”, the control charts for each outcome variables are developed based on the formulated model of chapter 4. Data simulation, performed with the help of MATLAB software, is briefed here.

In Chapter 6, termed as “Result and Discussion”, discusses on the different results and findings which can be interpreted from the formulated models and control charts. “Conclusions and Recommendation”, which is Chapter 7, incorporates the research conclusion, with potential recommendations for the future researchers. The “Reference” enlists all the relevant references, while the “Appendices” at the end focus on the programming language used to simulate the data for monitoring and to develop the control charts.

CHAPTER 2

THEORETICAL FOUNDATION

2.1 Multi-stage Maternal Care

Monitoring maternal healthcare can be a tricky business as like many healthcare and medical procedures, it comprises multiple stages. For example, in a major surgical procedure, the patient is prepared for the operation, anaesthetized and the surgery is then carried out. Broadly, maternal care can be divided into four periods. They are as follows –

2.1.1 Antepartum Period

The period starting from the conception to the initiation of true labor pain is termed as antepartum or antenatal or prenatal period and the corresponding maternal care is known as antenatal or prenatal care. So the systematic supervision of a pregnant woman can simply be called antenatal care. One of the major responsibilities of obstetrician providing antenatal care is to identify high risk factors based on past history, examination and investigation results. The objective of antenatal care therefore is to assure that every wanted pregnancy results in the delivery of a healthy baby without impairing the mother's health. In this period, many life threatening complications can occur, e.g. pre-mature labor, pre-mature rupture of membrane (PROM), antepartum hemorrhage (APH), eclampsia, intrauterine growth restriction or retardation (IUGR), etc. [13].

2.1.2 Dilation Period

The period of opening of the cervix, the entrance to the uterus, during childbirth, miscarriage, induced abortion, or gynecological surgery is called the dilation period. Cervical dilation may occur naturally, or may be induced by surgical or medical means. Prolonged dilation period poses a risk to the infant and the mother. The infant's vital signs are monitored during this stage and thus whether the signs indicate any complication can be detected in this phase [9].

2.1.3 Birth Period

This is the phase when the mother gives birth to the fetus and placenta. The maternal care for dilation and birth period is together known as intrapartum care. After the complete dilation phase, the infant must be delivered quickly to minimize risk and care must be taken not to cause excessive injury to the mother in the process. The entanglement of the umbilical cord can also make this phase challenging. So prolonged birth, tears, cord prolapse, etc. are some major complications to watch out for [9].

2.1.4 Postpartum Period

A postpartum period or postnatal period is the period beginning immediately after the birth of a child and extending for about six weeks. The maternal care for this period is termed as postnatal care. The World Health Organization (WHO) describes the postnatal period as the most critical and yet the most neglected phase in the lives of mothers and babies; most deaths occur during the postnatal period. It is the time after birth, a time in which the mother's body, including hormone levels and uterus size, returns to a non-pregnant state. In this period, complications are centered on the infant status and amount of maternal blood loss. Infant status is commonly measured using the APGAR score and checking the body weight. The excessive maternal bleeding in this period, known as postpartum hemorrhage (PPH), is a major indicator of mother's well-being after the childbirth [9].

2.2 Outcome Variables of Maternal Care

Outcome variables are parameters that represent a certain stage of the maternal care. For each of the stages, there must be at least one outcome variable to define the status of that stage. Such outcome variables are briefly discussed below -

2.2.1 Pre-mature Labor

A normal pregnancy lasts about 40 weeks. Occasionally, labor begins prematurely, before the 37th week of pregnancy. This happens because uterine contractions cause the cervix to open earlier than normal. Consequently, the baby is born premature and can be at risk for health problems. A preterm delivery, as defined by the World Health Organization, is one that occurs at less than 37 and more than 20 weeks' gestational age. In the United States, the preterm delivery rate is approximately 11%, whereas in Europe it varies between 5% and 7%.

In spite of advances in obstetric care, the rate of prematurity has not decreased over the past 40 years. In fact, in most industrialized countries it has increased slightly [21]. Prematurity is the leading cause of perinatal morbidity and mortality worldwide. It affects 5-10% of births. Preterm neonates have a 120 times higher risk of death than term neonate. Survivors are at risk for short-term and long-term morbidity, which includes bronchopulmonary dysplasia, blindness and psychomotor retardation [22].

2.2.2 Pre-mature Rupture of Membrane

Pre-mature rupture of membranes (PROM) refers to rupture of the fetal membranes prior to the onset of labor and can occur at any gestational age - even at 42 weeks' gestation. For this reason, it is also referred to as pre-labor ROM [23]. Women with PROM usually experience a painless gush of fluid leaking out from the vagina, but sometimes a slow steady leakage occurs instead. If rupture occurs before 37 weeks, the fetus and mother are at greater risk for complications. Preterm PROM is associated with a 4-fold increase in perinatal mortality and a 3-fold increase in neonatal morbidity, including respiratory distress syndrome (RDS), which occurs in 10% to 40% of women with preterm PROM and is responsible for 40% to 70% of neonatal deaths; polymicrobial intraamniotic infection, which occurs in 15% to 30% of women with preterm PROM and accounts for 3% to 20% of neonatal deaths; and intraventricular hemorrhage (IVH) [23-26]. Despite initial suggestions, the weight of evidence in the literature suggests that preterm PROM is not associated with acceleration in pulmonary maturation [27]. Other neonatal complications include fetal pulmonary hypoplasia, which develops in 26% of preterm PROM prior to 22 weeks; skeletal deformities, which complicate 12% of preterm PROM, related to severity and duration of preterm PROM; cord prolapse, especially in pregnancies with a nonvertex presentation; and increased cesarean delivery for malpresentation. PROM affects over 1,20,000 pregnancies annually in USA [28].

2.2.3 Antepartum Hemorrhage

In obstetrics, antepartum hemorrhage (APH), also known as prepartum hemorrhage, is genital bleeding during pregnancy from 28th week (sometimes defined as from the 20th week) gestational age to term. It can be associated with reduced fetal birth weight. In regard to treatment, it should be considered a medical emergency (regardless of whether there is pain)

and medical attention should be sought immediately, as if it is left untreated it can lead to death of the mother and/or fetus. APH occurs about for 3% of the pregnancies [29].

2.2.4 Eclampsia

Eclampsia is defined as the onset of convulsions or coma during pregnancy or postpartum in a patient who has signs and symptoms of preeclampsia [30]. Pre-eclampsia is a disorder of pregnancy in which there is high blood pressure and either large amounts of protein in the urine or other organ dysfunction. Pre-eclampsia is estimated to affect about 5% of deliveries while eclampsia affects about 1.4% of deliveries. In the developed world rates are about 1 in 2,000 deliveries due to improved medical care. Hypertensive disorders of pregnancy are one of the most common causes of death in pregnancy. They resulted in 46,900 deaths in 2015. Around one percent of women with eclampsia die [31-33].

2.2.5 Intrauterine Growth Restriction

Intrauterine growth restriction (IUGR), also known as fetal growth restriction (FGR) or intrauterine growth retardation refers to poor growth of a fetus while in the mother's womb during pregnancy. Intrauterine growth restriction describes a decrease in fetal growth rate that prevents an infant from obtaining his or her complete growth potential. IUGR infants are small for gestational age (SGA) if their birth weight measures less than 3% to 10% using standard growth curves [34-35]. The causes can be many, but most often involve poor maternal nutrition or lack of adequate oxygen supply to the fetus. Careful monitoring of fetal growth and well-being, combined with appropriate timing and mode of delivery, can best ensure a favorable outcome [36]. It results in increasing the chances of following complications:

- Increased risk for cesarean delivery
- Increased risk for hypoxia (lack of oxygen when the baby is born)
- Increased risk for meconium aspiration, which is when the baby swallows part of the first bowel movement. This can cause the alveoli to be over distended, a pneumothorax to occur, and/or the baby can develop bacterial pneumonia.
- Hypoglycemia (low blood sugar)
- Polycythemia (increased number of red blood cells)
- Hyperviscosity (decreased blood flow due to an increased number of red blood cells)
- Increased risk for motor and neurological disabilities

2.2.6 Prolonged Dilation and Birth

Sometimes, labor stalls or occurs much too slowly. Prolonged labor may also be referred to as "failure to progress." This can happen due to prolonged dilation or prolonged birth stage. Dilation is considered prolonged if it continues for longer than 18 h in a primi-paras (first time) mother or longer than 12 h in a multi-paras mother. The birth stage is prolonged if it continues for more than 2 h in a primi-paras mother or longer than 1 h in a multiparas mother [9, 37].

Prolonged labor increases the chances of getting C-section. Labor that takes too long can be dangerous to the baby as it may cause:

- Low oxygen levels for the baby
- Abnormal heart rhythm in the baby
- Abnormal substances in the amniotic fluid
- Uterine infection

2.2.7 Fetal Distress

The term fetal distress is commonly used to describe fetal hypoxia (low oxygen levels in the fetus), which can result in fetal damage or death if it is not reversed or if the fetus is not promptly delivered. Fetal distress can be detected via abnormal slowing of labor, changes in fetal heart rate, the presence of meconium (dark green fecal material from the fetus) or other abnormal substances in the amniotic fluid, or fetal monitoring with an electronic device that shows a fetal scalp pH of less than 7.2 [38].

2.2.8 3rd/4th Degree Tears

A 3rd-degree perineal tear is defined as a partial or complete disruption of the anal sphincter muscles, which may involve either or both the external (EAS) and internal anal sphincter (IAS) muscles. A 4th-degree tear is defined as a disruption of the anal sphincter muscles with a breach of the rectal mucosa. Being a primigravida is a risk factor for developing severe perineal tear during delivery, especially if the estimated weight of the baby is greater than 4 kg and particularly if instrumental delivery is performed [39].

2.2.9 Umbilical Cord Prolapse

Umbilical cord prolapse (UCP) is an obstetric emergency in which the umbilical cord comes through the cervical opening in advance of or at the same time as the fetal presenting part. It can lead to poor fetal outcomes because it may cause the cord to be compressed between the fetus and the maternal bony pelvis or soft tissues, leading to fetal hypoxia.

There are 2 types of UCP. The first is overt prolapse, in which the cord prolapses in advance of the fetal presenting part and is palpable within the vagina or perhaps even visibly extruding from the vagina. In contrast, if the cord presents alongside the fetal presenting part but not below it, it is referred to as occult prolapse. The cord is not visible or palpable in occult prolapse [40].

Prolapse of the umbilical cord continues to be a traumatic event to the patient as well as to the caregiver. A normal pregnancy might instantly become an acute condition requiring an emergency intervention. An optimal obstetric treatment should be focused in prevention by making a profile of a high-risk patient and by avoiding situations in which the occurrence is likely [41].

2.2.10 AGAR Score

Apgar is a quick test performed on a baby at 1 and 5 minutes after birth. The 1-minute score determines how well the baby tolerated the birthing process. The 5-minute score tells the health care provider how well the baby is doing outside the mother's womb [42, 43].
The Apgar test is done by a doctor, midwife, or nurse. The provider examines the baby's:

- ✓ Breathing effort
- ✓ Heart rate
- ✓ Muscle tone
- ✓ Reflexes
- ✓ Skin color

Each category is scored with 0, 1, or 2, depending on the observed condition.

Breathing effort:

- If the infant is not breathing, the respiratory score is 0.
- If the respirations are slow or irregular, the infant scores 1 for respiratory effort.
- If the infant cries well, the respiratory score is 2.

Heart Rate:

Heart rate is evaluated by stethoscope. This is the most important assessment:

- If there is no heartbeat, the infant scores 0 for heart rate.
- If heart rate is less than 100 beats per minute, the infant scores 1 for heart rate.
- If heart rate is greater than 100 beats per minute, the infant scores 2 for heart rate.

Muscle tone:

- If muscles are loose and floppy, the infant scores 0 for muscle tone.
- If there is some muscle tone, the infant scores 1.
- If there is active motion, the infant scores 2 for muscle tone.

Grimace:

Grimace response or reflex irritability is a term describing response to stimulation, such as a mild pinch:

- If there is no reaction, the infant scores 0 for reflex irritability.
- If there is grimacing, the infant scores 1 for reflex irritability.
- If there is grimacing and a cough, sneeze, or vigorous cry, the infant scores 2 for reflex irritability.

Skin color:

- If the skin color is pale blue, the infant scores 0 for color.
- If the body is pink and the extremities are blue, the infant scores 1 for color.
- If the entire body is pink, the infant scores 2 for color.

2.2.11 Low Infant Birth Weight

Low birth weight (LBW) is an important predictor of newborn health and survival and is associated with higher risk of infant and childhood mortality [44]. Low birth weight is defined by the World Health Organization as a birth weight of an infant of 2,499 g or less,

regardless of gestational age. LBW is either caused by preterm birth (that is, a low gestational age at birth, commonly defined as younger than 37 weeks of gestation) or the infant being small for gestational age (that is, a slow prenatal growth rate), or a combination of both [45]. Low birth weight constitutes as sixty to eighty percent of the infant mortality rate in developing countries. Neonatal mortality due to low birth weight is usually directly causal, stemming from other medical complications such as preterm birth, poor maternal nutritional status, lack of prenatal care, maternal sickness during pregnancy, and an unhygienic home environment [46-47].

2.2.12 Postpartum Hemorrhage

A number of different definitions have been used for post-partum hemorrhage (PPH). The most common of these defines PPH as blood loss of more than 1000 ml if delivery is through Cesarean section or more than 500 ml without a Caesarean section [9]. As more blood is lost the women may feel cold, their blood pressure may drop, and they may become restless or unconscious. The condition can occur up to six weeks following delivery. In the developing world about 1.2% of deliveries are associated with PPH and when PPH occurred about 3% of women died [48]. It is responsible for around 30% of maternal deaths, equivalent to 86,000 deaths per year annually or ten deaths every hour [49].

2.2.13 Maternal and Neonatal Mortality

Maternal mortality is the death of a woman while pregnant or within 30 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, but not from accidental or incidental causes [50]. On the other hand, neonatal mortality has been defined by the World Health Organization (WHO) as deaths among live births during the first 28 completed days of life which can be further sub-divided into early neonatal deaths (deaths between 0 and 7 completed days of birth) and late neonatal deaths (deaths after 7 days to 28 completed days of birth) [51].

2.3 Process Variables of Maternal Care

Process variables are process parameters that affect the outcome variables. For example, cesarean section process may affect the outcome variables of the birth and postpartum period. So it can be considered as a process variable. Such variables are discussed here –

2.3.1 Cesarean Section

Cesarean section, also known as C-section, is the use of surgery to deliver one or more babies. A caesarean section is often performed when a vaginal delivery would put the baby or mother at risk. This may include obstructed labor, twin pregnancy, high blood pressure in the mother, breech birth, problems with the placenta or umbilical cord. A C-section typically takes 45 minutes to an hour. It may be done with a spinal block such that the woman is awake or under general anesthesia. A urinary catheter is used to drain the bladder and the skin of the abdomen is then cleaned with an antiseptic. An incision of about 15 cm (6 inches) is then typically made through the mother's lower abdomen. The uterus is then opened with a second incision and the baby delivered. The incisions are then stitched closed. Often a number of days are required in hospital to recover sufficiently to return home. A fourfold increase in maternal mortality rate associated with CS was observed even after controlling for medical and obstetric complications, maternal age, and preterm delivery. Even elective CS had a 2.84 fold greater chance of maternal death as compared to vaginal birth [52].

2.3.2 Labor Induction

Inducing labor is the artificial start of the birth process through medical interventions or other methods. Induced labor may be more painful for the woman. This can lead to the increased use of analgesics and other pain-relieving pharmaceuticals. These interventions have been said to lead to an increased likelihood of caesarean section delivery for the baby and thus increase the complications of childbirth [53].

2.3.3 Use of Mechanical Instrument in Birth Stage

Sometimes mechanical instruments like forceps, vacuum extractors, etc. are used in the birth stage. In the United States, use of forceps declined by 22% between 1985 and 1992. In

developed countries, instrumental deliveries still account for 9.5% to 11.2% of all deliveries [54].

2.4 Risk Factors of Maternal Care

Risk factors are personal attributes of the patients which affect the outcome variables. For example, age, height, weight, etc. are personal attributes and these can affect different healthcare outcomes. Some medical terminologies related to the risk factors are as follows –

2.4.1 Gravida and Para

The term gravida comes from the Latin word gravidus. It is used to describe a woman who is pregnant and is also a medical term for the total number of confirmed pregnancies a woman has had, regardless of the outcome of the pregnancy. For example, a woman who is pregnant for the first time will be termed a primigravida, which means first pregnancy.

Para refers to the total number of pregnancies that a woman has carried past 20 weeks of pregnancy. This number includes both live births and pregnancy losses after 20 weeks, such as stillbirths. The term primipara may be used to describe a woman who has had one delivery after 20 weeks, and multipara is used for a woman who has had two or more births. Nulliparous is the term that describes a woman who has never given birth after 20 weeks of pregnancy.

Gravidity includes all confirmed pregnancies. Each pregnancy is only counted one time, even if the pregnancy was a multiple gestation, such as twins or triplets. For example, a woman who has had a miscarriage at 8 weeks of pregnancy, a birth of twins at 36 weeks of pregnancy, and a birth of a single baby at 40 weeks of pregnancy is a gravida 3; she has had 3 confirmed pregnancies.

Parity reflects the total number of births after 20 weeks, not the total number of infants born. Using the same example as above, the woman with one 8-week pregnancy loss, a live birth of twins, and a live birth of a single infant would be a para 2, even though she has given birth to 3 infants and has been pregnant 3 times.

2.4.2 Multiple Gestations

A multiple birth is the culmination of one multiple pregnancy, wherein the mother delivers two or more offspring. A term most applicable to placental species, multiple births occur in most kinds of mammals, with varying frequencies. Such births are often named according to the number of offspring, as in twins and triplets.

Each single fertilized egg (zygote) may produce a single embryo, or it may split into two or more embryos, each carrying the same genetic material. Fetuses resulting from different zygotes are called fraternal and share only 50% of their genetic material, as ordinary full siblings from separate births do. Fetuses resulting from the same zygote share 100% of their genetic material, and are hence called identical.

2.4.3 Bad Obstetric History

The term bad obstetric history (BOH) is often loosely used to signify that a woman has had previous disappointments, e.g. miscarriages, stillbirths and preterm births in childbearing. When a baby dies before delivery, many people commonly think of miscarriage. Both stillbirth and miscarriage are types of pregnancy loss, but they differ by when the loss occurs. A miscarriage (sometimes called a spontaneous abortion) is when a baby dies before the 20th week of pregnancy. Stillbirth is the death of a baby after the 20th week of pregnancy but before delivery. Whenever parents deal with the death of their baby, whether it be early in pregnancy, late in pregnancy, or sometime after birth, there can be a great sense of disappointment, loss, and suffering. Stillbirth and miscarriage are separately defined not because one or the other is an easier or more difficult loss with which to deal, but because they differ in many ways. Stillbirth and miscarriage have different causes, need different evaluations, and differ medically and in the ways that parents and families can best be helped.

2.5 Bayesian Network

A Bayesian network or a belief network is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Formally, Bayesian networks are DAGs whose nodes represent random variables in the Bayesian sense:

they may be observable quantities, latent variables, unknown parameters or hypotheses. Edges represent conditional dependencies; nodes that are not connected (there is no path from one of the variables to the other in the Bayesian network) represent variables that are conditionally independent of each other.

A Bayesian network can be a directed acyclic graph (DAG) with node set V representing random variables, $Y = \{Y_{v \in V}\}$ having a joint probability distribution function that can be written as -

$$P(Y) = \prod_{v \in V} P(Y_v \mid Y_{pa(v)}) \quad (2.1)$$

The term pa(v) represents the set of parent nodes of the node v. The power of a DAG representation is that once the structure is known, the joint probability distribution of Y can be written in the form of equation (2.1) using the conditional independence axioms. In equation (2.1), each node is conditionally independent of all non-descendants, given its parent nodes [9].

2.6 Logistic Regression

Logistic regression is a class of regression where the independent variable is used to predict the dependent variable. When the dependent variable has two categories, then it is a binary logistic regression. When the dependent variable has more than two categories, then it is a multinomial logistic regression. When the dependent variable category is to be ranked, then it is an ordinal logistic regression. To obtain the maximum likelihood estimation (MLE), transform the dependent variable in the logit function. Logit is basically a natural log of the dependent variable and tells whether or not the event will occur.

Logistic regression assumes the following:

- Data level: The dependent variable should be dichotomous in nature for binary regression.
- Error Term: The error term is assumed independently.
- Linearity: Does not assume a linear relationship, but between the odd ratio and the independent variable, there should be a linear relationship.
- No outliers: Assumes that there should be no outliers in data.

- Large sample: Uses the maximum likelihood method, so a large sample size is required for logistic regression.

2.7 Exponentially Weighted Moving Average Control Chart

The Exponentially Weighted Moving Average (EWMA) is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time.

If there are k subgroups, each of size n and x_{ij} represents the measurement in the j^{th} sample of the i^{th} subgroup.

The i^{th} subgroup mean is calculated as –

$$\bar{x}_i = \frac{\sum_{j=1}^{n} x_{ij}}{n} \tag{2.2}$$

According to Roberts [55], the statistic for the EWMA control chart is calculated as:

$$EWMA_i = \lambda \bar{x}_i + (1-\lambda) EWMA_{i-1} \tag{2.3}$$

Where,

$EWMA_0$ is the mean of historical data (target)

$0<\lambda\leq 1$ is an exponential smoothing constant that determines the depth of memory of the EWMA.

By the choice of weighting factor, λ, the EWMA control procedure can be made sensitive to a small or gradual drift in the process, whereas the Shewhart control procedure can only react when the last data point is outside a control limit. The parameter λ determines the rate at which older data enter into the calculation of the EWMA statistic. A value of λ=1 implies that only the most recent measurement influences the EWMA (degrades to Shewhart chart). Thus, a large value of λ (closer to 1) gives more weight to recent data and less weight to older data; a small value of λ (closer to 0) gives more weight to older data. The value of λ is usually set between 0.2 and 0.3.

The center line (CL) can be estimated as –

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{k} x_i}{k} \tag{2.4}$$

The lower control limit (LCL) and upper control limit (UCL) can be determined as follows –

$$LCL = \bar{\bar{x}} - m\bar{s}\sqrt{\frac{\lambda}{2-\lambda}} \quad (2.5)$$

$$UCL = \bar{\bar{x}} + m\bar{s}\sqrt{\frac{\lambda}{2-\lambda}} \quad (2.6)$$

Where,

m is a multiplier constant, generally set to 3.

$$\bar{s} = \frac{\sum_{i=1}^{k} s_i}{k} \quad (2.7)$$

CHAPTER 3

LITERATURE REVIEW

A growing demand in healthcare sector leads to the development of statistical process control (SPC) tools to measure and improve healthcare processes and outcomes. SPC techniques can be applied to different types of data such as clinical outcomes, risk management and patient satisfaction. There is, however, a sharp distinguishing element between industrial and healthcare applications. For the most part, industrial settings involved production of items manufactured under controlled processes, yielding largely homogenous products. Typical healthcare applications, on the other hand, while many of the aspects are under careful supervision, the end receivers are patients presenting great diversity in their personal profiles.

To take into account this diversity, risk-adjusted control charts come into the play. Some popular risk-adjusted SPC tools include "Observed-Expected Plot", "Variable Life-adjusted Display" (VLAD) chart, "Risk-adjusted Cumulative Sum" (CUSUM) chart and "Risk-adjusted Exponentially Weighted Moving Average" (EWMA) chart [10].

Poloniecky [56] developed observed-expected plot for detecting changes in death rate after heart surgery. Lovegrove et al. [57] developed VLAD chart which provided a graphical display of risk-adjusted survival figures for individual surgeons or units over time and could be modified to monitor performance over a range of treatments and outcomes. Later Pagel et al. [58] implemented VLAD chart for real time monitoring of risk-adjusted paediatric cardiac surgery outcomes in three UK centers considering patient diversity.

Risk-adjusted CUSUM charts for binary performance measures were first proposed by Steiner et al. [11] in monitoring 30-day mortality in cardiac surgeries, and then applied in other applications such as liver transplant to monitor 1-year mortality by Leandro et al. [59] and coronary artery bypass surgeries to monitor adverse outcomes by Novick et al. [60]. RA CUSUM charts for time to event were developed by Sego et al. [61], Gandy et al. [62], and Biswas and Kalbfeisch [63], who use different models for the survival time.

By approximating the correct exponential family likelihood, Grigg and Spiegelhalter [64] derived a risk-adjusted EWMA (RA–EWMA) that is essentially a standard EWMA applied to "pseudo observations," which are the original observations adjusted for differential risk. Later risk-adjusted EWMA charts were implemented by Cook et al. [12] using data on

mortality following admission for acute myocardial infarction from all public and private hospitals in Queensland, Australia.

Risk-adjusted models have been developed in many critical areas of healthcare in last two decades. Brunelli et al. [65] developed risk-adjusted morbidity and mortality models to compare the performance of two units after major lung resections. Daley et al. [66] implemented risk-adjustment in evaluating surgical outcomes. Krumholz et al. [67] compared mortality among hospitals in patients 65 years of age and older taking risk factors into account. Pinna-Pintor et al. [68] investigated inaccuracy of four coronary surgery risk-adjusted models to predict mortality in individual patients. Shroyer et al. [69] utilized 30-day operative mortality and morbidity risk models on thoracic surgeries. Sousa et al. [70] and Tu et al. [71] also implemented risk-adjusted models in cardiac surgeries.

Hendryx et al. [72] and Hermann et al. [73] developed models considering risk adjustment in public mental health. Benbassat and Taragin [74] implemented risk-adjustment model in general hospital care focusing on hospital readmission. Forthman et al. [75] investigated on risk-adjusted indices for measuring the quality of inpatient care.

While previously researchers focused on surveillance of outcomes at the final stage (e.g., mortality rate), healthcare procedures generally comprise multiple stages. For example, in a major surgical procedure, the patient is prepared for the operation, anaesthetized and the surgery is then carried out. A poor outcome at an upstream stage is likely, through variance propagation, to result in poor outcomes at downstream stages. Most studies on healthcare performance monitoring focus on monitoring end-stage clinical outcomes ignoring what occurs in the earlier stages of the procedure. Very recently Sibanda [9] has formulated the maternal delivery process as a 3-stage (namely – dilation, birth and postpartum period) process and proposed a "Risk-adjusted Multi-stage" chart which enables explicit monitoring of upstream stage (prior to the final stage) outcomes also. Moreover, it facilitates better understanding of inter-relationship and the most effective allocation of resources among different stages.

However, the swiftness and accuracy of this monitoring system not only depend on control chart selection, but also on incorporating the effects of significant factors for evaluating the pre-operative risks of the pregnant mothers. Sibanda's work has considered a total of 10 outcome variables, process variables and risk factors. This is the first time that the multi-stage monitoring is implemented in any healthcare and the variables and factors considered are

after the patient is admitted in a maternal healthcare. But to evaluate this case only taking into consideration the variables and factors after the mother has been admitted can be very misleading. A healthcare facility, a process or a doctor can be rated poor without any valid reason just because the patient is dead. The reason of the death can well be attributed to a factor which became uncontrollable well before the patient is admitted. A mother can die due to extreme antepartum bleeding and it might have been aggravated because of lack of visit to the healthcare facility as the patient did not think the bleeding was serious. So considering the pregnancy period before the admittance is very crucial as a lot of complications can arise. This period is the antepartum period and WHO recommends a pregnant mother to visit at least four times in a maternal healthcare. In fact, the focus of antepartum maternal care is the early detection of any pregnancy related risks as these complicacies can even cause death to the mother and the newborn.

Ramesh et al. [13] presented a comprehensive review on the complications associated with the pregnancy period before the delivery process (termed as antepartum period) and suggested that maternal mortality can be reduced to a great extent by monitoring these complications. Numerous researches have put emphasis on the antepartum period for reducing maternal and neonatal risks [14-20, 76, 77].

Nair et al. [14] investigated on a total of 135 women who died (cases) between 2009 and 2012 from eclampsia, pulmonary embolism, severe sepsis, amniotic fluid embolism, and peripartum hemorrhage, using data from the Confidential Enquiry into Maternal Death, and another 1661 women who survived severe complications caused by these conditions (2005–2013), using data from the UK Obstetric Surveillance System and found out antenatal care, eclampsia, gestational diabetes, multiple gestations, etc. as major factors for maternal death.

Bauserman et al. [15] collected and analyzed data describing all pregnancies from 2010 to 2013 among women enrolled in the multinational Global Network for Women's and Children's Health Research Maternal and Neonatal Health Registry and the result showed that anterpartum hemorrhage, eclampsia, mother's age, cesarean section, etc. are decisive for mortality.

Yego et al. [16] implemented logistic regression analysis on a manual review of records for 150 maternal deaths (cases) and 300 controls was undertaken using a standard audit form in which the sample included pregnant women aged 15-49 years admitted to the Obstetric and Gynaecological wards at the Moi Teaching and Referral Hospital (MTRH) in Kenya from

January 2004 and March 2011 and found antenatal care, eclampsia, mother's age, cesarean section, etc. statistically significant.

Savadogo et al. [17] performed retrospective cohort study from data of 1807 hospitalized women which indicated antenatal care, eclampsia, multiple gestations, mother's age, etc. to be the mortality factors. Other previous researchers like Say et al. [78], Chowdhury et al. [79] and Chakraborty et al. [80] have found antepartum hemorrhage and eclampsia as vital factors.

Similarly, pre-mature labor [19, 20] has been suggested significant by Kuo et al. [19] and Harper et al. [20]. Caughey et al. [23], Parry et al. [26] and Mercer et al. [28] found out pre-mature rupture of membrane to be a decisive factor. Significance of intrauterine growth restriction on maternal and neonatal mortality are discussed on researches of Brodsky et al. [34], Wollmann et al. [35], Resnik et al. [36], Pallotto et al. [81], etc.

Fawole et al. [82] and Parer et al. [83] demonstrated how sgnificant fetal distress is for maternal and fetal safety. Similarly, the importance of cord prolapse can be realized from the works of Holbrook et al. [40] and Kahana et al. [41]. Infant low birth weight can lead to neonatal mortality. This is suggested from the analysis by Kuo et al. [19] and Calle et al. [45].

Osoro et al. [84] reviewed retrospective 72 maternal death cases which occurred between January 01, 2009 and June 30, 2010 in Kenya and found out from their analysis that maternal anemia can be one of the decisive risk factors. Baby and Shaha [85] performed cross-sectional study on the cases from January 2001 to December 2005 and also found out the significance of maternal anemia.

Maternal height was proved crucial factor by performing Retrospective cohort study using 2006–2008 data from the Society for Reproductive Technology Clinic Outcome Reporting System by Dickey et al. [86]. Merchant et al. [87] investigated women who had their first prenatal visit between April 1984 and January 1986 in The antenatal clinic of the Gynecology and Obstetrics Hospital of the Guatemalan Social Security Institute in Guatemala City to demonstrate the significance of maternal height. This factor is also supported by the retrospective work of Witter et al. [88].

Mondestine et al. [89] performed a retrospective cohort study using data for singleton births delivered between 1995 and 1997 in the United States and showed gestational diabetes should be considered for monitoring and evaluating maternal healthcare.

Fawole et al. [90] studied twenty one health facilities in three states of Nigeria using stratified multi-stage cluster sampling strategy. A total of 9 208 deliveries were recorded. There were

79 maternal deaths and 8,526 live births, giving a maternal mortality ratio of 927 maternal deaths per 1,00,000 live births. No antenatal care and parity were significantly associated with maternal mortality. Low maternal education, high parity, emergency cesarean delivery, and high risk patients risk independently predicted maternal mortality.

The effect of the abovementioned factors on evaluating the prior risks of the pregnant mothers has not been considered for a multi-stage monitoring system in any previous work. So this study has formulated a comprehensive model by including the antepartum period as an additional upstream stage and the significant factors of the delivery period for a more realistic and accurate risk-adjusted multi-stage monitoring system.

CHAPTER 4

MODEL FORMULATION

4.1 Problem Definition

Previous researchers have modeled the maternal care as a three stage process. They are – Dilation, Birth and Postpartum period. These are actually the stages a mother passes through after she has been admitted to the healthcare facility. But to evaluate this case only taking into consideration the variables and factors after the mother has been admitted can be very misleading. A healthcare facility, a process or a doctor can be rated poor without any valid reason just because the patient is dead. The reason of the death can well be attributed to a factor which became uncontrollable well before the patient is admitted. A mother can die due to extreme antepartum bleeding and it might have been aggravated because of lack of visit to the healthcare facility as the patient did not think the bleeding was serious. Here the doctor or the facility must not be blamed. Good doctors can get demotivated due to these misevaluations. Similarly, bad doctors and facilities can also remain unnoticed for ignoring the variables and factors active before the admittance of the mother. In order to evaluate and improve the maternal healthcare processes, taking the variables and factors of the antepartum period is a must. Variables like Antepartum Hemorrhage, Pre-mature Rupture of Membrane (PROM), Intrauterine Growth Restriction/Retardation, etc. can lead to death of a mother or a newborn. Even some variables active after the admittance like Fetal Distress, Cord Prolapse, Low Birth Weight, etc. and risk factors like Age of Mother, Maternal Height, Maternal Anemia, Maternal Gestational Diabetes, etc. have been ignored in formulating multi-stage control chart monitoring. Many life threatening practices, doctors and facilities can remain at large as the evaluation procedure remains controversial for not taking these factors into account. The research aims at incorporating these stages, variables and factors in formulating the multi-stage control chart monitoring process and thus helps to evaluate the maternal care processes more accurately. The outline of the research methodology is as follows –

- Different process variables and risk factors affecting the outcome of a maternal delivery process are identified with the help of previous research works and expert knowledge.
- Antepartum period is modeled as the most upstream stage with relevant outcome variables.

- The maternal delivery process after the antepartum period is modeled as a 3-stage process with relevant outcome variables.
- After defining different variables and factors, a datasheet is developed and data are collected from the Dhaka Medical College Hospital.
- Logistic regression analysis is performed in Minitab software to identify the statistically significant variables, factors and their relationships.
- A Bayesian network and a mathematical model are formulated for predicting outcomes of each stage from a combination of empirical evidence, literature review and expert opinions.
- Data are simulated with the help of MATLAB software.
- Multi-stage EWMA control charts are developed to monitor different outcome deviations of each stage for the simulated data.

The specific objectives of this research are:

- To formulate a Bayesian Network model that predicts the outcomes of different stages of antepartum and delivery period considering the complex inter-relationship of significant factors.
- To develop risk-adjusted multi-stage control charts which help the healthcare facilities to monitor each stage simultaneously.

So, this research has developed risk-adjusted multi-stage control charts based on the output of a predictive model which will incorporate the effects of the significant factors of both the antepartum and the delivery period, leading to a more realistic and accurate monitoring system for maternal healthcare facilities.

4.2 Bayesian Network Formulation

A Bayesian network or a belief network is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases.

4.2.1 Definition of Study Variables and Factors

The whole maternal healthcare process is divided into four stages – Antepartum Period, Dilation Period, Birth Period and Postpartum Period. Fourteen outcome variables, three process variables and eight risk factors have been identified to represent these four stages with the help of an extensive study of over 50 research papers and expert opinions of doctors from Dhaka Medical College Hospital, Matuail Institute of Child & Mother Health, Sher-e-bangla Medical College & Hospital and International Center for Diarrhoeal Disease Research, Bangladesh (icddr,b).

The fourteen outcome variables are defined as binary variables as follows –

$$Y_{1jk} = \begin{cases} 1 \text{ if labor starts before 37 weeks of pregnancy} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{2jk} = \begin{cases} 1 \text{ if fetal membranes are ruptured prior to the onset of labor} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{3jk} = \begin{cases} 1 \text{ if maternal bleeding occurs after } 20^{th} \text{ week of pregnancy and before onset of labor} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{4jk} = \begin{cases} 1 \text{ if convulsions occur in pregnant mother suffering from high blood pressure} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{5jk} = \begin{cases} 1 \text{ if fetus weighs below } 10^{th} \text{ percentile for its gestational age} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{6jk} = \begin{cases} 1 \text{ if no prior births and } L_1 > 18 \text{ hr, or if } \geq 1 \text{ prior births and } L_1 > 12 \text{ hr} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{7jk} = \begin{cases} 1 \text{ if persistent fetal heart rate is } < 120/\text{minute or } > 160/\text{minute} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{8jk} = \begin{cases} 1 \text{ if no prior births and } L_2 > 2 \text{ hr, or if} \geq 1 \text{ prior births and } L_2 > 1 \text{ hr} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{9jk} = \begin{cases} 1 \text{ if a 3rd or 4th degree tear occurs} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{10jk} = \begin{cases} 1 \text{ if the umbilical cord protrudes through cervix and into birth canal ahead of the baby} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{11jk} = \begin{cases} 1 \text{ if 5-min Apgar score} < 7 \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{12jk} = \begin{cases} 1 \text{ if infant birth weight} < 2.5 \text{ kg} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{13jk} = \begin{cases} 1 \text{ if maternal blood loss} > 500 \text{ ml with no Cesarean, or} > 1000 \text{ ml with a Cesarean} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{14jk} = \begin{cases} 1 \text{ if anyone of mother and infant(s) dies within 30 days} \\ 0 \text{ otherwise} \end{cases}$$

Where,

$j = 1, 2, \ldots, n^{th}$ number of patient

$k = 1, 2, \ldots, K^{th}$ number of time interval

L_1 = Length of the Dilation period

L_2 = Length of the Birth period

The outcome variables are analyzed here in binary form to capture only the variation relevant in determining rates of adverse outcomes. Since the aim in quality improvement is to reduce rates of adverse outcomes, discretizing the variables in this way is more appropriate than analyzing the variables in their raw form.

Each outcome variable is influenced by one or more process variables or risk factors, and may also depend on an upstream outcome variable.

The process variables are defined as follows –

$$X_{1jk} = \begin{cases} 1 \text{ if cesarean section is performed} \\ 0 \text{ otherwise} \end{cases}$$

$$X_{2jk} = \begin{cases} 1 \text{ if labor induced} \\ 0 \text{ otherwise} \end{cases}$$

$$X_{3jk} = \begin{cases} 1 \text{ if mechanical instruments used during the birth stage} \\ 0 \text{ otherwise} \end{cases}$$

The eight risk factors are defined as –

$$Z_{1jk} = \begin{cases} 1 \text{ if the mother has given birth more than 4 times to a fetus of gestational age} \geq 24 \text{ weeks} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{2jk} = \begin{cases} 1 \text{ if mother's age} < 18 \text{ years or age during first pregnancy} > 35 \text{ years} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{3jk} = \begin{cases} 1 \text{ if hemoglobin concentration} < 110 \text{ gm/liter} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{4jk} = \begin{cases} 1 \text{ if maternal height} < 4'8'' \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{5jk} = \begin{cases} 1 \text{ if the mother delivers two or more offspring} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{6jk} = \begin{cases} 1 \text{ if presentation is posterior or transverse} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{7jk} = \begin{cases} 1 \text{ if the mother without diabetes develops high blood sugar level during pregnancy} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{8jk} = \begin{cases} 1 \text{ if the mother had preterm labor, miscarriage or still-birth before} \\ 0 \text{ otherwise} \end{cases}$$

So, three process variables, fourteen outcome variables and eight risk factors are considered for the Bayesian network model formulation totaling to a staggering twenty five variables.

4.2.2 Data Collection

Apart from the literature review and expert opinions, data for fourteen outcome variables, three process variables and eight risk factors from 100 random individual patients have been collected from the Dhaka Medical College Hospital for three months (March 2017 – May 2017) to provide an empirical evidence for the model formulation.

A summary of characteristics of collected data is presented in table 4.1. Among the mothers, 2% and 3% were below 18 years and above 35 years respectively. No mother was found who has delivered more than four babies already. 39% women were pregnant for the first time. 27% mothers had to gone through the cesarean section before which is quite high. And staggering 58% women ultimately went for the cesarean section for the current delivery. 10% mothers had diabetes; around 40% women experienced the complications in the antepartum period.

Among the infants, 12% weighed below 2 kg and 57% weighed below 2.5 kg which is quite high. 26% of the newborns had the APGAR score below 7 which means their survival in this new world is risky.

Table 4.1: Summary of Characteristics of Study Variables and Factors

Characteristics	Percentage of Patient
Age of Mother (year)	
<18	3.00
18-23	34.00
24-29	35.00
30-35	26.00
>35	2.00
Obstetric History	
Nulliparous	39.00
Parity 1-4	61.00
Parity >4	0.00
Prior Vaginal Delivery Only	34.00
Prior Cesarean Section Only	22.00
Prior both Vaginal Delivery & Cesarean Section	5.00
Infant Birth Weight (kg)	
< 2	11.86
2.0 - 2.5	45.76
2.6 - 3.0	23.73
3.1 - 3.5	15.25
> 3.5	3.39
Mode of Delivery	
Vaginal Delivery	42.00
Cesarean	58.00
Others	
Gestational Diabetes Mellitus	10.00
Antepartum Hemorrhage	13.00
Eclampsia	14.00
Pre-mature Rupture of Membrane	28.00
5-min APGAR Score < 7	25.42

4.2.3 Multivariate Binary Logistic Regression Analysis

The collected data of different outcome variables, process variables and risk factors are analyzed through multivariate binary logistic regression as they are dichotomous in nature. The analysis is carried out by Minitab 17 software. The analysis guides to determine which

factors and variables can truly predict an outcome variable. These factors and variables are said to be "statistically significant" for outcome variables through p-value and variance inflation factor (VIF).

The p-value is the probability of obtaining a statistically significant relationship due to random chance. So less p-value is better as it guarantees that the significant relationship is truly present. A conventional threshold of p-value is 5%, which means a p-value less than 0.05 is considered acceptable.

Again, VIF value is also another important parameter to decide whether a variable is truly significant as VIF indicates multicollinearity. Multicollinearity refers to a state when the model includes multiple factors that are correlated not just to the response variable, but also to each other. Multicollinearity increases the standard errors of the coefficients. Increased standard errors in turn make some variables statistically insignificant when they should be significant. Without multicollinearity (and thus, with lower standard errors), those coefficients might be significant. Higher VIF indicates a greater chance of multicollinearity among variables. VIF less than 10 is considered acceptable in general.

So a multivariate binary logistic regression analysis is performed for each of the outcome variables as the response variable and the statistically significant variables and factors are identified for the model formulation.

4.2.4 DAG Representation of Bayesian Network

The whole maternal healthcare process is divided into four stages for the Bayesian network formulation. They are – Antepartum Period, Dilation Period, Birth Period and Postpartum Period. Different outcome variables have been defined to represent each stage and different relevant process variables and risk factors have been considered. Their relationships have been depicted by the arrow signs in the Bayesian Network in figure. The inter-relationships between the outcome variables have been shown with the "Simple-headed Arrow" and the relationships between the process and outcome variables or the risk factors and outcome variables are shown with the "Triangle-headed Arrow". For example, the triangle-headed arrow from the risk factor "Multiple Gestations" to the outcome variable "Postpartum Hemorrhage" means that the chance of excessive bleeding of mother in the postpartum period is increased if the mother is pregnant with multiple fetuses.

The Directed Acyclic Graphical representation of the Bayesian network, presented in figure 4.1, is formulated with the help of the combination of expert opinions, empirical evidence and an extensive study of over 70 research papers. Sibanda first presented such a Bayesian network model for maternal healthcare, but only limited to the maternal delivery process with a total of ten variables. Variables like Antepartum Hemorrhage, Pre-mature Rupture of Membrane (PROM), Intrauterine Growth Restriction/Retardation, Fetal Distress, Cord Prolapse, Low Infant Birth Weight, etc. and risk factors like Age of Mother, Maternal Height, Maternal Anemia, Maternal Gestational Diabetes, etc. have been ignored in formulating multi-stage control chart monitoring. This research includes all of these important variables and factors in model formulation for multi-stage control chart totaling to 25 variables. The new variables and factors which have been incorporated in Sibanda's work, are justified not only to the numerous previous works various reputed researchers mentioned in the literature review, but also from the expert opinions and a detailed multivariate binary logistic regression analysis presented in the previous section.

Based on the multivariate binary logistic regression analysis of the data from Dhaka Medical College Hospital, use of mechanical instrument, parity > 4, Gestational Diabetes Mellitus, cord prolapse and low infant birth weight – these five variables and factors are found to have no relationship with the other variables and factors. Hence, they have been excluded from the Bayesian network model. Again, PROM, IUGR and $3^{rd}/4^{th}$ degree tears are found to have no reliable predictors, but they themselves are significant predictors for other outcome variables. So, these three variables are kept in the model. Ultimately this DAG representation of Bayesian network portrays the detailed relationship among twenty variables and factors of four different stages of maternal healthcare for Dhaka Medical College Hospital and provides a basis for formulating such models for any other healthcare facilities.

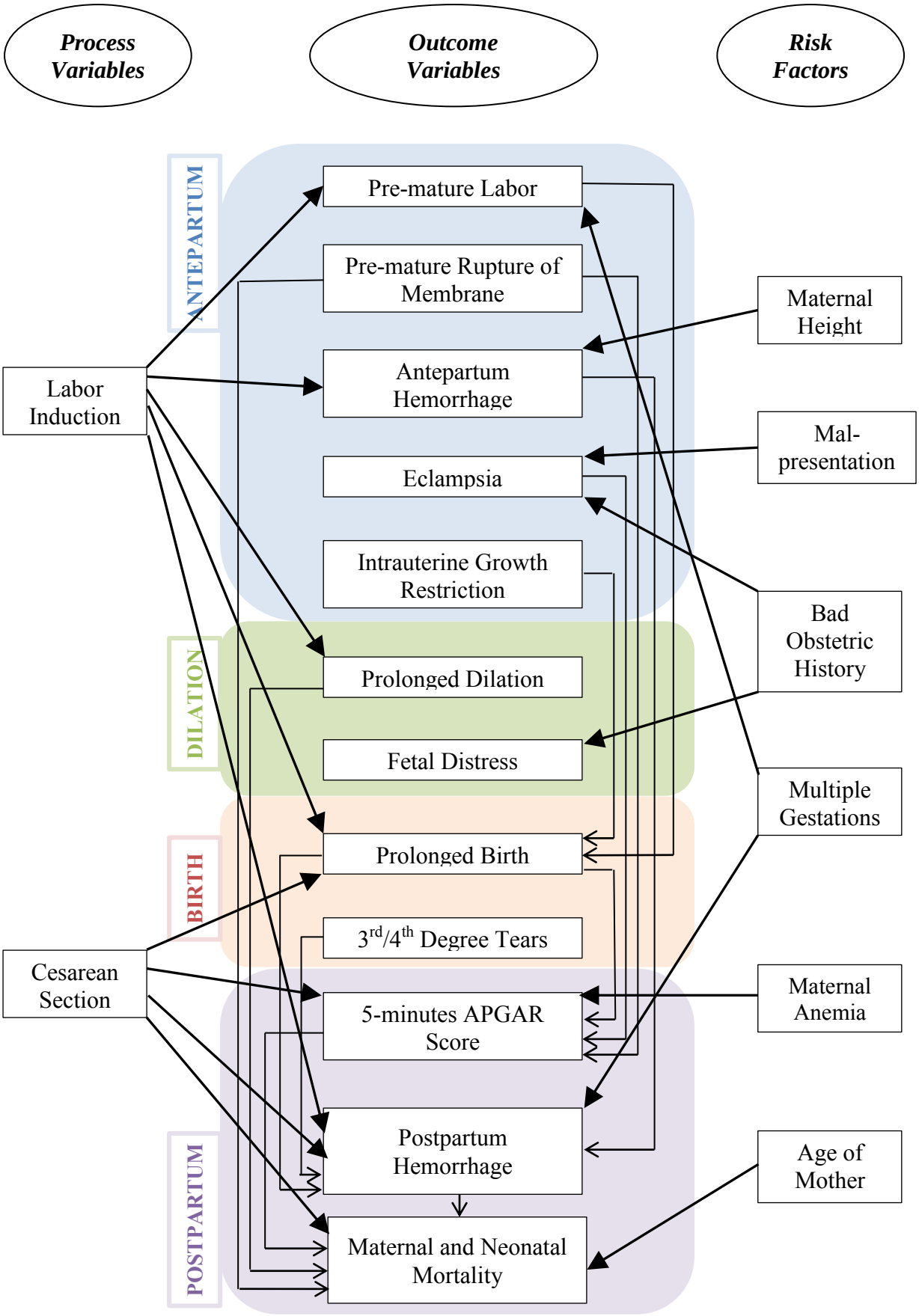

Figure 4.1: Directed Acyclic Graphical Representation of Bayesian Network

4.3 Mathematical Model Formulation

A DAG structure is formulated representing the relationships among the outcome variables, process variables and risk factors, with downstream outcome variables dependent on upstream variables. Based on the DAG structure, the joint probability distribution can be written as follows –

$$P(Y_{1jk}, Y_{3jk}, Y_{4jk}, Y_{6jk}, Y_{7jk}, Y_{8jk}, Y_{11jk}, Y_{13jk}, Y_{14jk} \mid Y_{1jk}, Y_{2jk}, Y_{3jk}, Y_{4jk}, Y_{5jk}, Y_{6jk}, Y_{7jk}, Y_{8jk}, Y_{9jk}, Y_{11jk}, Y_{13jk}, X_{1jk}, X_{2jk}, Z_{2jk}, Z_{3jk}, Z_{4jk}, Z_{5jk}, Z_{6jk}, Z_{8jk})$$

$$= P(Y_{1jk}| X_{2jk}, Z_{5jk})\, P(Y_{3jk}| X_{2jk}, Z_{4jk})\, P(Y_{4jk}| Z_{6jk}, Z_{8jk})\, P(Y_{6jk}| X_{2jk})\, P(Y_{7jk}| Z_{8jk})\, P(Y_{8jk}| X_{1jk}, X_{2jk}, Y_{1jk}, Y_{5jk})\, P(Y_{11jk}| X_{1jk}, Z_{3jk}, Y_{2jk}, Y_{4jk}, Y_{8jk})\, P(Y_{13jk}| X_{1jk}, X_{2jk}, Z_{5jk}, Y_{3jk}, Y_{8jk}, Y_{9jk})\, P(Y_{14jk}| X_{1jk}, Z_{2jk}, Y_{2jk}, Y_{6jk}, Y_{11jk}, Y_{13jk}) \quad (4.1)$$

Each outcome variable is a binary variable; hence a logistic regression model is formulated with the following model equations –

$$P_{ijk} = \frac{\exp(L_{ijk})}{1+ \exp(L_{ijk})} \quad (4.2)$$

Here,

$i = 1, 2, \ldots, 14^{th}$ number of outcome variable ($i \neq 10, 12$)

$j = 1, 2, \ldots, n^{th}$ number of patient

$k = 1, 2, \ldots, K^{th}$ number of time interval

P_{ijk} is the probability of outcome variable i for patient j in time period k and $0 \leq P_{ijk} \leq 1$.

L_{ijk} is defined –

$$L_{ijk} = \alpha_i + \sum_{m=1}^{p} \beta_{m,i} X_{mjk} + \sum_{m=1}^{q} \gamma_{m,i} Y_{mjk} + \sum_{m=1}^{r} \delta_{m,i} Z_{mjk} \quad (4.3)$$

Where,

$\beta_{m,i}$ = Direct effect of m^{th} process variable on Y_{ijk}

$\gamma_{m,i}$ = Direct effect of m^{th} outcome variable on Y_{ijk}, $m \in \{1, 2, \ldots, i-1\}$

$\delta_{m,i}$ = Direct effect of m^{th} risk factor on Y_{ijk}

p = Total number of process variable

q = Total number of outcome variable

r = Total number of risk factor

So for each outcome variables, the values of L_{ijk} can be determined from these equations –

$$L_{1jk} = \alpha_1 + \beta_{2,1}X_{2jk} + \delta_{5,1}Z_{5jk} \quad (4.4)$$

$$L_{3jk} = \alpha_3 + \beta_{2,3}X_{2jk} + \delta_{4,3}Z_{4jk} \quad (4.5)$$

$$L_{4jk} = \alpha_4 + \delta_{6,4}Z_{6jk} + \delta_{8,4}Z_{8jk} \quad (4.6)$$

$$L_{6jk} = \alpha_6 + \beta_{2,6}X_{2jk} \quad (4.7)$$

$$L_{7jk} = \alpha_7 + \delta_{8,7}Z_{8jk} \quad (4.8)$$

$$L_{8jk} = \alpha_8 + \beta_{1,8}X_{1jk} + \beta_{2,8}X_{2jk} + \gamma_{1,8}Y_{1jk} + \gamma_{5,8}Y_{5jk} \quad (4.9)$$

$$L_{11jk} = \alpha_{11} + \beta_{1,11}X_{1jk} + \gamma_{2,11}Y_{2jk} + \gamma_{4,11}Y_{4jk} + \gamma_{8,11}Y_{8jk} + \delta_{3,11}Z_{3jk} \quad (4.10)$$

$$L_{13jk} = \alpha_{13} + \beta_{1,13}X_{1jk} + \beta_{2,13}X_{2jk} + \gamma_{3,13}Y_{3jk} + \gamma_{8,13}Y_{8jk} + \gamma_{9,13}Y_{9jk} + \delta_{5,13}Z_{5jk} \quad (4.11)$$

$$L_{14jk} = \alpha_{14} + \beta_{1,14}X_{1jk} + \gamma_{2,14}Y_{2jk} + \gamma_{6,14}Y_{6jk} + \gamma_{11,14}Y_{11jk} + \gamma_{13,14}Y_{13jk} + \delta_{2,14}Z_{2jk} \quad (4.12)$$

By putting the constant and coefficient values from table 4.25, we can rewrite the equations (4.4) – (4.12) as follows –

$$L_{1jk} = -1.998 - 1.19X_{2jk} + 1.174Z_{5jk} \quad (4.13)$$

$$L_{3jk} = -0.764 + 0.477X_{2jk} - 0.312Z_{4jk} \quad (4.14)$$

$$L_{4jk} = 0.132 + 0.959Z_{6jk} + 0.536Z_{8jk} \quad (4.15)$$

$$L_{6jk} = -2.573 + 1.405X_{2jk} \quad (4.16)$$

$$L_{7jk} = -2.091 - 1.087Z_{8jk} \quad (4.17)$$

$$L_{8jk} = -3.968 + 0.952X_{1jk} + 0.653X_{2jk} + 0.849Y_{1jk} + 0.959Y_{5jk} \quad (4.18)$$

$$L_{11jk} = -1.066 + 1.337X_{1jk} - 0.275Y_{2jk} + 0.716Y_{4jk} + 0.999Y_{8jk} + 0.431Z_{3jk} \quad (4.19)$$

$$L_{13jk} = -0.937 - 0.492X_{1jk} + 0.882X_{2jk} + 0.604Y_{3jk} - 0.78Y_{8jk} + 1.20Y_{9jk} + 0.59Z_{5jk} \quad (4.20)$$

$$L_{14jk} = -3.838 - 1.359X_{1jk} + 0.568Y_{2jk} + 1.05Y_{6jk} + 1.64Y_{11jk} + 0.82Y_{13jk} + 0.49Z_{2jk} \quad (4.21)$$

The expected value, observed value and observed-expected (O-E) value for i^{th} outcome variable in k^{th} time period are determined from the following equations –

$$EY_{ik} = \sum_{j=1}^{n} P_{ijk} \quad (4.22)$$

$$OY_{ik} = \sum_{j=1}^{n} Y_{ijk} \quad (4.23)$$

$$OE_{ik} = OY_{ik} - EY_{ik} \quad (4.24)$$

CHAPTER 5

MULTI-STAGE CONTROL CHART DEVELOPMENT

For monitoring with the control charts, at first, data have been simulated. Then from the simulated data, the binary values of process variables, outcome variables and risk factors were achieved. Ultimately, observed outcomes and expected outcomes are determined; from which the test statistic observed – expected outcomes have been calculated. This data points were then plotted in the EWMA control charts.

5.1 Data Simulation

For developing multi-stage exponentially weighted moving average control charts, 1000 sets of data are generated for all the twenty five variables and factors by data simulation with the help of MATLAB R2016a software. The code for simulation is attached in the appendix. The simulation procedure is presented below –

- All the risk factors and process variables are simulated using Bernoulli distribution as it provides satisfactory performance for healthcare data simulation [9].
- The outcome variables are generated using equations (4.13)-(4.21). Other outcome variables, for which equations are not formulated, are generated using Bernoulli distribution.
- The means of Bernoulli distribution are determined from the expert opinions and empirical evidence of the Dhaka Medical College Hospital data.
- 1000 data for each variables and factors leading to a total of 25,000 data are simulated using this procedure. Then the data are equally distributed among twenty time periods, each time period containing 50 data for each variable and factor.

5.2 Test Statistic Estimation

The difference of observed and expected value (O-E) is selected as test statistic for the multi-stage EWMA control charts. O-E values are calculated as follows –

- For each patient in each time period, the binary values are inserted in equations (4.13)-(4.21) to get the values of L_{ijk}.

- By putting the L_{ijk} values in equation (4.2), the corresponding P_{ijk} values are obtained.
- The values of EY_{ik} are calculated using equation (4.22).
- Y_{ijk} values are generated from the data simulation mentioned above and ultimately OY_{ik} values are obtained with the help of equation (4.23).
- The values of OE_{ik} are finally achieved by using the equation (4.24).

5.3 Multi-stage EWMA Control Chart Development

The RA EWMA charts are chosen as they have similar performance to CUSUM charts in detecting small changes. Its main advantage over CUSUM charts lies in its intuitive interpretation as the EWMA statistic can be viewed as an estimate of the current level of the process. Moreover, the influence of previous observations is removed in the statistic gradually by adjusting the weights rather than resetting the statistic as CUSUM does, which is a more natural way to conduct monitoring and easier to accept by healthcare practitioners [12].

The test statistic O-E values are plotted in the EWMA control chart with the help of Minitab 2017 software. A value of 0.25 is used as the smoothing constant. Using equation (2.2)-(2.7), the control points, center line and control limits are calculated. Control charts are generated for each of the nine outcome variable for which multivariate binary logistic regression equations have been formulated.

CHAPTER 6

RESULT AND DISCUSSION

The results of and detailed discussion on this study have been presented in three categories here – multivariate binary logistic regression analysis, multi-stage EWMA control chart and potential applications for the predictive model.

6.1 Multivariate Binary Logistic Regression Analysis

The collected data of different outcome variables, process variables and risk factors are analyzed through multivariate binary logistic regression as they are dichotomous in nature. The analysis is carried out by Minitab 17 software. The analysis guides to determine which factors and variables can truly predict an outcome variable. These factors and variables are said to be "statistically significant" for outcome variables through p-value and variance inflation factor (VIF).

6.1.1 Pre-mature Labor

Pre-mature labor is selected as response variable, while all the risk factors and process variables are selected as predictors. The output of the analysis is summarized in table 6.1.

Table 6.1: Summary of Initial Output of Logistic Regression Analysis for Pre-mature Labor

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.696	1.01
Labor Induction***	0.009	1.01
Use of Mechanical Instrument	0.607	1.02
Parity > 4	0.077	1.01
Mother's Age <18 year or Age During 1st Pregnancy >35 year	0.823	1.01
Maternal Anemia	0.335	1.02
Maternal Height < 4'8"	0.988	1.02
Multiple Gestations***	0.001	1.02
Mal-presentations	0.807	1.02
Gestational Diabetes Mellitus	0.440	1.01
Bad Obstetric History	0.321	1.01

*** Statistically significant ($p < 0.05$)

Among the eleven predictors, labor induction and multiple gestations are found statistically significant for pre-mature labor as their p values are less than 0.05 with VIF less than 10. Only taking labor induction and multiple gestations as predictors, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.2.

Table 6.2: Summary of Final Output of Logistic Regression Analysis for Pre-mature Labor

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Labor Induction	-1.190	0.007	1.00
Multiple Gestations	1.174	0.000	1.00

The estimated value of the constant of the regression equation is found to be -1.998.

6.1.2 Pre-mature Rupture of Membrane

Pre-mature rupture of membrane is selected as response variable, while all the risk factors and process variables are selected as predictors. The output of the analysis is summarized in table 6.3.

Table 6.3: Summary of Final Output of Logistic Regression Analysis for PROM

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.948	1.02
Labor Induction	0.758	1.02
Use of Mechanical Instrument	0.068	1.02
Parity > 4	0.285	1.01
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.438	1.01
Maternal Anemia	0.585	1.02
Maternal Height < 4'8"	0.307	1.02
Multiple Gestations	0.572	1.01
Mal-presentations	0.509	1.01
Gestational Diabetes Mellitus	0.369	1.01
Bad Obstetric History	0.321	1.01

None of the predictors are found statistically significant for PROM as all of their p values are greater than 0.05.

6.1.3 Antepartum Hemorrhage

Antepartum hemorrhage is selected as response variable, while all the risk factors and process variables are selected as predictors. The output of the analysis is summarized in table 6.4.

Table 6.4: Summary of Initial Output of Logistic Regression Analysis for Antepartum Hemorrhage

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.565	1.01
Labor Induction***	0.041	1.02
Use of Mechanical Instrument	0.564	1.02
Parity > 4	0.195	1.01
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.122	1.01
Maternal Anemia	0.845	1.01
Maternal Height < 4'8"***	0.037	1.02
Multiple Gestations	0.272	1.01
Mal-presentations	0.256	1.01
Gestational Diabetes Mellitus	0.996	1.01
Bad Obstetric History	0.955	1.01

*** Statistically significant ($p < 0.05$)

Among the eleven predictors, labor induction and maternal height are found statistically significant for antepartum hemorrhage as their p values are less than 0.05 with VIF less than 10. Only taking these two as predictors, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.5.

Table 6.5: Summary of Final Output of Logistic Regression Analysis for Antepartum Hemorrhage

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Labor Induction	0.477	0.035	1.00
Maternal Height < 4'8"	-0.312	0.031	1.00

The estimated value of the constant of the regression equation is found to be -0.764.

6.1.4 Eclampsia

Eclampsia is selected as response variable, while all the risk factors and process variables are selected as predictors. The output of the analysis is summarized in table 6.6.

Table 6.6: Summary of Initial Output of Logistic Regression Analysis for Eclampsia

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.074	1.02
Labor Induction	0.888	1.02
Use of Mechanical Instrument	0.348	1.02
Parity > 4	0.374	1.01
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.560	1.01
Maternal Anemia	0.499	1.02
Maternal Height < 4'8"	0.137	1.02
Multiple Gestations	0.110	1.01
Mal-presentations***	0.000	1.01
Gestational Diabetes Mellitus	0.624	1.01
Bad Obstetric History***	0.016	1.01

*** Statistically significant ($p < 0.05$)

Among the eleven predictors, mal-presentations and bad obstetric history are found statistically significant for eclampsia as their p values are less than 0.05 with VIF less than 10. Only taking these two as predictors, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.7.

Table 6.7: Summary of Final Output of Logistic Regression Analysis for Eclampsia

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Mal-presentations	0.959	0.000	1.00
Bad Obstetric History	0.536	0.019	1.00

The estimated value of the constant of the regression equation is found to be 0.132.

6.1.5 Intrauterine Growth Restriction

IUGR is selected as response variable, while all the risk factors and process variables are selected as predictors. The output of the analysis is summarized in table 6.8. None of the predictors are found statistically significant for IUGR as all of their p values are greater than 0.05.

Table 6.8: Summary of Final Output of Logistic Regression Analysis for IUGR

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.586	1.02
Labor Induction	0.787	1.02
Use of Mechanical Instrument	0.447	1.03
Parity > 4	0.952	1.01
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.122	1.01
Maternal Anemia	0.209	1.02
Maternal Height < 4'8"	0.445	1.02
Multiple Gestations	0.369	1.01
Mal-presentations	0.915	1.01
Gestational Diabetes Mellitus	0.928	1.01
Bad Obstetric History	0.548	1.01

6.1.6 Prolonged Dilation

Prolonged dilation is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum period are selected as predictors. The output of the analysis is summarized in table 6.9.

Table 6.9: Summary of Initial Output of Logistic Regression Analysis for Prolonged Dilation

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.157	1.03
Labor Induction***	0.000	1.07
Use of Mechanical Instrument	0.557	1.04
Parity > 4	0.359	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.411	1.02
Maternal Anemia	0.090	1.03
Maternal Height < 4'8"	0.335	1.04
Multiple Gestations	0.759	1.05
Mal-presentations	0.131	1.05
Gestational Diabetes Mellitus	0.773	1.02
Bad Obstetric History	0.121	1.02
Pre-mature Labor	0.315	1.07
Pre-mature Rupture of Membrane	0.905	1.02
Antepartum Hemorrhage	0.878	1.02
Eclampsia	0.275	1.05
Intrauterine Growth Restriction	0.157	1.01

*** Statistically significant ($p < 0.05$)

Among the sixteen predictors, labor induction is found statistically significant for antepartum hemorrhage as their p values are less than 0.05 with VIF less than 10. Only taking this as predictor, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.10.

Table 6.10: Summary of Final Output of Logistic Regression Analysis for Prolonged Dilation

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Labor Induction	1.405	0.000	1.00

The estimated value of the constant of the regression equation is found to be -2.573.

6.1.7 Fetal Distress

Fetal distress is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum period are selected as predictors. The output of the analysis is summarized in table 6.11.

Table 6.11: Summary of Initial Output of Logistic Regression Analysis for Fetal Distress

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.297	1.03
Labor Induction	0.823	1.03
Use of Mechanical Instrument	0.258	1.03
Parity > 4	0.960	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.484	1.02
Maternal Anemia	0.682	1.02
Maternal Height < 4'8"	0.163	1.03
Multiple Gestations	0.322	1.06
Mal-presentations	0.637	1.07
Gestational Diabetes Mellitus	0.921	1.01
Bad Obstetric History***	0.017	1.01
Pre-mature Labor	0.874	1.06
Pre-mature Rupture of Membrane	0.868	1.02
Antepartum Hemorrhage	0.504	1.02
Eclampsia	0.362	1.07
Intrauterine Growth Restriction	0.104	1.02

*** Statistically significant ($p < 0.05$)

Among the sixteen predictors, BOH is found statistically significant. Only taking this as predictor, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.12.

Table 6.12: Summary of Final Output of Logistic Regression Analysis for Fetal Distress

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Bad Obstetric History	-1.087	0.015	1.00

The estimated value of the constant of the regression equation is found to be -2.091.

6.1.8 Prolonged Birth

Prolonged birth is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum and dilation period are selected as predictors. The output of the analysis is summarized in table 6.13.

Table 6.13: Summary of Initial Output of Logistic Regression Analysis for Prolonged Birth

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section***	0.036	1.03
Labor Induction***	0.049	1.03
Use of Mechanical Instrument	0.922	1.03
Parity > 4	0.405	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.856	1.02
Maternal Anemia	0.857	1.02
Maternal Height < 4'8"	0.065	1.03
Multiple Gestations	0.998	1.06
Mal-presentations	0.476	1.07
Gestational Diabetes Mellitus	0.835	1.01
Bad Obstetric History	0.176	1.01
Pre-mature Labor***	0.023	1.06
Pre-mature Rupture of Membrane	0.753	1.02
Antepartum Hemorrhage	0.448	1.02
Eclampsia	0.605	1.07
Intrauterine Growth Restriction***	0.032	1.02
Prolonged Dilation	0.216	1.01
Fetal Distress	0.564	1.05

*** Statistically significant ($p < 0.05$)

Among the eighteen predictors, cesarean section, labor induction, pre-mature labor and IUGR are found statistically significant. The final result is displayed in table 6.14.

Table 6.14: Summary of Final Output of Logistic Regression Analysis for Prolonged Birth

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Cesarean Section	0.952	0.036	1.03
Labor Induction	0.653	0.049	1.00
Pre-mature Labor	0.849	0.047	1.03
Intrauterine Growth Restriction	0.959	0.032	1.00

The estimated value of the constant of the regression equation is found to be -3.968.

6.1.9 $3^{rd}/4^{th}$ Degree Tears

$3^{rd}/4^{th}$ degree tears is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum and dilation period are selected as predictors. The output of the analysis is summarized in table 6.15. Among the eighteen predictors, none of them are found significant.

Table 6.15: Summary of Final Output of Logistic Regression Analysis for $3^{rd}/4^{th}$ Degree Tears

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.608	1.03
Labor Induction	0.261	1.03
Use of Mechanical Instrument	0.617	1.03
Parity > 4	0.665	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.293	1.02
Maternal Anemia	0.539	1.02
Maternal Height < 4'8"	0.740	1.03
Multiple Gestations	0.433	1.06
Mal-presentations	0.435	1.07
Gestational Diabetes Mellitus	0.639	1.01
Bad Obstetric History	0.728	1.01
Pre-mature Labor	0.539	1.06
Pre-mature Rupture of Membrane	0.882	1.02
Antepartum Hemorrhage	0.084	1.02
Eclampsia	0.104	1.07
Intrauterine Growth Restriction	0.749	1.02
Prolonged Dilation	0.998	1.01
Fetal Distress	0.545	1.05

6.1.10 Cord Prolapse

Cord prolapse is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum and dilation period are selected as predictors. The output of the analysis is summarized in table 6.16. Among the eighteen predictors, none of them are found significant. Although the predictors are displaying good VIF values which indicate that there is no multicollinearity among them, their p values are found to be more than 0.05.

Table 6.16: Summary of Final Output of Logistic Regression Analysis for Cord Prolapse

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.911	1.03
Labor Induction	0.767	1.07
Use of Mechanical Instrument	0.898	1.04
Parity > 4	0.393	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.700	1.02
Maternal Anemia	0.960	1.02
Maternal Height < 4'8"	0.816	1.03
Multiple Gestations	0.654	1.04
Mal-presentations	0.089	1.07
Gestational Diabetes Mellitus	0.379	1.02
Bad Obstetric History	0.877	1.03
Pre-mature Labor	0.190	1.06
Pre-mature Rupture of Membrane	0.525	1.03
Antepartum Hemorrhage	0.589	1.03
Eclampsia	0.509	1.08
Intrauterine Growth Restriction	0.896	1.01
Prolonged Dilation	0.948	1.05
Fetal Distress	0.666	1.01

6.1.11 5-min APGAR Score

5-min APGAR score is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum, dilation and birth period are selected as predictors. The output of the analysis is summarized in table 6.17.

Table 6.17: Summary of Initial Output of Logistic Regression Analysis for 5-min APGAR Score

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section***	0.000	1.04
Labor Induction	0.715	1.07
Use of Mechanical Instrument	0.305	1.03
Parity > 4	0.286	1.03
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.764	1.02
Maternal Anemia***	0.014	1.03
Maternal Height < 4'8"	0.459	1.03
Multiple Gestations	0.182	1.04
Mal-presentations	0.924	1.04
Gestational Diabetes Mellitus	0.613	1.02
Bad Obstetric History	0.802	1.03
Pre-mature Labor	0.942	1.05
Pre-mature Rupture of Membrane***	0.037	1.02
Antepartum Hemorrhage	0.097	1.03
Eclampsia***	0.000	1.07
Intrauterine Growth Restriction	0.890	1.02
Prolonged Dilation	0.776	1.05
Fetal Distress	0.593	1.02
Prolonged Birth***	0.011	1.03
$3^{rd}/4^{th}$ Degree Tears	0.740	1.02
Cord Prolapse	0.246	1.01

*** Statistically significant ($p < 0.05$)

Among the twenty one predictors, cesarean section, maternal anemia, pre-mature rupture of membrane, Eclampsia and prolonged birth are found statistically significant for 5-min APGAR score as their p values are less than 0.05 with VIF less than 10. Only taking these as predictors, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.18.

Table 6.18: Summary of Final Output of Logistic Regression Analysis for 5-min APGAR Score

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Cesarean Section	1.337	0.000	1.01
Maternal Anemia	0.431	0.013	1.01
Pre-mature Rupture of Membrane	-0.275	0.037	1.00
Eclampsia	0.716	0.000	1.01
Prolonged Birth	0.999	0.010	1.00

The estimated value of the constant of the regression equation is found to be -1.066.

6.1.12 Low Infant Birth Weight

Low infant birth weight is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum, dilation and birth period are selected as predictors. The output of the analysis is summarized in table 6.19. Among the twenty one predictors, none of them are found significant.

Table 6.19: Summary of Final Output of Logistic Regression Analysis for Low Infant Birth Weight

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section	0.987	1.03
Labor Induction	0.388	1.07
Use of Mechanical Instrument	0.623	1.03
Parity > 4	0.841	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.482	1.02
Maternal Anemia	0.834	1.02
Maternal Height < 4'8"	0.053	1.03
Multiple Gestations	0.869	1.04
Mal-presentations	0.295	1.06
Gestational Diabetes Mellitus	0.290	1.02
Bad Obstetric History	0.066	1.03
Pre-mature Labor	0.051	1.05
Pre-mature Rupture of Membrane	0.215	1.02
Antepartum Hemorrhage	0.489	1.03
Eclampsia	0.357	1.07
Intrauterine Growth Restriction	0.658	1.02
Prolonged Dilation	0.146	1.05
Fetal Distress	0.304	1.02
Prolonged Birth	0.717	1.03
$3^{rd}/4^{th}$ Degree Tears	0.602	1.02
Cord Prolapse	0.059	1.01

6.1.13 Postpartum Hemorrhage

Postpartum hemorrhage is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum, dilation and birth period are selected as predictors. The output of the analysis is summarized in table 6.20.

Table 6.20: Summary of Initial Output of Logistic Regression Analysis for Postpartum Hemorrhage

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section***	0.000	1.03
Labor Induction***	0.019	1.06
Use of Mechanical Instrument	0.589	1.03
Parity > 4	0.395	1.02
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.206	1.02
Maternal Anemia	0.943	1.02
Maternal Height < 4'8"	0.900	1.03
Multiple Gestations***	0.037	1.04
Mal-presentations	0.252	1.06
Gestational Diabetes Mellitus	0.121	1.01
Bad Obstetric History	0.740	1.03
Pre-mature Labor	0.466	1.04
Pre-mature Rupture of Membrane	0.308	1.02
Antepartum Hemorrhage***	0.000	1.04
Eclampsia	0.321	1.07
Intrauterine Growth Restriction	0.331	1.02
Prolonged Dilation	0.795	1.05
Fetal Distress	0.669	1.02
Prolonged Birth***	0.023	1.02
$3^{rd}/4^{th}$ Degree Tears***	0.001	1.02
Cord Prolapse	0.228	1.01

*** Statistically significant ($p < 0.05$)

Among the twenty one predictors, cesarean section, labor induction, multiple gestations, antepartum hemorrhage, prolonged birth and $3^{rd}/4^{th}$ degree tears are found statistically significant for postpartum hemorrhage as their p values are less than 0.05 with VIF less than 10. Only taking these as predictors, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.21.

Table 6.21: Summary of Final Output of Logistic Regression Analysis for Postpartum Hemorrhage

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Cesarean Section	-0.492	0.032	1.01
Labor Induction	0.882	0.000	1.01
Multiple Gestations	0.588	0.039	1.01
Antepartum Hemorrhage	0.604	0.000	1.02
Prolonged Birth	-0.780	0.027	1.01
$3^{rd}/4^{th}$ Degree Tears	1.201	0.001	1.01

The estimated value of the constant of the regression equation is found to be -0.937.

6.1.14 Maternal and Neonatal Mortality

Maternal and neonatal mortality is selected as response variable, while all the risk factors, process variables and outcome variables of antepartum, dilation, birth and postpartum period are selected as predictors. Though maternal and neonatal mortality is an outcome variable of postpartum period, other outcome variables of postpartum period are also considered as predictors as these variables can result in death in near future, even after a month. The output of the analysis is summarized in table 6.22.

Table 6.22: Summary of Initial Output of Logistic Regression Analysis for Maternal and Infant Mortality

Predictor Variables	P-value	Variance Inflation Factor
Cesarean Section***	0.000	1.21
Labor Induction	0.778	1.13
Use of Mechanical Instrument	0.117	1.04
Parity > 4	0.929	1.03
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year***	0.049	1.05
Maternal Anemia	0.882	1.05
Maternal Height < 4'8"	0.134	1.04
Multiple Gestations	0.589	1.07
Mal-presentations	0.331	1.08
Gestational Diabetes Mellitus	0.796	1.04
Bad Obstetric History	0.478	1.05
Pre-mature Labor	0.761	1.07
Pre-mature Rupture of Membrane***	0.033	1.03
Antepartum Hemorrhage	0.332	1.10
Eclampsia	0.250	1.13
Intrauterine Growth Restriction	0.375	1.03
Prolonged Dilation***	0.000	1.14
Fetal Distress	0.196	1.03
Prolonged Birth	0.872	1.04
$3^{rd}/4^{th}$ Degree Tears	0.343	1.07
Cord Prolapse	0.478	1.04
5-min APGAR Score***	0.000	1.22
Low Infant Birth Weight	0.168	1.05
Postpartum Hemorrhage***	0.000	1.13

*** Statistically significant ($p < 0.05$)

Among the twenty four predictors, cesarean section, mother's age, PROM, prolonged dilation, APGAR and postpartum hemorrhage are found statistically significant for maternal and neonatal mortality as their p values are less than 0.05 with VIF less than 10. Only taking

these as predictors, logistic regression analysis is performed again to achieve the final output. The result is displayed in table 6.23.

Table 6.23: Summary of Final Output of Logistic Regression Analysis for Maternal and Infant Mortality

Predictor Variables	Value of Coefficient	P-value	Variance Inflation Factor
Cesarean Section	-1.359	0.000	1.18
Mother's Age < 18 year or Age During 1st Pregnancy > 35 year	0.490	0.047	1.01
Pre-mature Rupture of Membrane	0.568	0.017	1.01
Prolonged Dilation	1.045	0.001	1.01
5-min APGAR Score	1.639	0.000	1.13
Postpartum Hemorrhage	0.823	0.000	1.06

The estimated value of the constant of the regression equation is found to be -3.838.

So, the whole final output of the multivariate binary logistic regression analysis for all the outcome or response variables can be summarized with their corresponding stages, constants and predictors as in table 6.24.

The Bayesian network presented in figure 4.1 and the mathematical model of chapter 4 are based on the data collected from the Dhaka Medical College Hospital. It is very important to keep in mind that the cause and effect relationship and the equations will vary among different hospitals, even among different time periods. But the method is a universal one which can be implemented even outside maternal healthcare.

The different relationships found in the multivariate binary logistic regression analysis are quite understandable in context of Bangladesh. Among the twenty five variables and factors, twenty were found highly associated with outcome variables. These relationships have also been proved in numerous previous researches. And the strong association of different variables of the antepartum period proves the necessity and significance of including this period in evaluating the maternal healthcare.

Table 6.24: Summary of Final Output of Multivariate Binary Logistic Regression Analysis

Stage	Response Variable	Constant and Significant Predictor	Constant and Coefficient Value
Antepartum Period	Pre-mature Labor	Constant	-1.998
		Labor Induction	-1.190
		Multiple Gestations	1.174
	Pre-mature Rupture of Membrane	None	None
	Antepartum Hemorrhage	Constant	-0.764
		Labor Induction	0.477
		Short Maternal Height	-0.312
	Eclampsia	Constant	0.132
		Mal-presentations	0.959
		Bad Obstetric History	0.536
	Intrauterine Growth Restriction	None	None
Dilation Period	Prolonged Dilation	Constant	-2.573
		Labor Induction	1.405
	Fetal Distress	Constant	-2.091
		Bad Obstetric History	-1.087
Birth Period	Prolonged Birth	Constant	-3.968
		Cesarean Section	0.952
		Labor Induction	0.653
		Pre-mature Labor	0.849
		Intrauterine Growth Restriction	0.959
	$3^{rd}/4^{th}$ Degree Tears	None	None
	Cord Prolapse	None	None
Postpartum Period	5-min APGAR Score	Constant	-1.066
		Cesarean Section	1.337
		Maternal Anemia	0.431
		Pre-mature Rupture of Membrane	-0.275
		Eclampsia	0.716
		Prolonged Birth	0.999
	Low Infant Birth Weight	None	None
	Postpartum Hemorrhage	Constant	-0.937
		Cesarean Section	-0.492
		Labor Induction	0.882
		Multiple Gestations	0.588
		Antepartum Hemorrhage	0.604
		Prolonged Birth	-0.780
		$3^{rd}/4^{th}$ Degree Tears	1.201
	Maternal and Neonatal Mortality	Constant	-3.838
		Cesarean Section	-1.359
		Mother's Age	0.490
		Pre-mature Rupture of Membrane	0.568
		Prolonged Dilation	1.045
		5-min APGAR Score	1.639
		Postpartum Hemorrhage	0.823

6.2.1 Stage 1 - Antepartum Period

The control charts, developed for the pre-mature labor, antepartum hemorrhage and eclampsia which are outcome variables of antepartum period, are presented in figure 6.2. For pre-mature labor, all control points are within the control limits, but there is a clear increasing trend in the chart which suggests for some investigation between time period 4 and 20. Time period 4, 17, 18 and 20 experienced a high observed complication compared to the expected. Similarly, while for antepartum hemorrhage, time period 2, 6, 8, 9 and 15 experienced high complications, time period 6, 7, 8, 13 and 18 show higher complications for eclampsia.

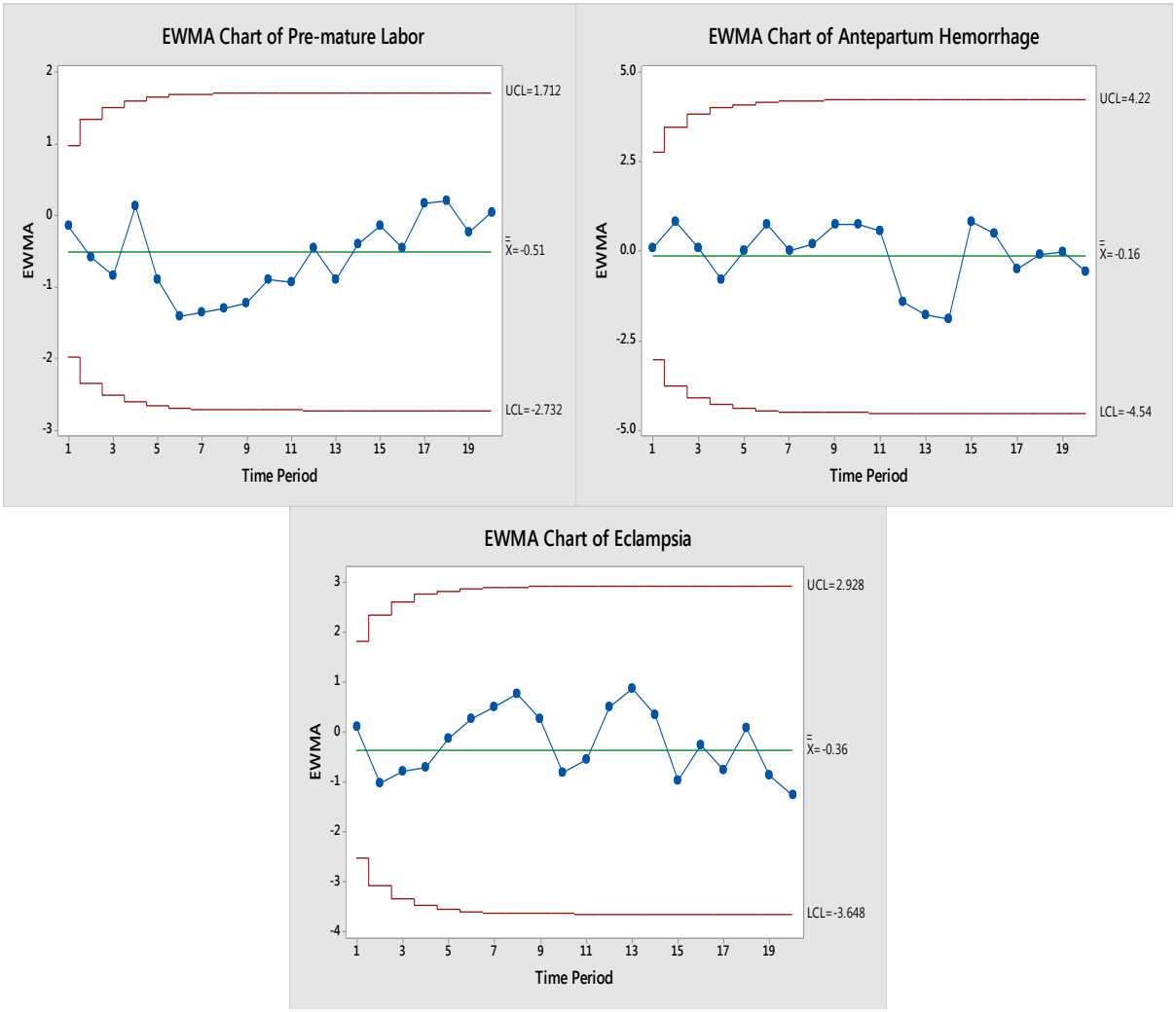

Figure 6.2: EWMA Control Chart for Outcome Variables of Antepartum Period

6.2.2 Stage 2 - Dilation Period

Figure 6.3 demonstrates the control charts developed for the prolonged dilation and fetal distress which are the outcome variables of the dilation period. For prolonged dilation, all control points are within the control limits, but there is a clear late increasing trend in the chart which suggests for some investigation between time period 17 and 20. Time period 9, 11 and 20 experienced a high observed complication compared to the expected. Similarly, time period 4, 5, 6, 10 and 11 show higher complications for fetal distress.

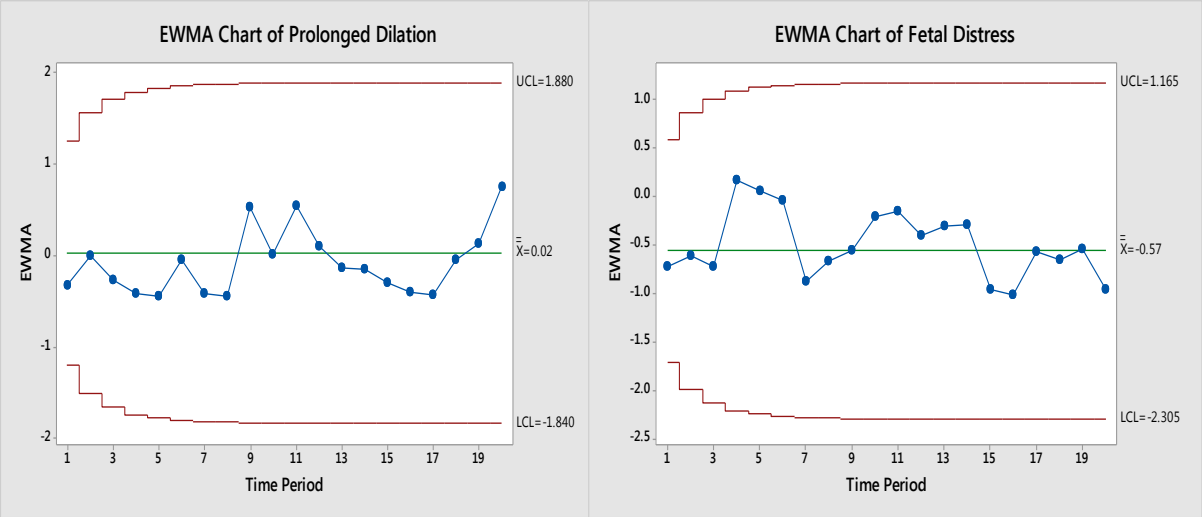

Figure 6.3: EWMA Control Chart for Outcome Variables of Dilation Period

6.2.3 Stage 3 - Birth Period

Figure 6.4 shows the control charts developed for prolonged birth. Although, all the control points are within the control limits, an upward trend is visible between the time periods 11 and 20. Time period 6, 18 and 20 can be marked for investigation.

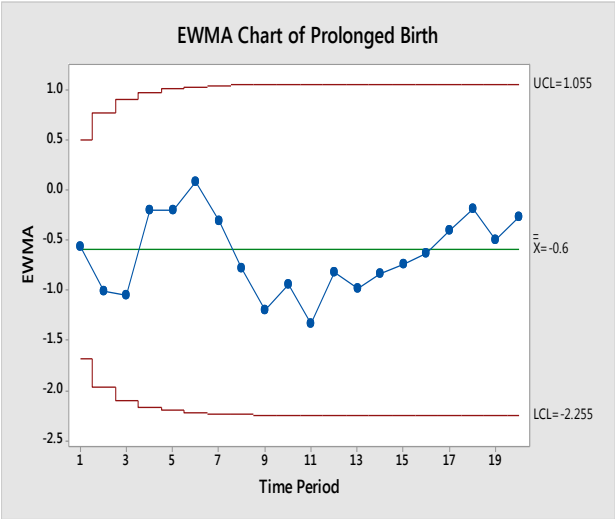

Figure 6.4: EWMA Control Chart for Outcome Variables of Birth Period

6.2.4 Stage 4 - Postpartum Period

Figure 6.5 presents the outcome of the final stage known as the postpartum period. The control charts are developed for 5-min APGAR score, postpartum hemorrhage and maternal and neonatal mortality which are the considered outcome variables. Time period 3, 17 and 18 show higher risky 5-min APGAR score for the newborns. A high hemorrhage in pregnant women is experienced after childbirth in time period 14 and 15. And ultimately, based on the maternal and neonatal mortality, time period 6, 7, 8, 16 and 17 require further investigation for higher observed death than expected.

So, here the healthcare management can monitor not only the end outcome which is the mortality, but also the outcome of the earlier stages simultaneously. Each specific time period can be traced back to its earlier stage to find out the root causes. As often the causes for an abnormal outcome do not present in the same stage, rather in the earlier stage, this multi-stage control chart surely provides a basis for investigating the reasons even if they are in the earlier stages. If the management only considered the final outcome mortality, it would find time period 6, 7, 8, 16 and 17 unacceptable and try to find out the reasons at that stage. But the reasons can well be present in 2 or 3 stages earlier, may be some days ago.

In the multi-stage control charts, time period 6 can be attributed to earlier postpartum hemorrhage, prolonged birth, fetal distress and ultimately to the antepartum hemorrhage of the pregnancy period which may have occurred even before the mother is admitted to the healthcare facility. So, there is even a chance that the mother or the family members were

mainly responsible for the unfortunate outcome. Thus each time period can be traced back to the earlier stages for identifying the actual reasons behind the abnormal outcomes.

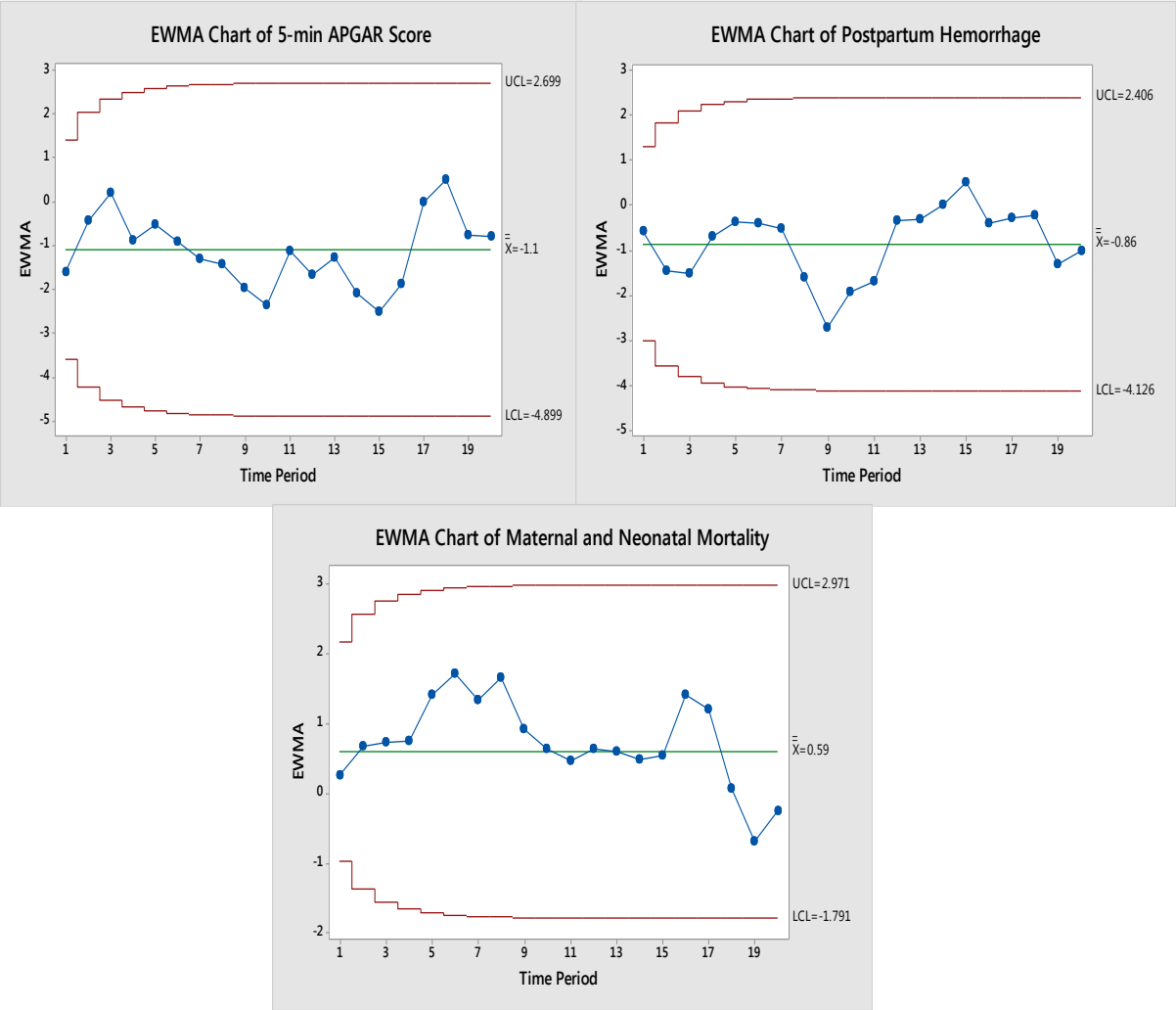

Figure 6.5: EWMA Control Chart for Outcome Variables of Postpartum Period

6.3 Potential Applications of the Predictive Model

The potential applications of the formulated model and the generated control charts are multi-faceted. Figure 6.6 demonstrates a brief idea about its potential implications. The developed Bayesian network can provide an insightful understanding of different variables and factors of different stages for a maternal healthcare facility.

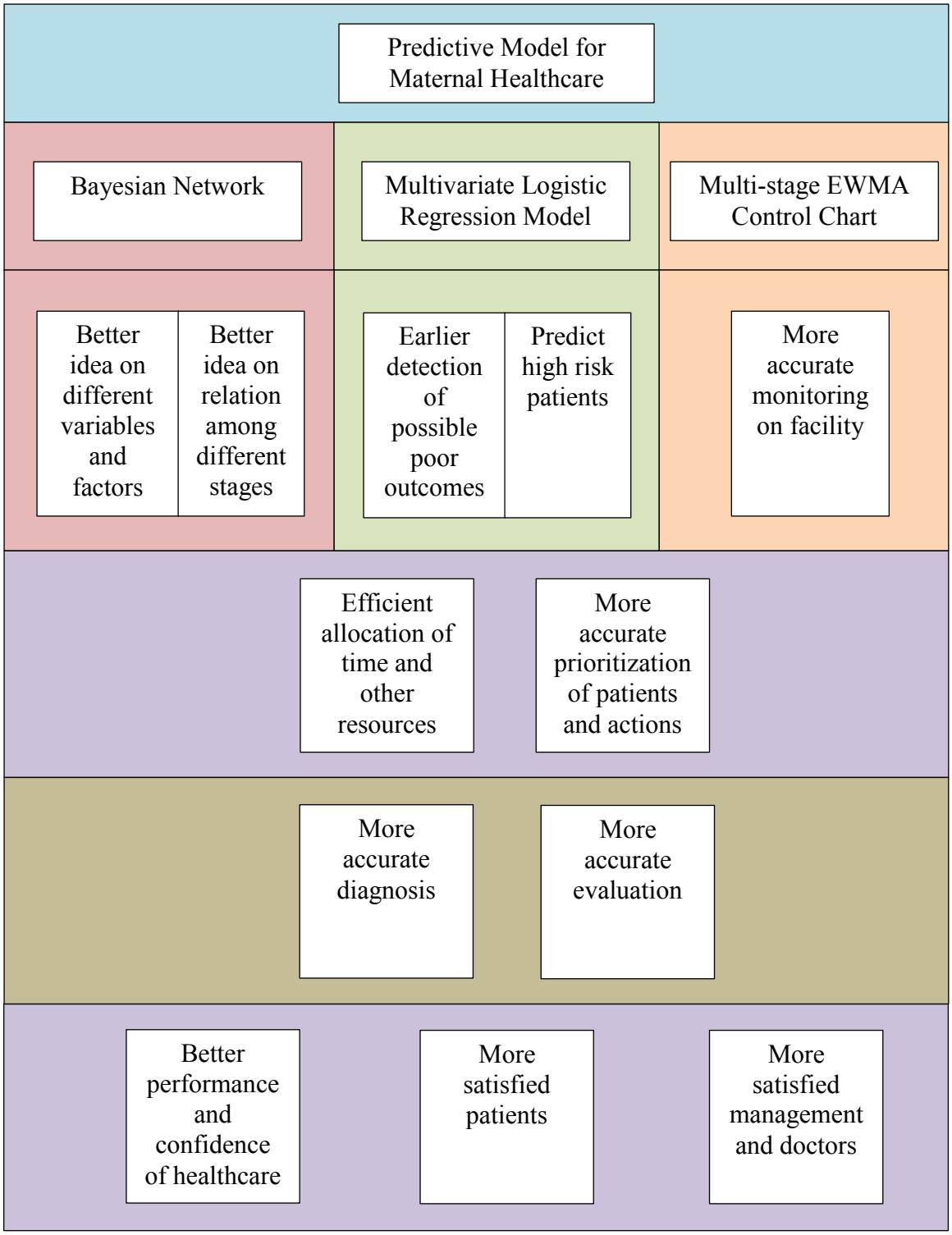

Figure 6.6: Potential Applications of the Predictive Model

The mathematical model can predict the possible poor outcomes. Then the management and the doctors can have the necessary equipment, medicines and other resources available in advance so that they can act promptly. This, in one hand, will ensure the efficient use of resources, and on the other hand, increase the chance of avoiding poor outcomes for patients. Thus, both the patients and the healthcare management can be highly benefited.

The multi-stage EWMA control charts in figures 6.2-6.5 also show how the maternal and neonatal mortality is linked with various factors and variables of earlier stages. Ignoring the earlier stages can lead to severe health risks and deaths as the actual causes will remain hard and time consuming to identify; often undetected. If for a certain time period, the test statistic O-E of maternal and neonatal mortality is unsatisfactory, the multi-stage control chart will immensely facilitate in identifying the root cause behind such scenario. Instead of guessing and assuming, the healthcare facility can detect the actual reason and act fast with efficient use of all sorts of resources. Even monitoring can be done on specific time period to identify any seasonal pattern. A healthcare management may also want to identify the performance of each doctor by monitoring through doctor specific control charts. The situation in each ward can also be monitored similarly. If a new procedure or equipment is adopted, its effect can also be analyzed with the help of this multi-stage control charts.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

In health care contexts, it is a must take into account patient characteristics and the possible changing nature of the patient population, since the risk of an adverse outcome prior to treatment depends on numerous patient factors (termed covariates) such as age, gender, underlying health status, etc. Although, the variation caused by patient mix in the actual health care process cannot be reduced, but the effect of the patient mix prior to medical treatment or surgery can be modeled and that model can be implemented to adjust the individual observed outcomes. Using risk adjustment to remove the effect of patient mix makes the monitoring method more sensitive to important process changes. Risk adjustment is also necessary to allow fair comparisons among surgical or medical care providers or institutions with different patient mixes. Intuitively, risk adjustment is needed because the death of the low risk patient is more indicative of poor performance than the death of a high risk patient, and similarly the survival of a high risk patient is more indicative of good performance than the survival of a low risk patient. This research has developed risk-adjusted multi-stage EWMA control charts based on the output of a predictive model which will incorporate the effects of the significant factors of both the antepartum and the delivery period, leading to a more realistic and accurate monitoring system for maternal healthcare facilities. The whole maternal healthcare process is divided into four stages – antepartum period, dilation period, birth period and postpartum period. Fourteen outcome variables, three process variables and eight risk factors have been utilized to represent these four stages. The directed acyclic graphical representation of Bayesian network and the multivariate binary logistic regression mathematical model have been developed from the combination of an extensive study of previous researches, expert opinions and empirical evidences. Based on the model, data have been simulated for monitoring by the multi-stage control charts. The formulated models and control charts demonstrate that different variables of antepartum period and other new variables incorporated in this study are crucial in evaluating the risk of the pregnant mothers and infants. The predictive model with control charts not only benefits the patients, but also gives the healthcare management a vital competitive edge by enhancing efficiency and accuracy of performance and better utilization of different resources.

7.2 Recommendations

There are some possible directions to which this research can be extended.

1. As the factors and variables will vary among different hospitals and regions, a comparative study can reveal insightful suggestions for better outcomes of different healthcare.
2. Other socio-economic factors like income, education, etc. can similarly be incorporated in the predictive model.
3. The model can be developed for the maternal mortality and the neonatal mortality separately based on a stratification analysis.
4. The Risk Priority Number can be assigned to the risk factors, as part of Failure Modes and Effects Analysis (FMEA), to take into account the likelihood of occurrence, likelihood of detection, and severity of impact.
5. Other control charts like cumulative sum charts, Shewhart charts, etc. can be developed and compared to EWMA charts in order to find out the suitable one.
6. The predictive model can also be implemented in healthcare other than maternity as a better method for identifying root causes and monitoring performances are of high demand in every sector.

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