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Predicting Admission to Neonatal Care Unit at Mid-Pregnancy and Delivery using data from a General Obstetric Population

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Abstract

Objectives: Development and validation of risk prediction models at mid-pregnancy and delivery to predict admission to the neonatal care unit.

Methods: We used data from all singleton deliveries at Cork University Maternity Hospital (CUMH), Ireland during 2019. Admission to the neonatal care unit was assumed if length of stay in the unit was >24 hours. Multivariable logistic regression with backward stepwise selection was used to develop the models. Discrimination was assessed using the ROC curve C-statistic, and internal validation was assessed using bootstrapping techniques. We conducted temporal external validation using data from all singleton deliveries at CUMH during 2020.

Results: Out of 6,077 women, 5,809 (95.6%) with complete data were included in the analyses. A total of 612 infants (10.54%) were admitted to the neonatal care unit for >24 hours. Six variables were informative at mid-pregnancy: male infants, maternal smoking, advancing maternal age, maternal overweight/obesity, nulliparity and history of gestational diabetes (C-statistic: 0.600, 95% CI: 0.567, 0.614). Seven variables were informative at delivery: male infants, nulliparity, public antenatal care, gestational age <39 weeks', non-spontaneous vaginal delivery, premature rupture of membranes and time of birth between 17:01-07.59 hours (C-statistic: 0.738, 95% CI: 0.715, 0.760). Using these predictors, we developed nomograms to calculate individualised risk of neonatal care unit admission. Bootstrapping indicated good internal performance and external validation suggested good reproducibility.

Discussion: Our nomograms allow the user to quickly estimate individualised risk of neonatal care unit admission. Future research should aim to improve accuracy in early pregnancy to better assist counselling of parents.

Keywords: Neonatal care unit; Prediction model; Internal validation; External validation

Introduction

Most infants admitted to neonatal care units are born preterm and have a low birth weight (Quinn et al., 2016; Standford Children's Hopsital, 2021). However, there has been an increase in admission rates over the past decade across all gestational ages and birthweights. For example, a retrospective study conducted in the United States suggested that between 2007 and 2012, there was a 23% increase in neonatal care unit admission rates, with more than half of those admitted weighing at least 2500 grams at birth by 2012 (Harrison & Goodman, 2015).

Other factors increasing the risk of admission to neonatal care units may include maternal factors such as advanced maternal age, high body mass index (BMI) and maternal smoking, whereas delivery and infant factors may include premature rupture of membranes, instrumental delivery or caesarean delivery (Adams et al., 2002; Standford Children's Hopsital, 2021).

While advances in neonatology and access to such highly specialised care by neonatal multidisciplinary teams have contributed to a significant reduction in severe neonatal morbidity and mortality (Harrison & Goodman, 2015; Health Service Executive & Faculty of Pediatrics, 2015), prediction models may further assist by identifying risk factors for neonatal care unit admission and aiding effective planning of level of newborn care. Previous studies have developed prediction models for admission to neonatal care units, however these are often limited to specific populations such as small for gestational age (SGA) infants and use composite outcome criteria combining neonatal unit admission with adverse neonatal outcomes (Blue et al., 2021; Flatley, Gibbons, Hurst, Flenady, & Kumar, 2019; Kalafat, Morales-Rosello, Thilaganathan, Dhother, & Khalil, 2019). For example, Blue et al developed a prediction model for composite perinatal morbidity, which may include admission to the neonatal intensive care unit (NICU), among infants born SGA. However,

authors did not examine NICU admission in isolation, nor perform an internal or external validation of their model (Blue et al., 2021). In a separate study, a prediction model for a composite severe adverse neonatal outcome, which may also include NICU admission, was developed and internally validated in an Australian cohort of term infants. However, again, NICU admission was not predicted in isolation (Flatley et al., 2019). Kalafat and colleagues developed and internally validated a prediction model for risk of prolonged neonatal unit admission specifically, however this study included SGA infants born at term only (Kalafat et al., 2019).

Development and validation of a model to predict neonatal care unit admission for use in a general obstetric population is warranted. Identifying such risk factors would allow clinicians to recognise those who may be at high risk of admission to the neonatal care unit, and thus inform clinical decision-making and assist counselling of parents. Therefore, the aim of this study was to develop and validate (internally and externally) a prediction model at mid-pregnancy and delivery to predict admission to the neonatal care unit in a general obstetric population.

Materials/Subjects and Methods

Study Population

In December 2016, the Republic of Ireland rolled out a national project called The Maternal and Newborn Clinical Management System (MN-CMS), implementing an electronic health record for all women and their infants. With this system, all pregnant women in maternity services in Ireland were switched from paper clinical notes to an electronic health record, allowing all maternal and newborn information to be stored on one record. As Cork University Maternity Hospital (CUMH) was the first maternity hospital to implement the electronic health record, we used data from all singleton deliveries at CUMH during 2019 for

development of our prediction model, and all singleton deliveries during 2020 for temporal external validation of our model. This was the most up-to-date validated data available for research when the current study began. This study has been performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki and its later amendments. Ethical approval was obtained from the Clinical Research Ethics Committee of the Cork Teaching Hospitals (ECM4(v)09/04/2020). The Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) checklist was used as a guideline for reporting our study (available at https://www.tripod-statement.org).

Predictors and Outcome

We considered routinely measured variables when identifying candidate predictors using a combination of expert opinion (comprising a neonatologist, obstetricians, epidemiologists and experts on the MN-CMS), a review of existing literature (Altman, Vanpée, Cnattingius, & Norman, 2009; Lee, Bennett, Schulman, Gould, & Profit, 2016; Seaton et al., 2016), and the distribution of the predictor in the data that were available to us, (for example, any variables with <5 exposed cases were not included) (Grant, Collins, & Nashef, 2018).

Predictors during mid-pregnancy included: fetal sex, maternal smoking, maternal age, maternal body mass index (BMI), parity, assisted fertility, history of gestational diabetes, maternal Rhesus status and public/private antenatal care.

Predictors at delivery included: infant sex, maternal smoking, maternal age, maternal BMI, parity, assisted fertility, history of gestational diabetes, maternal Rhesus status, public/private antenatal care, SGA, gestational age, mode of delivery, premature rupture of membranes, prolonged rupture of membranes, season of birth and time of birth.

A description of candidate predictors are as follows: infant sex was categorised as male/female. Whether a woman currently smoked any tobacco products was recorded at the

initial prenatal visit and was categorised as yes/no. Maternal age in years was recorded at initial prenatal visit. Maternal height (cm) and weight (kg) at initial prenatal visit were used to calculate maternal body mass index (BMI). BMI was categorised as underweight <18.5, normal weight ≥18.5 to ≤24.9, overweight ≥25 to ≤29.9 and obese ≥30, with underweight and normal weight combined due to small numbers. Parity was recorded as number of previous completed pregnancies and was recategorised nulliparous or multiparous. Assisted fertility was categorised as yes/no. History of gestational diabetes was recorded at the initial prenatal visit and categorised as yes/no. Maternal Rhesus status was determined through a blood test at the initial prenatal visit and whether the woman was Rhesus negative was recategorised as yes/no. Public antenatal care is free at the point of care through the Maternity and Infant Care Scheme in Ireland. This is available to anyone who lives in Ireland or intends to live there for at least one year. With public antenatal care, hospital appointments will usually be with a midwife, however if the pregnancy is deemed higher risk, obstetricians and midwives will provide the care. Private antenatal care was defined as choosing to pay a consultant's fee/hospital fee so that a particular obstetrician would provide the care throughout the pregnancy/birth and that recovery would take place in a private/semi-private hospital room. All deliveries (both public and private) are performed within the same maternity unit.

SGA was defined as birthweight <10th percentile for gestational age and sex of child. Gestational age (estimated through first trimester ultrasound) was recorded as number of completed weeks at delivery and recategorised as preterm, early term and full-term birth (i.e., <37 weeks, ≥37 to ≤38 weeks, and ≥39 weeks). We categorised term birth into early term and full term as early term infants (≥37 to ≤38 weeks) have an increased risk of mortality and short and long-term morbidities compared to infants born at full term (Ghartey et al., 2012; Stewart & Barfield, 2019). Furthermore, this allowed for a more even distribution of cases in each category of gestational age, while still maintaining the standard definition of preterm

birth. Mode of delivery was recorded as spontaneous vaginal delivery, operative vaginal delivery, emergency caesarean section and prelabour caesarean section (i.e., elective/planned caesarean section). Premature rupture of membranes (breaking open of the amniotic sac before labour begins) and prolonged rupture of membranes (breaking open of the amniotic sac before labour begin, lasting longer than 24 hours between time of rupture and time of delivery) was diagnosed through assessment of maternal history and physical examination, and categorised as yes/no. Season of birth was categorised according to the common grouping system of meteorological practice in the middle and northern latitudes as follows: spring was birth in March, April or May; summer was birth in June, July or August; autumn was birth in September, October or November, and winter was birth in December, January or February (Met Éireann, 2024). Time of birth was recategorised as typical office hours (08:00-17:00 hours) and an on-call service (17:01-07.59 hours).

Outcome: Admission to the neonatal care unit was assumed if length of stay in the unit was >24 hours. This was to increase the likelihood that admission was medically indicated and not driven by hospital protocol.

Statistical Analysis

Statistical analysis was performed using Stata MP 14.2. Univariable analysis examined associations between candidate predictors and admission to the neonatal care unit. Multivariable logistic regression with backward stepwise selection (with a p-value of 0.1 for exclusion) was used to develop the prediction models. Therefore, all candidate predictors were included at first and the least useful predictors (i.e. the variable that is the least statistically significant) were subsequently removed one by one.

Sample Size: We used the *pmsampsize* command to calculate the minimum sample size and number of events required for new model development and to minimise overfitting.

Assuming an outcome event proportion (prevalence) of 0.10, a target shrinkage factor of 0.9, a c-statistic of 0.70, and 22 candidate predictors/categories, a minimum sample size of 4067 (with 407 events) would be required to minimise overfitting, indicating that we had a sufficient sample size for the current study (Riley, Van Calster, & Collins, 2021).

Model Performance and Internal Validation: We assessed overall fit, discrimination and calibration to examine model performance. Brier Score and Cragg & Uhler's (Nagelkerke) R^2 assessed overall fit. The area under the receiver operating characteristic (ROC) curve C-statistic assessed discrimination (i.e. how well the model differentiates between those patients who experience the outcome and those who do not (Grant et al., 2018)). Calibration-in-the-large (CITL), a calibration slope (C-slope) and calibration plot (*pmcalplot*) of observed against expected probabilities across ten risk groups of individuals assessed calibration (i.e. how closely the predictions of the model match the observed outcomes in the data (Grant et al., 2018; Joie Ensor, Kym IE Snell, & Martin, 2018)).

Bootstrapping (with 1000 repetitions) was used for internal validation of our models in order to assess overfitting and calculate the optimism adjusted C-statistic, CITL and C-slope. Finally, two nomograms (graphical representation of prediction model) were developed to provide individualised risk assessment for admission to the neonatal care unit.

External validation: A temporal external validation was conducted using data from all singleton deliveries at CUMH in 2020. Discrimination was assessed using the C-statistic, and calibration was assessed using the CITL and C-slope.

Results

There were 6,077 singleton deliveries at CUMH in 2019, of which 5,809 (95.6%) had complete data on candidate predictors. A total of 612 infants (10.54%) were admitted to the neonatal care unit for >24 hours. Maternal and child characteristics are outlined in Table 1.

Univariable analysis examining associations between candidate predictors and neonatal care unit admission are shown in eTable 1 in the Supplement. Factors significantly associated with admission to the neonatal care unit included infant sex, parity, assisted fertility, gestational age, mode of delivery, premature rupture of membranes and prolonged rupture of membranes (eTable 1).

Risk Prediction Models

Mid-pregnancy: Six variables at mid-pregnancy were considered the best combined predictors of admission to the neonatal care unit using multivariable logistic regression with backward stepwise selection (ROC curve C-statistic: 0.600, 95% CI: 0.567, 0.614). These included infant sex (specifically male infants), maternal smoking, maternal age, maternal overweight and obesity, parity (specifically nulliparous) and history of gestational diabetes (Table 2).

We developed a nomogram to provide an individualised risk assessment for neonatal care unit admission using these predictors (Figure 1). For example, for a nulliparous woman (score 5.5), BMI categorised as obese (score 2.5), aged 33 years (score 6.5), smoker (score 4) and male infant (score 3.5); the total score is 22 corresponding to an over 20% risk of having their infant admitted to the neonatal care unit.

At delivery: Seven variables at delivery were considered the best combined predictors of admission to the neonatal care unit (ROC curve C-statistic: 0.738, 95% CI: 0.715, 0.760). These were infant sex (specifically male infants), parity (specifically nulliparity), public antenatal care compared to private antenatal care, gestational age (specifically those born <37 weeks, or those born ≥37 to ≤38 weeks compared to those born ≥39 weeks), mode of delivery (including emergency caesarean section, operative vaginal delivery, or prelabour caesarean

section compared to spontaneous vaginal delivery), premature rupture of membranes and time of birth (specifically on-call service compared to typical office hours) (Table 3).

Similar to above, we developed a nomogram to provide an individualised risk assessment for neonatal care unit admission using these predictors (Figure 2). For example, a woman receiving public antenatal care (score 1), birth outside of typical office hours (score 0.6), nulliparous (score 0.9), emergency caesarean section (score 2.5), premature rupture of membranes (score 1.4), born at 38 weeks' (score 1.9) and male infant (score 0.8); the total score is 9.1 corresponding to a ~30% risk of having their infant admitted to the neonatal care unit.

Model Performance and Internal Validation

Mid-pregnancy: Brier Score and Cragg & Uhler's (Nagelkerke) R^2 were 0.093 and 0.020 respectively. The calibration plot suggested that average model predictions match average observed outcomes for the ten risk groups of individuals, indicating good calibration. Deciles are clustered at the bottom left, indicating most infants have low risk of admission to the neonatal care unit (eFigure 1 in the Supplement).

The original apparent C-statistic was 0.600 (95% CI: 0.567, 0.614). After bootstrapping, there was minimal optimism adjustment to the C-statistic, indicating good internal performance (optimism adjusted C-statistic: 0.590). The miscalibration in CITL and C-slope were small suggesting that overfitting was unlikely to be an issue. (Table 4).

At delivery: Brier Score and Cragg & Uhler's (Nagelkerke) R^2 were 0.077 and 0.212 respectively indicating better overall performance than the mid-pregnancy model. The calibration plot suggested that average model predictions match average observed outcomes for the ten risk groups of individuals, indicating good calibration. Similar to above, most of the deciles are clustered at the bottom left, suggesting most infants have low risk of

admission to the neonatal care unit. The lowess smoother shows that there is very little miscalibration at the individual level in the higher risk individuals, though there is little data at the higher risk probabilities as suggested by the spike plot at the bottom of the graph (eFigure 2 in the Supplement).

The original apparent C-statistic was 0.738 (95% CI: 0.715, 0.760). Again, there was minimal optimism adjustment to the C-statistic after bootstrapping, indicating good internal performance in terms of discrimination (optimism adjusted C-statistic: 0.725). The miscalibration in CITL and C-slope were small indicating that overfitting was unlikely an issue. (Table 4).

External validation

This analysis included 6,529 (97.4%) women with data on all predictors and there were 757 (11.59%) admissions to the neonatal care unit. The C-statistic was 0.594 (95% CI: 0.572, 0.617), and 0.745 (95% CI: 0.726, 0.763) based on the mid-pregnancy and at delivery model respectively. The CITL and C-slope were 0 and 1 for both models, suggesting good overall calibration of the models.

Discussion

This study developed and validated (both internally and externally) a prediction model for admission to the neonatal care unit in a general obstetric Irish population at mid-pregnancy and delivery. Firstly, we identified six variables at mid-pregnancy to predict admission to the neonatal care unit, including male infants, maternal smoking, advanced maternal age, maternal overweight and obesity, nulliparity and history of gestational diabetes. The C-statistic for this model was 0.600, with good overall calibration, and the external validation result was comparable with this development model.

Secondly, we identified seven variables at delivery to predict admission to the neonatal care unit. These included male infants, nulliparity, public antenatal care, gestational age <39 weeks' (with risk of admission to the neonatal care unit increasing as gestational age decreases), non-spontaneous vaginal delivery, premature rupture of membranes and time of birth between 17:01-07.59 hours. The C-statistic for this model was 0.738 and therefore had better discriminative performance than the mid-pregnancy model. Similar to above, there was good overall calibration, and the external validation result was comparable with the development model.

While our outcome of interest was admission to the neonatal care unit for >24 hours, several prediction models have been developed to predict length of stay. For example, a systematic review (Seaton et al., 2016) identified nine studies (Altman et al., 2009; Bender et al., 2013; Berry, Shah, Brouillette, & Hellmann, 2008; Hinchliffe et al., 2013; Hintz et al., 2010; Lee, Bennett, Schulman, & Gould, 2013; Lee et al., 2016; Manktelow, Draper, Field, & Field, 2010; Zernikow et al., 1999) predicting length of stay in the neonatal care unit, with inherent factors such as birthweight, gestational age and infant sex identified as informative for prediction.

However, fewer studies predict admission to the neonatal care unit specifically and are often limited to specific populations or may lack validation. A recent US study used machine learning to develop three models to predict NICU admission among infants with low illness acuity diagnoses (Mahendra et al., 2021). These included a patient characteristic model (including infant sex, birthweight, night admission, weekend admission, birth year) with a ROC curve of 0.64 (95% CI: 0.62, 0.65), a hospital characteristic model (including hospital in which the infant was born) with a ROC curve of 0.81 (95% CI: 0.81, 0.82) and a patient characteristic plus hospital characteristic model with a ROC curve of 0.84 (95% CI: 0.83, 0.84). However, this study did not report on internal or external validation. A UK-based study

developed and internally validated a prediction model for NICU admission and demonstrated good accuracy of their model. Predictors identified as clinically informative included gestational age, estimated fetal weight below the third centile and cerebroplacental ratio, with a ROC curve of 0.71 (95% CI: 0.63-0.79) (Kalafat et al., 2019). However, inclusion criteria for model development were limited to SGA infants born at term only and therefore may not be generalisable beyond this population.

The current study developed and validated risk prediction models for use in a general obstetric population and may have the potential to assist counselling of parents and planning of care. However, before a risk prediction model is applied in clinical practice, an impact study is first needed to determine its clinical usefulness. Impact studies can be used to quantify the effect of using a prediction model on patient outcome compared with usual care without the model (Moons, Altman, Vergouwe, & Royston, 2009). As suggested by Vickers et al, this can be achieved using net benefit and decision curve analyses, and ideally through cluster randomised trials. These analyses can be used to assess clinical value of a prediction model and in turn assist healthcare professionals when making clinical decisions (Vickers, Van Calster, & Steyerberg, 2016).

Strengths and Limitations

This study contained limitations that should be noted. First, while we included a wide range of candidate predictors, it is possible that not all relevant predictors were available in the MN-CMS for inclusion in the prediction models. Therefore, including more candidate predictors, for example quality data on hypertensive disorders of pregnancy, may improve prediction and aid counselling of parents. However, inclusion of more predictors should be considered in terms of feasibility and availability of an appropriate sample size to minimise overfitting. Second, we did not have access to quality information on indication for neonatal

care unit admission which may be a more reliable measure of our outcome. However, we limited cases to those whose length of stay in the neonatal care unit was >24 hours to increase the likelihood that admission was medically indicated and not driven by hospital protocol.

Third, some candidate predictors such as maternal smoking may be subject to recall bias. However, as data on maternal smoking is collected prospectively at booking visit, misclassification is thought to be non-differential and not influenced by the study outcome. Fourth, although a temporal external validation was carried out to examine reproducibility, differences in characteristics of the health care system and type of insurance coverage in other countries may lead to varying results. Therefore, a geographical external validation using data from other countries is needed in order to assess generalisability of findings. As it is recommended that external validation is carried out by an independent research team, we included the figures needed to calculate the linear predictor of our model. This would allow for an independent external validation in order to objectively evaluate our models' performance (Collins & Altman, 2010). Fifth, missing data may have introduced bias. However, as the total amount of missing data in the current study was <5%, this may not have a large impact on results (Harrell FE., 2015). Finally, we did not include multiple pregnancies in our study as they carry a higher inherent risk of admission to the neonatal care unit, therefore the prediction model should not be generalised to this group.

There are also several strengths in this study. First, we developed and validated two risk prediction models; one to be applied at mid-pregnancy and one at delivery. The mid-pregnancy model was based on predictors that could be acquired by approximately 20 weeks' gestation to potentially assist in effective planning of level of newborn care. Second, we conducted an internal and temporal external validation of our model allowing us to assess overfitting, calculate an optimism adjusted C-statistic and assess reproducibility of our model. Third, we conducted an appropriate sample size calculation to ensure a sufficiently

large sample size in order to minimise overfitting. We conducted an appropriate sample size calculation to ensure a sufficiently large sample size in order to minimise overfitting. Our large sample size (N=5809 with 612 events) allowed for more detailed categorisation of certain variables, reducing the amount of statistical information lost due to collapsing variables. For example, gestational age was categorised as preterm, early term and full-term birth (i.e., <37 weeks, ≥37 to ≤38 weeks, and ≥39 weeks' gestation), while mode of delivery was categorised as spontaneous vaginal delivery, operative vaginal delivery, emergency caesarean section and prelabour caesarean section. Finally, we developed a nomogram to graphically represent our prediction model. This provides an individualised risk assessment enabling the user to quickly and easily estimate the probability of admission to the neonatal care unit.

Conclusion

We developed and validated two risk prediction models to predict admission to the neonatal care unit; one to be applied at mid-pregnancy, and a second to be applied at delivery. Six routinely collected variables were considered the best combined predictors at mid-pregnancy, while seven routinely collected variables were considered informative at delivery and showed better discriminative performance than the mid-pregnancy model. Use of our nomograms can provide an individualised risk assessment of neonatal care unit admission at both time points; however, future research should aim to improve accuracy in early pregnancy to better assist counselling of parents.

Supplementary Material

Refer to Web version for supplementary material.

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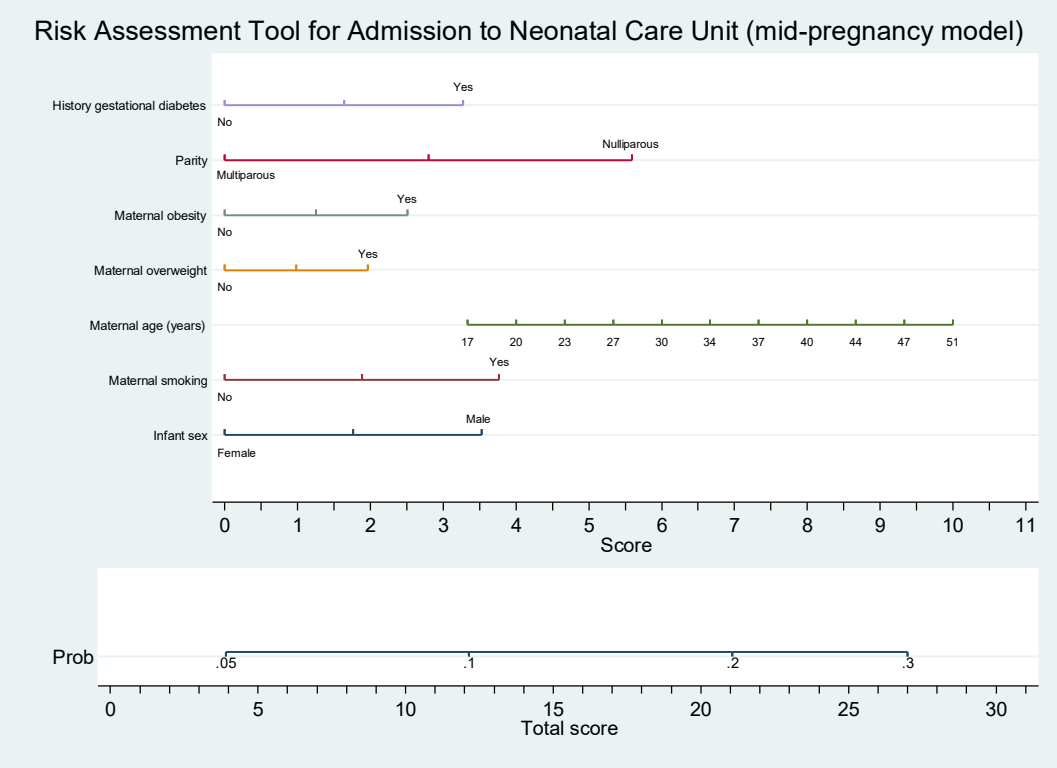
Table 1: Characteristics of study participants		
Characteristic	**Not admitted to neonatal care unit N=5197**	**Admitted to neonatal care unit N=612**
Infant sex		
Female	2634 (50.68)	261 (42.65)
Male	2563 (49.32)	351 (57.35)
Maternal smoking		
No	4795 (92.26)	552 (90.20)
Yes	402 (7.74)	60 (9.80)
Maternal age (years)	34.60 (5.08)	34.63 (5.36)
Maternal BMI		
Underweight/normal weight	2588 (49.80)	275 (44.93)
Overweight	1,604 (30.86)	202 (33.01)
Obese	1005 (19.34)	135 (22.06)
Parity		
≥1	3229 (62.13)	314 (51.31)
0	1968 (37.87)	298 (48.69)
Assisted fertility		
No	5028 (96.75)	582 (95.10)
Yes	169 (3.25)	30 (4.90)
History of gestational diabetes		
No	4905 (94.38)	566 (92.48)
Yes	292 (5.62)	46 (7.52)
Maternal Rhesus negative		
No	4582 (88.17)	542 (88.56)
Yes	615 (11.83)	70 (11.44)
Public/private antenatal care		
Private	1004 (19.32)	104 (16.99)
Public	4193 (80.68)	508 (83.01)
Small for gestational age		
Yes	4713 (90.69)	546 (89.22)
No	484 (9.31)	66 (10.78)
Gestational age		
≥39 weeks	3893 (74.91)	278 (45.42)
≥37 to ≤38 weeks	1200 (23.09)	148 (24.18)
<37 weeks	104 (2.00)	186 (30.39)
Mode of delivery		
SVD	2781 (53.51)	226 (36.93)
Operative vaginal delivery	807 (15.53)	105 (17.16)
Emergency caesarean section	549 (10.56)	100 (16.34)
Prelabour caesarean section	1060 (20.40)	181 (29.58)
Premature rupture of membranes		
No	5112 (98.36)	524 (85.62)
Yes	85 (1.64)	88 (14.38)
Prolonged rupture of membranes		
No	4778 (91.94)	527 (86.11)
Yes	419 (8.06)	85 (13.89)
Season of birth		
Spring	1288 (24.78)	147 (24.02)
Summer	1344 (25.86)	178 (29.08)
Autumn	1323 (25.46)	152 (24.84)
Winter	1242 (23.90)	135 (22.06)
Time of birth		
08:00-17:00 hours	2407 (46.32)	280 (45.75)
17:01-07:59 hours	2790 (53.68)	332 (54.25)
N (%) for categorical variables, mean (SD) for continuous variables. Abbreviations: SD, standard deviation; BMI, body mass index; IVF, in vitro fertilisation; SVD, spontaneous vaginal delivery.		

Table 2: Best combined mid-pregnancy predictors for admission to the neonatal care unit			
	Coefficient (95% CI)	**N (%) or mean (SD)**	**OR (95% CI)**
Infant sex			
Female	-	2895 (49.84)	ref
Male	0.320 (0.150, 0.489)	2914 (50.16)	1.37 (1.16, 1.63)
Maternal smoking			
No	-	5347 (92.05)	ref
Yes	0.342 (0.045, 0.639)	462 (7.95)	1.40 (1.04, 1.89)
Maternal age (years)	0.017 (0.0003, 0.035)	34.61 (5.11)	1.01 (1.00, 1.03)
Maternal BMI			
Underweight/normal weight	-	2863 (49.29)	ref
Overweight	0.178 (-0.014, 0.371)	1806 (31.09)	1.19 (0.98, 1.44)
Obese	0.227 (0.003, 0.451)	1140 (19.62)	1.25 (1.00, 1.57)
Parity			
≥1	-	3543 (60.99)	ref
0	0.508 (0.332, 0.684)	2266 (39.01)	1.66 (1.39, 1.98)
History of gestational diabetes			
No	-	5471 (94.18)	ref
Yes	0.297 (-0.033, 0.628)	338 (5.82)	1.34 (0.96, 1.87)
Intercept	-3.299 (-2.638, -3.960)	-	-
Abbreviations: SD, standard deviation; OR, odds ratio; 95% CI, 95% confidence interval; ref, reference category; BMI, body mass index.			

Table 3: Best combined predictors at delivery for admission to the neonatal care unit			
	Coefficient (95% CI)	**N (%)**	**OR (95% CI)**
Infant sex			
Female	-	2895 (49.84)	ref
Male	0.250 (0.063, 0.436)	2914 (50.16)	1.28 (1.06, 1.54)
Parity			
≥1	-	3543 (60.99)	ref
0	0.254 (0.047, 0.460)	2266 (39.01)	1.28 (1.04, 1.58)
Public/private antenatal care			
Private	-	1108 (19.07)	ref
Public	0.256 (0.009, 0.504)	4701 (80.93)	1.29 (1.01, 1.65)
Gestational age			
≥39 weeks	-	4171 (71.80)	ref
≥37 to ≤38 weeks	0.580 (0.363, 0.797)	1348 (23.21)	1.78 (1.43, 2.22)
<37 weeks	3.053 (2.728, 3.378)	290 (4.99)	21.18 (15.30, 29.31)
Mode of delivery			
SVD	-	3007 (51.76)	ref
Operative vaginal delivery	0.607 (0.328, 0.887)	912 (15.70)	1.83 (1.38, 2.43)
Emergency caesarean section	0.759 (0.467, 1.050)	649 (11.17)	2.13 (1.59, 2.85)
Prelabour caesarean section	0.658 (0.400, 0.917)	1241 (21.36)	1.93 (1.49, 2.50)
Premature rupture of membranes			
No	-	5636 (97.02)	ref
Yes	0.402 (-0.027, 0.831)	173 (2.98)	1.49 (0.97, 2.29)
Time of birth			
08:00-17:00 hours	-	2687 (46.26)	ref
17:01-07:59 hours	0.197 (-0.007, 0.402)	3122 (53.74)	1.21 (0.99, 1.49)
Intercept	-3.579 (-3.243, -3.914)	-	-
Abbreviations: SD, standard deviation; OR, odds ratio; 95% CI, 95% confidence interval; ref, reference category; SVD, spontaneous vaginal delivery.			

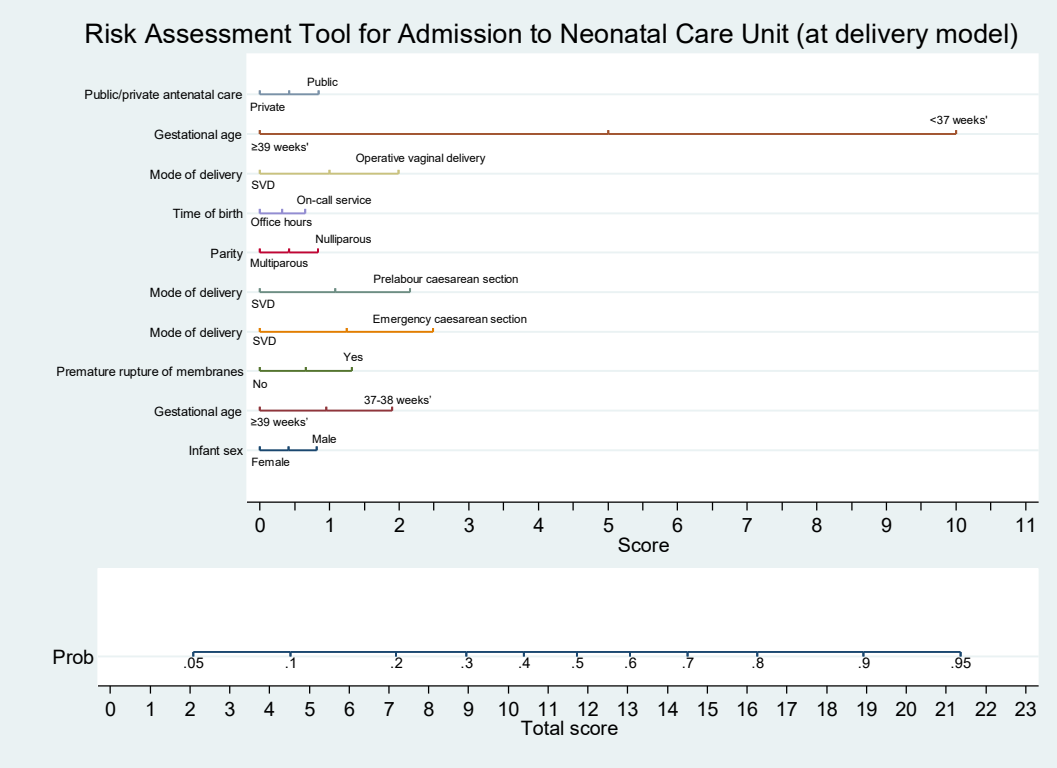
Table 4: Assessment of model performance			
Mid-pregnancy	**Original apparent**	**Optimism**	**Optimism adjusted**
Discrimination			
C-statistic	0.600 (95% CI: 0.567, 0.614)	0.010	0.590
Calibration			
CITL	0 (95% CI: -0.084, 0.084)	0.002	-0.002
C-slope	1 (95% CI: 0.739, 1.260)	0.119	0.881
At delivery			
Discrimination			
C-statistic	0.738 (95% CI: 0.715, 0.760)	0.013	0.725
Calibration			
CITL	0 (95% CI: -0.092, 0.092)	0.001	-0.001
C-slope	1 (95% CI: 0.918, 1.081)	0.033	0.967
Abbreviations: CITL, calibration-in-the-large; C-slope, calibration slope; 95% CI, 95% confidence interval.			

Figure 1 top



Nomogram providing individualised risk assessment for admission to the neonatal care unit based on mid-pregnancy predictors. For example, a nulliparous woman (score 5.5), BMI categorised as obese (score 2.5), aged 33 years (score 6.5), smoker (score 4), male infant (score 3.5); the total score is 22 corresponding to an over 20% risk of having their infant admitted to the neonatal care unit.

Figure 2 top



Nomogram providing individualised risk assessment for admission to the neonatal care unit based on predictors at delivery. For example, a woman receiving public antenatal care (score 1), birth outside of typical office hours (score 0.6), nulliparous (score 0.9), emergency caesarean section (score 2.5), premature rupture of membranes (score 1.4), born at 38 weeks' (score 1.9) and male infant (score 0.8); the total score is 9.1 corresponding to a ~30% risk of having their infant admitted to the neonatal care unit.