Modelling Uncertainty in the Risk of Intensive Care Unit Readmission I: Data Extraction and Modelling

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1 Introduction

Unplanned readmission to an intensive care unit (ICU) during the same hospital admission is a relatively common event, affecting between 1.3% and 13.7% of all ICU patients (Elliott *et al.*, 2014). Not only do readmissions to ICU represent a substantial strain on hospital resources, but also readmitted patients tend to have worse prognoses, increased length of ICU stay, and greater risks of morbidity and mortality (Markazi-Moghaddam *et al.*, 2020). Despite this, the precise factors contributing to ICU readmission risk remain unclear. Several models for risk prediction have been developed which tend to use very different variable sets, and no model has been widely externally validated. Accordingly, this project does not aim to develop or validate a novel model for ICU readmission, but to tackle an issue that affects the implementation and interpretation of all risk prediction models - how to deal with missing or incomplete data in the predictor variables (Steyerberg, 2008).

1.1 Scope and Aims of Phase I

This document provides a written overview of the first phase of the project. The aims of this phase were twofold:

1. To extract a dataset from the MIMIC-III database of surgical ICU patients, consisting of a clearly defined outcome measure (ICU readmission), and a range of predictors.
2. To compare the performance of a range of published models for the prediction of ICU readmission risk and identify the best model to take forward. This will form the prediction model at the core of a system for quantifying uncertainty and dealing with missing data.

1.2 Readmission prediction models

This report will investigate five models for ICU risk prediction. I will give a brief overview of all five here. Further details on their predictors, statistical approaches and validations are given in Section 2.4. The first 'model' is the APACHE-II scoring system devised by Knaus *et al.* (1985). 'Model' is used in inverted commas, as this model was not designed for predicting ICU readmission risk, but instead is a general system to score the severity of a patient's condition using 12 routine physiological variables, age, and medical history. Increasing APACHE-II score has been shown to correlate well with increasing risk of in-hospital mortality for ICU patients. Frost *et al.* (2010) used a logistic regression model to develop a nomogram for predicting ICU readmission risk based on 14,952 patients in a single hospital in Australia. Unfortunately, as they do not present the coefficients from their model directly, only in the form of the nomogram, several of these coefficients can only be approximated, which may hinder external validation of the model.

Fialho *et al.* (2012) developed a model using data mining and fuzzy logic approaches with the MIMIC-II database, precursor to the MIMIC-III used here. Their model focusses on the values of physiological variables during the 24 h before discharge. The fuzzy rules provide a significant barrier to external validation, however. Martin *et al.* (2018) also developed their model into a nomogram, but unlike Frost, also provided coefficients and a precise formula to generate risk estimates. Their model used 3,109 patients in a single academic centre, and narrowed an initial 179 candidate variables down to 7 variables, covering demographics, physiological measurements and medical history. Finally, Hammer *et al.* (2020) developed the 'RISC' score (Readmission to the Intensive care unit in Surgical Critical care patients, henceforth simply called 'Hammer' for consistency with other models) using logistic regression. Their model aimed to include a number of modifiable variables to aid its use as a clinical tool.

2 Methods

2.1 Data Source

2.2 Inclusion criteria

2.3 Outcome measure

2.4 Candidate models

2.5 Model comparisons

2.6 Recalibration

2.7 Novel model

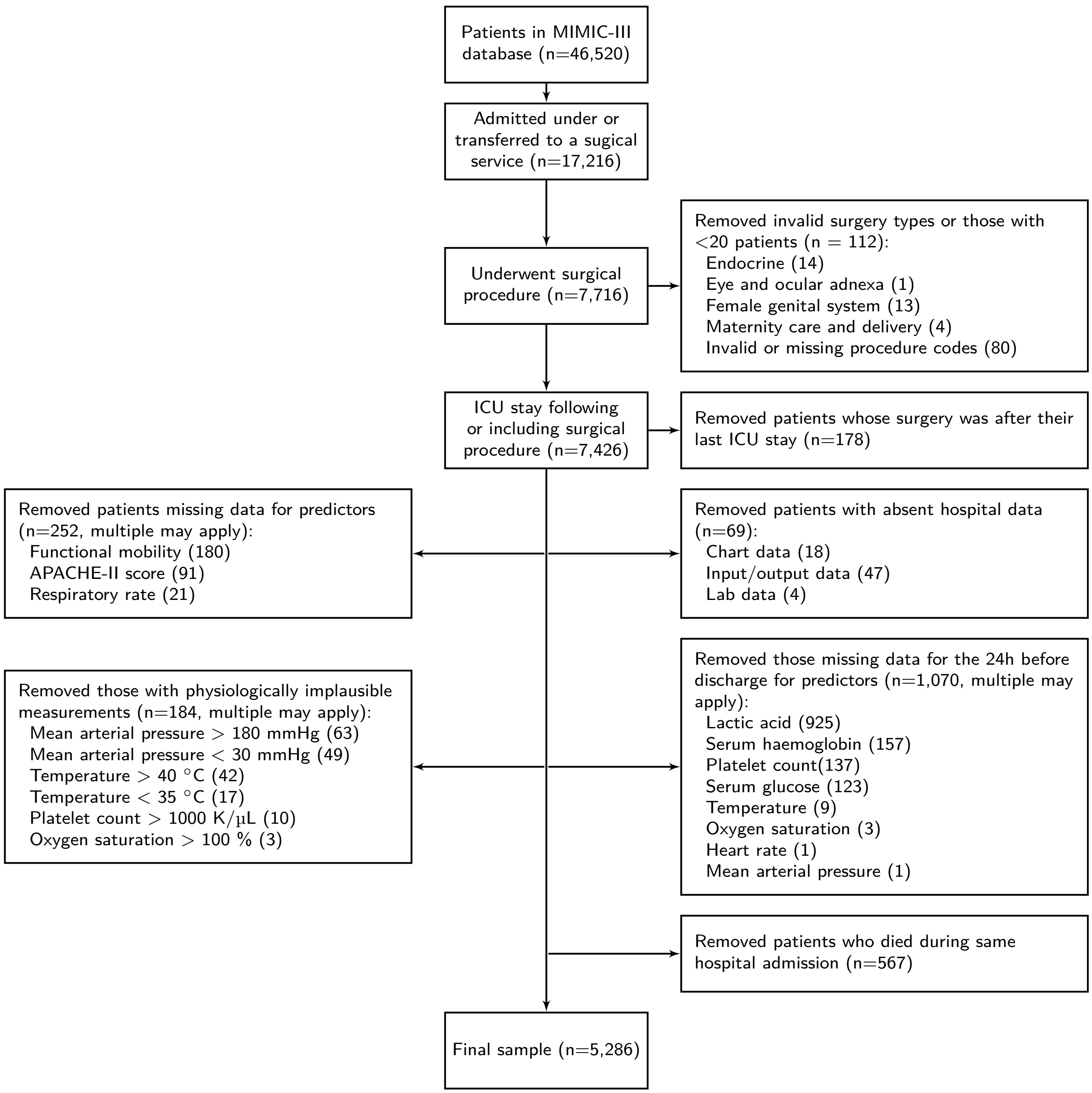
3 Results

3.1 Descriptive statistics

Table 1

Variable	No Readmission	Readmitted to ICU
N	4944 (93.5%)	342 (6.5%)
Sex		
Male	3121 (63.1%)	207 (60.5%)
Female	1823 (36.9%)	135 (39.5%)
General surgery	1167 (23.6%)	136 (39.8%)
Cardiac surgery	2423 (49%)	93 (27.2%)
Hyperglycaemia	475 (9.6%)	35 (10.2%)
Severe anaemia	35 (0.7%)	1 (0.3%)
APACHE-II > 20	2397 (48.5%)	164 (48%)
Positive fluid		
balance >5L	768 (15.5%)	95 (27.8%)
No ambulation	3882 (78.5%)	298 (87.1%)
ICU stay >5 days	1244 (25.2%)	124 (36.3%)

Figure 1: Flowchart of participants' progress through the phases of the trial



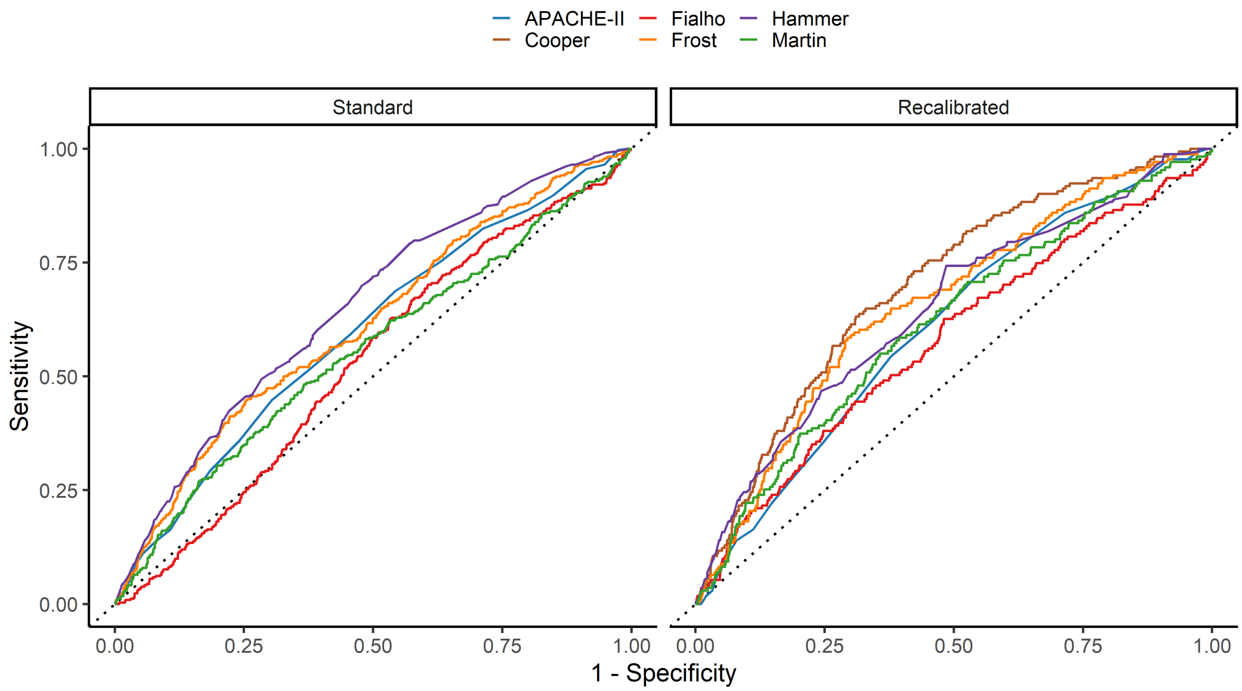


Figure 2

3.2 Discrimination

3.3 Calibration

3.4 Variables retained in novel model

4 Discussion

4.1 Model performance

4.2 Next steps

References

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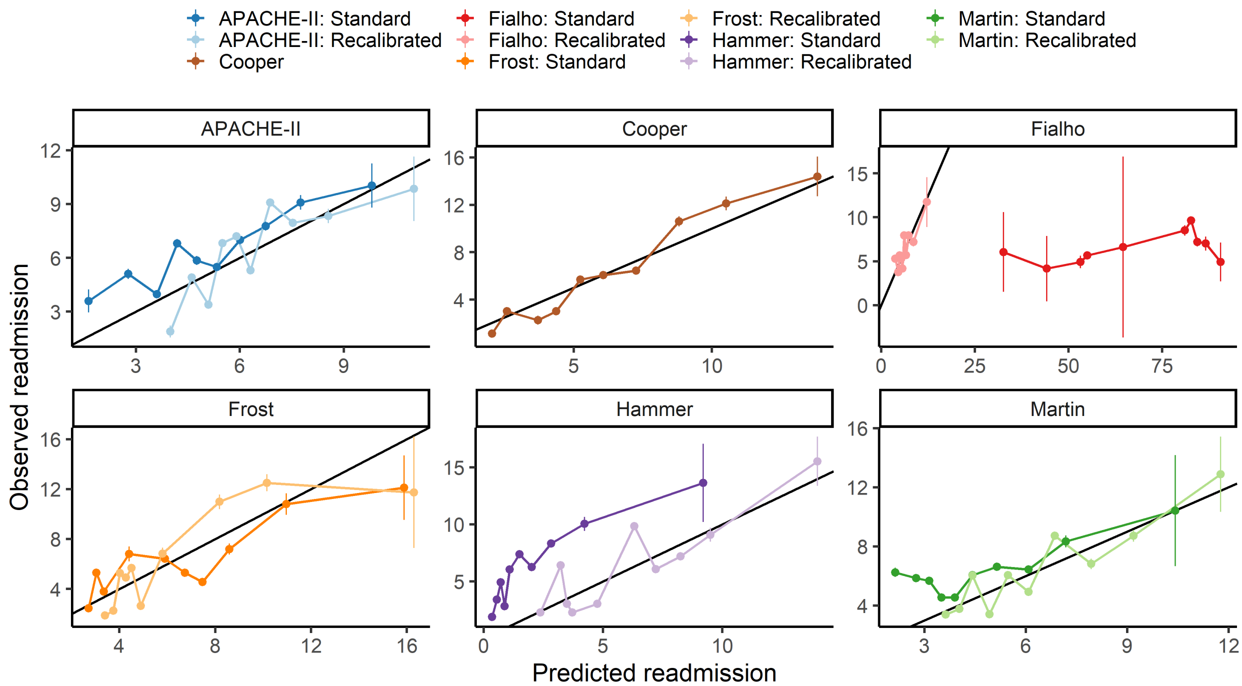

Figure 3

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Table 2

Variable	No Readmission	Readmitted to ICU
N	4944 (93.5%)	342 (6.5%)
Age	64.2 ± 14.5	63.5 ± 14.5
Sex		
Male	3121 (63.1%)	207 (60.5%)
Female	1823 (36.9%)	135 (39.5%)
Elective admission	1980 (40%)	104 (30.4%)
Admission source		
Operating theatre	2246 (45.4%)	120 (35.1%)
Emergency room	769 (15.6%)	91 (26.6%)
Other hospital	976 (19.7%)	69 (20.2%)
Ward	953 (19.3%)	62 (18.1%)
APACHE-II score	10.4 ± 4.70	12.0 ± 4.87
ICU stay >7 days	864 (17.5%)	98 (28.7%)
Discharged after hours	2874 (58.1%)	223 (65.2%)
Acute renal failure	788 (15.9%)	125 (36.5%)

Table 3

Variable	No Readmission	Readmitted to ICU
N	4944 (93.5%)	342 (6.5%)
Age	64.2 ± 14.5	63.5 ± 14.5
Respiratory rate	18.4 ± 3.89	19.2 ± 3.91
Blood urea nitrogen	22.8 ± 16.3	27.8 ± 20.9
Serum glucose	129 ± 29.0	126 ± 29.2
Serum chloride	105 ± 4.4	105 ± 4.7
Hx atrial fibrillation	1565 (31.7%)	129 (37.7%)
Hx renal insufficiency	261 (5.3%)	31 (9.1%)

Table 4

Variable	No Readmission	Readmitted to ICU
N	4944 (93.5%)	342 (6.5%)
Heart rate	83.9 ± 12.2	84.8 ± 13.4
Temperature	36.8 ± 0.51	36.8 ± 0.55
Oxygen saturation	96.8 ± 1.64	96.8 ± 1.69
Mean arterial pressure	81.2 ± 14.6	85.0 ± 16.0
Platelets	221 ± 131	241 ± 154
Lactic acid	1.68 ± 0.82	1.58 ± 0.82

Table 5

Model	AUC	χ^2	AUC$_{rc}$	χ^2_{rc}
APACHE-II	0.60	296.8	0.61	**6.29**
Cooper	—	—	0.70	**6.17**
Fialho	0.53	19010.1	0.58	**6.70**
Frost	0.61	402.3	0.66	17.48
Hammer	0.65	130	0.65	**7.57**
Martin	0.56	273.7	0.61	**6.06**