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Derivation and Validation of A Risk Score To Predict Mortality of Early Neonates at Felege Hiwot Specialized Hospital Neonatal Intensive Care Unit, Bahir Dar

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DERIVATION AND VALIDATION OF A RISK SCORE TO PREDICT MORTALITY OF EARLY NEONATES AT FELEGE HIWOT SPECIALIZED HOSPITAL NEONATAL INTENSIVE CARE UNIT, BAHIR DAR

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A THESIS REPORT SUBMITTED TO DEPARTMENT OF EPIDEMIOLOGY AND BIOSTATISTICS, SCHOOL OF PUBLIC HEALTH, COLLEGE OF MEDICINE AND HEALTH SCIENCE, BAHIR DAR UNIVERSITY FOR PARTIAL FULFILMENT OF REQUIREMENTS FOR THE DEGREE OF MASTER OF PUBLIC HEALTH IN EPIDEMIOLOGY.

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DERIVATION AND VALIDATION OF A RISK SCORE TO PREDICT MORTALITY OF EARLY NEONATES AT BAHIR DAR FELEGE HIWOT SPECIALIZED HOSPITAL NEONATAL INTENSIVE CARE UNIT, 2021

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Approval of Thesis Report for Defense

I hereby certify that I have supervised, read, and evaluated this thesis Report titled **DERIVATION AND VALIDATION OF A RISK SCORE TO PREDICT MORTALITY OF EARLY NEONATES AT BAHIR DAR FELEGE HIWOT SPECIALIZED HOSPITAL NEONATAL INTENSIVE CARE UNIT, 2021** by Yitayeh Belsti who prepared under my guidance. I recommend the thesis report to be submitted for final oral defense.

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Acronyms and Abbreviations

ANC=Anti Natal Care

APGAR= Appearance Pulse Grimace Activity Respiration

CPAP= Continuous Positive Airway Pressure

CRIB= Clinical Risk Index for Babies

DM=Diabetes Mellitus

END=Early Neonatal Death

ETB= Ethiopian Birr

HIV=Human Immune Deficiency

HTN=Hypertension

KMC=Kangaroo Mother Care

LMICs=Low and Middle-Income Countries

NICU=Neonatal Intensive Care Unit

NMR=Neonatal Mortality Rate

NNJ= Neonatal Jaundice

NPV=Negative Predictive Value

PNC=Post Natal Care

PPV=Positive Predictive Value

ROC= Receiver Operative Curve

SDI= Socio-Demographic Index

SGA=Small for gestational age

SNAP=Score for Neonatal Acute Physiology

SNAP-II=Score for Neonatal Acute Physiology, Version II

SNAP-PE= Score for Neonatal Acute Physiology, Perinatal Extension

SNAPPE-II=Score for Neonatal Acute Physiology, Perinatal Extension, Version II

SSA=Sub Saharan Africa

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Abstract

Background: Early neonatal death is death of infants in the first week of life. In 2019, 2.4 million newborns died globally, and 99, 000 live births died in Ethiopia. Of this death, 34%-92% of deaths happen within 7 days of postnatal period. Thus, the early neonatal period is the most critical time for an infant, requiring different strategies to prevent mortality. Among strategies deriving and implementing early warning scores is crucial to predict early neonatal mortality earlier upon hospital admission. However, no risk score has been derived in our country and the study area. Therefore, this study will help for screening high-risk early neonates at admission using easily measurable and accessible maternal and neonatal variables to estimate, and predict early neonatal death.

Objectives: To derive and validate a risk score to predict mortality of early neonates at Felege Hiwot Specialized Hospital neonatal intensive care unit, Bahir Dar, 2021

Methods: The document review was conducted from February 24, to April 08, 2021, on all early neonates admitted to neonatal intensive care unit from January 1, 2018 to December 31, 2020. The total number of early neonates included in the derivation study was 1100. Data were collected by using structured checklists prepared on EpiCollect5 software. After exporting the data to R version 4.0.5 software, variables with ($p < 0.25$) from the simple binary regression were entered into a multiple logistic regression model, and significant variables ($p < 0.05$) were kept in the model. The discrimination and calibration were assessed. The model was internally validated using bootstrapping technique. To make the score easily applicable the regression coefficients from the final multiple binary logistic regressions were used to assign integers to each variable.

Results: Admission weight, birth Apgar score, perinatal asphyxia, respiratory distress syndrome, mode of delivery, sepsis, and gestational age at birth remained in the final multiple logistic regression prediction model. The area under curve of receiver operating characteristic curve for early neonatal mortality score was 90.7%. The model retained excellent discrimination under internal validation. Using the "Youden Index" optimal cutoff point for predicted probabilities of mortality 0.1363, the sensitivity, specificity, and positive predictive value, negative predictive value was 89.4%, 82.5%, 55.5%, and 96.9%, respectively. The positive and negative likelihood ratios of the model were also 5.10 and 0.13, respectively.

Conclusion and recommendation: The derived score has an excellent discriminative ability and good prediction performance. This is an important tool for predicting early neonatal mortality in neonatal intensive care units just at admission. Therefore, after external validation, this score will be a better model for application in low and middle-income countries.

Keywords: derivation, validation, risk score, early neonatal mortality, NICU, Ethiopia

1 Introduction

7.1. Background

World Health Organization (WHO) defined neonatal death as “deaths among live births during the first 28 completed days of life”(1). It 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)(2). Grouping of a child’s lifetime into well-defined ages has become a vital standardization to determine the care and interventions necessary to increase the chances of child survival. The neonatal age which is globally accepted as beginning at birth and ending at 28 completed days of life(1) is recognized as the most susceptible time in an infant’s life.

The early neonatal mortality rate is the number of live-born infants that die in the first week of life per 1000 live born deliveries. Only live-born infants are considered when calculating the early neonatal mortality rate(1).

Early neonatal mortality is one of the most important measures of perinatal care. It is mainly a marker of the standard of health care given to the mother during labor and to the infant during the first week of life. A high early neonatal death rate strongly suggests a poor standard of newborn care(3).

Early neonatal mortality is affected by maternal factors, neonatal-related factors, maternal health services, and obstetrics-related factors. Early neonatal death can be caused by obstetric causes during pregnancy, labor, or delivery and also by neonatal factors, commonly immaturity related (born too soon), perinatal hypoxia (too little oxygen to the fetus or newborn infant), Infection (both fetal and neonatal), congenital abnormalities. Less common causes include birth trauma, hemorrhagic disease of the newborn, Rhesus disease, and sudden infant death syndrome (cot death)(4–7). Among these, prematurity, asphyxia, infections, congenital abnormalities, and other causes are the four preventable causes of early neonatal mortality (8–11).

7.2.The statement of the problem

In 2018, the neonatal mortality rate was estimated as 18 deaths per 1,000 live births globally. About half (47 percent) of the under-five deaths occurred in the neonatal period (2.5 million), of which 34%-92% of neonatal death happen within 7 days of the postnatal period showing significant variation across different regions and countries(11–24), 46%-62% of neonatal mortality happens within 3 days of postnatal life(20,23,25,26), and 11.4%-58.6% of neonatal death occurs within 24 hours of birth(12,17,18,27–29). Therefore, the first 7 days are the most critical period of a neonate's life(30), which warrants close observation.

The majority of these newborn deaths occurred in low- and middle-income countries(31–33). South Asia and sub-Saharan Africa (SSA) account for 79% of the total burden of neonatal deaths(33). Sub-Saharan Africa has the highest burden of neonatal mortality with one death in every 38 newborns before the age of 1 month(34). Sub-Saharan Africa had the highest neonatal mortality rate in 2018 at 28 deaths per 1,000 live births, followed by Central and Southern Asia with 25 deaths per 1,000 live births. The risk of dying for a newborn in Sub-Saharan Africa is about 33 times higher than in the lowest mortality country(9). Tanzania, Ethiopia, and Nigeria are the countries with the highest neonatal mortality rate in SSA(34,35). Thus, the early neonatal period is among the major public health challenges in low- and middle-income countries(3,5–7) and the most critical time for an infant(8).

Strategies have been implemented with given emphasis on the packages of care provided at the prenatal, antenatal, intra-natal, and post-natal periods to reduce early neonatal mortality. As a result, though it is not satisfactory as under-five and neonatal mortality little improvement is there to reduce early neonatal mortality. Ethiopia has implemented different strategies targeting at reduction of neonatal mortality through governmental and non-governmental organizations. However, it has amongst the highest neonatal mortality rates of any country, even when compared to the regional average for Africa(36). In 2019, the neonatal mortality rate for Ethiopia was 27.6 deaths per 1,000 live births.

The implementation of the National Child Survival Strategy (2005–2015) helped in the reduction of child mortality and to make significant progress in achieving many of national health indicators in Ethiopia. However, under-five and neonatal mortality rates remain too high(37). Between 2000 and 2016, under-five mortality in Ethiopia decreased from 166 to 67 per 1000 live births (reduction of 60%). However, NMR is decreasing at a slower rate and now accounts for 41% of under-five deaths(38,39). The leading causes for neonatal death in Ethiopia are prematurity, asphyxia, and neonatal sepsis(14,37).

Among strategies that have been implemented to address the global burden of neonatal mortality, one strategy is to improve the early identification of patients at risk of dying, by deriving and implementing early warning scores in hospitals(40). Early warning scores in neonatal intensive care unit (NICU) assign a number to maternal and neonatal parameters to derive a composite score that identifies patients who need additional interventions and monitoring. Implementation of evidence-based practices would decrease early neonatal deaths both in high-income countries and in low- and middle-income countries(LMICs) (41).

Studies have demonstrated the usefulness of early warning scores in adult and pediatric patient populations(42–44). Among available scores, the Apgar score provides an accepted and convenient method for reporting the status of the newborn infant immediately after birth and the response to resuscitation if needed. However, the Apgar score alone does not predict individual neonatal mortality or neurologic outcome, and should not be used for that purpose(45).

The assessment of the severity of illness is very important to determine prognosis, including predicting mortality in neonates hospitalized in neonatal intensive care unit (46). Mortality risk and illness severity measurement in newborns admitted to NICUs is gaining increasing attention. In 1993 three scores were developed for measuring illness severity and neonatal mortality among infants admitted to NICUs: CRIB (Clinical Risk Index for Babies)(47,48). SNAP (Score for Neonatal Acute Physiology)(49), and SNAP-PE (Score for Neonatal Acute Physiology - Perinatal Extension)(49). The SNAP score is based on 34 variables, evaluated during the worst moment of the first 24 hours after admission; SNAP-PE adds to SNAP birth weight, small size for gestational age (SSGA), and low Apgar score at 5 minutes after delivery. The CRIB score evaluates six factors during the first 12 hours of life, but is appropriate only for newborns with gestational age 31 weeks or less and/or birth weight up to 1,500 gm.

Although the above and other prognostic scores have been implemented in neonates(48,50–54), all include laboratory tests that are not available in low-resource settings, include ventilator support metrics, and require trained providers for scoring, and doesn't consider maternal factors as a prognostic indicator. Derivation of a simple, easily applicable score for LMICs would allow over-burdened health care personnel to rapidly identify at-risk neonates. However, there are no validated early neonatal mortality prediction tools for low and middle income countries (LMICs) like Ethiopia. Therefore, by considering the above limitations this study aimed to derive and validate a risk score that provides clues for screening high-risk early neonates at admission to NICU using easily measurable and accessible maternal and neonatal variables to estimate, forecast, and predict early neonatal death.

7.3.Significance of the study

A convenient and easily applicable prognosis is a very crucial tool to predict early neonatal mortality earlier upon admission. Therefore, the END NICU score that was derived can be used by clinicians (especially, pediatricians, pediatric residents, neonatal nurses, and neonatologists) and public health professionals working on maternal and child health unit to predict early neonatal mortality earlier at admission using easily measurable and accessible maternal neonatal variables. END in NICU score will also inform early neonatal parents about the future course of their neonate (or their risk of deriving early neonatal death) and guide doctors and neonatal parents in joint decisions on further treatment.

2 Literature review

1.1 The magnitude of early neonatal death

Globally, in 2019, about 2.4 (2.3, 2.7) million newborn died overall. Neonatal deaths accounted for a larger share of under-five deaths over time. In 2019, 47 (45 - 49) percent of all under-five deaths occurred in the neonatal period(55). Widespread regional disparities in the chances of survival children continue to face. Sub-Sahara Africa remains the region with the top under-five mortality rate in the world. In 2019, the region had an average under-five mortality rate of 76 (71 - 87) deaths per 1,000 live births. That is 1 child in 13 dying before reaching age 5. This rate is 20 times higher than that of 1 in 264 in the region of New Zealand and Australia and two decades behind the world average, which achieved a 1 in 13 rates by 1999(55).

According to a study in 2018, admission and mortality at the main neonatal intensive care unit in Guinea-Bissau, overall mortality among admitted children was 19.6% (289/1476), declining from 26.7% (68/255) in 2008 to 13.0% (16/123) in 2013(56).

A study conducted in Taleghani Hospital, Iran showed that neonatal mortality in NICU was 7.5% of which 55.9% death was between 2 and 7 days(57). A study done in Nepal showed that neonatal mortality rate was 46 per 1000 live births(58) and 33 per 1000 live births(59) using national demographic health survey data of 2006 and 2011 respectively.

In Africa, a study conducted in Nigeria and eastern Uganda states that neonatal mortality rate was 38,34 per 1000 live births respectively(60,61). A study conducted in Uganda in the neonatal intensive care unit (NICU) of a tertiary hospital also indicated that in-hospital neonatal mortality of 31.6% (95% CI: 26.9–36.7) was noted, with 65.8% of deaths occurring within 72 hours from admission(62).

A facility-based cross-sectional study conducted on neonates in the NICU of Ayder Comprehensive Specialized Hospital and Debre Markos Hospital reported that the overall neonatal mortality rate was 16.7% and 25.8 deaths per 1, 000 neonate-days, respectively. Of all the deaths, 83.5%- 98.3% occurred during the first 7 days of age(30,63). Likely, according to studies conducted in the Tigray region, Gondar and Eastern Ethiopia indicated that the probability of dying newborn within 28 days is 62.5 per 1000 births ,43.8per 1000 births, and 28.3 per 1000 live birth respectively(64–66)

A retrospective cohort study conducted in southern Ethiopia showed that, overall, the neonatal mortality incidence was 27 per 1000 neonates-days(67). Likely, of neonates admitted during the study period, 13.3% were died, equating to a rate of 30 deaths per 1,000 institutional live births in a study conducted in Jimma Hospital(68).

1.2 Determinants of Neonatal mortality

1.2.1 Demographic factors

A mother's age at birth is an important determinant of early neonatal mortality. Studies show that mothers age less than 20 and greater than 35 at birth have an increased risk of early neonatal death than mothers age 20-35(62,69–73).

The place of residence of a family may affect infant death in the early neonatal period. Living in the rural area of residence increase the risk of newborn mortality(60,74). But in other studies residence is not significant influencer of neonatal mortality(64,75).

The study conducted Felege Hiwot hospital shows that being in early age increases the probability of death than being in late neonatal age(76).

Sex of neonate is a risk factor for early neonatal mortality. Being male increased the risk of death for newborn within one month than female neonates(12,62,72,77,78).

1.2.2 Neonatal related factors

Birth asphyxia(15,20,26,35,57,72,79), neonatal respiratory distress syndrome (35,57,62,72,80), prematurity(preterm delivery)(15,20,26,35,57,62,72,79,81),and neonatal sepsis (infection)(15,26,35,57,72,80) are consistently found to be the leading causes of admission and early neonatal death in NICU.

Neonatal hypothermia and axillary temperature less than 36.5 °c(1H), are the important causes for neonatal death and morbidity in deriving countries, which increases mortality by five times, and recent studies showed that every 1 °c decrement of body temperature increases mortality by 80%(82–84).

Neonatal jaundice (NNJ) is the leading cause of early neonates especially if it is associated with comorbidity. Neonatal jaundice accounted for 1309.3 deaths per 100 000 (95% CI: 1116.8–1551.3) and ranked seventh globally. The burden was highest in countries with socio-demographic index (SDI) values in the low-middle or low quintiles, especially in Sub-Saharan Africa and South Asia, where NNJ was the seventh and eighth leading cause of mortality, respectively(31,85).

According to studies conducted on neonatal mortality, birth size affects the probability of dying of newborn in neonatal life. The result of studies concludes that babies with birth sizes greater than average and smaller than average increase the risk of neonatal death than average size neonate(21–23,65,71,72,80,86).

The finding of the studies shown that neonates not initiating breastfeeding within one hour increase the probability of dying within 28 days than neonates immediately initiate breastfeeding(76,87).

1.2.3 Maternal health service and Obstetric related factors

Maternal health-services related factors like antenatal care determine the occurrence of neonatal death. Babies born from mothers with the adequate antenatal care have decreased the risk of death of newborn within neonatal life than babies born from inadequate number of antenatal care(11,62,87,88).

Specifically from antenatal care services taking one or more tetanus vaccine during pregnancy affect the death of neonate. Neonates born from mothers taking TT vaccine during pregnancy have reduced the probability of dying within 28 days of life(75,89,90). According to studies done in Ghana and Indonesia, neonates who have postnatal care have low risk of mortality during neonatal period than neonates who have no postnatal care(87,91).

The choice of a mother to **a** place of delivery is the risk factor for the death of neonate. Mothers who deliver at health facilities reduce the risk of death of neonate than mothers born at home(15,62,86,91). Mode of delivery of the mother may affect the death of infants in neonatal period. Mothers who deliver by the caesarian section have increased risk of death of their neonate than those who deliver normally(70,72). Some literature findings show that the probability of neonatal death in multiple births is higher compared with single births(62,66,91). Gravidity and parity were significant factors to neonatal death according to case-control study done in Adama NICU(88,92–94).

3 Conceptual framework

The design of the conceptual framework used for the prognostic study was taken from scientific literature(95). Input variables recorded at the time t_0 or during NICU admission includes socio-demographic, neonatal, and maternal factors were selected based on literature review and expert advice which can be easily accessed just at admission in NICU. They can be quickly and simply determined (e.g. no complex or invasive tests and no extensive questionnaires) to enhance the practical applicability of the score derived.

Then the early neonatal death in NICU is outcome variable that is recorded at the time t_1 after admission.

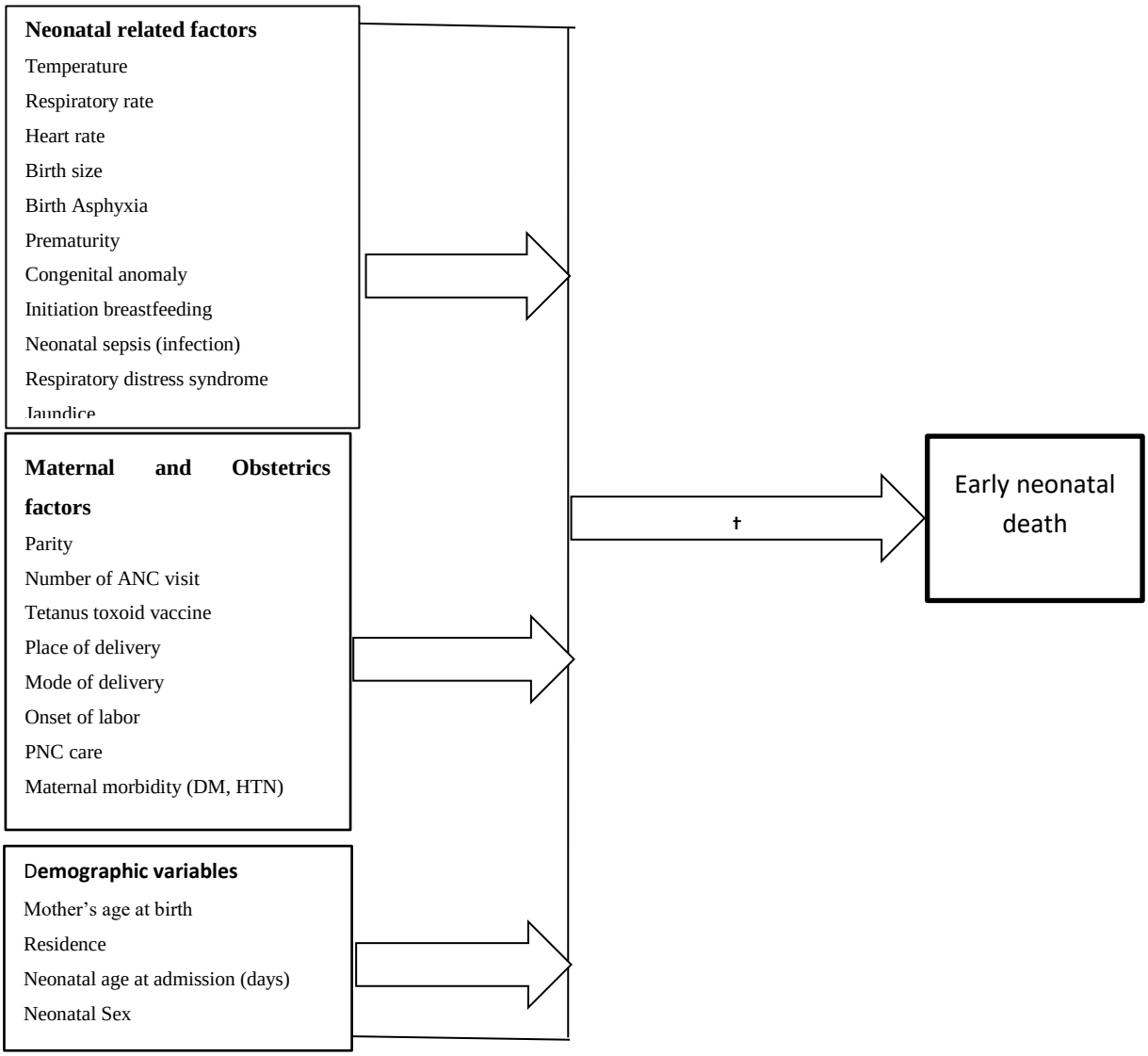

Figure 1*:* Variables for conceptual framework of the study derived from literatures

(1–4,7,10,11,13–31)

4 Research question and objectives

Research Question:

Which combination of maternal, neonatal, and demographic variables best predicts the future occurrence of death in early neonatal admitted to NICU?

Therefore the **occurrence relation** is:

Early neonatal death = f (Neonatal age, Sex, T, RR, HR, Birth size, Birth Asphyxia, Prematurity, Congenital anomaly, Initiation breastfeeding, Neonatal sepsis (infection), RDS, etc.)

The **determinants** include parameters (neonatal, maternal, and demographic) measured at admission,

The **outcome** is early neonatal death measured after admission but before 7 days of neonatal life and

Early neonates (<7 days age) to be admitted to Felege Hiwot hospital NICU represent the **domain**.

4.1.General objective

- To derive and validate a risk score to predict mortality of early neonates at Bahir Dar Felege Hiwot Specialized Hospital neonatal intensive care unit, 2021

4.2.Specific objectives

- To derive a risk score to predict mortality of early neonates at Bahir Dar Felege Hiwot Specialized Hospital neonatal intensive care unit, 2021
- To validate a risk score to predict mortality of early neonates at Bahir Dar Felege Hiwot Specialized Hospital neonatal intensive care unit, 2021

5 Methods

5.1.Study design/ setting /area/ period

This risk score was derived and validated from a retrospective cohort document review at Felege Hiwot Specialized Hospital in Bahir Dar, Ethiopia from February 24, to April 08, 2021.

The study setting (Felege Hiwot Specialized Hospital) is found in Bahir Dar, North West Ethiopia. It is found 563 KMs far from Addis Ababa. It officially began its function in 1963 and now it delivers health care services with medical, orthopedic, surgical, gynecological, pediatrics, intensive care units, and ophthalmological wards.

The NICU has 83 neonatal beds and 8 Kangaroo mother care (KMC) beds. The unit also has 10 radiant warmers, 3 continuous positive airways pressure (CPAP), 12 phototherapy, and 3 oxygen concentrator machines. Additionally, there are 3 pulse oximetry, glucometer, and 150 pieces of neonatal resuscitation equipment. The unit is staffed with 6 pediatricians, 12 neonatal nurses, 2 pediatrics nurses, and pediatric residents, and located adjacent to the labor ward to receive high-risk newborns from this unit.

The NICU admission criteria include the following: birth weight less than 2000g, electrolyte derangements, suspected or confirmed infection, cyanosis, respiratory distress, gestational age less than 34 weeks, apnoea, ABO and Rh incompatibility, temperature instability, birth trauma, seizures, altered mentation, feeding problem, signs of bowel obstruction, birth asphyxia, hyperbilirubinemia, anemia, polycythemia, bilious emesis, bleeding disorder, a cardiovascular disease requiring monitoring or interventions, any baby whom the physician or nurse feels the baby requires observation or treatment, and social issues like abandoned babies.

5.2.Domain (Source population)

The domain is all early neonates admitted to Felege Hiwot Specialized Hospital NICU.

5.3.Study population

The study population was all early neonates admitted to Felege Hiwot Specialized Hospital NICU from January 1, 2018, to December 31, 2020.

5.4.Inclusion and Exclusion criteria

5.4.1. Inclusion criteria

All early neonates who were admitted to the Neonatal Intensive Care Unit (NICU) of Felege Hiwot Specialized Hospital from January 1, 2018, to December 31, 2020

5.4.2. Exclusion criteria

Early neonates with a missing diagnosis of admission and missing clinical outcome during discharge will be excluded from the study. Early neonates whose mother ANC follow up and delivery were not in Felege Hiwot Specialized Hospital also excluded from the study.

5.5.Variables of the study

5.5.1. Dependent variable (outcome variable)

Early neonatal death (Yes/No)

5.5.2. Prognostic determinants (Independent variables)

5.5.2.1.Neonatal related factors

Temperature, Respiratory rate, Heart rate, Birth size, Birth Asphyxia, Prematurity, Congenital anomaly, Initiation breastfeeding, Neonatal sepsis (infection), Respirators distress syndrome, Jaundice

5.5.2.2.Maternal and Obstetrics factors

Parity, Number of ANC visit, Tetanus toxoid vaccine, Place of delivery, Mode of delivery, Onset of labor, PNC Care, Maternal comorbidity (HIV, HTN, DM)

5.5.2.3.Scio economic and demographic variables

Mother's age at birth, Place of residence, neonatal age, neonatal Sex

5.6.Sample size determination and sampling techniques

5.6.1. Sample size determination

Ideally, prognostic studies require several hundred outcome events. There are no straightforward methods for sample size calculation for prognostic studies. Various studies have suggested that for each candidate predictor studied at least 10 events are required(108–112)**.** Additionally, no prior estimates were available to calculate the sample size for the derivation study. Hence, as the rule of thumb of at least 10 events per candidate variable for logistic regression prediction models was used to estimate the sample size(112–115) in line with by Hosmer and Lemshow recommendation(116). Since there are 23 candidate prognostic determinants considered, by taking 10 events per predictor parameter the estimated number of outcome events for the derivation study becomes 230. Taking into account that early neonatal death itself happens in 21% of early neonates in NICU(117) an initial model of 23 independent variables would require a minimum of 1095 early neonates admitted in NICU to get estimated events(230) (early neonatal death). Therefore required final sample size for the derivation dataset was 1095.

5.6.2. Sampling techniques

All early neonates fulfilling the inclusion criteria were recruited from the NICU registry for derivation datasets. It includes all early neonates admitted from January 1, 2018, to December 31, 2020.

5.7.Data extraction procedure

Data were collected using structured checklists prepared from studies that have been conducted on related topics (15,18,76,94,118). The checklist consists of socio-demographic information, maternal or obstetrics, and neonatal risk factors of early neonatal deaths. All required variables were entered on the EpiCollect5 form builder. Data for this study were collected by using the EpiCollect5 software platform.

Infant records and registers were requested and reviewed for data including gestational age at birth, sex, birth weight, and complications during the first hospitalization of life, and early neonatal outcome at discharge. Maternal records and registers was requested and reviewed for demographic data, medical and obstetrical histories, and course of pregnancy and delivery.

Four data collectors and two supervisors were participated in the data collection. Before the actual data collection, training was given for data collectors and supervisors for 1 day about data collection and recording. Data were collected using a data extraction form prepared to extract the necessary information for the study based on the World Health Organization (WHO) standard neonatal and maternal register.

5.8.Data quality control

To ensure data quality, training was given to all data collectors before data collection. The investigators and assigned supervisors have supervised the overall activities of data extraction, and 5% of the data collected was randomly selected and checked with the neonatal register by the principal investigator. Tool Validity was checked by doing a pretest on 110 early neonates at the University Of Gondar Hospital (out of the study area). Modification of the tool (the order and content of questionnaires) was made based on the pre-test result. To make sure the questions are externally and internally consistent we validated through pilot testing and Cronbach's Alpha test. We did Cronbach's Alpha test for all questions and the result was greater than 0.7, indicating excellent internal consistency in the responses.

5.9.Data processing and Analysis

5.9.1. Data exporting and cleaning

The data were exported to R version 4.0.5 software for analysis. Data were checked for missing values. Multi collinearity between each predictor was assessed and if strongly correlated (VIF >10) the variable most strongly associated with the outcome measure, or the measure that is easiest to measure was selected(119). Descriptive

statistics including mean, standard deviations (SD), median, inter-quartile range (IQR), percentages, and rates were conducted. Then results were presented in tables and graphs as necessary.

5.9.2. Missing data handling and categorization

There were; admission weight 69(6.3%); Age of mother 67(6.1%); Gravidity 66(6.0%); Parity 65(5.9%) RR 61(5.5%); Gestational age 59(5.4%); Birth APGAR score 57(5.2%); Birth weight 55 (5.0%); Heart rate 50(4.5%); Temperature 47(4.3%); Neonatal age at admission 42(3.8%); Place of delivery 16(1.5%) missing values. Missing data pattern was assessed and we assumed data were missing at random, and we, therefore, implemented a multiple imputations by creating up to 10 imputed datasets via chained equations(120) was considered(112). However, since maternal TT vaccination status and number of ANC attended had more than 30 percent of missing values we excluded from imputation and further consideration.

Although categorization is not regarded as advisable from a statistical point of view, due to loss of information and power, it is a common practice in medical research to categorize variables for ease of interpretation depending on standard classifications. In this regard, in this paper temperature in Celsius was categorized into three categories as normal from 36.5 to 37.5, cold stress from 36.0 to 36.4, hypothermia below 36.0, and fever above 37.5(89). Heart rate is categorized into three categories as normal 100 to 160 beats per minute, bradycardia less than 100 beats per minute, and tachycardia above 160 beats per minute(121). The respiratory rate also as bradypnea less than 30 breaths per minute, normal respiratory rate was defined as 30 to 60 breaths per minute, and tachypnea was above 60 breaths per minute(122,123). Birth weight and admission weight have been defined as first weight recorded within hours of the birth of Low birth weight <2500 g, Very low birth weight (VLBW) is accepted as <1500 g and normal >2500 g (124). Gestational age at birth (prematurity): very preterm < 32 weeks, preterm between 32-37 weeks, and term > 37 weeks(49). Post neonatal age was also mostly classified and studied as before 1 day (24 hours) between 1 to 3 days(24 hours to 72 hours) and greater than 72 hours(11,12). APGAR score was also categorized as 0-3, 4-6, 7-10 as a standard(125,126). Gravidity and parity were also categorized based on clinical practicability primi gravida(1 pregnancy), multigravida (2-4 pregnancies), and grand multigravida(>=5 pregnancies)(127–129).

5.9.3. Derivation of score

5.9.3.1.Variable selection

To select variables for the final model; the statistical method p-value of <0.25 from simple logistic regression, the correlation between each predictor variable, ease of interpretation, their strength of association with the outcome variable, and their clinical relevance were used. Statistically, simple logistic regression was conducted on the derivation dataset to investigate the relationship between each predictor and early neonatal mortality in NICU. Variables with ($p < 0.25$) from the simple binary logistic regression were selected.

Based on the above procedures eight predictors were selected for the final model, which includes age of mother, admission weight, birth APGAR score, perinatal asphyxia, respiratory distress syndrome, mode of delivery, sepsis, and gestational age.

5.9.3.2.Building the model

All selected variables from simple logistic regression and other criteria mentioned above were firstly entered at the same time into a model. Subsequently, the variables with the highest p-values were removed. Then the model was run. This step was repeated until all variables were left with a p-value smaller than 0.05(130). Among eligible models, those that best fulfilled the following characteristics were chosen: suitable calibration (Hosmer- Lemeshow), area under the ROC curve (AUC of ROC), parsimony (small number of explanatory variables), ease of interpretation, and clinical plausibility. Therefore, based on the above criteria, the model with the following variables: admission weight, birth APGAR score, perinatal asphyxia, respiratory distress syndrome, mode of delivery, sepsis, and gestational age were selected. Using the results, a prediction model was developed, and equation for the prediction model was obtained (**Table 2**).

5.9.4. The performance of the prognostic score

Once a prognostic model is derived, the model was investigated how well it works, how well the model does predicts early neonatal death in NICU.

5.9.4.1.Calibration

In a calibration plot groups of predicted probabilities of the outcome were plotted against groups of observed probabilities. Calibration can be used to assess how well the observed probability of the early neonatal death in NICU agrees with the probability predicted by the model. Accordingly, the calibration plot of the END in NICU showed that it has good calibration (**Figure 3**). The Hosmer-Lemeshow goodness of fit test was 0.56 indicating that there is no difference between predicted and observed values.

5.9.4.2.Discrimination

The discriminatory power of the model was assessed by AUC of ROC curve plotting sensitivity against 1-specificity of the model (**Figure 4)**.

5.9.5. Creating a prediction rule

The regression coefficients were transformed into risk scores to facilitate the use of the prediction rule in practice. To create a clinically useful and accurate Early Neonatal Death Score (END in NICU score), the regression coefficients from the final multiple logistic regression model were used to assign integers to each variable. A frequently used method for this is to divide the regression coefficients by the lowest value. A risk score containing these scores can then be generated to allow the probability of an outcome to be easily

calculated for a given individual. The Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis checklist was followed(131).

5.9.6. Internal Validation of the score

The same dataset used for model derivation was used for internal validation by bootstrapping technique to adjust for optimism. Beta coefficients of logistic regression model, AUC of ROC curve, sensitivity, specificity, positive predictive value, negative predictive value of the model after bootstrapping was compared with the original result before bootstrapping techniques. Then the level of optimism was assessed.

6 Ethical consideration

Ethical clearance was obtained from the Institutional Review Board of the Institute of Public Health, Bahir Dar University (letter Reference number /11302/1.4.4 and Protocol number 086/2021) on February 26, 2021. A letter of permission was also obtained from Felege Hiwot Specialized Hospital administration office to conduct the study. Individual identifiers were removed to maintain the anonymity of patients by assigning a unique number to each questionnaire. All data were collected from the register which was kept in a secure place and all data were fully anonymized before we access them. After collection of data, all the patient records and patients' cards were placed back into a secure place. Data were not shared with anybody other than authors for ethical reasons. All data were entered into password-protected computer. Only the investigators had access to the data.

7 Results

7.1.Result of descriptive analyses

The derivation dataset includes 1100 early neonates, of which 617 were males. About twenty percent (19.6%) of early neonates admitted died in NICU. Half of all admitted neonate's weight was below 2500gramm. Two hundred seventy-two (24.7%) were born before 32 gestational weeks. Cesarean section was used to deliver 28.6% of admitted neonates. The APGAR score of 56.3% of early neonates was greater than 7. Prematurity and low birth weight were present in 425(38.6%), and 539 (49.0%) of admitted early neonates respectively. The respective figures for sepsis, RDS, perinatal asphyxia, and congenital malformation were 121(11.0%), 144(13.1%), 178(16.2%), and 37(3.4%) (**Table 1)**.

Table 1: Baseline characteristics of study participants for derivation and validation of a risk score of early neonatal death among early neonates in neonatal intensive care unit at Bahir Dar Felege Hiwot specialized hospital, 2021(N= 1100)

Variables	***Response***	**Frequency**	**Percent**
Sex of the neonate	*Male*	617	56.1
	Female	483	43.9
Age at admission	<=24 hours	793	72.1
	24-72 hours	158	14.4
	>= 72 hours	149	13.5
Admission weight(gram)	*<1500*	169	15.4
	1500-2499	379	34.5
	>=2500	552	50.2
Admission Temperature	<36	563	51.2
	36--36.4	113	10.3
	36.5-37.5	278	25.3
	>37.5	146	13.3
Admission heart rate	<100	38	3.5
	100-160	849	77.2
	>160	213	19.4
Admission respiratory rate	<30	53	4.8
	30-60	710	64.5
	60	337	30.6
Gestational age(weeks)	*<32*	272	24.7
	32-36	153	13.9
	>=37	675	61.4
Mode of delivery	Cesarean section	315	28.6
	spontaneous delivery	785	71.4
Place of delivery	Home delivery	102	9.3
	Same facility	998	90.7

APGAR Score at birth	0-3	42	3.8
	4-6	439	39.9
	7-10	619	56.3
Birth weight(gram)	<1500	158	14.4
	1500-2499	381	34.6
	>=2500	561	51.0
Prematurity	Yes	425	38.6
	No	675	61.4
Low birth weight	Yes	539	49.0
	No	561	51.0
Sepsis	Yes	121	11.0
	No	979	89.0
RDS	Yes	144	13.1
	No	956	86.9
Perinatal Asphyxia	Yes	178	16.2
	No	922	83.8
Congenital malformation	Yes	37	3.4
	No	1063	96.6
Age of mother	<=20	144	13.1
	21-29	360	32.7
	>=30	596	54.2
Residence of mother	Urban	523	47.5
	Rural	577	52.5
Gravidity	1	130	11.8
	2-4	811	73.7
	>=5	159	14.5
Parity	1	60	5.5
	2-4	923	83.9
	>=5	117	10.6
TT vaccination status	No not vaccinated	76	6.9
	Unknown	4	0.4
	Yes vaccinated	690	62.7
	Missing data	330	30.0
Number ANC attended	1-3	570	51.8
	>=4	200	18.2
	Missing data	330	30.0
Discharge status	Not died	884	80.4
	Died	216	19.6

Abbreviations: *PICT: Provider Initiated Counseling and Testing, APGAR: Appearance, Pulse, Grimace, Activity, and Respiration, VDRL: The Venereal Disease Research Laboratory test, TT: Tetanus Toxoid, RDS: Respiratory Distress Syndrome, ANC: Antenatal Care*

7.2.Regression results and risk score

From those variables with p-value<0.25, eight variables were selected for the final model after passing several reduction processes and reiteration process based on a correlation between each predictor variables, ease of interpretation, their strength of association with the outcome variable, and their clinical relevance, which includes age of mother, admission weight, birth APGAR score, perinatal asphyxia, respiratory distress syndrome, mode of delivery, sepsis, and gestational age.

The risk score was generated by dividing the regression coefficients by the lowest value and rounding to the nearest integer. Accordingly, the total risk score becomes 29.

Table 2: Simple and multiple binary logistic regression between predictor variables and discharge status for derivation and validation of a risk score of early neonatal death among early neonates in neonatal intensive care unit at Bahir Dar Felege Hiwot specialized hospital, 2021(N=1100)

Variables	Discharge status		COR (95% CI)	AOR(95%CI)	B-coefficients of AOR	Score
	Died	Not died				
Birth APGAR Score						
0-3	32	10	27.27(12.82, 58.04)**	6.20 (2.36, 16.30)**	1.824	4
4-6	119	320	3.17(2.27, 4.42)**	1.62 (1.05, 2.51)*	0.483	1
7-10	65	554	1	1		0
Presence of Perinatal asphyxia						
Yes	61	117	2.58(1.81, 3.68)**	5.23 (2.86, 9.59)**	1.655	3
No	155	767	1	1		0
Modes of delivery						
Cesarean section	77	238	1.50(1.10, 2.06)*	3.89 (2.26, 6.70)**	1.357	3
Spontaneous delivery	139	646	1	1		0
Presence of respiratory distress syndrome						
Yes	77	67	6.76(4.65, 9.81)**	4.67 (2.72, 8.03)**	1.542	3
No	139	817	1	1		0
Admission weight(gram)						
<1500	105	64	11.88(7.94,17.76)**	3.96 (1.77, 8.88)**	1.377	3

1500-2499	44	335	0.95(0.63,1.43)	1.80 (1.32, 2.65)*	0.589	1
>=2500	67	485	1	1		0
Age of mother						
<=20	15	129	1			
21-29	48	312	1.32(0.72, 2.45)	1.43(0.65, 3.16)		
>=30	153	443	2.97(1.69, 5.23)**	1.81(0.89,3.68)		
Gestational age(weeks)						
<32	148	124	14.60(10.07, 21.19)**	10.21 (5.23, 19.94)**	2.324	5
32-36	17	136	1.53(0.86, 2.73)	2.32 (1.07, 5.03)*	0.842	2
>=37	51	624	1	1		0
Sepsis						
Yes	69	52	3.74(2.52, 5.57)**	5.38 (3.06, 9.45)**	1.683	4
No	815	164	1	1		0
Total score						**29**

** P-value<0.001, * P-value<0.05; Abbreviations: *APGAR: Appearance, Pulse, Grimace, Activity, and Respiration*

Based on Youden Index method the cutoff point of predicted probabilities were 0.1363, based on maximizing efficiency method (MaxEfficiency) it was 0.4192, and based on maximizing specificity (MaxSp) it was 0.8560. Based on different methods applied the cutoff point might vary.

However, we selected the cutoff point of 0.1363 which was based on Youden Index method. The sensitivity of the model was 89.4% and the specificity of the model was 82.5%. The model also has the positive predictive value of 55.5% and negative predictive value of 96.9%. The positive and negative likelihood ratios of the model were also 5.10 and 0.13, respectively. The accuracy was 88.4%

Similarly, the cutoff point was made for the risk score derived from beta coefficients. Based on the maximum efficiency the risk score developed from beta coefficients was stratified as low risk score (<7 score), high risk score (> = 7 score). The risk score have comparable discrimination ability with the model having AUC 0.91(0.89, 0.93). The derived score have also the following comparative measures with original beta coefficients. Sensitivity = 87.5% specificity = 83.6%, Positive likelihood ratio = 5.33, Negative likelihood ratio = 0.15 Negative predictive value 96.5%, Positive predictive value 56.6%. The accuracy of the score was 84.4%.

7.3.Performance measures

7.3.1. Decision curve of the model

Figure 2 showed that the model (apparent curve) has the highest net benefit across the entire range of threshold probabilities, which clearly indicates that the model has the highest clinical and public health value.
Hence, decision made using the model has a higher net benefit than not using at all regardless of their risk threshold to predict early neonatal death in NICU upon admission.

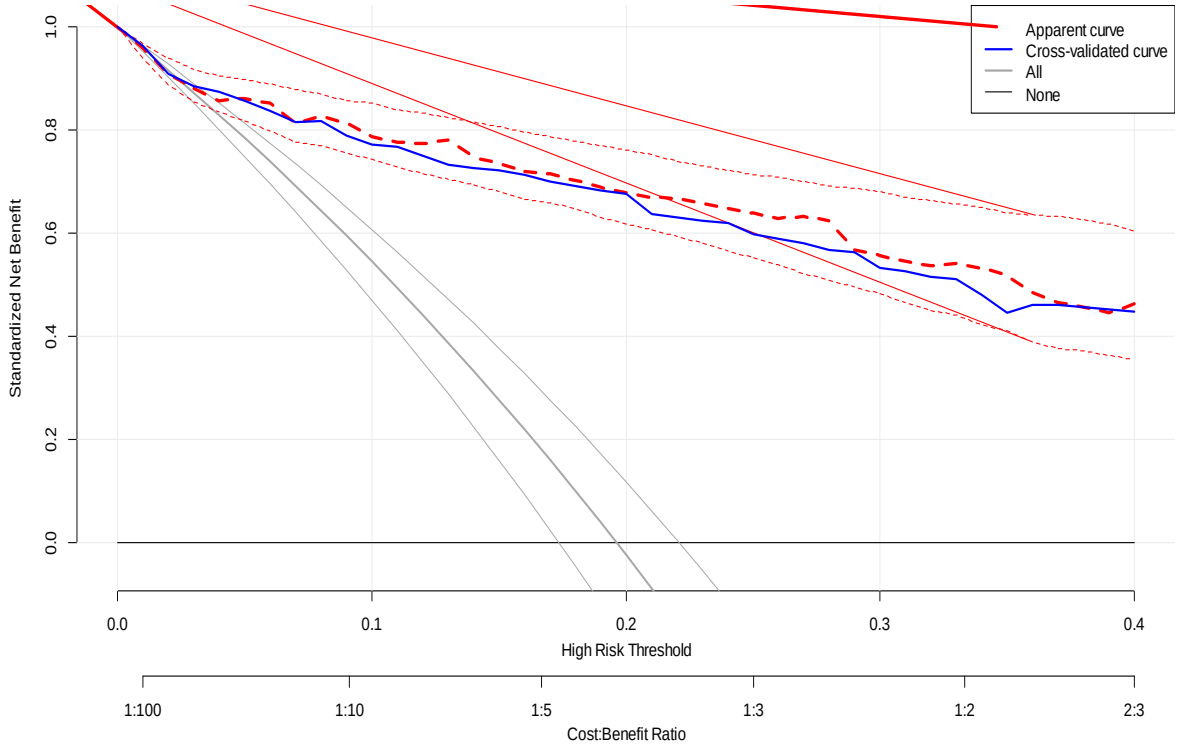

Figure 2: Decision curve for a model to predict early neonatal death in early neonates admitted to neonatal intensive care unit.

7.3.2. Calibration Curve

The calibration plot shows the predicted probabilities in X-axis against the observed probabilities in Y-axis. If our model is perfect in calibration it should be in 45-degree line meaning predicted and observed probabilities should be the same. When we look at our model calibration confidence interval it is good throughout the probabilities. The p-value is 0.138, which is less than 0.05, showing that the predicted probabilities and the observed probabilities are the same null hypothesis is correct. Therefore, the model is well calibrated (**Figure 3**).

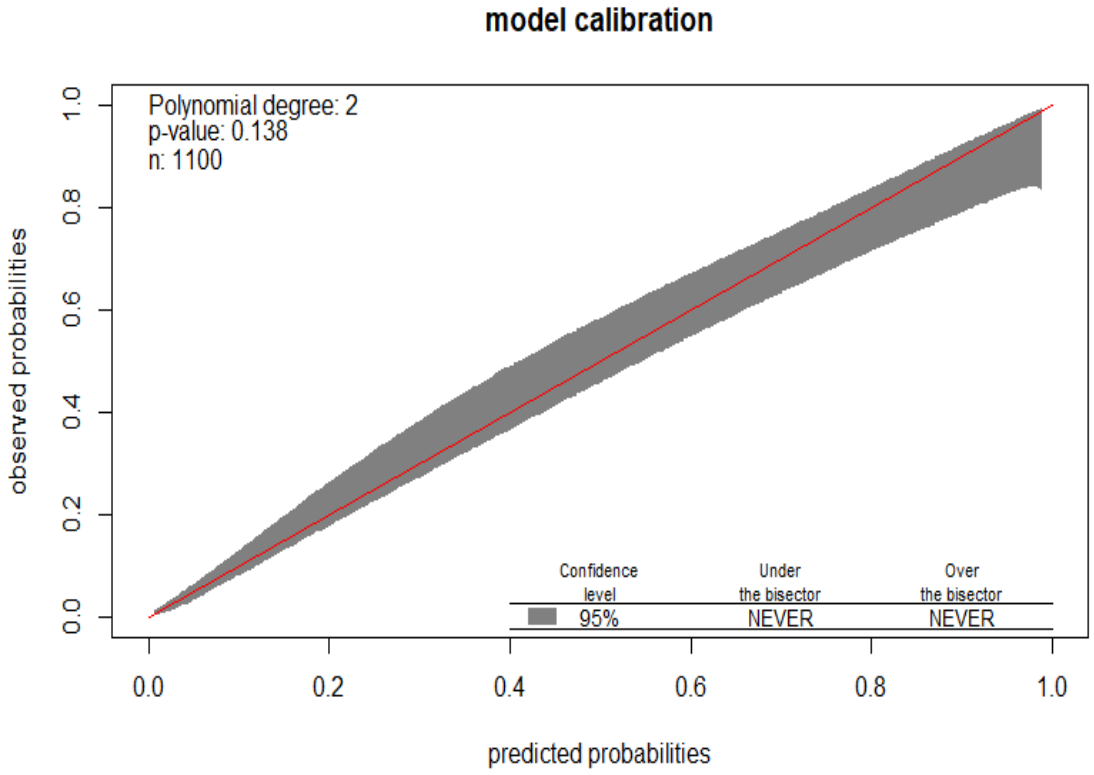

Figure 3: Calibration plots of derivation datasets. Calibration plots demonstrating observed versus predicted probability of early neonatal intensive care unit mortality in the derivation dataset from the multiple regression model.

7.3.3. Receiver Operating Curves

The receiver operating characteristic curve shows that the AUC of this model is 90.7% (95%CI: 88.2%- 92.9%) showing that it is a strong performing model or has excellent discriminatory power. Powerful models have ROC curves that approach the upper left corner, which indicates that the model achieves the maximum of 100% sensitivity and 100% specificity simultaneously. Conversely, a poor model with no predictive value will have a ROC curve close to the y = x or 45-degree line. It shows the probability that the model will give a higher predicted probability to a randomly chosen positive patient than a randomly chosen negative patient.

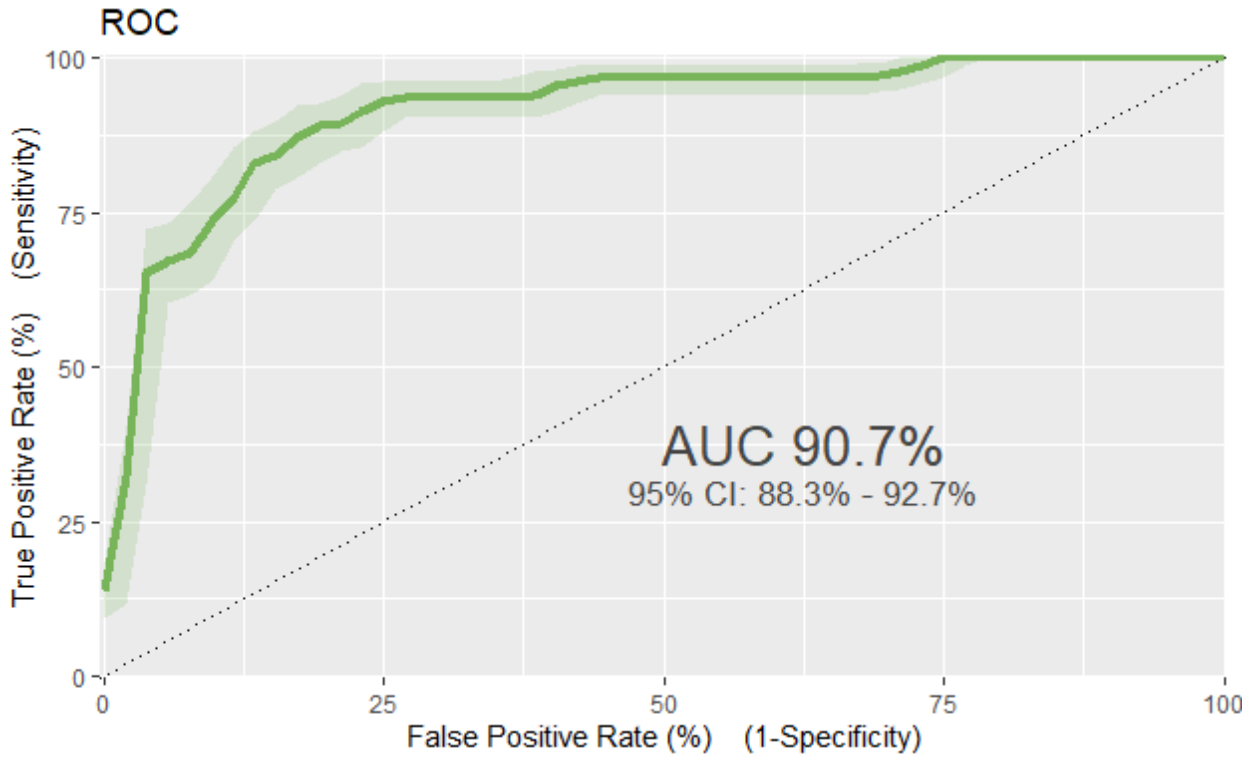

Figure 4: The Receiver Operating Curves with the area under the curve of the derivation datasets of the final multiple logistic regression model.

7.3.4. Density plot

As shown in the graph the total sample size is 1100, early neonatal death (positive cases) are 19.6%.The red one represents early neonates who are at low risk of death and the blue one those who are at high risk of death. As we can see there is some overlap indicating that the model is not 100 percent perfect.

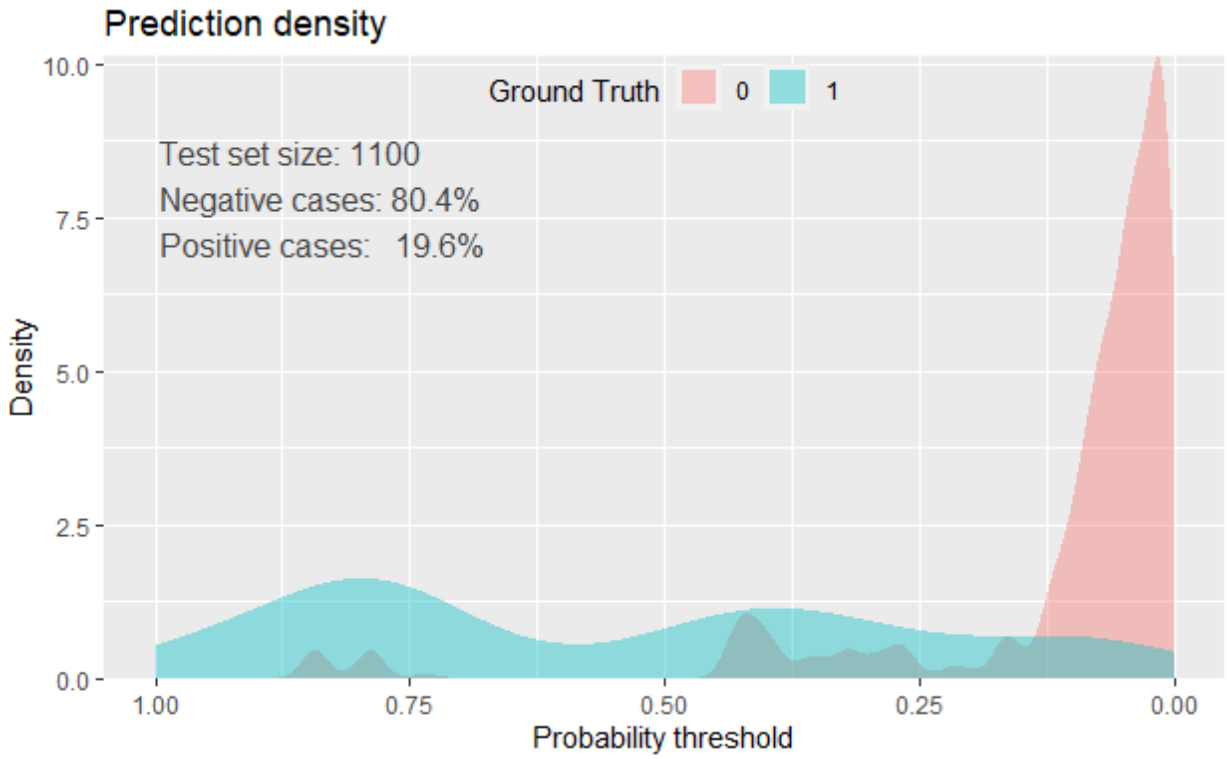

Figure 5: The density plots of the derivation datasets of the final multivariate model.

7.4.Internal validation

Internal validation of the model was conducted on the derivation dataset using bootstrap sampling. Bias-corrected mean, 95% CIs of the receiver operating curve, sensitivity, and specificity were calculated by bootstrapping 2000 samples with replacement. Therefore, after bootstrap internal validation, optimism corrected AUC was 0.904 with 95%CI (0 .87, 0.92). Model optimism was estimated as 0.003 indicating minimal over fitting of the model to the data. The bootstrap sampling also have 80.5%, 86.6%, 53.2%, 97.4% specificity, sensitivity PPV, and NPV, respectively. The positive and negative likelihood ratio was 4.44 and 0.17 respectively. The bootstrapped sample also has an accuracy of 88.4%. Beta coefficients are also almost similar with minimal variation.

8 Discussion

This study has derived a predictive model for predicting early neonatal mortality in early neonates who were admitted to neonatal intensive care units that suggests an excellent predictive ability in the derivation cohort AUC: 0.907 (95%CI: 88.2%- 92.9%). The score was named as END in NICU score, which is a simple tool for a clinical decision that uses seven easily accessible variables for predicting early neonatal mortality just upon admission to neonatal intensive care unit. The developed END in NICU score has excellent discrimination and calibration on the developed dataset. Accordingly, the study identified admission weight, birth Apgar score, perinatal asphyxia, and respiratory distress syndrome, mode of delivery, sepsis, and gestational age during birth as a predictor of mortality just at admission. By using these variables a prediction score was developed and a score for the prediction model was obtained. In this regard, none of the proposed models put forward so far has demonstrated such a suitable predictive ability and didn't consider maternal factors specifically for early neonates which are the highest risky period in neonatal age.

No tool was developed to predict specifically early neonatal mortality in NICU. However, there are tools developed to predict the mortality of neonates in NICU in general. In 1989 and 1990 SNAP model was developed based on 28 objective physiologic measurements that occur within the first 24 hours after admission (eg, blood gas pH, mean arterial pressure)(49). Later on, SNAP-PE includes the physiologic variables of SNAP and adds birth weight, 5-minute Apgar score, and gestational age(53). However, needs intensive data collection. In 1993 CRIB was developed which is based on 6 variables less intensive to collect collected within the first 12 hours after birth but still based on physiologic parameters measured laboratory-based(48). The CRIB II was published in 2003 by Parry et al14 to update the original CRIB(52). Updated SNAP II and SNAP-PE II highly predictive of neonatal morality and were published in 2001. However, all above mentioned include a laboratory test that is not available in low-resource settings, include ventilator support metrics, and require trained providers for scoring and doesn't consider maternal factors as a prognostic indicator. The development of such easily applicable scores for LMICs would allow over-burdened health care personnel to rapidly identify at-risk neonates. Therefore, this END in NICU score would be used to fulfill this gap for low and middle-income countries.

There was also an attempt made to develop a tool to predict neonatal mortality in NICU in Ethiopia(118). It was named as neonatal mortality score which was based on four prognostic determinants. In line with this finding, the study included respiratory distress and gestational age as prognostic determinants of neonatal mortality. The

study also included birth weight as prognostic factors, though it was excluded from the final analysis in our study because it correlates with admission weight. Therefore, in our study admission weight was found to be a risk indicator. The discriminatory performance of END in NICU score is higher than that of neonatal mortality score which is 0.88. Even the sensitivity and specificity of END in NICU is more performing than that of neonatal mortality score. This difference might be due to sample size variation, overall approach and design.

Most scores developed before were physiology-based intensive care unit scores(132,133) having an AUC of ROC between 0.80 and 0.90 such us SNAP-II, which is lower than END in NICU score discriminative ability of 90.7%. In addition, these physiologic-based scores need intensive training, specialize professionals, and high cost to collect data which minimizes the utility of the scores. In SNAPE-II(53), However, an attempt was made to include many perinatal risk factors such as gestational age, birth weight, sex, white race, multiple births, and size for gestational age, and Apgar scores as determinants in addition to physiologic factors in SNAP-II. Finally, the model includes Birth weight, Apgar score, and gestational age as prognostic determinants of neonatal mortality, which is similar to END in NICU score, though it is still less applicable, cumbersome and expensive to be applied in resource limited countries.

The derived END in NICU score can easily be applied in resource-limited countries like Ethiopia, since it was derived from easily accessible maternal and neonatal variables by health professionals. When we look at some variables included in the model admission weight was the first. Admission weight might be the best over birth weight in less developed countries where home delivery is still a headache for health service system utilization and difficult to get birth weight. Most studies were developed considering birth weight(53).

The score which is converted to an integer will ease easy interpretation and implementation in the neonatal intensive care unit and can result in more similar accuracy with the multiple logistic regression coefficients. Additionally, the study was based on a large sample size and tried to include multiple variables of maternal obstetrics characteristics and neonatal characteristics. Additionally, after external validation, the finding can be applicable in NICU of hospitals in Ethiopia.

The Early Neonatal Mortality Score may be utilized by bedside nurses and clinicians in understaffed NICUs in low-resource settings to quickly identify sick neonates needing additional interventions. These results provide an opportunity to improve the identification of neonates at risk of dying, guide triage decisions within and between NICUs, and allow for the appropriate allocation of personnel resources. Furthermore, neonates identified from the score may benefit from a prioritized bundle of interventions that are part of NICU care: correcting hypothermia by rewarming neonates, assessment of point-of-care glucose, insertion of an IV for

parenteral fluids or antibiotics, and bubble-CPAP for respiratory distress. Moreover, the score may help frontline providers caring for neonates to identify when consultation with senior physicians may be essential.

In LMICs, there are barriers in obtaining supporting laboratory data for all admitted early neonates. The Neonatal Mortality Score may result in a paradigm shift of identifying early neonatal mortality without laboratory evaluation prior to death. A nurse in our setting will easily be caring for 5–20 patients in any given shift. The nurse often relies on the clinical exam of direct observation and the measured vital signs, but no continuous monitors. Therefore, having a score that allows rapid assessment of the neonates to identify the babies at risk of mortality with only seven easily accessible parameters can prove to be an incredible tool at the bedside. Once identified, at-risk neonates can quickly receive the required interventions. Moreover, such a score can also allow for appropriation of limited devices such as a bubble-CPAP to be used only on those patients that require it. The score may help prioritize the early neonates needing limited resources.

9 Limitations of the study

The findings have limitations that should be considered while using the study. This study excluded maternal TT vaccination status and number of ANC attended from further analysis because these variables had more than 30 percent of missing values. These variables might have influence early neonatal mortality. Additionally, data abstractors were not blind to the predictors and outcome, which could introduce a biased estimation of the predictors for mortality. Categorizing continuous variables for ease of clinical application might affect its predictive power and accuracy.

10 Conclusion and recommendations

10.1.Conclusion

This study shows the possibility of predicting early neonatal mortality using a simple prediction model constructed from easily accessible and applicable maternal and neonatal characteristics, including admission weight, birth Apgar score, perinatal asphyxia, and respiratory distress syndrome, mode of delivery, sepsis, and gestational age at birth. The derived END in NICU score has good sensitivity for predicting early neonatal mortality. It has an excellent discriminative ability (accuracy) with the area under the curve of 0.907. This new and relatively simple early neonatal mortality risk score had a good prediction performance. Therefore, the prediction score will help to do a risk stratification of early neonates and to identify those at higher risk of death at admission. Subsequently, high-risk groups linked to a center, which is equipped with good facilities for further assessment and better management. Hence, this feasible prediction score would offer an opportunity to decrease early neonatal complications and hence improving the overall child health care.

10.2.Recommendation

This is an important tool for predicting early neonatal mortality in NICU just at admission. Therefore, this score may prove to be a better model for application in low and middle-income countries also after external validation.

We strongly recommend for researchers validating the prediction tool in another context before introducing it to clinical and public health practices, preferably using real-world data through prospective validation studies.

The present study also recommended to the Amhara Health bureau or other responsible organization that targeted on reducing early neonatal mortality through disseminating and creating awareness on how to utilize this END in NICU score and assist on validation.

We recommend health care professionals or clinicians (especially, pediatricians, pediatric residents, neonatal nurses, and neonatologists) working on maternal and child health unit to use END in NICU score to predict early neonatal mortality earlier at admission using easily measurable and accessible maternal neonatal variables after external validation.

We recommend policy makers to incorporate this convenient and easily applicable score in health care system to be used by health care professionals to inform early neonatal parents about the future course of their neonate (or their risk of deriving early neonatal death) and guide doctors and neonatal parents in joint decisions on further treatment after external validation.

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12 Annexes

12.1. Checklists used to extract data

Checklists that was used for derivation and validation of a risk score of early neonatal death among early neonates in neonatal intensive care unit at Bahir Dar Felege Hiwot Specialized Hospital, 2021

Section I: Socio-demographic characteristics

1. Code --------
2. Sex 1, Male 2, Female
3. Residence 1. Urban 2, Rural

Section II: Admission Information

4. Admission date(DD/MM/YY) _____
5. Admission weight(gm)_____
6. Temperature at admission(℃)_____
7. Respiratory rate per minute at admission_____
8. Apical heart rate per minute at admission _____

Section III: Delivery information

9. Gestational age (weeks)_____
10. Delivery date (DD/MM/YY) _____
11. Mode of delivery: 1, Vaginal spontaneous 2, Cesarean section
12. Place of delivery: 1, Home delivery 2, Health facility
13. APGAR Score 1'/5_____
14. Birth weight(gm) _____

Section IV: Maternal health condition

15. Maternal health condition

1. PICT
2. Hepatitis b
3. Hepatitis c
4. VDRL
5. DM
6. HTN
7. CVDS
8. Other--

Section V: Admission problem

16. Diagnosis at admission

1. Prematurity
2. Low birth weight
3. Sepsis
4. Respiratory distress syndrome(RDS)
5. Perinatal asphyxia
6. Congenital malformations
7. Jaundice
8. Other specify__

17. Discharge status/outcome----------

18. If died age in days----------

19. What is presumed cause of death_____

Maternal and obstetrics factors

20. Age of the mother at childbirth(in Years)---------
21. Parity------

22. TT Vaccine status 1, Yes 2, No

23. Number of ANC Visit----------

24. Onset of labor

1. Induced
2. Spontaneous