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Predicting all-cause unplanned readmission within 30 days of discharge using electronic medical record data: A multi-centre study

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Abstract

Objective: To develop a predictive model for identifying patients at high risk of all-cause unplanned readmission within 30 days after discharge, using administrative data available before discharge.

Materials and methods: Hospital administrative data of all adult admissions in three tertiary metropolitan hospitals in Australia between July 01, 2015, and July 31, 2016, were extracted. Predictive performance of four mixed-effect multivariable logistic regression models was compared and validated using a split-sample design. Diagnostic details (Charlson Comorbidity Index CCI, components of CCI, and primary diagnosis categorised into International Classification of Diseases chapters) were added gradually in the clinically simplified model with socio-demographic, index admission, and prior hospital utilisation variables.

Results: Of the total 99 470 patients admitted, 5796 (5.8%) were re-admitted through the emergency department of three hospitals within 30 days after discharge. The clinically simplified model was as discriminative (C-statistic 0.694, 95% CI [0.681-0.706]) as other models and showed excellent calibration. Models with diagnostic details did not exhibit any substantial improvement in predicting 30-days unplanned readmission.

Conclusion: We propose a 10-item predictive model to flag high-risk patients in a diverse population before discharge using readily available hospital administrative data which can easily be integrated into the hospital information system.

1 | INTRODUCTION

Unplanned hospital readmissions are widely reported across the world and highly associated with adverse patient outcomes. A systematic review estimated around a quarter (range 5.0%-78.9%) of readmissions to medical, surgical, and geriatric services as potentially avoidable.[1] Readmissions in Australia contribute to more than 600 000 potentially avoidable hospitalisations each year.[2] In the United States, potentially avoidable 30-days readmissions cost Medicare more than US$17 billion annually.[3] Several attempts have been made to quantify the risk of unplanned readmission in specific patient populations including disease-specific, age-specific, and intensive care unit (ICU) patients.[4-6] Consideration of non-specific care deficits including poor care transitions and comorbidity that contribute to readmissions has often been ignored.

Predictive models using data from the entire adult population such as the LACE+ (length of stay, acuity of admission, comorbidity, ED visits in the 6 months before admission, age, sex, teaching status of discharge hospital, number of urgent and elective admissions in previous year, case-mix group score, and number of days on the alternative level of care status) index[7] developed in Canada and the HOSPITAL (haemoglobin at discharge, discharge from an oncology service, sodium level at discharge, procedure during index admission, type of index admission, frequency of admission in past 12 months, and length of stay) score[8] in the United States performed fairly (C-statistic 0.77 and 0.72, respectively) in discriminating between high and low-risk patients when validated internally and externally. However, the LACE+ index was validated only internally and was reported to be suitable for the local population. Besides, case-mix group score and alternative level of care information are not available in many hospital databases. The HOSPITAL score, because of the requirement of variables reflecting discharge health conditions, does not allow the opportunity to intervene during the hospital stay. In addition, clinical and laboratory variables are not always available in hospital administrative databases which limit the application of this score to other health systems.

The aim of this study was to develop a predictive model of all-cause unplanned readmission within 30 days of discharge in a multi-centre patient population, using administrative data available before discharge.

What's known

- Risk assessment of unplanned readmission in general medicine patients remains a major challenge because of the unavailability of detail clinical and pathological data required by the available risk prediction tools.

What's new

- Diagnostic details have not been shown to predict unplanned readmission any better than the simplified model with variables reflecting socio-demographic status, index admission and prior hospital utilisation.
- The simplified model constructed using large multicentre data is generalisable and easy to use in the Australian clinical setting.

2 | MATERIALS AND METHODS

2.1 | Retrospective cohort data

We sourced de-identified data from three metropolitan tertiary hospitals in Melbourne, Victoria, Australia, including Melbourne Health (MH), Northern Health (NH) and Austin Health (AH). All adult admissions between July 01, 2015, and July 31, 2016, were extracted from the administrative database of MH and NH and from the electronic medical record of AH. Planned admissions to sub-acute units (transition care programme, rehabilitation, and geriatric evaluation and management) following discharge from acute care on the same day, psychiatric admissions, in-hospital deaths, and dialysis and oncology follow-up visits were excluded from the analyses (Figure 1) to avoid the overestimation of unplanned readmission rate. Patients who had multiple admissions, the first admission during our study period was considered as index admission and only the first readmission within 30 days after index discharge was counted.

2.2 | Study variables

Factors representing the socio-demographic characteristics of patients (age, sex, country of birth other than Australia, interpreter required flag, preferred language, indigenous status); lifestyle risk factor (history of alcohol use); and social support (marital status and family doctor) were considered as candidate variables which were identified through a systematic literature review of potential risk factors of unplanned readmission. A variable, "not fluent in English," was generated combining interpreter required flag and preferred language variables to indicate patient's fluency in English. Patients who required an interpreter and preferred a language other than English were classified as "not fluent in English." Variables characterising index hospitalisation (unplanned admission, season of hospital admission, length of stay, primary and secondary diagnoses, hours spent in ICU, separation ward different from admission ward, and day of discharge) were also included. The Charlson Comorbidity Index (CCI) for the index hospitalisation was calculated using the primary and secondary International Classification

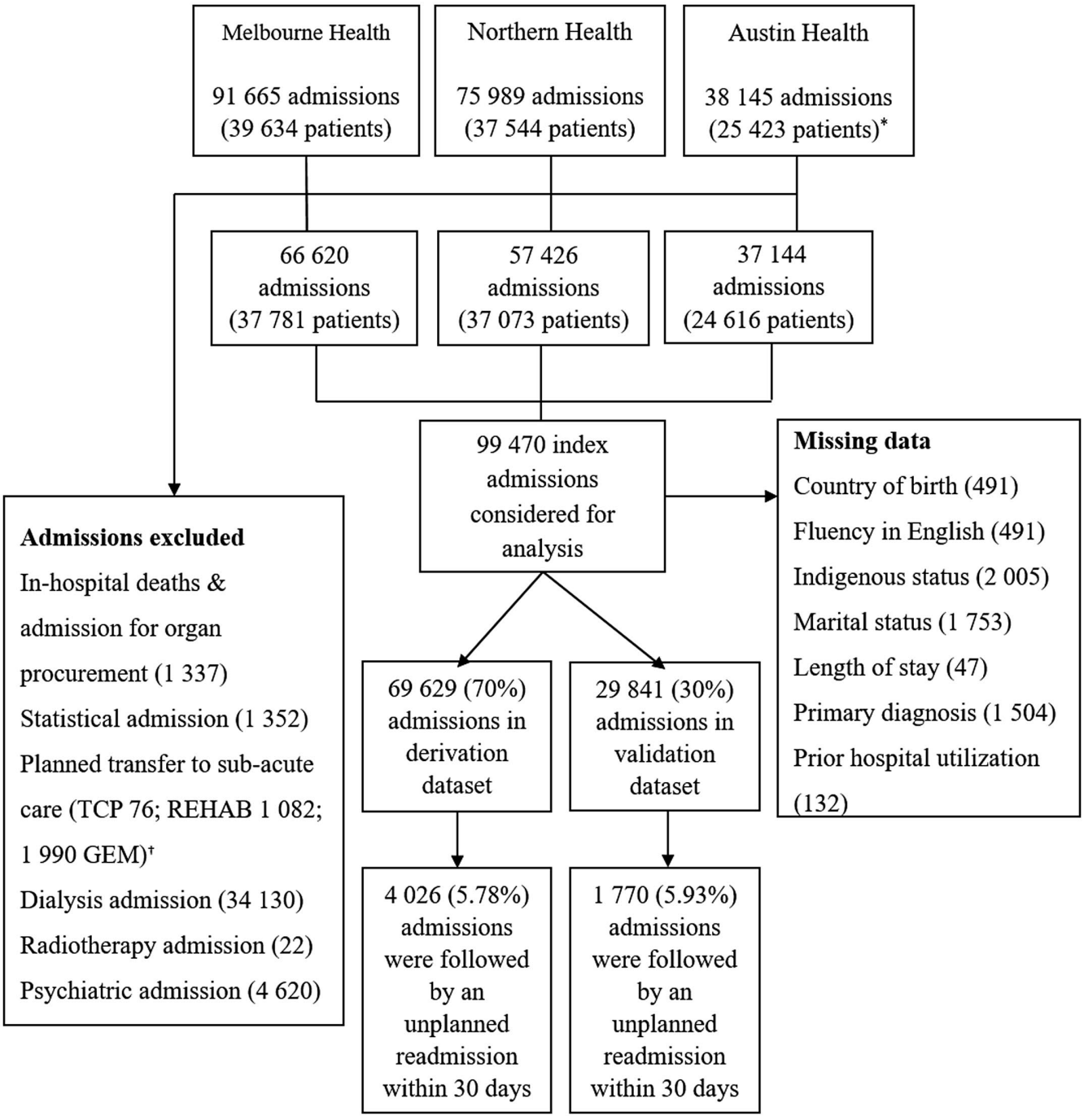

FIGURE 1 Flow diagram showing number of included, excluded and readmitted patients along with missing data. *In Austin Health, of the 64 734 adult discharges between January 01, 2016 and December 31, 2016, 38 145 admissions took place during the study period comprising of 25 423 patients. †TCP: Transition Care Programme; REHAB: Rehabilitation; GEM: Geriatric Evaluation and Management

of Diseases, Tenth Revision, Australian Modification (ICD-10-AM) diagnosis codes listed for each patient following Quan et al.[9] The primary diagnosis of each patient was also classified according to the 21 chapters of ICD-10-AM.[10] Dummy variables were generated for each day of discharge and admission season. Another dummy variable was generated to flag if the separation ward was different from the admission ward for the index discharge. Discharges on public holidays were identified and represented using a dummy variable. The number of inpatient admissions and ED presentations in the previous 12 months was categorised and included in the analyses to reflect the patients' prior hospital utilisation.

2.3 | Model development

The outcome variable was the first unplanned readmission within 30 days after the index discharge which was compared against all other index discharges comprising of those not followed by any

readmission and those followed by readmission but after 30 days. Re-hospitalisation in the same hospital occurring through the ED for any cause was considered unplanned readmission. A 30-day time frame was chosen for a higher likelihood of readmissions that are related to the index admission and likely to be avoidable.[11]

Data from all three hospitals were combined and randomly divided into two cohorts; a derivation cohort comprising 70% of the data was used for model development and a validation cohort with the remaining 30% data was used for internal model validation.

A mixed-effect multivariable logistic regression model was developed using variables that were significant at 5% level of significance at the univariate level (univariate logistic regression). Random effects for each hospital were introduced to account for the correlation of patients within the hospitals. Four different models were generated: (1) Model 1 included socio-demographic, social support, index admission, and prior hospital utilisation variables (2) Model 2: model 1 with CCI score at index hospitalisation (3) Model 3: model 1 with individual CCI components instead of CCI score at index hospitalisation and (4) Model 4: model 1 with principal diagnosis at index hospitalisation categorised into ICD-10-AM chapters. The model with the minimum Akaike Information Criterion (AIC) value was selected as the favoured model. Predicted probability of a 30-day unplanned readmission was calculated for each patient using the final predictive model.

2.4 | Model validation

Predictive performance of the final model was evaluated using the validation cohort. The discriminatory power of the model was assessed using the area under the receiver operating characteristic (ROC) curve (also referred to as C-statistic) which was constructed using the predicted probabilities of the final model. Higher area under the ROC curve provides evidence for better predictive performance.

Model calibration was assessed using Hosmer-Lemeshow test showing the ability of the model to generate probabilities that match the observed rates of 30-days unplanned readmission.

2.5 | Risk score calculation

A regression coefficient-based risk score was then generated using a multivariable logistic regression model of variables with P value < .05 in the final model.[8,11] The age of the patient (18-75, 76-80, 81-85, 86-90, and ≥91 years) and the index length of stay (1, 2-3, 4-59, and ≥60 days) were categorised for risk score development following the univariate odds ratio (OR) associated with each value of the corresponding continuous variables. Categorisation was performed to assess the risk of readmission in clinically meaningful categories. All analyses were performed using Stata 14 (StataCorp, College Station, Texas).

3 | RESULTS

During the study period, there were 205 799 admissions comprising 102 601 adult patients. Forty-four thousand six hundred and nine admissions were excluded following the exclusion criteria (Figure 1). Of the 161 190 admissions that remained including multiple readmissions, 99 470 index admissions were considered in the analyses. A total of 5796 (5.8%) index admissions were followed by unplanned readmission within the first 30 days after discharge.

Patients who were readmitted within 30 days were older (median age 64 vs 54 years), more likely to be male (51.6% vs 48.3%), had higher emergency admissions (77.7% vs 56.0%), had a higher CCI score (58.0% vs 73.7% with 0 point), and had higher frequency of admissions (20.2% admitted more than once vs 10.2%) and ED presentations (21.9% presented more than once vs 8.6%) in 12 months prior to the index hospitalisation, compared with the reference group (Table 1).

3.1 | Prediction models

The derivation cohort was consisted of 69 629 admissions, of which 4026 (5.8%) were followed by an unplanned 30-days readmission. The validation cohort included 29 841 admissions with an unplanned 30-days readmission rate of 5.9%.

Covariates of the multivariable regression model included socio-demographic factors (age, sex, country of birth other than Australia, not fluent in English, and indigenous status); social support factors (marital status and family doctor); factors relating to index hospitalisation (unplanned admission, length of stay, ICU hours more than one, CCI score, components of CCI except cerebrovascular disease, rheumatoid disease, and peptic ulcer disease, ICD-10-AM chapters of principal diagnosis except chapter 2, 3, 8, 11, 12, 13, and 17, separation ward different from admission ward, and day of discharge-Tuesday and Saturday), and prior hospital utilisation (number of inpatient admissions and number of ED presentations). Parameter estimates and predictive performances of the four models are summarised in Table 2. Overall, discrimination (C-statistic 0.70) is similar across all four models. However, model 3 with individual CCI components has the smallest AIC, although not substantially different from model 4 with the principal diagnosis categorised into ICD-10-AM chapters. Considering clinical applicability, model 3 was preferred over model 4. In addition, model 1 with socio-demographic, social support, index admission, and prior hospital utilisation variables was also considered as a candidate model considering the relatively fewer number of variables required to predict unplanned readmission within 30 days.

The Hosmer-Lemeshow goodness of fit statistic for model 1 and model 3 was 15.73 (P = .05) and 13.93 (P = .08) in the validation cohort, respectively.

TABLE 1 Patient characteristics in the entire dataset

	Unplanned readmission within 30 days	
	Yes	No
Characteristics	**n = 5796**	**n = 93 674**
Socio-demographic factors		
Age, year, median (Quartiles)	64 (43-78)	54 (36-71)
Male, n (%)	2993 (51.64)	45 280 (48.34)
Country of birth other than Australia, n (%)	2688 (46.51)	39 577 (42.46)
Not fluent in English, n (%)	825 (14.30)	9975 (10.70)
Indigenous[a], n (%)	65 (1.13)	776 (0.85)
Lifestyle risk factor		
History of alcohol use[b], n (%)	96 (1.66)	1079 (1.15)
Social support factors		
Divorced/Separated/Widowed/Single, n (%)	2632 (45.88)	39 014 (42.42)
Has a family doctor (GP), n (%)	5727 (98.81)	91 260 (97.42)
Factors relating to index hospitalisation		
Unplanned admission, n (%)	4504 (77.71)	52 483 (56.03)
Season of admission, n (%)		
Summer	1009 (17.41)	16 251 (17.35)
Autumn	1286 (22.19)	25 366 (27.08)
Winter	1787 (30.83)	28 201 (30.11)
Spring	1714 (29.57)	23 856 (25.47)
Length of stay, median (Quartiles)	1.5 (1-5)	1 (1-2)
Admitted at ICU, n (%)	1762 (30.40)	23 585 (25.18)
Hours spent in ICU >1, n (%)	284 (6.57)	2638 (3.63)
Separation ward different from admission ward, n (%)	1895 (32.69)	26 025 (27.78)
Day of discharge, n (%)		
Monday	846 (14.60)	14 446 (15.43)
Tuesday	913 (15.75)	15 748 (16.82)
Wednesday	961 (16.58)	16 082 (17.18)
Thursday	974 (16.80)	15 882 (16.96)
Friday	1011 (17.44)	15 693 (16.76)
Saturday	626 (10.80)	8971 (9.58)
Sunday	465 (8.02)	6805 (7.27)
Discharged on holidays, n (%)	155 (2.67)	1908 (2.04)
Prior hospital utilisation		
No. of prior admissions (emergency & non-emergency), n (%)		
0	3740 (64.71)	72 610 (77.61)
1	871 (15.07)	11 445 (12.23)
More than 1	1169 (20.22)	9503 (10.16)
No. of prior ED presentations, n (%)		
0	3147 (54.45)	69 116 (73.88)
1	1369 (23.69)	16 410 (17.54)
More than 1	1264 (21.87)	8032 (8.59)
Diagnostic details		
CCI score at index hospitalisation[c], n (%)		
0	3351 (57.96)	67 968 (73.73)

(Continues)

TABLE 1 (Continued)

	Unplanned readmission within 30 days	
	Yes	No
Characteristics	**n = 5796**	**n = 93 674**
1	892 (15.43)	10 615 (11.52)
2	609 (10.53)	7023 (7.62)
3	350 (6.05)	2480 (2.69)
4	181 (3.13)	1364 (1.48)
5	113 (1.95)	699 (0.76)
6	54 (0.93)	404 (0.44)
7	21 (0.36)	106 (0.11)
8	155 (2.68)	1190 (1.29)
9	27 (0.47)	193 (0.21)
10	17 (0.29)	78 (0.08)
11	6 (0.10)	39 (0.04)
12	1 (0.02)	17 (0.02)
13	3 (0.05)	6 (0.01)
14	2 (0.03)	0 (0.00)
15	0 (0.00)	2 (0.00)
Primary diagnosis at index hospitalisation, n (%)		
Chapter 1-Infectious & parasitic	205 (3.55)	2632 (2.86)
Chapter 2-Neoplasms	372 (6.43)	5846 (6.34)
Chapter 3-Blood & immune mechanism	94 (1.63)	1932 (2.10)
Chapter 4-Endocrine, nutritional & metabolic	165 (2.85)	1937 (2.10)
Chapter 5-Mental & behavioural disorders	127 (2.20)	1307 (1.42)
Chapter 6-Nervous system	199 (3.44)	4216 (4.57)
Chapter 7-Eye & adnexa	22 (0.38)	1194 (1.30)
Chapter 8-Ear & mastoid process	25 (0.43)	605 (0.66)
Chapter 9-Circulatory system	795 (13.75)	9315 (10.10)
Chapter 10-Respiratory	471 (8.15)	5089 (5.52)
Chapter 11-Digestive	652 (11.28)	10 646 (11.55)
Chapter 12-Skin & subcutaneous tissue	133 (2.30)	2206 (2.39)
Chapter 13-Musculoskeletal system & connective tissue	314 (5.43)	5247 (5.69)
Chapter 14-Genitourinary system	484 (8.37)	5406 (5.86)
Chapter 15-Pregnancy, childbirth & puerperium	123 (2.13)	3949 (4.28)
Chapter 16-Perinatal period	0 (0)	0 (0)
Chapter 17-Congenital malformations, deformations & chromosomal abnormalities	12 (0.21)	246 (0.27)
Chapter 18-Abnormal clinical & laboratory findings	765 (13.23)	12 813 (13.90)
Chapter 19-Injury, poisoning & external causes	715 (12.37)	13 460 (14.60)
Chapter 20-External causes of morbidity & mortality	0 (0)	0 (0)
Chapter 21-Health status & health services	109 (1.89)	4137 (4.49)

Abbreviations: CCI, Charlson Comorbidity Index; ED, emergency department; ICU, intensive care unit.

[a]Indigenous refers to either aboriginal patients or Torres Strait Islander or Both.

[b]History of alcohol use was ICD-10-AM coded.

[c]Charlson Comorbidity Index score was calculated using 1 point for myocardial infarction, congestive heart failure, peripheral vascular disease, cerebrovascular disease, dementia, chronic pulmonary disease, rheumatic disease, peptic ulcer disease, mild liver disease, and diabetes without chronic complication; 2 points for diabetes with chronic complication, hemiplegia or paraplegia, renal disease, and any malignancy; 3 points for moderate or severe liver disease; 6 points for metastatic solid tumor and AIDS/HIV.

TABLE 2 Parameter estimates of risk factors of 30-days unplanned hospital readmission from four mixed-effect multivariable logistic regression using derivation cohort

	Model 1		Model 2		Model 3		Model 4	
	Socio-demographic + social support + index admission + prior hospital utilisation variables		Model 1 + CCI score		Model 1 + CCI components		Model 1 + ICD-10-AM chapters	
Characteristics	**OR (95% CI)**	***P* value**	**OR (95% CI)**	***P* value**	**OR (95% CI)**	***P* value**	**OR (95% CI)**	***P* value**
Socio-demographic factors								
Age/year	1.008 (1.006, 1.010)	.000	1.005 (1.004, 1.007)	.000	1.006 (1.004, 1.008)	.000	1.009 (1.007, 1.011)	.000
Male	1.119 (1.047, 1.197)	.001	1.091 (1.019, 1.168)	.013	1.095 (1.023, 1.173)	.009	1.130 (1.056, 1.210)	.000
Country of birth other than Australia	1.074 (0.997, 1.157)	.061	1.057 (0.980, 1.140)	.151	1.056 (0.979, 1.139)	.160	1.053 (0.976, 1.135)	.182
Not fluent in English	1.137 (1.024, 1.262)	.016	1.126 (1.012, 1.252)	.029	1.119 (1.004, 1.248)	.043	1.144 (1.027, 1.274)	.014
Indigenous	1.504 (1.089, 2.077)	.013	1.447 (1.034, 2.025)	.031	1.453 (1.045, 2.019)	.026	1.497 (1.081, 2.074)	.015
Social support factors								
Divorced/Separated/Widowed/Single	1.120 (1.044, 1.202)	.002	1.118 (1.044, 1.197)	.001	1.121 (1.050, 1.197)	.001	1.143 (1.065, 1.226)	.000
Has a family doctor	1.823 (1.370, 2.426)	.000	1.804 (1.350, 2.411)	.000	1.816 (1.361, 2.424)	.000	1.764 (1.326, 2.345)	.000
Factors relating to index hospitalisation								
Unplanned admission	2.503 (2.301, 2.723)	.000	2.426 (2.232, 2.638)	.000	2.468 (2.255, 2.701)	.000	2.535 (2.316, 2.775)	.000
Length of stay/day	1.006 (1.003, 1.009)	.000	1.003 (0.999, 1.006)	.128	1.003 (0.999, 1.007)	.098	1.006 (1.003, 1.010)	.000
ICU hours >1	1.365 (1.136, 1.641)	.001	1.263 (1.061, 1.504)	.009	1.246 (1.039, 1.495)	.018	1.357 (1.141, 1.614)	.001
Separation ward different from admission ward	1.282 (1.186, 1.385)	.000	1.208 (1.120, 1.303)	.000	1.214 (1.123, 1.312)	.000	1.220 (1.128, 1.319)	.000
Discharged on Tuesday	0.990 (0.905, 1.083)	.825	0.986 (0.904, 1.075)	.746	0.989 (0.903, 1.083)	.804	0.993 (0.904, 1.091)	.887
Discharged on Saturday	1.052 (0.944, 1.172)	.360	1.055 (0.946, 1.175)	.337	1.052 (0.941, 1.176)	.371	1.043 (0.936, 1.163)	.447
Prior hospital utilisation								
No. of prior admissions								
0	Ref		Ref		Ref		Ref	
1	1.190 (1.071, 1.322)	.001	1.168 (1.048, 1.301)	.005	1.157 (1.037, 1.291)	.009	1.193 (1.072, 1.327)	.001
More than 1	1.663 (1.471, 1.880)	.000	1.543 (1.365, 1.744)	.000	1.512 (1.340, 1.706)	.000	1.669 (1.478, 1.885)	.000
No. of prior ED presentations								
0	Ref				Ref		Ref	
1	1.384 (1.253, 1.529)	.000	1.381 (1.255, 1.519)	.000	1.387 (1.259, 1.529)	.000	1.362 (1.234, 1.505)	.000
More than 1	1.940 (1.697, 2.217)	.000	1.928 (1.697, 2.190)	.000	1.934 (1.701, 2.199)	.000	1.887 (1.653, 2.154)	.000

(Continues)

TABLE 2 (Continued)

Characteristics	Model 1 Socio-demographic + social support + index admission + prior hospital utilisation variables OR (95% CI)	*P* value	Model 2 Model 1 + CCI score OR (95% CI)	*P* value	Model 3 Model 1 + CCI components OR (95% CI)	*P* value	Model 4 Model 1 + ICD-10-AM chapters OR (95% CI)	*P* value
Diagnostic details								
CCI score at index hospitalisation								
0			Ref					
1			1.265 (1.142, 1.400)	.000				
More than one			1.657 (1.517, 1.810)	.000				
CCI components at index hospitalisation								
Myocardial infarction					1.042 (0.833, 1.305)	.717		
Congestive heart failure					1.447 (1.228, 1.706)	.000		
Peripheral vascular disease					1.184 (0.846, 1.655)	.324		
Dementia					1.018 (0.799, 1.298)	.882		
Chronic Pulmonary Disease					1.156 (0.988, 1.354)	.071		
Mild Liver Disease					1.396 (1.112, 1.751)	.004		
Diabetes without chronic complication					1.102 (0.985, 1.234)	.091		
Diabetes with chronic complication					1.243 (1.105, 1.397)	.000		
Hemiplegia or Paraplegia					0.960 (0.712, 1.293)	.787		
Renal disease					1.350 (1.160, 1.572)	.000		
Malignancy					1.629 (1.366, 1.941)	.000		
Moderate or severe liver disease					1.261 (0.803, 1.980)	.315		
Metastatic solid tumor					1.307 (1.034, 1.652)	.025		
Primary diagnosis at index hospitalisation								
Chapter 1-Certain infectious and parasitic diseases							0.831 (0.687, 1.006)	.058
Chapter 4-Endocrine, nutritional and metabolic diseases							1.113 (0.906, 1.367)	.310
Chapter 5-Mental and behavioural disorders							1.021 (0.802, 1.299)	.868
Chapter 6-Diseases of the nervous system							0.895 (0.749, 1.069)	.222
Chapter 7-Diseases of the eye and adnexa							0.362 (0.196, 0.667)	.001
Chapter 9-Diseases of the circulatory system							1.044 (0.935, 1.167)	.441
Chapter 10-Diseases of the respiratory system							1.009 (0.883, 1.154)	.895

(Continues)

TABLE 2 (Continued)

Characteristics	Model 1 Socio-demographic + social support + index admission + prior hospital utilisation variables OR (95% CI)	*P* value	Model 2 Model 1 + CCI score OR (95% CI)	*P* value	Model 3 Model 1 + CCI components OR (95% CI)	*P* value	Model 4 Model 1 + ICD-10-AM chapters OR (95% CI)	*P* value
Chapter 14-Diseases of the genitourinary system							1.434 (1.257, 1.636)	.000
Chapter 15-Pregnancy, childbirth and the puerperium							1.222 (0.966, 1.546)	.095
Chapter 18-Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified							0.788 (0.704, 0.881)	.000
Chapter 19-Injury, poisoning and certain other consequences of external causes							0.667 (0.596, 0.746)	.000
Chapter 21-Factors influencing health status and contact with health services							0.667 (0.518, 0.858)	.002
n	66 999		65 986		65 986		65 986	
AIC*	28 248.39		27 988.89		27 970.56		27 972.06	
C-statistic (95% CI)	0.691 (0.682, 0.699)		0.694 (0.686, 0.702)		0.695 (0.687, 0.704)		0.700 (0.692, 0.708)	

Note: 95% confidence intervals were calculated from 1000 bootstrap samples. *AIC-Akaike Information Criterion. Reference categories: age, analysed as a continuous variable; Country of birth other than Australia, born in Australia; Not fluent in English, preferred language English and did not require an interpreter or preferred language not English but did not require an interpreter; Either Aboriginal or TSI or Both, neither Aboriginal nor TSI; Marital status, in a relationship; Has a family doctor, no family doctor; Unplanned index admission, planned admission; Length of stay, analysed as a continuous variable; ICU hours > 1, no or less than 1 hour ICU stay; Charlson score, a score of 0; Charlson components, condition absent at index episode; Diagnostic categories (Chapter), absent in principal diagnosis of index episode; Separation ward different from admission ward, discharged from same ward where admitted to; Discharged on Tuesday, any other day of week; Discharged on Saturday, any other day of week; Number of prior admissions, no prior admission; Number of prior ED presentations, no prior ED presentation.

3.2 | Risk score

A total risk score for each of the patients was generated separately for the two models (models 1 and 3). Covariates included from model 1 were: age (categorical), sex, English fluency, indigenous status, family doctor, unplanned admission, length of stay (categorical), ICU hours more than one, number of prior inpatient admissions and ED presentations. From model 3, covariates included in risk score calculation were: age (categorical), sex, English fluency, indigenous status, family doctor, unplanned admission, ICU hours more than one, separation ward different from admission ward, congestive heart failure, mild liver disease, diabetes (complicated), renal disease, cancer, and metastatic cancer, and number of prior inpatient admissions and ED presentations. The risk score ranged from 0 to 35 and 0 to 57 in model 1 and model 3, respectively. In model 1, at a risk score threshold of 16 (C-statistic 0.641; 95% CI [0.629, 0.652]), the model correctly identified 65.2% of patients who were readmitted and 62.9% of patients who were not readmitted in the validation cohort (Table 3). In model 3, the optimal sensitivity (63.3%) and specificity (64.6%) were obtained at a risk score threshold of 20 (C-statistic 0.640; 95% CI [0.628, 0.651]) (Table 3).

A comparative assessment of sensitivity and specificity at different thresholds of risk score and predicted probability of model 1 and model 3 is shown in Figure 2.

4 | DISCUSSION

In this study, we developed and internally validated a 10-item predictive model using administrative/electronic medical record data of 99 470 index admissions from adults of all ages. The model identified patients at highest risk of unplanned readmission before discharge, which would allow an efficient and resource-intensive care planning for patients with greatest needs. The predictive model was generated based on the demographics, clinical characteristics and use of hospital services before and during hospital stay of patients admitted to three large hospitals. The patients had a wide range of clinical and socio-demographic background resulting in a high likelihood of the model being applicable in other hospitals. All variables used to calculate the risk of unplanned readmission were readily available in the electronic medical record ensuring easy integration of the predictive model into the hospital information system.

The rate of 30-days unplanned readmission was 5.8% which is similar to the previously known rate of 6.2% calculated for the public and private hospitals of Victoria, Australia.[12] It is important to note that in our analyses, only the first readmission within 30 days after index discharge was considered for patients with multiple admissions. Unplanned index admissions, as expected and reported in previous studies, were associated with a high risk of unplanned 30-days readmission followed by the prior hospital utilisations.[8,11,13] These factors reflect illness severity and presumably the presence of chronic conditions or comorbidity which lead to more frequent and unplanned presentations at the hospitals. Longer index stay[8,11,13] and hours spent in ICU also represent the severity of illness and thereby higher risk of unplanned readmission.

Patients who were discharged from a ward different from where they were admitted to, were at higher risk of unplanned readmission compared with those discharged from the same ward. This presumably indicates the lack of stability in a patient's condition along with a poor care transition. No previous studies, to our knowledge, considered this as predictive of unplanned readmission.

Older age was found to be associated with a higher risk of unplanned readmission. This contrasts with some previous studies which reported no influence of age on readmission.[8,13] A potential explanation could be that age was modelled as a continuous variable in our study whereas it was categorised in previous studies. However, studies amongst heart failure patients have reported age as a risk factor of 30-days readmission or death.[14,15]

Males were found to be at higher risk of readmission compared with female adult patients. However, in the literature, both sexes have been found to be at high- risk of readmission.[16,17] Interestingly, being born in countries other than Australia did not increase the risk, but lack of fluency in English was identified as a risk factor of unplanned readmission.

TABLE 3 Sensitivity, specificity and C-statistic at different thresholds of predicted probability and risk score derived from model 1 and model 3 in validation dataset

	Model 1				Model 3			
	Socio-demographic + social support + index admission + prior hospital utilisation variables				Model 1 + CCI components			
	Threshold	Sensitivity	Specificity	C-statistic (95% CI)	Threshold	Sensitivity	Specificity	C-statistic (95% CI)
Predicted probability	0.06	64.36%	64.09%	0.64 (0.63, 0.65)	0.06	63.92%	63.82%	0.64 (0.63, 0.65)
	0.05	80.33%	45.58%	0.63 (0.62, 0.64)	0.05	80.07%	46.23%	0.63 (0.62, 0.64)
	0.08	43.41%	80.21%	0.62 (0.61, 0.63)	0.08	45.79%	80.04%	0.63 (0.62, 0.64)
	Overall			0.69 (0.68, 0.71)	Overall			0.70 (0.68, 0.71)
Risk score	16	65.20%	62.94%	0.64 (0.63, 0.65)	20	63.33%	64.56%	0.64 (0.63, 0.65)
	14	78.19%	48.33%	0.63 (0.62, 0.64)	17	85.54%	39.43%	0.63 (0.62, 0.63)
	19	46.10%	78.52%	0.62 (0.61, 0.64)	24	42.00%	82.00%	0.62 (0.61, 0.63)
	Overall			0.69 (0.69, 0.70)	Overall			0.70 (0.68, 0.71)

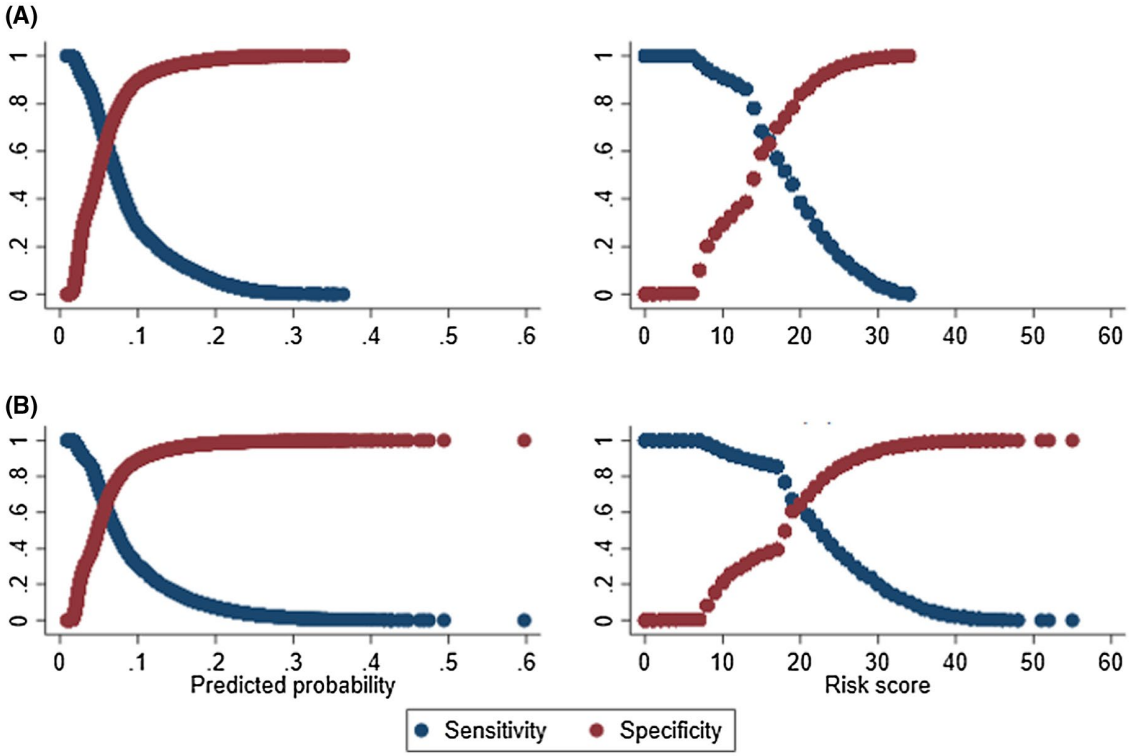

FIGURE 2 Sensitivity and specificity for each value of predicted probability and risk score derived from model 1 (a) and model 3 (b) in validation dataset

Aboriginal and Torres Strait Islanders (TSI) when compared with non-indigenous patients were more likely to get readmitted within 30 days of discharge. This is particularly relevant considering the poorer health outcomes of indigenous population at the national level.[7] This finding is consistent with an earlier study reporting higher relative risk of unplanned readmission in aboriginal patients compared with non-aboriginals in public hospitals of New South Wales, Australia.[18]

Patients without a spouse were found to be at a higher risk, presumably because of the risk of living alone and is consistent with an existing readmission prediction model in general medicine patients aged 18 years and older.[13]

Surprisingly, having a family doctor was associated with a higher risk of readmission through ED. This may reflect the group of patients with chronic conditions who are likely to have a regular GP. This finding had been reported previously amongst adult patients in general medicine with an explanation that having a regular physician allows for the earlier detection of clinical deterioration, which then leads to unplanned readmission.[13]

Many of the existing readmission risk prediction models lack validation and generalisation with poor discriminative ability, complex model structure, and inability to predict readmission before hospital discharge.[4] The hospital score, which is one of the most studied scores, may not be generalisable for surgical patients and the requirement of laboratory values at discharge also reduces the applicability of this model.[8,19] Another widely cited readmission prediction tool is the LACE+ index[7] which requires data of case-mix group score and alternative level of care that are not available in many Australian databases. Furthermore, the predictive tool was discriminative in the original Canadian adult patient population, but, its generalisability has not been tested externally. A recent study proposed a 24-item predictive model which requires information on hospital-acquired *Clostridium difficile* infection, vital sign instability on discharge, and hyponatremia on discharge which are not available in many databases.[20] Besides, the model when compared with the hospital score did not perform any better in discriminating between high and low-risk patients (C statistic 0.69 vs 0.77).

Unlike existing electronic risk scores, the clinically simplified model, we propose here utilises variables reflecting socio-demographic, index admission, and prior hospital utilisation that are readily available before discharge and is as discriminative as complex models. We have shown that the inclusion of detailed diagnostic information including CCI score, components of CCI, and categories of primary diagnosis at index admission do not substantially improve the prediction of 30-days unplanned readmission. The comparable performance of the risk score and predicted probability-based prediction suggests that an additional step of developing a risk score is not required. An automated system of calculating the predicted probability of readmission from the predictive model could easily be implemented in clinical settings with greater efficiency. This will enable clinicians to identify high-risk patients with the opportunity to provide better pre-discharge care. However, before this model can be implemented, external validation in a different geographical location is necessary to confirm the generalisability of the model. Future work will be benefitted from linking hospitals to track readmissions

to different hospitals since this study considered readmissions to the same hospital as discharged from and potentially excluded readmissions to alternative hospitals. Furthermore, the identification of patients at risk of unplanned readmissions should be followed by interventions to eventually reduce preventable hospital utilisation.[21,22]

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DISCLOSURES

The authors report no conflict of interest.

ETHICS APPROVAL

This study was approved by the Melbourne Health Human Research Ethics Committee at the Royal Melbourne Hospital (QA2017038).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available because of ethical restrictions.

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