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# A Neonatal Mortality Risk Modelling Scoring System

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## Abstract

Infections are the commonest cause of death in infants less than four weeks old. Treatment, in a neonate with signs of sepsis needs to be initiated as soon as possible, before the causative organism is known. In the developed world neonatal severity scores have been created to estimate the risk of a neonate having a poor outcome. These scores rely on biochemical and haematological parameters which are often unavailable in the developing world. The objective of this study is to derive a mortality severity score for neonates who live in developing countries. The neonate mortality risk score is based on clinical signs that predict the likelihood of death. Neonatal patient risk models are built applying two popular methodologies: Logistics Regression and Decision Tree. Input variables that were used in established models in literature was selected to build the neonatal mortality risk modelling scoring system. Important factors that contributed to the resulting neonatal mortality risk score was birth weight, temperature, heart rate and seizure. Model accuracy was at least 85% amongst all models built.

## Keywords

Neonatal, Mortality Risk, Severity Score, Patient Risk Model, Sepsis, Infections

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## 1. Introduction

Neonatal mortality is increasingly recognized as an important global public health challenge that must be addressed if we are to reduce child health disparities between rich and poor countries [14]. There are many situations when a clinician, parent, nurse, manager, or researcher may wish to quantify the morbidity of a neonate. Poverty is an underlying cause of many neonatal deaths, either through increasing the prevalence of risk factors such as maternal infection, or through reducing access to effective care. However, poverty is not just a problem in poor countries. Results of a Canadian study [3] suggest a disparity in stillbirths and neonatal deaths between the richest and poorest 20% of the population that has persisted for almost 20 years. Further, Demographic and Health Survey (DHS) data from 20 countries in sub-Saharan Africa and three large countries in south Asia reveal consistently higher Neonatal Mortality Rate (NMR) for those in the poorest 20% of households than for those in the top quintile. Most of the estimated 4 million neonatal deaths per year occur in low and middle income countries.

Three conditions: infection, birth asphyxia, and consequences of premature birth/low birth weight, are responsible for majority of these deaths. More than one-third are estimated to be due to severe infections, and a quarter are due to the clinical syndrome of neonatal sepsis/pneumonia. Case fatality rates for neonatal infections remain high among both hospitalized newborns and those in the community [15].

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In general, the identification and treatment of newborns with infection is unsatisfactory in many developing country settings. Because sick newborns present with nonspecific signs and symptoms, a clinical diagnosis of neonatal sepsis is difficult in even the most sophisticated settings.

The neonatal period is only 28 days and yet accounts for 38% of all deaths in children younger than age 5 years [1]. Mortality is very high in the first 24 h after birth (25–45% of all neonatal deaths in this analysis). Globally some three quarters of neonatal deaths happen in the first week after birth [2]. Estimates from 2000 of the distribution of direct causes of death indicate that preterm birth (28%), severe infections (36%, including sepsis/pneumonia [26%], tetanus [7%], and diarrhoea [3%]), and complications of asphyxia (23%) account for most neonatal deaths. Of the remaining 14%, 7% of deaths were related to congenital abnormalities [4].

Scoring systems involve using appropriately weighted demographic, physiological, and clinical data collected on the infant to calculate a score that quantifies its morbidity. According to Ridley [9], the principle for such an approach has been long established in many branches of medicine and that the desirable properties of neonatal scores have been described as including: "(1) ease of use; (2) applicability early in the course of hospitalisation; (3) ability to reproducibly predict mortality, specific morbidities, or cost for various categories of neonates; (4) usefulness for all groups of neonates to be described."

In the developed world neonatal severity scores have been created to estimate the risk of a neonate having a poor outcome. They also allow standardized comparisons of outcome overtime or between units [5]. These scores rely on biochemical and haematological parameters which are often unavailable in the developing world. To date there have been no published studies looking at the use of simple clinical signs and observations to develop a general neonatal severity score for developing countries. Such a score would have be beneficial as it would provide the medical professional an objective measure of when the level of care should be increased and referral appropriate. It would also have a benefit for the community in the evaluation of neonatal care interventions and help to identify early whether the neonatal is at high risk of death and thereby help to save lives.

The paper is structured into 6 sections. While Section 1 is the introduction, Section 2 a brief overview of the statistical methods used, Section 3 the statistical analysis results, after which Section 4 presents the conclusion.

# 2. Objective of Study

Severity scoring systems such as CRIB, CRIB 11, SNAP, SNAP-PE, SNAP-11, SNAPPE-11 were well suited for developed countries but not suited for developing countries. Many factors contribute to the high mortality due to infections, including under-recognition of illness, delay in care seeking at the household level, and lack of access to both appropriately trained health workers and to high quality services to manage sepsis. Even if quality services are available, the cost of treatment is beyond the reach of many families. It is particularly poignant that many neonatal deaths occur in the community, without the newborn ever having contact with the appropriate health services. Illness severity scores are now well accepted as essential tools.

Child deaths are commonly the result of several risk factors. The joint effects of two or more risk factors cause of neonatal death should can be estimated. Thus, the total effect of interventions to prevent or mitigate the effects of various sets of risk factors could be established.

The objective of this study is to derive a mortality severity score for neonates who live in developing countries. The neonate mortality risk score is based on clinical signs that predict the likelihood of death. Neonatal patient risk models are built applying two popular methodologies: Logistics Regression and Decision Tree. Input variables that were used in established models in literature was selected to build the neonatal mortality risk modelling scoring system.

Further, in this study, we analyse epidemiological data to help guide efforts to reduce deaths of new born children in countries where most neonatal deaths take place. Data from Angkor Hospital for Children (AHC) and the AHC Satellite Clinic (SC) located in Siem Reap and Sotnikum respectively was used for building the neonatal mortality risk modelling scoring system.

# 3. Methodology

## 3.1. Data Collection and Cleaning

Using the hospital database all infants less than 28 days who were admitted to AHC or SC from 1st January 2012 to 31st December 2013 was selected and registered for this study. Hospital records for these infants are retrieved to complete a Case Record Form (CRF) for each admission case. All study CRFs are anonymized and kept in a locked storage area. Each case is reviewed and a standardized diagnosis for each infant determined.

Once the data was collected, we formatted the data in a structured format so that we could further process and analyse the data using statistical tools. We next checked for the presence of incorrect, incomplete and duplicate data. It was interesting to see that even though AHC neonates' birth weights situate slightly on the lower side of weight band, most of them are within the 3rd and 97th centile boundary, signifies the fact that the neonates admitted to hospital and satellite clinics are largely appropriate for gestation. An exploratory data analysis is performed in this study using simple descriptive statistics such as frequency counts and percentages, visual displays and hypothesis testing, to better understand the neonates that visit the Angkor Hospital for Children and the Angkor Hospital for Children Satellite Clinic.

### 3.2. Logistic Regression

Simple linear or multiple linear regression is applicable when the relationships between variables are assumed to be linear [16]. A number of nonlinear techniques can be used to obtain a more accurate regression if the relationship between variables is not linear in parameters. The logistic regression is preferred when the response variable takes on binary values (yes or no). It also has the advantage of being less affected when the normality of the variable cannot be assumed. Logistic regression also has the capacity to analyze a mix of all types of predictors [16]. For example, a logistic regression allows one to predict a discrete outcome, such as group membership, from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these.

### 3.3. Decision Trees

Decision trees are a form of multiple variable analyses and are powerful and popular tools for classification and prediction. The most attractive about decision tree is that such models require minimum data pre-processing as well as automatic feature selection during model building. After the tree is finalized, the rules derived from decision tree are readily interpretable.

On the other hand, when we have a few data points, the decision tree can be of substantial help to build a non-parametric model because it does not require the normal distribution assumption of independent variables.

The attractiveness of decision trees also lies in their ease of interpretation, relative power, robustness with a variety of data and levels of measurement, and ease of use. Decision trees attempt to find a strong relationship between input values and target values in a group of observations that form a data set [17]. In contrast to neural networks, decision trees represent rules and rules can readily be expressed so that humans can understand them or even directly used in database access language like SQL so that records falling into particular category may be retrieved. In our study, the decision trees generated some rules for scoring new neonates as new neonates were born and data became available.

## 4. Statistical Analysis Results

### 4.1. Exploratory Data Analysis and Assessment of Neonate Mortality Risk

The cause of death in neonatal around the world varies from region to region as shown in table 1 below:

**Table 1.** Frequency Distribution for Causes of Neonatal Deaths.

| Cause | Cambodia (%) | AHC and SC (%) | Europe (%) | South East Asia (%) |
|---|---|---|---|---|
| Preterm birth complications | 31.5 | 36 | 37 | 37 |
| Neonatal sepsis | 21.7 | 33 | 8 | 17 |
| Birth asphyxia | 28.7 | 15 | 16 | 19 |
| Congenital abnormalities | 6.6 | 9 | 20 | 9.6 |
| Other | 11.4 | 8 | 20 | 17 |

The reported figures of Cambodia, Europe and South-east Asia are referenced in [1]. Compared to developing countries like Europe, the admitted patient profile is very different in which there is only 9% of cases in our data that died due to congenital abnormality whereas this figure is 20% for Europe (developed country). On the other hand, there is four times more cases of death from sepsis in AHC and SC than in Europe. Such contrast requires very different public health strategy to deal with neonatal mortality and since the patient profiles are different, severity score and risk models built using developed country's data such as CRIB or SNAP cannot be used.

However, it is important to point out that even though infection (sepsis and skin infection) is not always preventable, it is certainly possible to reduce the number of deaths from it. The causes of infection can be either from mother during delivery or from the environment (including family) after three days of age, under-recognition of illness, delay in care seeking or detected too late at the household level, lack of access to both appropriately trained health workers and to high quality services to manage sepsis [9]. There are few suggestions to tackle the issues of delayed treatment of neonatal sepsis in which public health program can play an integral part such as management of neonatal infections in community setting [18]. In other papers, [19] [20] proposes available data on the use of oral and injectable antibiotics for the management of neonatal sepsis. Such preventive medicine can be an effective tool to reduce the neonatal mortality due to infection and requires further research in health services and epidemiology to make it a successful intervention.

### 4.2. Results of the Logistic Regression Analysis

The stepwise selection is used to deploy both logistics regressions for CRIB and SNAP scoring systems which combines backward and forward steps. The table below manifests the p-value coefficient of each variable at the last step in which Gestation Category is removed from CRIB model while Respiratory Rate is not selected in SNAP score.

**Table 2.** CRIB Logistic Regression Coefficient Results.

| | Coefficient | Odd ratio | Pr(>\|z\|) |
|---|---|---|---|
| Intercept | 13.4472 | 691902.2726 | 0.0031** |
| Birth weight | -0.6201 | 0.537890646 | 0.00735** |
| Temperature | -0.3842 | 0.680995215 | 0.00391** |
| Congenital Abnormality | 1.0706 | 2.917129253 | 0.01366** |

The results in table 1 tells us that birth weight, temperature and congenital abnormality are statistically significant as their p-values are less than 0.05. This means that birth weight, temperature and congenital abnormality contribute significantly to neonatal mortality. Further, the receiver operating characteristic (ROC) area under the curve for the CRIB Logistic Regression was 0.7161. In general, the accuracy of the test depends on how well the test separates the group being tested into those with and without the disease in question. Accuracy is measured by the area under the ROC curve. An area of 1 represents a perfect test; an area of .5 represents a worthless test.

A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system:

- .90-1 = excellent
- .80-.90 = good
- .70-.80 = fair
- .60-.70 = poor
- .50-.60 = fail

Using the traditional academic point system, we may conclude that the CRIB Logistic Regression model results are fair.

**Table 3.** SNAP Logistic Regression Coefficient Results.

| | Estimate | Odd ratio | Pr(>\|z\|) |
|---|---|---|---|
| Intercept | 15.565349 | 5753673.049 | 0.001094** |
| Birth weight | -0.762359 | 0.466564502 | 0.001506** |
| Temperature | -0.501508 | 0.605616701 | 0.000709** |
| Heart Rate | 0.017332 | 1.017483071 | 0.045765** |
| Seizure | 2.22604 | 9.263111432 | 0.000276** |

The results in table 2 tell us that birth weight, temperature, heart rate and seizure are statistically significant as their p-values are less than 0.05. This means that birth weight, temperature, heart rate and seizure contribute significantly to neonatal mortality. Further, the receiver operating characteristic (ROC) area under the curve for the SNAP Logistic Regression was 0.7557. Using the traditional academic point system, we may conclude that the SNAP Logistic Regression model results are fair but provides a better accuracy model than the CRIB Logistic Regression model.

Both the CRIB Logistic Regression Model and the SNAP Logistic Regression Model have supported and validated that birth weight and temperature and important factors in determining a neonate mortality risk. Other factors that may be important are congenital abnormality, heart rate and seizure, as they are either significant in the CRIB or SNAP Logistic Regression Models.

### 4.3. Results of Decision Tree Analysis

The CRIB decision tree results provided 5 rules which can be broadly divided into 2 categories: Premature Gestation and Term Gestation. While premature gestation branches and terminal node rules illustrate symptoms associated with pre-term condition (genetic variables) such as Congenital Abnormality and Gender, the rules concerning full-term gestation reflect temperature as the only defining variable. Such division does make intuitive sense as the reasoning agrees with the explanation above in which can classify conditions into two separate risk groups: one concerned with inherent conditions that developed before labor while the second group focuses on clinical assessment suitable to post-labor conditions such as temperature. It is remarkable that birth weight, even as proven highly significant in previous section was not selected in the final model while gestation category is chosen at the first split. It comes at no surprise as the majority of preterm infants weigh less than full-term neonates, gestation is selected over birth weight. The discriminative performance of the decision tree computed as the area under curve is only 0.745, slightly better than CRIB logistics regression.

The SNAP decision tree is less interpretable than the CRIB decision tree as the first node split starts with temperature. Again, birth weight is not selected and respiratory rate is set at the lowest hierarchy in the tree. The SNAP area under the curve reports a higher result of 0.784 which is the highest score among four established models so far, and thus indicates better discrimination between neonates who are at high risk at dying versus neonates who are at high probability of surviving.

## 5. Conclusion

In this paper, an assessment of epidemiological risk factors and clinical conditions was carried out to highlight and ascertain the role of key risk factors related to neonatal mortality in Siam Reap, Cambodia.

The Data Preparation step explores the association between attributes in order to find out the relationship among variables, connection between cases and the co-occurrence of symptoms. The reduction in the number of attributes are particularly necessary in our research as there are very few cases in the data, and this poses a great risk of over fitting the model and preventing effective generalization of established models. Preliminary models with two popular methodologies: Logistic Regression and Decision Trees was built.

Our model results illustrated numerous indicators related to neonatal mortality risk, which should be heeded if neonatal survival is to be improved. Results from the logistic regression showed that birth weight, temperature and congenital abnormality significantly contributed to neonatal mortality while the decision tree results showed that birth weight, temperature, heart rate and seizure significantly contributed to neonatal mortality and are important attributes for predicting neonatal mortality risk in infant less than 28 days of age. These conditions were not included in established severity score models yet related to mortality in Cambodia where neonatal sepsis is prevalent.

Furthermore, the discriminative performance of the models was very good and ranged within 0.7-0.79 for the Receiver Operating Characteristic (ROC) area under curve. Child health epidemiology is developing and increasingly can provide information useful for public health planning, monitoring, and evaluation.

To conclude, in a nutshell, we have shown that neonatal mortality risk can be reduced or prevented by scoring each neonatal at birth and then determining the level of care that is required to prevent death. Hospitals and healthcare authorities may use the neonatal mortality risk model to help to proactively identify the high risk neonates, and provide the right care level to the high risk neonates. This in return is likely to result in saving more lives.

Further, future researchers may utilize these important factors such as birth weight, temperature, congenital abnormality, heart rate and seizure to assess the mortality risk of other hospital admitted neonatal cases.

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