

Early detection of six-week post-discharge mortality and readmission among postpartum women and newborns in Uganda: development and temporal validation of multivariable prediction models

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Abstract

Background

The postnatal period accounts for up to one-third of maternal deaths and half of newborn deaths globally. Early intervention can prevent progression along the continuum of illness severity. The aim of this study was to develop prognostic models to predict post-discharge outcomes in women and newborns following hospital delivery in Uganda.

Methods

This prospective observational cohort study enrolled women presenting for delivery at two regional referral hospitals. The maternal outcome was readmission due to obstetric infection within the six-week postnatal period; newborn outcomes were six-week mortality and readmission resulting from acute illness likely due to an infectious cause. Parsimonious models were derived for each outcome using the top eight variables based on variable importance of available predictors and internally validated using 10-fold cross-validation.

Results

Among 6,996 women discharged postpartum with six-week follow-up data: none died; 224 (3.2%) were readmitted, with 126 (1.8%) due to infection. The maternal model's mean (range) cross-validated area under the receiver operating characteristic curve (AUROC) was 0.784 (0.738 to 0.824) and the area under the precision-recall curve (PRAUC) was 0.099 (0.053 to 0.263); at an 80% sensitivity threshold, it had mean specificity 0.697 and Brier score 0.017. Among 6,044 newborns discharged alive: 35 (0.6%) died; 228 (3.8%) were readmitted. The newborn mortality model's AUROC was 0.731 (0.600 to 0.854) and PRAUC was 0.029 (0.010 to 0.071); at 80% sensitivity, it had mean specificity 0.539 and Brier score 0.006. The newborn readmission model's mean (95% confidence interval) bootstrapped AUROC was 0.712 (0.672 to 0.747) and PRAUC was 0.080 (0.065 to 0.109); at an 80% sensitivity threshold, it had mean specificity 0.532 and Brier score 0.036.

Conclusions

Maternal and newborn morbidity remains high in Uganda. Routine parameters used in clinical care at discharge can identify mothers and newborns at risk of serious infection or death and inform risk-based postnatal care.

Trial registration

This observational study was retrospectively registered at clinicaltrials.gov (NCT05730387, 15-Feb-2023).

Background

Maternal and neonatal mortality remain significant global issues with approximately 2.6 million deaths recorded in 2023 [1, 2]. The majority of deaths occurred in sub-Saharan Africa, where mortality rates are not improving, despite an increase in facility births [3]. Efforts to reduce mortality focus on intrapartum complications, stillbirths, and preterm births; however, almost one-third of maternal and half of neonatal deaths occur during the first week of life [4]. Many of these deaths could be prevented by recognizing and treating complications earlier [5].

In low-resourced settings with overburdened health systems, postpartum women and their infants are often discharged without completing the first postnatal checks [6]. Post-discharge outcomes are inadequately addressed [7], with fragmented coverage and inconsistent quality of care during the discharge process and post-discharge period [3]. The World Health Organization (WHO) recommends at least three postnatal care visits for mothers and facility-born infants within the first six weeks [8], but many mother-infant dyads do not receive any care during this period [9]. Attempts to improve postnatal home care visits have achieved limited success [10, 11].

Evidence-informed postnatal care using a risk-based, patient-centred approach is urgently needed. The health of a postpartum woman and their newborn/s are closely related [12]. Maternal mortality and postpartum complications are associated with neonatal mortality and failure to thrive [10, 11, 13]. In high-risk cases, clinical decision-making is complicated by the need to balance maternal and newborn risks and outcomes simultaneously. Approaches to improve decision-making must integrate information about both mother and newborn. By identifying vulnerable dyads and delivering interventions to those who need it most, prognostic models may help detect and treat high-risk cases early, inform specific discharge counselling opportunities, or create tailored recommendations for follow-up care.

The aim of this study was to develop and validate post-discharge risk prediction algorithms that identify high-risk mother-newborn dyads prior to discharge after hospital birth. We used an integrated approach that allowed us to model outcomes for the mother and newborn separately, while considering variables from both as potential predictors in each model.

Methods

Study design and approvals

We conducted a prospective observational cohort study of mother-newborn dyads at two regional referral hospitals in Uganda [14], to generate prediction models for maternal readmission due to obstetric infection and newborn readmission and mortality within six weeks. This research was conducted in accordance with the Declaration of Helsinki. Ethics approval was obtained from the Makerere University School of Public Health Institutional Review Board (ref. SPH-2021-177, approved 25-Feb-2022), the Uganda National Council of Science and Technology (HS2174ES, 07-Apr-2022), and the University of British Columbia – Children’s and Women’s Health Centre of BC Research Ethics Board (H21-03709, 14-Apr-2022). The study was registered as an observational study at clinicaltrials.gov

(NCT05730387, 15-Feb-2023). This manuscript adheres to the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement [15].

Study setting and cohort selection

Study enrolment started after all approvals were granted. Enrolment and follow-up were conducted between 14-Apr-2022 and 30-Sep-2023 at Mbarara Regional Referral Hospital in southwestern Uganda and Jinja Regional Referral Hospital in eastern Uganda. Together, these facilities cover two different districts in Uganda, serve a combined population of approximately 973,000 people, and provide a reasonable representation of the Ugandan population outside of the capital city of Kampala. A retrospective temporal validation dataset comprised data collected at Mbarara Regional Referral Hospital between Apr-2019 and Mar-2020 [12].

Eligible participants included all women and adolescent girls, over the age of 12, living within the catchment districts and admitted to hospital for delivery. Those who refused or who were unable to provide consent, had a language barrier (i.e., unable to speak either local language, *Runyankole* or *Lusoga*), resided in a refugee camp, or who did not have access to a phone during the post-discharge period were ineligible. A quasi-random sampling method was used to reduce sampling bias, with separate sampling for day-time (8am-8pm) and night-time (8pm-8am) admissions [14]. Only mothers who survived to discharge and neonates who survived to discharge, without an intensive care unit admission, were included in the modelling cohort. Newborns who were admitted immediately following birth were excluded, as we aimed to build a model for patients deemed fit for discharge.

Data collection

Enrolment materials, data collection tools, and study procedures are available via the Smart Discharges Mom & Baby 2.0 Borealis Dataverse [14, 16]. All participants received routine care at the discretion of their medical team. In cases where study nurses noted danger signs, referrals were made and recorded.

Following delivery and written informed consent, trained study nurses collected data grouped according to four periods of care: admission, delivery, discharge, and six-week post-discharge follow-up. For admission and delivery, we prioritized gathering data from the hospital medical record, followed by interviews with the postpartum women and, finally, confirmation with the medical team if there were discrepancies, missing information, or questions the postpartum woman was unable to answer. Socioeconomic status was described using the Global Network Socioeconomic Status Index score developed using the multidimensional poverty index and previously validated [17, 18].

Discharge data were collected by study nurses on all postpartum women and infants discharged alive from the facility, including the following physical measurements: maternal hematocrit, using a HemataSTAT Hematocrit Centrifuge (EKF Diagnostics, Cardiff, United Kingdom); maternal blood pressure, using a Microlife Cradle VSA semi-automated blood pressure monitor (Microlife Corporation,

Widnau, Switzerland); maternal and neonatal oxygen saturation (SpO₂) and heart rate, using the Masimo iSpO₂® (Masimo Corporation, California, USA) or Nellcor OxiCable with Covidien Flexible SpO₂ sensors (Medtronic Minneapolis, Minnesota, USA); mother and infant respiratory rate, using the RRate application [19]; mother and infant temperature, using Exergen Temporal Scanners (Exergen, Massachusetts, USA).

Six weeks post-discharge, nurse field officers contacted participants via phone to determine vital status, readmission (at any facility), and the timing and frequency of care-seeking, or via in-person follow-up in situations where participants could not be reached by phone.

Data were collected using a custom-built application installed on Android tablets with an encrypted database and uploaded daily to a Research Electronic Data Capture (REDCap) database hosted at the BC Children's Hospital Research Institute in Vancouver, Canada [20, 21].

Model development

Outcome definition and ascertainment

The primary outcome for the maternal model was readmission resulting from a direct obstetric infection during the six-week post-discharge period. This outcome was defined using established criteria for direct maternal morbidity and infection [22, 23]; we included readmissions due to surgical site infection or puerperal sepsis; we excluded mastitis and readmissions that were not infection-related or that were due to infections unrelated to pregnancy or delivery (e.g., malaria, typhoid), as these have diverging aetiologies, and temporal and clinical risk factors; further details in *Additional File (S0)*.

The newborn model had two primary outcomes: all-cause death and all-cause readmission during the six-week post-discharge period. Our protocol had originally intended for newborn readmission and mortality to be analysed as a composite outcome in anticipation of low event rates for mortality [14]. However, recent investigations suggested that this was not appropriate for our cohort, as newborn readmission may act as both a beneficial outcome, reflecting appropriate health-seeking, or a serious illness and poor health, resulting in inconsistent relationships between the predictor variables and mortality vs. readmission [24].

To build the maternal prediction model, we used data from surviving postpartum women who were discharged from the facility with a successful follow-up. For the newborn model-building cohort, we included only newborns with successful follow-up who were discharged with their mothers after delivery.

Variable selection

Candidate predictors were selected based on a pilot study conducted at Mbarara Regional Referral Hospital (2019–2020) and updated according to expert consensus and recent literature [7, 12, 14]. Variables describing the newborn's outcome in the hospital (e.g., stillbirth) were used only as potential

predictors in the maternal model, since the newborn model is conditional on the newborn being discharged alive. See *Additional File (Table S1)* for a full list of candidate variables used in modelling.

Adjustment and transformation of candidate predictors

All continuous variables were centred and scaled, and categorical variables converted to indicator (i.e., dummy) variables, with low-frequency categories combined where applicable. Additional variables were created via categorization of continuous variables (e.g., mother's age < 18 years vs. ≥18 years, weight of newborn ≤ 2.5 kg vs. >2.5 kg), combining variables due to branching logic (e.g., was mother previously admitted during pregnancy [conditional variable], and if so, how long [dependent variable]), and calculation of relevant clinical variables (e.g., the mean neonatal temperature, SpO₂, and heart rate).

Statistical analysis

The primary sample size was calculated based on the observed combined readmission and mortality rates of 2.7% for mothers and 4.4% for newborns in the retrospective temporal validation dataset [12]. It was estimated that a sample size of 6,700 was sufficient to develop a prediction model with up to 30 candidate predictors with a mean absolute prediction error of no more than 1%, a uniform shrinkage of 90%, a Cox-Snell R² value of at least 0.10, a maximum R² of 0.05, and expected optimism of 0.05 [25].

Continuous variables were summarized as mean (standard deviation [SD]) or median (Q1, Q3) and categorical variables as count (%). Missing data were addressed using single-imputation via K-nearest neighbours [26]. Multiple imputation was considered, but not used as the missing data rate for individual predictors was very low.

Recognizing the challenges of implementing large prediction models in low-income settings, we first developed models using all available predictors, herein referred to as **intermediate** models. The variable importance of the intermediate models was then used to inform the selection of a reduced set of 8–9 variables that were included in the **final** models. Priority was given to clinical variables since socio-economic variables may be indicators for positive care-seeking behaviour and reduced barriers to care rather than poor health [24]. Elastic net regression was used to develop prediction models, with a binary outcome for the maternal model and a multinomial outcome for the newborn model (no outcome vs. readmission vs. death).

We used stratified 10-fold nested cross-validation to optimize the tuning parameters (least absolute shrinkage and selection operator [LASSO] vs. ridge regression mixing parameter α and the strength of the regularization penalty λ) to evaluate the performance of the maternal model. Due to low mortality rates in the newborn cohort, we used a stratified nested bootstrap to evaluate the newborn model, with 100 outer bootstraps for performance evaluation and 50 inner bootstraps to optimize the tuning parameters [27]. For each outer fold or bootstrap, we estimated the area under the receiver operative characteristic curve (AUROC), the specificity, positive predictive value, negative predictive value, and the

harmonic mean of precision and recall (F1 score) using the probability threshold that gave 80% sensitivity, the area under the precision-recall curve (PRAUC), and the Brier score. The mean values across all folds and bootstraps were used to evaluate the internal performance of the model and are reported with the range for the maternal models (evaluated using 10-fold cross-validation) and with the 2.5th and 97.5th percentiles for the newborn models (evaluated using bootstrapping).

Retrospective temporal validation was performed for the final maternal readmission model, using a 2019–2020 dataset collected at one of the study sites [12]. This validation was only performed for the maternal model as the temporal validation dataset for newborns did not include several of the key features that were used in building the newborn model. Temporal validation performance was evaluated with the AUROC and PRAUC.

All analyses were conducted in R version 4.5.2 (R Foundation for Statistical Computing, Vienna, Austria) [28] using the *caret* package (version 7.0–1) for model development and validation [29] and the *DALEX* package (version 2.5.3) for measuring variable importance [30].

Results

Study population

A total of 9,497 women presented to the maternity ward for care, of which 701 (7.4%) did not meet the eligibility criteria or could not be enrolled. From these, 7,131 (75.1%) were selected according to the sampling strategy and enrolled into the study, delivering 7,359 newborns. The clinical and demographic information of this cohort have been described.[31] Among the enrolled participants, 6,996 (98.1%) postpartum women and 6,044 (82.1%) newborns completed the study with six-week follow-up data (Fig. 1).

Among the 6,996 women analysed, the mean $\pm$ SD maternal age was 26.6 ± 6 years, the median (Q1, Q3) parity was 2 (1, 3), and the Global Network Socioeconomic Status Index score was 3 (2, 4) out of 10 (Table 1). A total of 4,477 (64.0%) women had vaginal deliveries with a median (Q1, Q3) length of stay from delivery to discharge of 15.7 hours (9.6, 22.0). In comparison, 2,519 (36%) women had a caesarean section with a longer length of stay of 64.8 hours (53.0, 79.7). Among the 582 (8.3%) women who delivered preterm, the length of stay from delivery to discharge was 23.0 hours (13.0, 63.7).

Table 1

Demographic summary of eligible postpartum women (N = 6,996) and newborns (N = 6,044) with complete six-week follow-up.

Variable	N (%) / Mean (SD) / Median (Q1, Q3)	N Missing (%)
A) Maternal Demographic and Social Variables ^a		
Maternal age (years), mean (SD)	26.6 (6)	0 (0%)
Lives with father of the baby	6329 (90.5%)	3 (0.04%)
Education level		3 (0.04%)
No school	251 (3.6%)	
P4-P7	2218 (31.7%)	
S1-S6	3142 (44.9%)	
Post-secondary	1382 (19.8%)	
Mother or household member had less food than needed	1211 (17.3%)	3 (0.04%)
Had any children who have died	843 (12%)	2 (0.03%)
Socioeconomic Index Score, median (Q1, Q3)	3 (2, 4)	2 (0.03%)
Transport time		1 (0.01%)
≤ 30 minutes	3349 (47.9%)	
30 minutes to 1 hour	2660 (38%)	
> 1 hour	986 (14.1%)	
Transport mode		1 (0.01%)
Motor transport	2136 (30.5%)	
Non-motor transport	4421 (63.2%)	
Ambulance	438 (6.3%)	
Delayed by > 1 hour coming to the hospital		
No delay	6078 (86.9%)	0 (0%)
Terrain	47 (0.7%)	0 (0%)
Transport cost	523 (7.5%)	0 (0%)
General transport delay	258 (3.7%)	0 (0%)
Weather (rain)	20 (0.3%)	0 (0%)

Variable	N (%) / Mean (SD) / Median (Q1, Q3)	N Missing (%)
A) Maternal Demographic and Social Variables ^a		
Other	136 (1.9%)	0 (0%)
B) Pregnancy and Health History Variables ^a		
Parity (previous pregnancies only), median (Q1, Q3)	2 (1, 3)	3 (0.04%)
Pregnancy loss, median (Q1, Q3)	0 (0, 0)	3 (0.04%)
Diagnosed with chronic illness before pregnancy ^b	845 (12.1%)	0 (0%)
Diagnosed with pregnancy-related illness during this pregnancy ^c	4205 (60.1%)	0 (0%)
Antepartum haemorrhage (third trimester)	92 (1.3%)	0 (0%)
Malaria	2149 (30.7%)	0 (0%)
Urinary tract infection	2734 (39.1%)	0 (0%)
Previous caesarean section	1589 (22.7%)	2 (0.03%)
Diagnosed with HIV		0 (0%)
No HIV diagnosis	6554 (93.7%)	
Before pregnancy	377 (5.4%)	
During pregnancy	65 (0.9%)	
Referral for delivery visit	3102 (44.3%)	1 (0.01%)
Admitted to hospital during pregnancy	974 (13.9%)	2 (0.03%)
≥ 4 Antenatal care visits	5168 (73.9%)	2 (0.03%)
C) Maternal Delivery Variables ^a		
Vaginal delivery	4477 (64.0%)	1 (0.01%)
Delivery at < 37 weeks	582 (8.3%)	0 (0%)
Meconium in amniotic fluid	206 (2.9%)	15 (0.21%)
Vaginal exams		19 (0.27%)
< 3 exams	3636 (52%)	
3–5 exams	2576 (36.8%)	
> 5 exams	765 (10.9%)	

Variable	N (%) / Mean (SD) / Median (Q1, Q3)	N Missing (%)
A) Maternal Demographic and Social Variables ^a		
PROM	300 (4.3%)	182 (2.6%)
Single baby delivered	6781 (96.9%)	1 (0.01%)
D) Newborn Delivery Variables ^d		
Male newborn	3057 (50.6%)	120 (1.99%)
Birthweight (kg), median (Q1, Q3)	3.2 (2.8, 3.5)	121 (2%)
Length (cm), median (Q1, Q3)	49.6 (48.5, 50.4)	138 (2.28%)
Apgar at 1 minute, median (Q1, Q3)	9 (8, 9)	122 (2.02%)
Apgar at 5 minutes, median (Q1, Q3)	10 (10, 10)	122 (2.02%)
Resuscitation at birth		134 (2.22%)
Not resuscitated	4183 (69.2%)	
Resuscitated with oxygen	61 (1%)	
Resuscitated without oxygen	1666 (27.6%)	
E) Maternal Discharge Variables ^a		
Admitted to higher level of care for post-delivery complications	552 (7.9%)	2 (0.03%)
Discharge systolic blood pressure, mean (SD)	114.6 (11.8)	38 (0.54%)
Discharge diastolic blood pressure, mean (SD)	75.6 (9.4)	38 (0.54%)
Respiratory rate, mean (SD)	19.4 (3.5)	54 (0.77%)
Temporal artery temperature (°C), mean (SD)	36.3 (0.4)	43 (0.61%)
Best SpO ₂ (%), mean (SD)	98.5 (1.2)	47 (0.67%)
Best heart rate (beats per minute), mean (SD)	94.6 (15.3)	42 (0.6%)
Haematocrit (%), mean (SD)	37.7 (4.7)	55 (0.79%)
Discharge destination, own home	5301 (75.8%)	0 (0%)
Home support systems		0 (0%)
Mother	1538 (22%)	
Mother-in-law	656 (9.4%)	

Variable	N (%) / Mean (SD) / Median (Q1, Q3)	N Missing (%)
A) Maternal Demographic and Social Variables ^a		
Husband/partner/father	5180 (74%)	
Other relative (sister/cousin, etc.)	1591 (22.7%)	
Friend	165 (2.4%)	
No substantial support at home	61 (0.9%)	
Prior history of poor milk production	206 (2.9%)	4 (0.06%)
Symptoms present at discharge ^e	4205 (60.1%)	0 (0%)
Disposition of newborn at discharge ^f		0 (0%)
Discharged alive with mother	6123 (83.2%)	
Died (including stillbirths)	391 (5.3%)	
Admitted to the NICU	749 (10.2%)	
Referred	4 (0.1%)	
Discharged, but admitted after study nurse assessment	53 (0.7%)	
Other or unknown status	39 (0.5%)	
F) Newborn Discharge Variables ^d		
Baby defecated	5403 (89.4%)	36 (0.6%)
Baby made urine	5617 (92.9%)	101 (1.67%)
Latching and suckling well when breast feeding	5985 (99%)	5 (0.08%)
Jaundice	76 (1.3%)	3 (0.05%)
Discharge in their eyes	27 (0.4%)	3 (0.05%)
Neonatal temporal artery temperature (°C), mean (SD)	36.8 (0.5)	50 (0.83%)
Normal, 36.5 to 37.5°C	3655 (60.5%)	
Hypothermic, < 36.5°C	1883 (31.2%)	
Fever, > 37.5°C	456 (7.5%)	
SpO ₂ (%), mean (SD)	94.2 (3.2)	52 (0.86%)

Variable	N (%) / Mean (SD) / Median (Q1, Q3)	N Missing (%)
A) Maternal Demographic and Social Variables ^a		
Hypoxia, SpO₂ < 90%	514 (8.5%)	52 (0.86%)
Neonatal best heart rate (beats per minute), mean (SD)	134.6 (15.6)	52 (0.86%)
Neonatal respiratory rate (breaths per minute), mean (SD)	48.1 (8.1)	55 (0.91%)
Newborn discharged on antibiotics	46 (0.8%)	19 (0.31%)
^a Denominator is postpartum women discharged alive with follow up		
^b Includes diabetes, chronic hypertension, other heart disease, kidney disease, HIV, sickle cell, hepatitis B/C, tuberculosis, chronic mental illness, or other chronic health conditions		
^c Includes gestational diabetes, pre-eclampsia, eclampsia, gestational hypertension, antepartum haemorrhage/vaginal bleeding, PROM, preterm labour, malaria, HIV, urinary tract infection, tuberculosis, anemia, or other infections		
^d Denominator is newborns discharged alive with follow up		
^e Includes headache, visual changes, chest pain, shortness of breath, nausea with vomiting, abdominal pain on the right side, foul smelling vaginal discharge, stiff neck, or cough.		
^f Denominator is total births		
Abbreviations: HIV = human immunodeficiency virus; NICU = neonatal intensive care unit; PROM = premature rupture of membrane; Q1 = first quartile; Q3 = third quartile; SD = standard deviation; SpO ₂ = oxygen saturation		

Table 1. Demographic summary of eligible postpartum women (N = 6,996) and newborns (N = 6,044) with complete six-week follow-up. *[Table at end of document]*

Outcomes

We observed 224 (3.2%) maternal readmissions, including 126/224 (56.3%) due to obstetric infections (*Additional File, Figure S1*). Other maternal readmission causes included malaria (28.7%), other infections (9.1%), and heavy bleeding (8.3%). There were no maternal deaths during the six-week follow-up period. We observed 228 (3.8%) newborn readmissions and 35 (0.6%) newborn deaths within six weeks post-discharge (*Additional File, Figure S2*).

Prediction models

Maternal prediction model

The mean (range) AUROC over the 10-fold nested cross-validation for the *intermediate* maternal readmission model was 0.786 (0.738 to 0.851) and the PRAUC was 0.075 (0.048 to 0.148) (*Additional File, Table S2*). Based on the variable importance across each of the 10 folds, with prioritization given to clinical variables (*Additional File, Table S3*), the variables selected for the final maternal model were: delivery mode, discharge maternal heart rate, urinary tract infection diagnosis during pregnancy, need for resuscitation of the newborn at birth, discharge against medical advice, malaria infection during pregnancy, HIV+ diagnosis during pregnancy, and category of gestation period (< 37 weeks [preterm], 37–40 weeks [term], or > 40 weeks [late-term]) if known (*Additional File, Table S4* for coefficients).

The *final* maternal model had a mean (range) cross-validated AUROC of 0.784 (0.738 to 0.824) and PRAUC of 0.099 (0.053 to 0.263) (Fig. 2; *Additional File, Table S5* and **Figure S3** for the performance metrics fit on the whole dataset). At a sensitivity threshold of 80%, the model had a mean specificity of 0.697 and Brier score of 0.017 (Table 2).

Table 2

Summary of performance of the final set of models with reduced number of variables using the probability threshold that gave 80% sensitivity.

Average Cross-Validated / Bootstrapped Performance	Maternal Readmission due to Obstetric Infection	Newborn Readmission	Newborn Mortality
Specificity	0.697	0.532	0.539
Area under the receiver operating characteristic curve (AUROC)	0.784	0.712	0.731
Positive predictive value (PPV)	0.048	0.063	0.011
Negative predictive value (NPV)	0.994	0.985	0.998
Area under the precision-recall curve (PRAUC)	0.099	0.080	0.029
F1 score	0.090	0.117	0.022
Brier score	0.017	0.036	0.006

Table 2. Summary of performance of the final set of models with reduced number of variables using the probability threshold that gave 80% sensitivity. [Table at end of document]

Newborn prediction models

For the readmission outcome, the mean (2.5th to 97.5th percentile) AUROC over the bootstrapped samples for the *intermediate* newborn model was 0.689 (0.654 to 0.723) and the PRAUC was 0.076 (0.061 to 0.096); for the mortality outcome, the AUROC was 0.693 (0.587 to 0.786) and the PRAUC was 0.022 (0.007 to 0.072) (*Additional File, Table S6*). Based on the variable importance across each of the 100 outer fold bootstraps, with prioritization given to clinical variables and balancing both readmission and mortality outcomes *Additional File, (Table S7)*, the variables selected for the *final* newborn model

were: delivery mode, antibiotic use during admission, number of vaginal exams, travel time to hospital, at least one condition diagnosed during pregnancy (Table 1 footnote for full list of conditions evaluated), weight of the newborn, maternal HIV diagnosis during pregnancy, history of poor milk production (not applicable if the current pregnancy is their first baby), and antepartum haemorrhage/vaginal bleeding (*Additional File, Table S8* for coefficients).

The *final* newborn model had a mean (2.5th to 97.5th percentile) bootstrapped AUROC of 0.712 (0.672 to 0.747) and PRAUC of 0.080 (0.065 to 0.109) for the readmission outcome, and an AUROC of 0.731 (0.600 to 0.854) and PRAUC of 0.029 (0.010 to 0.071) for the mortality outcome (Fig. 3; *Additional File, Table S6, Figure S4, Figure S5* for the performance metrics fit on the whole dataset). At a sensitivity threshold of 80%, the model had a mean specificity of 0.532 and Brier score of 0.036 for the readmission outcome, and mean specificity 0.539 and Brier score 0.006 for the mortality outcome (Table 2).

Temporal validation (maternal model)

The retrospective temporal validation dataset consisted of 2,561 eligible women that had data on the required predictors for the *final* maternal readmission model, with a total of 51 (1.99%) readmissions due to obstetric infection. The distribution of the predictor variables between the temporal and development datasets are reported in *Supporting Information (Additional File, Figure S6)*. The AUROC (95% CI) was 0.759 (0.704 to 0.813) in this cohort and the PRAUC was 0.048 (Fig. 4).

Discussion

In this prospective observational study conducted at two regional referral hospitals in Uganda, we developed and internally validated parsimonious multivariable prediction models to identify high-risk postpartum women and newborns prior to discharge following facility-based delivery. These findings underscore the feasibility of integrating simple, routinely-collected clinical data into risk-stratified approaches to enhance postnatal care and avert preventable morbidity and mortality in low-resource settings.

Despite global efforts to reduce maternal and neonatal deaths, significant gaps persist in adherence to postnatal care, particularly in sub-Saharan Africa where up to one-third of maternal deaths and half of neonatal deaths occur in the postnatal period [4]. The WHO recommends at least three postnatal care contacts within the first six weeks postpartum [8], yet utilization remains alarmingly low. Many mother-infant dyads receive no follow-up care at all due to factors such as overburdened health systems, early hospital discharges (often within 24 hours), geographic barriers, socioeconomic constraints, and poor quality of fragmented services [8, 9, 32]. Traditional blanket approaches to postnatal care, which apply uniform recommendations to all dyads, have achieved limited success in improving coverage and outcomes, as evidenced by stalled progress in mortality reduction despite increased facility-based deliveries [4]. In contrast, risk-differentiated strategies offer a more targeted and efficient alternative by identifying vulnerable dyads at discharge and enabling personalized interventions, such as intensified counselling, prioritized home visits, or referral to community health workers for those at highest risk of

adverse outcomes [33, 34]. This patient-centred paradigm is increasingly advocated by global experts [35], as it not only optimizes scarce resources in low-resource environments but also has the potential to boost overall postnatal care adherence and effectiveness, ultimately preventing progression to severe illness and contributing to equitable improvements in maternal and newborn survival. Using risk models directly addresses this need by providing a practical and interpretable risk stratification tool at the point of discharge. By incorporating shared maternal-newborn predictors they enable dyad-focused decision-making that aligns with the continuum of care framework and can triage high-risk cases for more intense follow-up without overburdening healthcare providers.

Through internal validation using 10-fold cross-validation for the maternal model and bootstrapping for the newborn models, our prediction algorithms demonstrated robust discriminative ability and calibration. Validation of the maternal model using an independent cohort of postpartum women from one of the same hospitals at a different time period confirmed comparable predictive accuracy, though this represents a retrospective temporal validation rather than external validation. These models gain relevance in the context of the increasingly digitized health system in low- and middle-income country settings where basic reminder-based digital innovations (e.g., SMS reminders) are already improving maternal and newborn care [36]. Risk algorithms are poised to elevate these platforms by adding augmented clinical decision support that leverages routine data to deliver a more personalized approach to care.

Limitations

This study has several limitations that should be considered when interpreting the results. First, the maternal prediction model focused exclusively on readmissions due to direct obstetric infection (such as surgical site infections and puerperal sepsis), which was the most common condition reported in our cohort and also the one most closely related to delivery. However, this approach did not account for other reasons for readmission, including non-obstetric conditions like malaria, psychiatric conditions, or injuries, which may be less directly tied to the delivery process. Consequently, postpartum women classified as low-risk for obstetric infections might still be vulnerable to these alternative adverse events, potentially leading to undetected risks and missed opportunities for broader preventative care. Despite this limitation, identifying those at elevated risk for obstetric infections can still inform targeted counselling, follow-up strategies, and early diagnosis to mitigate these specific, preventable complications.

Second, the study was conducted at only two regional referral hospitals in Uganda, limiting the diversity of settings and populations represented and necessitating further external validation across additional sites, including primary health facilities, rural areas, and other low- and middle-income countries to assess generalizability. Although the maternal prediction model was temporally validated, this may not reflect future performance as the validation data were collected a few years prior to the development data.

Finally, the relatively low event rates for the primary outcomes, particularly newborn readmissions and mortality, constrained the statistical power and robustness of the models. The newborn algorithms were especially affected due to sparse outcomes and the absence of an independent validation cohort, which could introduce overfitting and reduce confidence in their predictive performance in varied contexts.

Conclusions

This study demonstrates the feasibility of developing parsimonious, integrated prediction models using routinely-collected clinical data to identify high-risk postpartum women and newborns at hospital discharge in Uganda, thereby enabling targeted interventions to prevent post-discharge readmissions and mortality. By focusing on key predictors shared across maternal and newborn domains, these tools offer a practical, risk-differentiated approach to postnatal care that addresses critical gaps in adherence and coverage within overburdened health systems. When embedded within digital platforms they hold strong potential to advance AI-assisted precision post-natal care across Africa. Ultimately, implementing such models could enhance patient-centred care, optimize resource allocation, and contribute to reducing preventable maternal and neonatal deaths in low-resource settings. Future work will focus on model validation and real-world trials to evaluate integrated, risk-based, post-discharge care pathways for mother-newborn dyads following delivery.

Abbreviations

AUROC	Area under the receiver operating characteristic curve
LASSO	Least absolute shrinkage and selection operator
NPV	Negative predictive value
PRAUC	Area under the precision-recall curve
PPV	Positive predictive value
REDCap	Research Electronic Data Capture
SD	Standard deviation
TRIPOD	Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis
WHO	World Health Organization

Declarations

Ethics approval and consent to participate

This research was conducted in accordance with the Declaration of Helsinki. Ethics approval was obtained from the Makerere University School of Public Health Institutional Review Board (ref. SPH-2021-177, approved 25-Feb-2022), the Uganda National Council of Science and Technology (HS2174ES, 07-Apr-2022), and the University of British Columbia – Children’s and Women’s Health Centre of BC Research Ethics Board (H21-03709, 14-Apr-2022).

Consent for publication

Not applicable.

Availability of data and materials

Study materials are available on request to the corresponding author (Matthew O. Wiens, matthew.wiens@bcchr.ca) or to the Institute for Global Health at BC Children’s and Women’s Hospital (globalhealth@cw.bc.ca). The study protocol has been published at Front Epidemiol. 2023;3:1233323 (<https://doi.org/10.3389/fepid.2023.1233323>) and other study materials, including the protocol, consent form, data collection tools, de-identified participant data, data dictionary, and the analysis code, are available from the Smart Discharges for Mom & Baby 2.0 Borealis dataverse (<https://doi.org/10.5683/SP3/EIUHJF>). Owing to the sensitive nature of clinical data, access to the de-identified data is granted on a case-by-case basis and will require the signing of a data sharing agreement.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Conceptualization – MOW, NK-M, LMB, MV, AC-D, BAP, JMA, NK, PML, JN; **Funding Acquisition** – MOW, JN, JNB, SKN; **Methodology** – MOW, YP, VN, JNB; **Project administration** – CK, DM, HAT, JT, AT, AN; **Software** – DD; **Supervision** – MOW, JN; **Formal analysis** – VN, JNB; **Writing Original Draft** – YP, MOW, VN, NK, NW, JN; **Writing-Review and Editing** – all authors.

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Figures

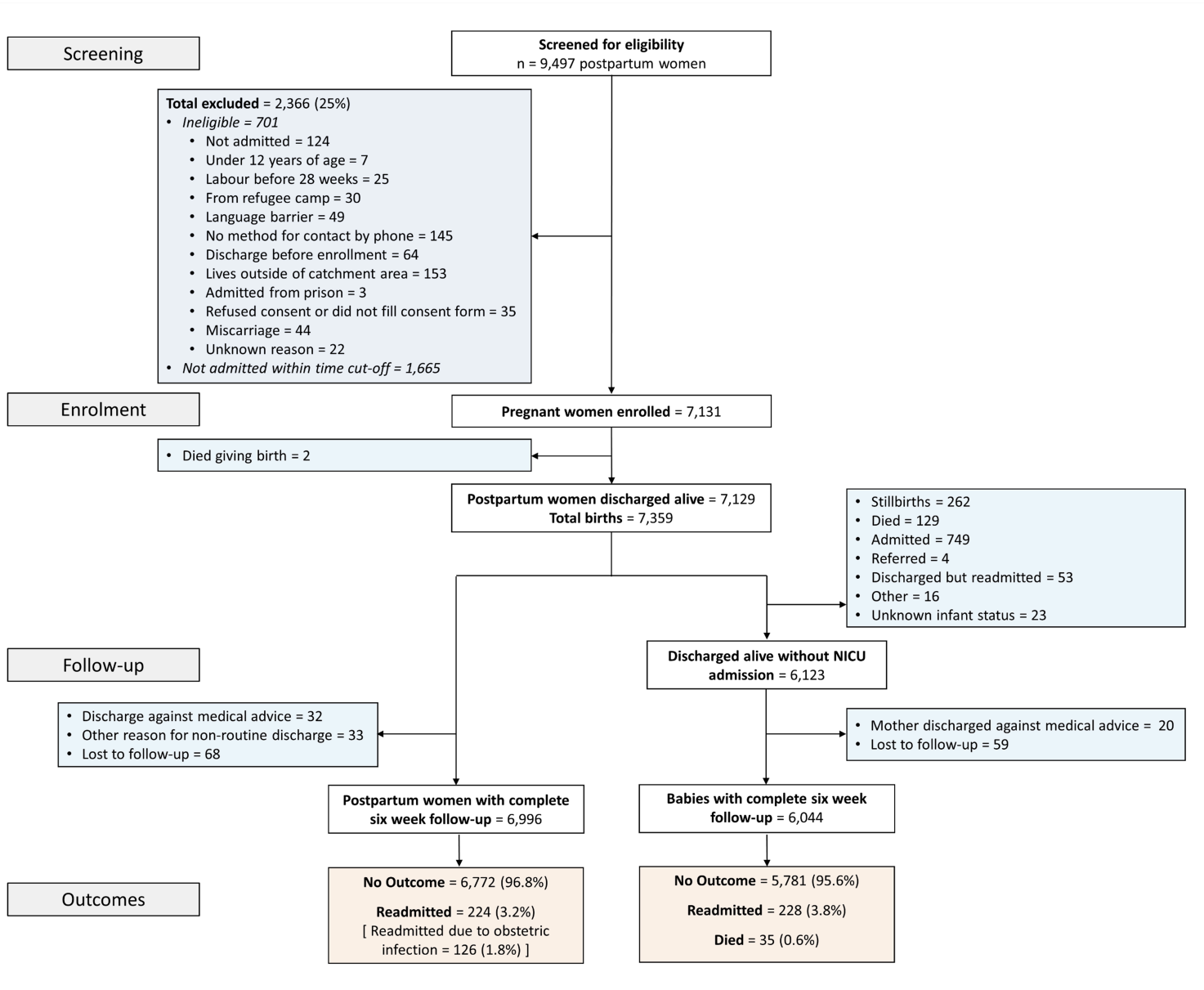


Figure 1

Study enrolment flow diagram

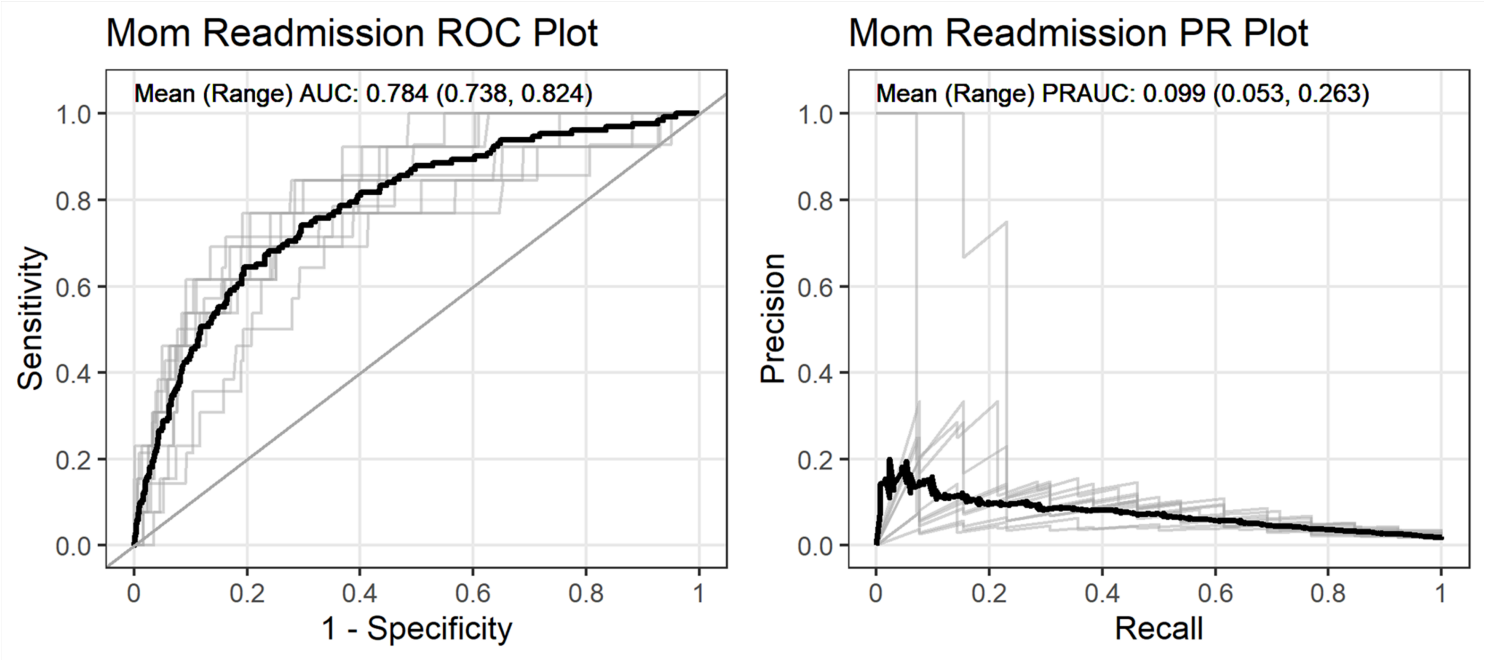


Figure 2

Performance of model for 6-week post-discharge readmission due to obstetric infections in postpartum women: left, 10-fold cross-validated receiver operating characteristic (ROC) curve; right, 10-fold cross-validated precision-recall (PR) curve. Grey lines represent the curves of each individual fold while the black line is the averaged curve over the folds; plots show mean (range) for area under the curve (AUC) and area under the PR curve.

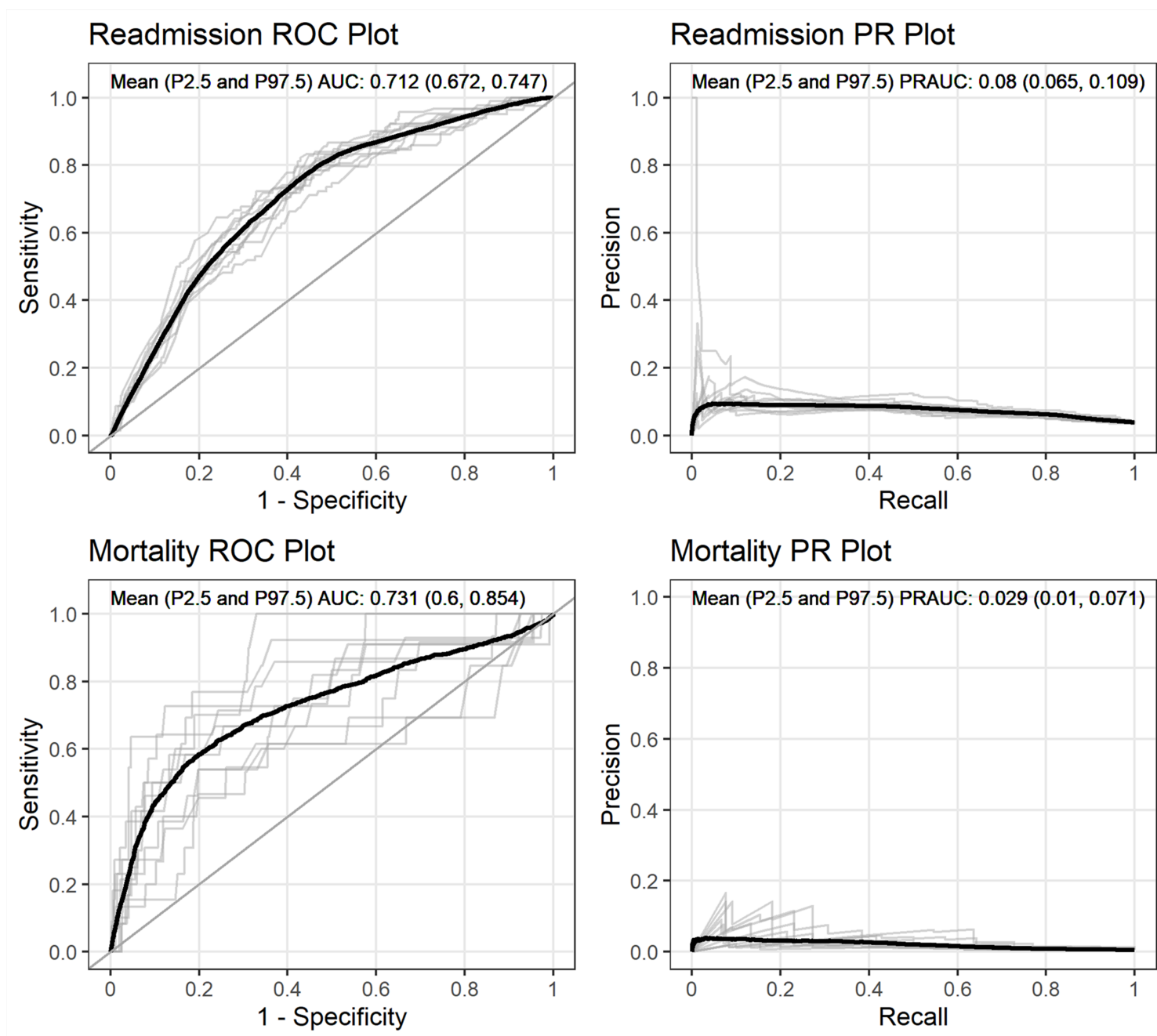


Figure 3

Performance of models for 6-week post-discharge readmission and mortality in newborns: top left, bootstrapped receiver operating characteristic curve (ROC) for readmission; top right, bootstrapped precision-recall (PR) curve for readmission; bottom left, bootstrapped ROC for mortality; bottom right bootstrapped PR curve for mortality. A random sample of 10 bootstraps were selected for display represented by the grey lines, while the black line represents the averaged curve over all bootstraps; plots show the mean with 2.5th and 97.5th percentiles for area under the curve (AUC) and area under the precision recall curve (PRAUC).

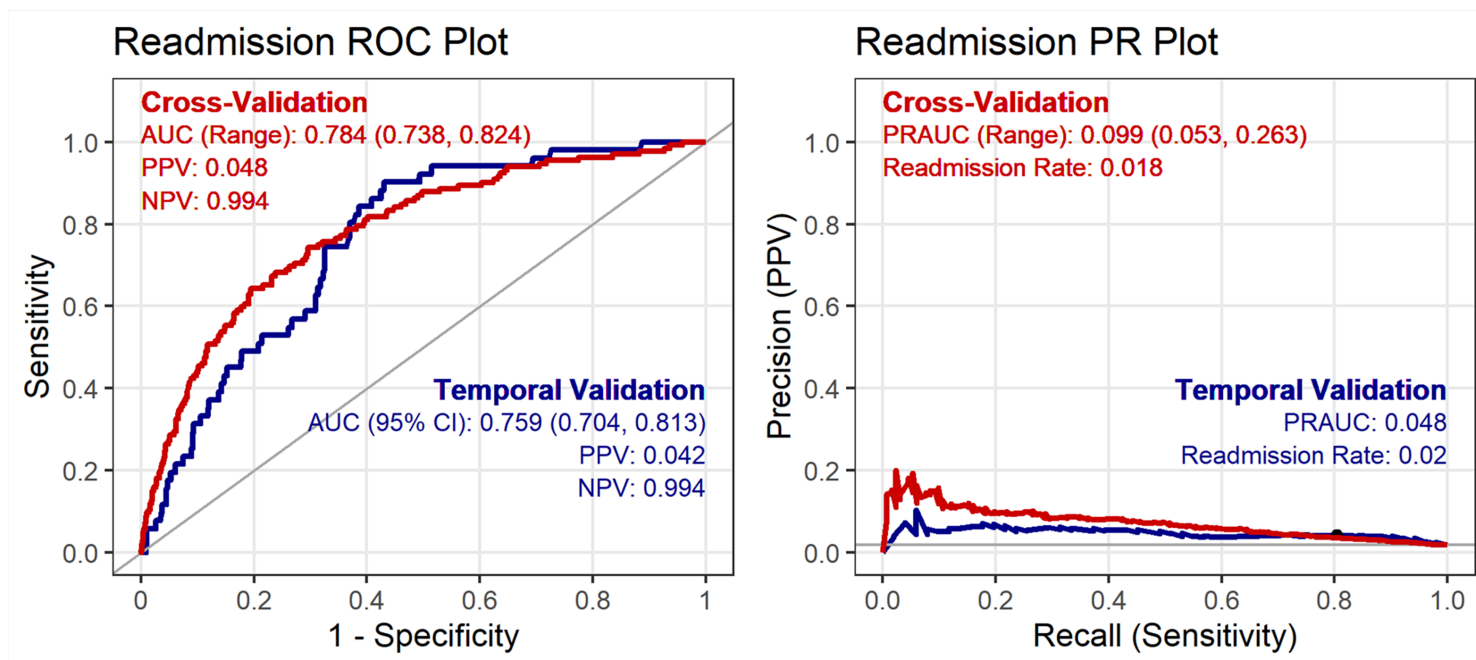


Figure 4

Temporal validation of readmission due to obstetric infections in postpartum women. Temporal validation used a previously collected cohort of postpartum women from Mbarara Regional Referral Hospital between April 2019 and March 2020 with complete data on the required predictors (n = 2,561). Left plot displays receiver operating characteristic (ROC) curve and right plot displays precision-recall curve (PR) curve for both cross-validation set (red) and temporal validation set (blue), with statistics given for area under the curve (AUC), positive predictive value (PPV), negative predictive value (NPV), and area under the precision-recall curve (PRAUC).

Supplementary Files

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