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Monitoring Maternal Healthcare Performance in Hospital Setting Using a Multi-stage Bayesian Network Approach

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Abstract Most studies on healthcare process monitoring focus on surveillance end-stage clinical outcomes and thus may ignore interaction from earlier stages. For a complex multi-stage healthcare process such as maternal delivery in hospital settings, ignoring what occurs in earlier stages of the procedure may inadvertently lead to poorer outcomes, if continued. Therefore, this study employs a holistic approach to developing a Bayesian network-based monitoring process by considering interaction among multiple maternal healthcare stages. A total of fourteen outcome variables, three process variables, and eight risk factors from antepartum and subsequent periods are considered. Data are obtained from the Dhaka Medical College Hospital and Rajshahi Medical hospitals of Bangladesh from March 2017 to May 2017. The Bayesian network parameters were estimated using logistic regression models for each outcome variable and then simulated for monitoring by multi-stage exponentially weighted moving average control charts. Our findings demonstrate that different variables of the antepartum period and other new variables incorporated in this paper are crucial in evaluating the risk for pregnant mothers and infants. This corroborates the significance of tracing back to earlier stages to identify the causes for an abnormal outcome and provides a clearer understanding of the potential sources of excess variation that lead to a shift in final stage outcomes.

Keywords: *maternal health, childbirth, predictive modeling, Bayesian network, control chart*

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1. Introduction

The experience of giving birth has profound implications for a woman's health, and most healthy childbearing women want a safe, comfortable, and positive birth experience [1]. Although there is a significant improvement in childbirth experiences in the last decades, still many unfortunate women experience suffering, ill-health, and even death during pregnancy, childbirth, and the postpartum period, particularly in underdeveloped countries [2,3]. Avoidable maternal and neonatal morbidity and mortality remain unacceptably high during hospital care [4,5]. The majority of the avoidable maternal, fetal, and newborn adverse health outcomes occur in low and middle-income countries due to poor quality of care and disparities in pregnancy care [6]. The world health organization (WHO), has set improving maternal health as one of the major policy concerns and considered this one of the seventeen sustainable development goals by 2030 [7].

In Bangladesh, the reduction in maternal mortality and improvement of maternal health has been a major government policy interest and program goal for the past two decades [8]. As a result of implementing evolving maternal health strategies by government and non-government organizations (NGO), neonatal and maternal mortality in Bangladesh gradually decreased during the last decades [9]. Ensuring proper access to all community segments and monitoring maternal hospital care from a holistic approach can significantly boost this improvement. Every year, around 5,200 women in Bangladesh die due to pregnancy and childbirth-related problems, making up 8% of the total deaths among women of reproductive age. In addition, 83,100 babies are stillborn, and there are 76,000 neonatal deaths every year which is likely related to low skilled birth attendance (42%) and institutional delivery (38%) [10]. In hospital child delivery, there are some scattered unfortunate and tragic events such as the death of 10 babies within 24 hours in MAG Osmani Medical College and Hospital (OMCH), Sylhet, Bangladesh [11]. This case study and other alarming statistics provide a strong rationale pursuing a more precise and sound method for monitoring maternal healthcare performance in Bangladesh.

Comprehensive and robust hospital process monitoring is critical to building a safe and effective healthcare system, particularly for clinical procedures susceptible to medical error [12,13]. Centers for Disease Control and Prevention (CDC) suggests medical errors as the third leading cause of death. Each year more than 250,000 deaths happen per year are due to medical error in the U.S. [14]. Therefore, statistical process control techniques such as control charts have played a valuable role in monitoring hospital performance and ensuring the quality of the clinical procedures [15]. Previous studies have widely adopted process control techniques to monitor and isolate process variation and adverse events in mortality rate, postoperative complications, and number of infections in the hospital [16]. However, there is limited research to monitor maternal delivery operations in hospitals. Most prior studies have focused on case-control analysis and surveillance of outcome of the final stage (e.g., maternal mortality) rate and specific comorbid conditions influencing neonatal outcome (e.g., neonatal morbidity) [12,13,16]. Monitoring maternal and neonatal healthcare can become fairly complicated since this clinical procedure comprises multiple interrelated stages [17]. The outcome of the prior stages can affect the outcome of the final stage which warrants to implementation of a more comprehensive risk-adjusted multivariate process monitoring [18]. Only one study in New-Zealand hospital till now have shown promising results in monitoring the maternal delivery process through a three-stage process monitoring and multivariate control chart [19]. However, this study did not consider important risk factors during the pregnancy period and other critical risk factors such as antepartum hemorrhage, Eclampsia, mother education level, high parity, emergency cesarean delivery, and premature rupture of membrane. These factors, particularly during the antepartum period, can be very crucial for any pregnancy-related complications and monitoring associated adverse health outcomes [20,21]. Besides, to our best knowledge, there is no other inclusive multivariate statistical process control study till now that have explored the performance of maternal hospital care operation in any developing countries. This paper addresses and fulfills these research gaps by developing a more comprehensive and pragmatic risk-adjusted multi-stage maternal care monitoring system that can identify any variation in the maternal delivery process and medical errors.

2. Materials and Methods

The complete maternal delivery operation in the hospital setting is considered as an interconnected Bayesian network with multiple stages of operations. A Bayesian network or a belief network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). The objective of this Bayesian formulation is to develop a model that predicts the outcomes of different delivery periods considering the complex inter-relationship of significant factors and leading to risk-adjusted multi-stage control charts based on the output of a predictive model. To accomplish this, we first identify risk factors, process variables, and outcomes for different stages in maternal care. Then we quantify the relationship between the variables through regression analysis, develop a directed acyclic graph for interconnected stages for the risk factors and predict each stage outcomes. Finally, we develop a risk-adjusted control chart for the difference in observed-expected value for each stage of maternal care.

2.1. Dataset, Study Variables and Outcomes

Based on the previous studies and physician and gynecologist specialist expert opinions from three hospitals in Dhaka, Bangladesh, we divide the complete maternal care process into four distinct connected stages. These stages of maternal care in an inpatient setting are the Antepartum Period, Dilation Period, Birth Period, and Postpartum Period. Each stage has at least one outcome measure and may or may not have associated process variables and patient-specific risk factors that affect each outcome variable. We consider fourteen outcome variables, three process variables, and eight risk factors associated with the aforementioned four stages. For the first stage - Antepartum, we consider six outcome variables and two risk factors. The second stage - Dilation, consists of a latent and the first stage of labor. We define two outcome variables and one risk factor for this stage. The third stage - Birth, consists of a passive and an active second stage of labor. We define three outcomes, two risk factors, and two process variables for this stage. The fourth stage - the Post-partum period, is the time from the birth of the baby to the birth of the placenta. We consider three outcome variables and three risk factors for this period. All of the outcome variables, process variables, and risk factors considered, are listed along with definitions in Table 1.

We utilized a de-identified hospital administrative dataset of 315 patients from the maternal delivery unit in Dhaka Medical College Hospital and Rajshahi Medical hospitals for the March 1 2017 to May 30 2017. These databases are de-identified by hospital authority, therefore considered limited datasets and non-human subjects, as determined by the local Institutional Review Board and ethics committee approval was therefore not required. Dataset and related patient information was screened and validated by the expert specialist and physician from the Dhaka Medical College Hospital, Matuail Institute of Child & Mother Health, and Sher-e-Bangla Medical College & Hospital. Descriptive statistics regarding patient information is presented in Table 2. This obtained and validated dataset is used to estimate baseline parameters for the Bayesian framework. We then use these model parameters to inform our simulations for testing the control charts.

Table 1. Outcome variables, process variables, and risk factors considered in this paper

Outcome Variables	
Y_{1jk}	Whether labor starts before 37 weeks of pregnancy for patient j in time interval k, where $Y_{1jk} \in \{0,1\}$
Y_{2jk}	Whether fetal membranes are ruptured before the onset of labor for patient j in time interval k, where $Y_{2jk} \in \{0,1\}$
Y_{3jk}	Whether maternal bleeding occurs after the 20th week of pregnancy and before the onset of labor for patient j in time interval k, where $Y_{3jk} \in \{0,1\}$
Y_{4jk}	Whether patient j experiences convulsion from high blood pressure in time interval k, where $Y_{4jk} \in \{0,1\}$
Y_{5jk}	Whether fetus weighs below 10th percentile for its gestational age for patient j in time interval k, where $Y_{5jk} \in \{0,1\}$
Y_{6jk}	Whether length of dilation period is more than 18 hours with no prior birth or more than 12 hours with prior birth for patient j in time interval k, where $Y_{6jk} \in \{0,1\}$
Y_{7jk}	Whether persistent fetal heart rate is less than 120/minute or more than 160/minute for patient j in time interval k, where $Y_{7jk} \in \{0,1\}$
Y_{8jk}	Whether length of birth period is more than 2 hours with no prior birth or more than 1 hour with prior birth for patient j in time interval k, where $Y_{8jk} \in \{0,1\}$
Y_{9jk}	Whether a 3rd or 4th-degree tear occurs for patient j in time interval k, where $Y_{9jk} \in \{0,1\}$
Y_{10jk}	Whether the umbilical cord protrudes through the cervix and into the birth canal ahead of the baby for patient j in time interval k, where $Y_{10jk} \in \{0,1\}$
Y_{11jk}	Whether the 5-min APGAR score is less than 7 for patient j in time interval k, where $Y_{11jk} \in \{0,1\}$
Y_{12jk}	Whether infant birth weight is less than 2.5 kg for patient j in time interval k, where $Y_{12jk} \in \{0,1\}$
Y_{13jk}	Whether maternal blood loss is more than 500 ml with no Cesarean or more than 1000 ml with a Cesarean for patient j in time interval k, where $Y_{13jk} \in \{0,1\}$
Y_{14jk}	Whether any one of mother and infant(s) dies within 30 days for patient j in time interval k, where $Y_{14jk} \in \{0,1\}$
Process Variables	
X_{1jk}	Whether a cesarean section is performed for patient j in time interval k, where $X_{1jk} \in \{0,1\}$
X_{2jk}	Whether labor is induced for patient j in time interval k, where $X_{2jk} \in \{0,1\}$
X_{3jk}	Whether mechanical instrument is used in the birth stage for patient j in time interval k, where $X_{3jk} \in \{0,1\}$
Risk Factors	
Z_{1jk}	Whether patient j has given birth more than 4 times to a fetus of gestational age of at least 24 weeks in time interval k, where $Z_{1jk} \in \{0,1\}$
Z_{2jk}	Whether mother's age is less than 18 years or age during first pregnancy is more than 35 years for patient j in time interval k, where $Z_{2jk} \in \{0,1\}$
Z_{3jk}	Whether hemoglobin concentration is less than 6.83 mmol/L for patient j in time interval k, where $Z_{3jk} \in \{0,1\}$
Z_{4jk}	Whether maternal height is less than $4'8''$ for patient j in time interval k, where $Z_{4jk} \in \{0,1\}$
Z_{5jk}	Whether patient j delivers 2 or more offspring in time interval k, where $Z_{5jk} \in \{0,1\}$
Z_{6jk}	Whether presentation is posterior or transverse for patient j in time interval k, where $Z_{6jk} \in \{0,1\}$
Z_{7jk}	Whether patient j without diabetes develops high blood sugar level during pregnancy in time interval k, where $Z_{7jk} \in \{0,1\}$
Z_{8jk}	Whether patient j had preterm labor, miscarriage, or stillbirth before in time interval k, where $Z_{8jk} \in \{0,1\}$

2.2. Parameters Estimation and Bayesian Network

Bayesian network in our model is formulated similar to prior study as a directed acyclic graph (DAG) with node set V representing random variables, $Y = \{Y_{v \in V}\}$ having a joint probability distribution as

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

Where term $pa(v)$ represents the set of parent nodes of the node v.

We fit a separate multivariate logistic regression model for each outcome to quantify the relationship between variables and formulate DAG Bayesian framework. This analysis guides to determine which factors and variables can truly predict an outcome variable after adjusting process variables, risk factors, and upstream outcome variables. Multicollinearity within variables is also checked through a variance inflation factor (VIF) screening filter. We consider factors as significant in our model if the p-value is less than 0.05 and VIF is less than 5. All the statistical analysis is performed in R studio. For each outcome variable, the formulation of a multivariate generalized linear model is given by,

$$\begin{aligned} g(\pi_i) &= \tau_i \\ &= \alpha_i + \sum_{l=1}^{p} \beta_{li} y_l + \sum_{l=1}^{q} \gamma_{li} x_l + \sum_{l=1}^{r} \delta_{li} z_i + \epsilon_i \end{aligned}$$

Where, $\pi_i = E(Y_i)$; β_{li} = direct effect of lth process variable on Y_i; γ_{li} = direct effect of lth outcome variable on Y_i; δ_{li} = direct effect of lth risk factors on Y_i; p, q, r = number of process, outcome, and risk factor variables respectively and ϵ_i = random error term with zero mean and variance.

Hence, for the logit link function the expected value of the outcome Y_i can be written using estimated parameters from the above regression equation as follows

$$\pi_i = \frac{\exp(\tau_i)}{1 + \exp(\tau_i)}$$

We then use this expected value for each outcome to develop a multistage observed-expected control chart for the maternal delivery process.

2.3. Control Chart and Simulation

A control chart based on the difference of the number of observed values and expected values were used for monitoring outcomes in multistage maternal healthcare processes. The difference of observed-expected is easily interpretable statistical and has been used in the surgical operation and longitudinal performance monitoring. This type of control chart can be used for surveillance of outcome rates over time within a single hospital or department, where shifts from historical practice are the main targets for detection.

To detect deviation from historical rates for an outcome variable Y_i, for patients in a given unit, we compare the number of observed outcomes O_i to that predicted E_i using a model developed from historical practice. Our control chart statistic observed - expected value, $(O_i - E_i)$, can be calculated for a regular time interval (e.g., 7 days, 30 days) and this time interval depends on the volume of the patients and hospital administrations. For a regular time interval and n number of patients, expected value, observed value, and observed-expected value are determined from the following equations.

Observed count for outcome i for period k, $O(Y_{ik}) = \sum_{j=1}^{n} Y_{ijk}$

The expected value for outcome i for period k, $E(\hat{Y}_{jk}) = \sum_{j=1}^{n} \hat{\pi}_{ijk}$

Observed- Expected charted for time interval k,

$$\mathrm{OE}(\hat{Y}_{jk}) = \sum_{j=1}^{n} Y_{ijk} - \sum_{j=1}^{n} \hat{\pi}_{ijk}$$

Where, $\hat{\pi}_{ijk}$ value estimated from the logistic regression equation and estimated parameters.

After estimating the observed-expected value for each outcome variable, we develop an exponential moving average (EWMA) control chart with 0.25 as a smoothing constant for monitoring each outcome of the maternal delivery process. EWMA charts have been used widely for monitoring healthcare processes and service operations [16]. For developing multi-stage EWMA control charts, a total of 1000 sets of data for 20-time intervals are simulated for variables described in the previous study [19]. All the risk factors and process variables are simulated using Bernoulli distribution and Bernoulli distribution parameters were determined from the expert opinions and empirical evidence of the historical Hospital data. While generating synthetic dataset, we considered 50 maternal deliveries per week consistent with the maternal delivery unit-1 in Dhaka Medical Hospital. Lower and upper control limits for each outcome for the EWMA Control chart are obtained based on normal assumption with a 95% confidence level.

Table 2. Characteristics of the patient's information from the maternal delivery operation

Characteristics	Number (%)
Total patients	315
Mode of Delivery	
Vaginal Delivery	172 (54.60)
Cesarean	143 (45.40)
Age of Mother (year)	
<18	10 (3.12)
18-23	108 (34.28)
24-29	112 (35.55)
30-35	83 (26.34)
>35	2 (0.63)
Obstetric History	
Nulliparous	123 (39.04)
Parity 1+	192 (60.96)
Prior Cesarean Section	72 (22.85)
Multiples	12 9 (3.80)
Infant Birth Weight (kg)	
< 2	35 (11.11)
2.0 - 2.5	142 (45.07)
2.6 - 3.0	73 (23.17)
3.1 - 3.5	48 (15.23)
> 3.5	17 (5.39)
APGAR score	
Bellow 7	34 (10.79)
Over 7	281 (89.20)

3. Results

The summary of patient characteristics of the collected dataset is showed in Table 2. Majority of the mother's age distributed between 18-23 years (34.28%) and 24-29 years (35.55%). Over 60% of the mother have prior birth and the percentage of mothers who went through the cesarean section before is around 27%. Besides, the percentage of cesarean delivery was 45.40% where 3.80 % of the mother had multiple births. Among the infants, around 12.1% weighed below 2 kg and 57.7% weighed below 2.5 kg. Also, 10.79 % of the newborns had a below 7 APGAR score after birth.

Table 3. Parameter estimates for the logistic regression models for different maternal care stages

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
	Premature 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
		Poor Obstetric History	0.536

Stage	Response Variable	Constant and Significant Predictor	Constant and Coefficient Value
	Intrauterine Growth Restriction	None	None
Dilation Period	Prolonged Dilation	Constant	-2.573
		Labor Induction	1.405
	Fetal Distress	Constant	-2.091
		Poor Obstetric History	-1.087
Birth Period	Prolonged Birth	Constant	-3.968
		Cesarean Section	0.952
		Labor Induction	0.653
		Premature 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
		Premature 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
		Premature Rupture of Membrane	0.568
		Prolonged Dilation	1.045
		5-min APGAR Score	1.639
		Postpartum Hemorrhage	0.823

3.1. Model Parameters and Bayesian Network

The results from the multivariate binary logistic regression analysis for outcome variables are summarized with their corresponding stages and significant predictors variables in Table 3. Out of 14 outcome variables, five of them including premature rupture of membrane, $3^{rd}/4^{th}$-degree tears, intrauterine growth restriction, cord prolapse, and low infant birth weight were found not significant for any predictor variable. However, premature rupture of membrane, $3^{rd}/4^{th}$-degree tears, and intrauterine growth restriction are significant predictors for other outcome variables and included in the network. Besides, the use of a 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 response variable and excluded from the network. Based on the significant association found from the regression analysis, we formulate a Bayesian network for maternal delivery care. The DAG representation of the Bayesian network is presented in Figure 1.

3.2. Multi-stage EWMA Control Chart

The control charts, developed for the pre-mature labor, antepartum hemorrhage, and Eclampsia which are outcome variables of the antepartum period, are presented in Figure 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 some investigation between periods 4 and 20.

Figure 3 demonstrates the control charts developed for the prolonged dilation and fetal distress outcome variables for 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 period 17 and 20. Period 9, 11, and 20 experienced a high observed complication compared to the expected. On the other hand, for the birth period, all the control statistics were within the control limits (Figure 4). However, there is an upward trend is visible between the periods 11 and 20.

Finally, control charts for outcome variables for the postpartum period are illustrated in Figure 5. For the Apgar score period, 17 and 18 can be investigated for process variation. Similarly, postpartum hemorrhage after childbirth in period 14 and maternal and neonatal mortality, period 6, 7, 8, 16, and 17 may require further investigation.

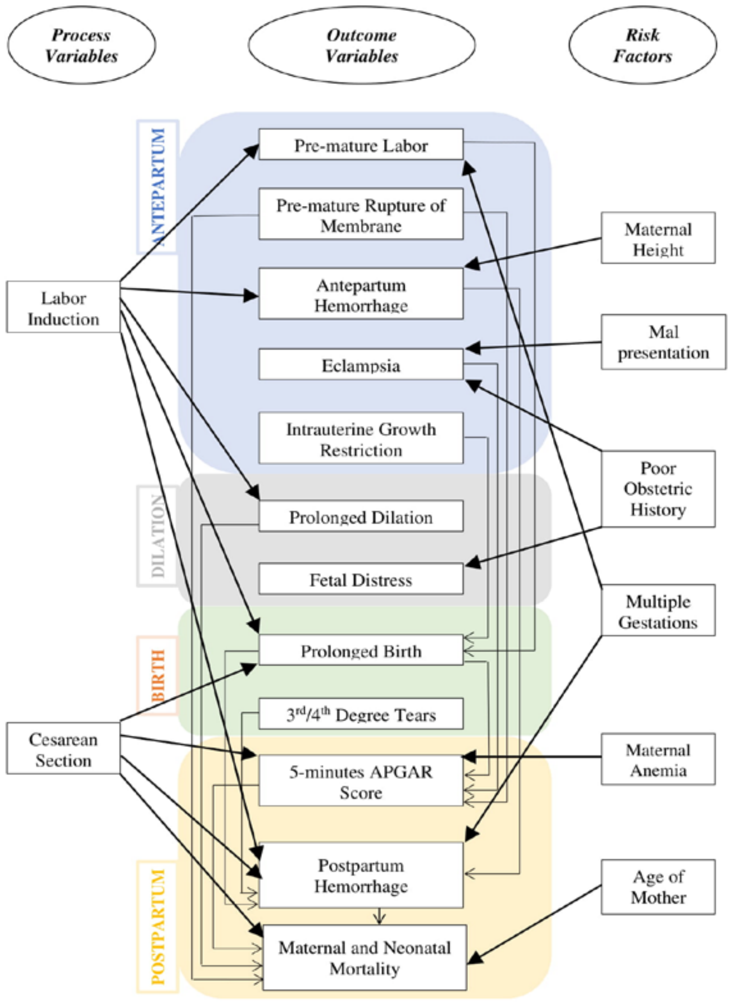

Figure 1. Directed Acyclic Graphical representation of Bayesian Network for maternal care

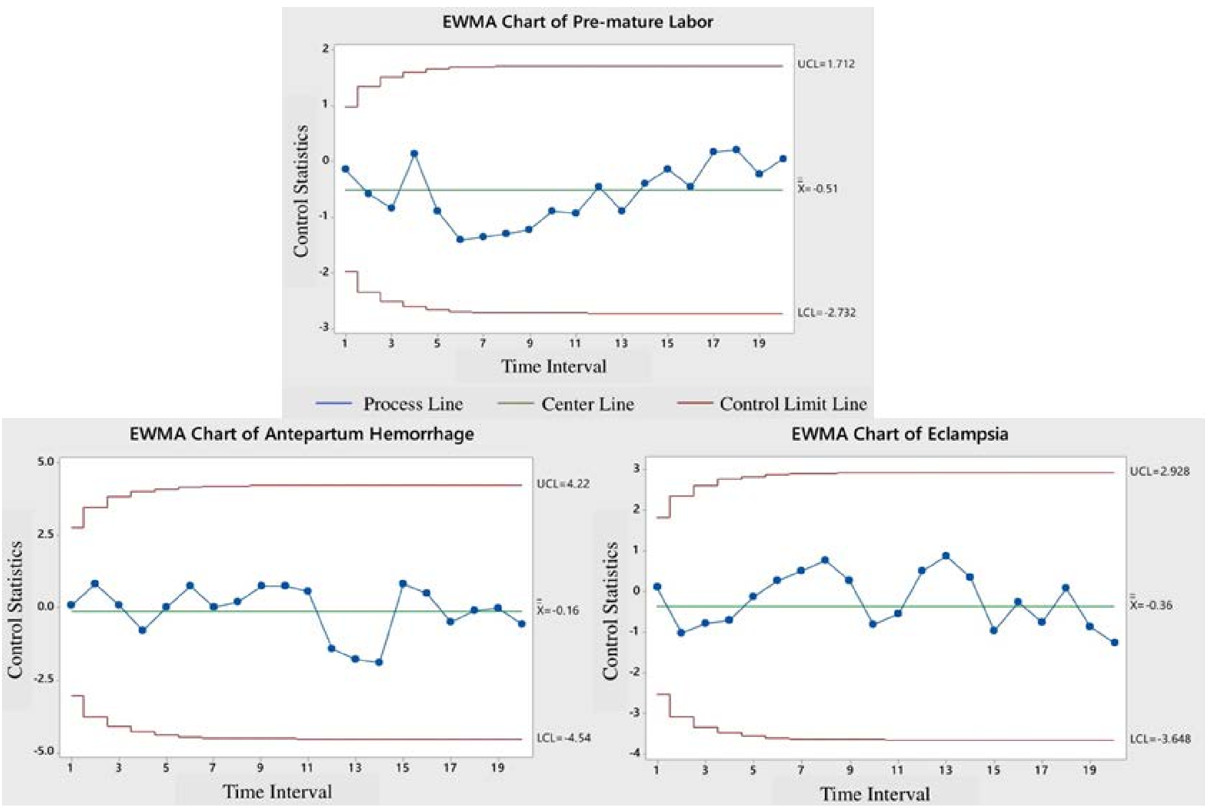

Figure 2. EWMA Control Chart for Outcome Variables of Antepartum Period

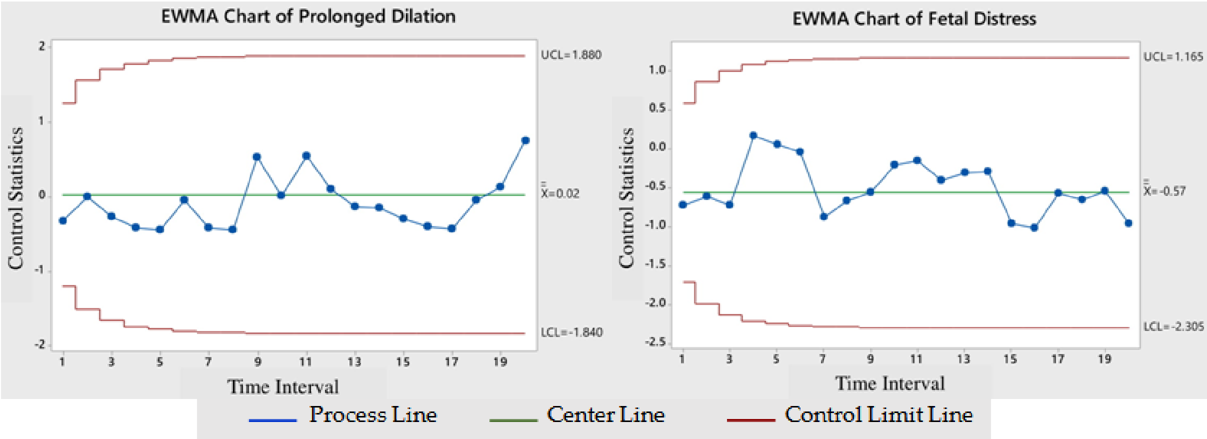

Figure 3. EWMA Control Chart for Outcome Variables of Dilation Period

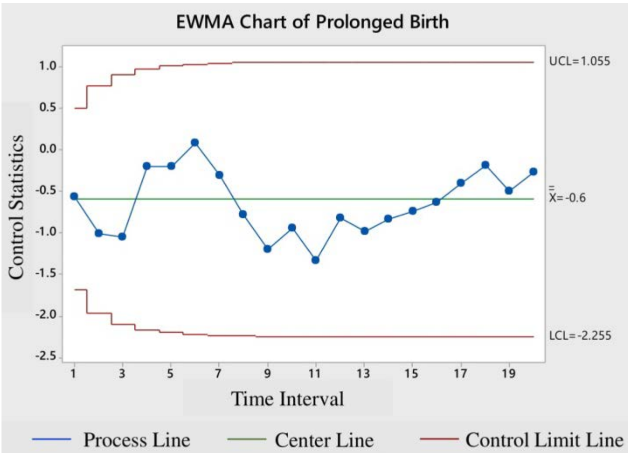

Figure 4. EWMA Control Chart for Outcome Variables of Birth Period

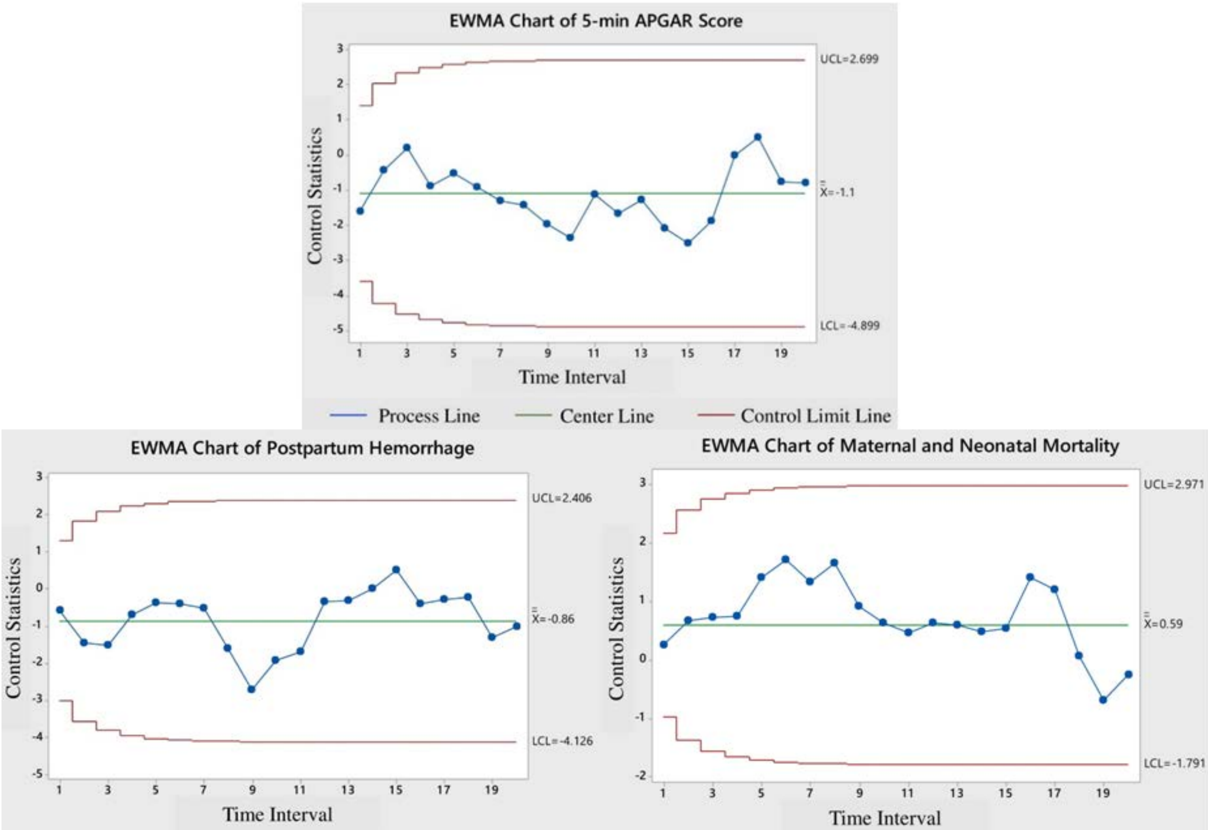

Figure 5. EWMA Control Chart for Outcome Variables of the Postpartum Period

Finally, control charts for outcome variables for the postpartum period are illustrated in Figure 5. For the Apgar score period, 17 and 18 can be investigated for process variation. Similarly, postpartum hemorrhage after childbirth in period 14 and maternal and neonatal mortality, period 6, 7, 8, 16, and 17 may require further investigation.

4. Discussion

In this study, we have three salient findings. First, we propose and develop a Bayesian network-based DAG representation portraying the sequential relationship among twenty variables and factors of four different stages of maternal hospital care. Second, we propose the use of multi-stage observed-expected based on the established Bayesian network for monitoring outcomes of maternal healthcare procedures. Third, the simulation of our proposed control chart shows significant potential to monitor any adverse and unwanted events in the maternal hospital wards. Overall, the study highlights the potential of integrating the Bayesian framework and control chart in monitoring multistage material healthcare operations to prevent undesirable incidents and provides a basis for formulating such models for any other healthcare facilities.

A well-established Bayesian network can provide healthcare professionals an insightful understanding of the cross-relationship between different risk factors and process variables throughout different stages of the maternal healthcare facility. Besides, a multistage EWMA control chart can inform the health administrator about any potential poor outcome in real-time and therefore appropriate countermeasures can be taken promptly. Furthermore, monitoring can be also performed for a specific period to detect any seasonal pattern and examine the performance of specific physician groups or a hospital ward. In case of a new procedure or equipment is adopted, its effect can also be analyzed with the help of these multi-stage control charts. However, model parameters and the choice of candidate explanatory variables must be made carefully to avoid any measurement error [19,22]. Since the model uses historical data to estimate parameters and Bayesian network, the building of logistic regression models is crucial to the entire procedure and must be well-calibrated and have good predictive ability [23]. Inclusion of patient cohort in this should be in control process with any unnatural variation and can be achieved with a thorough inspection by expert personals [5,20]. For this reason, our study dataset has been validated by three different physicians' groups from different maternity wards hospitals. Furthermore, the choice of explanatory variable variables must be selected carefully to maintain consistency and accuracy in developing a multi-stage process [24]. Beside model construction should also need to take into account local practice and guidelines. Different hospitals practice different guidelines followed by different protocols enforced by regional and federal health official guidelines.

We found in our study that 5-mins score is significantly associated with patient risk factors (e.g., pre-mature rupture, maternal anemia) and associated process variables (e.g., cesarean section and prolonged birth) from earlier stages. This finding contradicts the prior study where 5-mins score was only associated with gestation weeks. The finding of patient risk factors may be associated with the higher prevalence of anemia and premature birth during pregnancy in Bangladesh compared with prior study data setting (i.e., United Kingdom) [25]. Southeast Asia is one of the most affected areas where over half of all women are estimated to have anemia which can affect the health of both mother and child leading to preterm delivery and low birthweight [26,27]. Since pregnancy risk factors and other variables vary widely among different population demographics and hospitals, a comparative study can reveal insightful understanding suggestions for better pregnancy outcomes in the diverse regional setting. Besides, understanding the impact of risk factors and process variables can also give healthcare management a vital opportunity to plan and develop interventions program to reduce pregnancy-related outcomes. Interventions to improve continuity of care, particularly in the early stage of the maternal delivery process, could lower pregnancy complications and thus contribute to reducing healthcare utilization, costs, and adverse health outcomes [27,28].

Our study has some limitations, most of which are related to the retrospective analysis of administrative datasets. First, we utilize an administrative dataset that uses codes to classify patients' medical diagnoses, procedures, and outcomes. The possibility of coding inaccuracy cannot be dismissed, and which could lead to different estimations than presented. Second, our study only considers patients from rural area hospitals in Bangladesh. Therefore, results from this study may not be generalized for rural area hospitals and other country settings. Therefore, including hospitalization from other diverse area hospitals in our analysis might have improved the accuracy of our findings. Finally, our analysis was limited to patient-level risk factors and process variables. Other risk factors such as socioeconomic factors (e.g., income, education) may have some impact on the parameter estimation and accuracy of the control charts.

Author Contributions

"Conceptualization, R.A. and H.S.; methodology, R.A. and H.S.; software, R.A. and H.S.; validation, R.A. and H.S. and N.M.; formal analysis, R.A.; investigation, R.A. and H.S. and N.M.; resources, A.A.; data curation R.A.; writing—original draft preparation, R.A. and A.A. and N.M.; writing—review and editing, R.A. and H.S. and N.M.; visualization, R.A.; supervision, A.A.; project administration, A.A.; All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Hospital administrative databases are de-identified by hospital authority, therefore considered limited datasets and non-human subjects, as determined by the local Institutional Review Board and ethics committee approval was therefore not required.

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Data Availability Statement

Data is available upon request.
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Statement of Competing Interest

The authors declare no competing interest.

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