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Utility of models to predict 28-day or 30-day unplanned hospital readmissions: an updated systematic review

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ABSTRACT

Objective: To update previous systematic review of predictive models for 28-day or 30-day unplanned hospital readmissions.

Design: Systematic review.

Setting/data source: CINAHL, Embase, MEDLINE from 2011 to 2015.

Participants: All studies of 28-day and 30-day readmission predictive model.

Outcome measures: Characteristics of the included studies, performance of the identified predictive models and key predictive variables included in the models.

Results: Of 7310 records, a total of 60 studies with 73 unique predictive models met the inclusion criteria. The utilisation outcome of the models included all-cause readmissions, cardiovascular disease including pneumonia, medical conditions, surgical conditions and mental health condition-related readmissions. Overall, a wide-range C-statistic was reported in 56/60 studies (0.21–0.88). 11 of 13 predictive models for medical condition-related readmissions were found to have consistent moderate discrimination ability (C-statistic ≥0.7). Only two models were designed for the potentially preventable/avoidable readmissions and had C-statistic >0.8. The variables 'comorbidities', 'length of stay' and 'previous admissions' were frequently cited across 73 models. The variables 'laboratory tests' and 'medication' had more weight in the models for cardiovascular disease and medical condition-related readmissions.

Conclusions: The predictive models which focused on general medical condition-related unplanned hospital readmissions reported moderate discriminative ability. Two models for potentially preventable/avoidable readmissions showed high discriminative ability. This updated systematic review, however, found inconsistent performance across the included unique 73 risk predictive models. It is critical to define clearly the utilisation outcomes and the type of accessible data source before the selection of the predictive model. Rigorous validation of the predictive models with moderate-to-high discriminative ability is essential, especially for the two models for the potentially preventable/avoidable readmissions. Given the limited available evidence, the development of a predictive model specifically for paediatric 28-day all-cause, unplanned hospital readmissions is a high priority.

Strengths and limitations of this study

- This is an updated systematic review (2011–2015) of the literature relating to risk predictive models for unplanned hospital readmissions.
- This updated systematic review followed rigorous methodology applying comprehensive electronic database search, strict inclusion, exclusion and quality assessment criteria to synthesise current literature on characteristics and properties of risk predictive models for 28-day or 30-day unplanned hospital readmissions.
- The outcomes of the predictive models included in this systematic review were restricted to 28-day or 30-day unplanned hospital readmission.

INTRODUCTION

Unplanned hospital readmissions cause a disruption to the normality of patients and/or family/carers' lives and result in a significant financial burden on the healthcare system.[1 2] In the USA, it has been estimated that 7.8 million (20%) of hospital-discharged patients were readmitted. This accounted for $17.4 billion of hospital payments by Medicare.[3 4] In the UK, the figures suggested ~35% of unplanned hospital readmissions, costing 11 billion pounds per annum (5.3 million admissions in 2010/2011).[5]

Unplanned hospital readmission rate is considered as a performance indicator to measure a hospital's quality of care.[6 7] Unplanned hospital readmission is defined as the percentage of unplanned or unexpected readmission to the same hospital within 28 days of being discharged.[8 9] However, the literature has widely used

30 days within the context of measurement of hospital readmissions.[1 6 7]

One of the strategies to reduce the unplanned hospital readmission rate is the application of predictive models to identify patients at high risk for readmission. Preventive approaches can then be developed and applied to target the identified high-risk patients. A previous systematic review[10] was conducted in 2011 on the risk predictive models for adult medical patients' hospital readmissions. A total of 30 studies with 26 predictive models were included, and the overall performance of reviewed models was poor. It is, however, worth noting that studies conducted in developing nations and studies that focused on paediatric patients and adult psychiatric and surgical patients were excluded.

Since 2011, there has been increased interest in either developing new predictive models or validating existing models due to high inpatient demand on the healthcare system.[11–15] However, the performance of risk predictive models has varied significantly. The purpose of this systematic review is to update previous systematic review on predictive models for 28-day or 30-day unplanned hospital readmissions and to investigate and assess the characteristics of these models.

METHODS

Search strategy and data sources

An electronic database search was carried out using the CINAHL, Embase and MEDLINE to identify studies published between 2011 and 2015. The key search terms included 'unplanned readmission* or rehospitali*' AND ('predict*' AND 'model*') OR 'ROC or C-statistic*' OR 'sensitivity or specificity' (see online supplementary appendix 1 for full search strategy).

Inclusion/exclusion criteria

Articles eligible for inclusion were those published in English with full-text access from 2011 to 2015. Only peer-reviewed studies were included in this review. The study design of included studies needed to be clearly stated together with details of the performance of the risk predictive model reported. Abstract-only references were excluded. Studies included in the previous systematic review[10] were excluded due to overlapping of the search period (1985–August 2011). Studies that included patients discharged from hospital but still receiving treatment, that is, intravenous antibiotics, via ambulatory care or hospital in the home programmes were also excluded.

Study selection and data extraction

Initial literature searches were conducted by HZ and PD. Two authors (HZ and LG) independently screened titles, abstracts and appraised full papers against the inclusion and exclusion criteria. The process of exclusion was relatively straightforward and only a handful of studies warranted discussion between the authors (HZ, LG, SD, PD and PR) and to reach consensus as to whether they met the inclusion criteria.

Data were extracted from the final included studies by three authors (HZ, LG and SD). The data extraction included study characteristics, model performance and key variables of the predictive model. Study characteristics included study setting, population, data source, the timing of data collection, sample size, study design, model name if applicable, model utilisation outcome and readmission rate (table 1). Measures assessing predictive model performance, including discrimination, calibration, cut-off values used to identify patients at high risk of being readmitted to the hospital, sensitivity, specificity, positive predictive value (PPV) or negative predictive value (NPV), were extracted (table 2). Model discrimination is commonly assessed using C-statistic or the area under the receiver operating characteristic curve. Values of the C-statistic measurement range from 0.5 to 1.0. A value of 0.5 indicates that the model is no better than chance at making a prediction of membership in a group, and a value of 1.0 indicates that the model perfectly identifies those within and not within a group. Models are typically considered reasonable when the C-statistic is higher than 0.7 and strong when the C-statistic exceeds 0.8.[71] Variables of the readmission risk predictive model were also extracted and presented in table 3. The studies were grouped based on the model utilisation outcome in the three tables. Disagreements between two reviewers about the extracted data were resolved through group discussion.

Quality appraisal

Six domains of potential bias[72] were used to appraise the quality of included studies critically. The assessment of risk for bias was completed by two independent reviewers (HZ and SD). The ratings of 'yes', 'partly', 'no' or 'unsure' were given to each domain and then an overall risk of 'low' or 'high' was assigned to each study. The six domains are:

1. Study participation: 'Was source population clearly defined?' and 'Was the study population described?' or 'Did the study population represent source population or population of interest?'
2. Study attrition: 'Was completeness of follow-up described and adequate?'
3. Prognostic factor measurement: 'Did prognostic factors measure appropriately?'
4. Outcome measurement: 'Was outcome defined and measured appropriately?'
5. Confounding measurement and account: 'Were confounders defined and measured?'
6. Analysis: 'Was analysis described and appropriate?' and 'Did analysis provide sufficient presentation of data?'

Data synthesis

Pooling of quantitative data was not possible as the included studies were not homogeneous. Therefore, the

Table 1 Characteristics of 49 included studies on 28-day or 30-day unplanned hospital readmission (UHR) predictive models

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
All-cause UHRs (14)							
Escobar *et al*[16] USA	ED 30 Discharge 30 LACE (validation)	30-day all-cause readmissions	Retrospective cohort *21 hospitals Electronic medical records*	A total of 360 036 patients 179 978 derivation set 180 058 validation set	Mean=64.1	1 June 2010–31 December 2013	Derivation: 12.5%; Validation: 12.4%
Yu *et al*[17] USA	Institution-specific prediction model LACE (validation)	30-day all-cause readmission	Retrospective cohort *3 hospitals*	Hospital 1=2441 Hospital 2=26 520 Hospital 3=45 785	≥65	Not reported	H1=23% H2=20% H3=18%
Baillie *et al*[18] USA	Prediction model	30-day all-cause readmissions	Retrospective and prospective cohort *3 hospitals*	Retrospective: 120 396 discharges prospective validation	Not reported—adult	August 2009–September 2012	Retrospective: 14.4%; Prospective: 15.1%
Choudhry *et al*[12] USA	ACC Admission and Discharge model	30-day all-cause readmissions	Retrospective cohort *8 hospitals*	A total of 126 479 patients 94 859 derivation set 31 619 internal and 6357 external validation	Mean=66.01 (readmission) 57.65 (no readmission)	1 March 2010–31 July 2012	7.25%
Gildersleeve and Cooper[19] USA	Risk of readmission score (RRS)	30-day all-cause readmission	Retrospective cohort *1 community hospital*	Derivation: 8700 patients Validation: 8189 patients	Mean=60.6 Mean=65	2010 2011	14.1% 14.8%
Kruse *et al*[20] USA	Unnamed	30-day all-cause readmission	Retrospective cohort *91 hospitals—Health Facts Database*	463, 351 Index admissions	≥18	1 October 2008–31 August 2010	9.7%
Richmond[21] USA	Unnamed	30-day all-cause readmission for patients≥65 years	Retrospective cohort *state-level database*	4717 patients split into a derivation (80%) and validation sample (20%)	Mean=77.27	January 2010–December 2012	14.4%
Shulan *et al*[22] USA	Unnamed	30-day all-cause readmission	Retrospective cohort *centralised database*	8718 patients Derivation (50%) Validation (50%)	Mean=67.04 (UHRs); 66.43 (no UHRs)	2011	16.2%
van Walraven *et al*[23] Canada	LACE+ (extension of a validated index)	30-day all-cause readmission	Retrospective cohort *centralised database*	499 996 patients/ 858 410 index hospitalisations	>18	2004–2009	11.8%
Cotter *et al*[13] UK	LACE index (validation)	30-day all-cause readmission	Retrospective cohort *centralised database*	507 patients	Mean=85	2010	17.8%

Continued

Table 1 Continued

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
	Regression model		Retrospective cohort *centralised database*	502 patients (validation cohort)			14.8%
Khan *et al*[24] USA	Rehospitalisation Risk Score	30-day all-cause readmission	Retrospective cohort *10 hospitals/EMRs*	227 patients	Average=79	Single day on 26 January 2011	15%
Lee[25] Korea	Unnamed	28-day all-cause readmission	Retrospective cohort *1 tertiary hospital*	11 951 patients Derivation (70%); Validation (30%)	Ranged from 0 to 70 +	2009	28.9%
van Walraven *et al*[26] Canada	CMG score (case-mix groups) LACE index (validation) Combined CMG score and LACE index	30-day all-cause readmission	Retrospective cohort *4 health databases*	Random 200 000 patients of 3 277 033 Derivation: 100 000 Validation: 100 000	Mean age of Derivation: 58 Validation: 57.9	1 April 2003–31 March 2009	6.8%
van Walraven *et al*[27] Canada	LACE+ LACE+ with CMG score	30-day all-cause readmission	Retrospective cohort *4 health databases*	Random 500 000 of 3 277 033 patients then 1/2 derivation and ½ validation	Mean=57.9 (derivation); 57.9 (validation)	1 April 2003–31 March 2009	14%
Cardiovascular disease-related UHRs including pneumonia (11)							
Hebert *et al*[15] USA	CHF model PNA model AMI model Combined model	30-day readmission on Congestive heart failure/ pneumonia/acute myocardial infarction	Retrospective cohort *A tertiary medical centre*	A total of 3968 patients Derivation: 3572 Historical validation: 1756 Random sample: 396	Mean=61	1 August 2009–31 July 2011 1 August 2008–31 July 2009	16.2% 17.7% 16.2%
Iannuzzi *et al*[28] USA	Vascular surgery readmission risk score	30-day readmission on patients after vascular surgery	Retrospective cohort *National Surgical Database*	24 929 patients	Mean=69.5 (UHRs); 69.7 (no UHRs)	2011	10.1%
Keyhani *et al*[29] USA	CMS-based model CMS-based model plus social Risk factors CMS-based model plus social risk and clinical factors	30-day readmission on patients with stroke	Retrospective cohort *114 hospitals*	3436 patients	Mean=69.5 (UHRs); 66.9 (no UHRs)	2007	12.8%
Rana *et al*[30] Australia	Electronic medical record (EMR) model HOSPITAL score (validation) Comorbidities (validation)	30-day readmission on ischaemic heart disease of patients after AMI	Retrospective cohort *A regional health service—tertiary hospital*	1660 AMI admissions Derivation cohort: 1107 Validation cohort: 553	Mean=67.8 (derivation cohort); validation cohort: 68.4	January 2009–December 2011	6.3%

Continued

Table 1 Continued

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
Shahian *et al*[31] USA	Unnamed	30-day readmission post coronary artery bypass grafting	Retrospective cohort *National Database (846 hospitals)*	162 572 admissions	≥65	2008–2010	12.6–23.6%
Shams *et al*[32] USA	Potentially avoidable readmission (PAR)	30-day avoidable readmission on pneumonia/HF/AMI/ COPD	Retrospective cohort *Veterans Health Administration data* Internal validation	5600 admissions	HF: mean=71.3 (PAR); vs 68.6 (no UHRs) AMI: mean=73.3 (PAR) vs 69.3 (no UHRs)	2011–2012	13.09%
			External validation	478 patients		August and September 2012	
	CMS endorsed model (validation)	30-day readmission					
Sharif *et al*[33] USA	Unnamed	30-day readmission on patients aged 40–64 years with COPD	Retrospective cohort *A large national commercial insurance database*	8263 patients	Mean=57 (UHRs); no UHRs—age not reported	January 2009–November 2011	8.9%
Lucas *et al*[34] USA	Complex all-variable model; parsimonious readmission score	30-day readmissions on patients post general, vascular, and thoracic surgery	Retrospective cohort *National Surgery Database*	A total of 230 864 patients Derivation: 162 159 (70%): Validation: 68 705 (30%)	Median=56	2011	5–16% across surgical specialties
Wallmann *et al*[35] Spain	Unnamed	30-day readmission on cardiac-related disease	Retrospective cohort *1 tertiary centre*	35 531 admissions Derivation cohort: 24 881 Validation cohort: 10 650	Mean=67.9	2003–2009	Derivation: 4.4%; Validation: 4.7%
Wasfy *et al*[36] USA	Risk score for 30-day readmission after PCI (parsimonious)	30-day readmission after percutaneous coronary intervention	Retrospective cohort *centralised database*	36 060 surviving to discharge	Mean=68.1 (UHRs); 64.3 (no UHRs)	1 October 2005–30 September 30 2008	10.4%
Krumholz *et al*[37] USA	Claims model	30-day readmission on acute myocardial infarction (AMI)	Retrospective cohort *Medicare Claims Database*	Derivation cohort: 100 465 Validation cohort: 321 088	Mean=78.7	Half of 2006	18.9%
	Medical record model			Derivation cohort: 130 944 Validation cohort: 130 944		2005 and half of 2006	19.96%
Cardiovascular disease-related UHRs including pneumonia—heart failure only (11)							
Betihavas *et al*[38] Australia	Unnamed	28-day readmission on patients with chronic heart failure	Retrospective cohort Multicentre	280 patients 94 (no UHRs); 37 (28-D UHRs)	Mean=69 (no UHRs); 79 (UHRs)	Not reported	13%

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Table 1 Continued

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
Di Tano *et al*[39] Italy	Unnamed	30-day readmission on acute HF	Prospective cohort *National Registry Database*	1520 patients	Mean=72	Not reported	6.25%
Huynh *et al*[40] Australia	The non-clinical model The clinical model The combined model	30-day readmission on HF	Retrospective cohort *state-wide data linkage*	Non-clinical—1537 patients Clinical—977 patients available	Mean=80	2009–2012	25.4%
Raposeiras-Roubin *et al*[41] Spain	GRACE risk score	30-day readmission on HF after acute coronary syndrome	Retrospective cohort A single centre	4429 patients	Mean=77 (UHRs); 68 (no UHRs)	2004–2010	1.3%
Sudhakar *et al*[42] USA	Readmission Risk score	30-day readmission on patients with CHF	Retrospective cohort *A tertiary hospital/ chart review*	1046 admissions from 712 patients	Mean=65.2	September 2011–August 2013	35.28%
Fleming *et al*[43] USA	Unnamed	30-day readmission on patients with HF	Retrospective cohort *1 tertiary medical centre*	3413 admissions Derivation: Validation=3:1 (2566:847)	Mean=74 (derivation cohort); validation cohort: 74.6	1 October 2007–30 August 2011	24.2% (derivation)
Wang *et al*[44] USA	LACE index (validation)	30-day readmission on patients with CHF	Retrospective cohort *An urban public hospital*	253 patients	Mean: 57.67 (no UHRs); 56.17 (UHRs)	June 2012–June 2013	24.5%
Eapen *et al*[45] USA	Unnamed	30-day readmission on heart failure	Retrospective cohort *Centers for Medicare database*	33 349 patient 70% in derivation cohort 30% in validation cohort	Median=80	1 January 2005–31 December 2009	22.8%
Zai *et al*[46] USA	The telemonitoring-based readmission model; the psychosocial readmission model (validation)	30-day readmission on heart failure	Retrospective cohort *Patients enrolled in the telemonitoring program*	100 patients	Average age of 66.8	July 2008–November 2011	38%
Au *et al*[47] Canada	Five administrative data-based models: Charlson; CMS Krumholz Keenan; LACE; LACE+	30-day readmission on HF	Retrospective cohort *4 health databases*	59 652 patients	Mean=76	April 1999 and 2009	19%
Watson *et al*[48] USA	The psychosocial readmission model	30-day readmission on HF	Retrospective cohort *1 tertiary hospital*	729	Mean=71.4	1 October 2007–30 September 2008	13.3% (all female)
Cardiovascular disease-related UHRs including pneumonia—pneumonia only (2)							
Mather *et al*[49] USA	Hartford Hospital model CMS Model (validation)	30-day readmission on pneumonia	Retrospective cohort *A tertiary hospital*	956 index admissions	≥65	January 2009–March 2012	15.5%

Continued

Table 1 Continued

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
Lindenauer *et al*[50] USA	Administrative claims model	30-day readmission on pneumonia	Retrospective cohort *Medicare enrolment database*	Derivation cohort: 226 545 Validation cohort: 762 721	Mean=80	Half of 2006	17.4%
	Medical record model			47 429 cases		Half of 2006 and 2005	17.0%
General medical condition-related UHRs (10)							
Shadmi *et al*[51] Israel	Preadmission Readmission Detection Model	30-day readmission on medical patients	Retrospective cohort *Clalit Health Services/EMR*	Total: 33 639 admissions Derivation: 22 406 Validation: 11 233	Mean=68.2; 67.5 (no UHRs); 72.5 (UHRs)	1 January 2010–31 March 2010	16.8%
Tsui *et al*[52] Hong Kong	Unnamed	28-day readmission on elderly medical patients	Retrospective cohort *41 hospitals/EMS*	Total: 327 529 episodes Derivation: 165 216 Validation: 162 313	≥65	Derivation: 2005 Validation: 2006	7.8% 7.6%
Donzé *et al*[53] USA	Unnamed	30-day readmission on medical patients due to end-of-life care	Retrospective cohort *1 tertiary medical centre including 3 hospitals*	10 275 admissions	Mean=61.5 (no UHRs); 60.8 (potentially avoidable readmissions (PARs)	1 July 2009–30 June 2010	Total:22.3%; 8% —PARs
He *et al*[54] USA	Unnamed	30-day readmission on medical patients and chronic pancreatitis (CP)	Retrospective cohort *JHH (tertiary centre) BMC (community hospital)*	Medical patients: 26 091 (JHH)+16 194 (BMC)	Mean=50.3 (JHH) 51.5 (BMC)	Medical patients: January 2012–April 2013;	11.5% (JHH) 8.7% (BMC)
				Patients with CP: 3218 (JHH)+706 (BMC)	Mean age: 51.4 (JHH) 51.4 (BMC)	CP discharged from January 2007–April 2013	15.6% (JHH) 7.8% (BMC)
Taha *et al*[55] USA	Readmission Risk Score (RRS)	30-day readmission on general internal medicine services	Retrospective cohort *4 teaching and 2 non-teaching general internal medicine services*	858 index hospitalisations Derivation cohort: 613 Validation cohort: 245	Mean=54 (derivation); validation cohort: 54	1 April 2010–30 June 2010	16%
Donzé *et al*[14] USA	HOSPITAL score	30-day readmissions on general medical patients	Retrospective cohort *Multicentre health services*	10 731 discharges	Mean=61.3	1 July 2009–30 June 2010	8.5%
Tan *et al*[56] Singapore	LACE index (validation)	30-day readmission on general medical patients	Retrospective *The largest tertiary general hospital*	127 550 patients	≥21	1 January 2006–31 December 2010	4.87–18.43%

Continued

Table 1 Continued

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
Billings *et al*[11] USA	PARR-30	30 days readmission on general medical patients	Retrospective cohort *centralised database*	576 868 admissions	Adult	1 April 2008 and 31 March 2009	12.2%
Zapatero *et al*[57] Spain	SEMI INDEX	30-day readmission on general medical patients	Retrospective cohort *National Health Database*	Derivation cohort: 999 089 patients; Validation cohort: 510 588 patients (internal)	Median=70 for two cohorts	January 2006–December 2007 2008	12.4% 12.5%
Gruneir *et al*[58] Canada	LACE index (validation)	30-day readmission on general medical patients	Retrospective cohort *6 hospitals*	26 045 patients	18–105	2007	12.6%
Medical condition UHRs—cirrhosis only (2)							
Singal *et al*[59] USA	Unnamed	30-day readmissions on patients with cirrhosis	Retrospective cohort *1 large safety-net hospital*	A total of 838 patients with 1291 admissions Derivation: 968 Validation: 323	Mean=52.5	January 2008–December 2009	27%
Volk *et al*[60] USA	Cirrhosis readmission prediction model	30-day readmission on cirrhosis	Retrospective cohort *1 tertiary hospital*	402 patients	≥18	1 July 2006–1 July 2009	41%, 22% of which are PARs
Medical condition UHRs—chronic kidney disease only (1)							
Perkins *et al*[61] USA	Unnamed	30-day readmission on patients with CKD second to HF	Retrospective cohort *2 inpatient facilities*	607 patients with chronic kidney disease	Mean=72.3 (UHRs); 74.1 (no UHRs)	1 July 2004–28 February 2010	19.1%
Medical condition UHRs—HIV only (1)							
Nijhawan *et al*[62] USA	Unnamed	30-day readmission on HIV-infected patients	Retrospective cohort *1 tertiary hospital*	2402 index admissions randomly split (1/2) into derivation vs validation	Mean=43	March 2006–November 2008	24.4%
Medical condition UHRs—acute pancreatitis (1)							
Whitlock *et al*[63] USA	Unnamed	30-day readmission on acute pancreatitis	Retrospective cohort *2 hospitals*	Derivation cohort: 248 Validation cohort: 198	Mean=51.6 derivation Validation: 52.3	1 June 2005–31 December 2007 1 January 2008–31 October 2009	19% 23%
Surgical condition-related UHRs (6)							
Taber *et al*[64] USA	30DRA with fixed variable vs 30DRA with fixed variables and dynamic clinical data	30-day readmission on patients following kidney transplantation	Retrospective cohort *An institution*	1147 patients Derivation; internal validation using random iteration of 50% sampling	Mean=51 (no UHRs); 52 (UHRs)	2005–2012	11%
Lawson *et al*[65] USA	Unnamed (demographic, preoperative and postoperative risk factors)	30-day readmission on patients following colectomy	Retrospective cohort *NSQIP*	12 981 patients	≥65	2005–2008	13.5%

Continued

Table 1 Continued

Reference	Model name	Model outcome	Study design/data source	Sample size	Age group (years)	Duration of retrieved data source	Readmission rate
Iannuzzi *et al*[66] USA	Endocrine surgery Readmission Risk Score	30-day readmission on patients following cervical endocrine operations	Retrospective cohort *NSQIP—a large national clinical database*	34 046 cases Derivation and validation cohort (numbers were not specified)	Mean=54 (no UHRs); 55 (UHRs)	2011–2012	2.8%
Mesko *et al*[67] USA	Unnamed	30-day readmission on total hip and knee arthroplasty	Retrospective cohort *A readmission database*	1291 admissions/1236 patients	Mean=65.6 (UHRs); 68.3 (no UHRs)	1 May 2010–30 April 2011	3.6%
Moore *et al*[68] Canada	Unnamed (quality indicator based)	30-day readmission on trauma	Retrospective cohort *57 trauma centres*	57 524 patients	≥16	1 April 2005–28 February 2010	6.6%
Graboyes *et al*[69] USA	Unnamed	30-day readmission on otolaryngology patients	Retrospective cohort *A tertiary hospital*	1058 patients—1271 hospital admissions	Mean=52 (no UHRs); 56 (UHRs)	1 January 2011–31 December 2011	7.3%
Mental health condition-related UHRs (1)							
Vigod *et al*[70] Canada	READMIT (41 points)	30-day readmission after discharge from acute psychiatric units	Retrospective cohort *National health data*	Derivation: 32 749 patients Validation: 32 750 patients	Median=41 (UHRs); 44 (no UHRs)	1 April 2008–31 March 2011	8.42–10%

ACS, acute coronary syndrome; AMI, acute myocardial infarction; AP, acute pancreatitis, CHF, congestive heart failure; CKD, chronic kidney disease; COPD, common obstructive pulmonary disease; EMRs, electronic medical records; GRACE, global registry of acute coronary events; HF, heart failure; PCI, percutaneous coronary intervention; PREADM, preadmission readmission detection model; PNA, peptide nucleic acid.

Table 2 Performance of predictive models for 28-day or 30-day unplanned hospital readmissions (UHRs)

Reference	Model name	Discrimination (ROC)	Calibration (H&L)	Threshold (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
All-cause UHRs (14)								
Escobar *et al*[16]	ED 30	Validation: 0.739	0.40	≥20				
	Discharge 30	Validation: 0.756	0.60	≥30				
	LACE (validation)	Validation: 0.729	0.40	≥60				
Yu *et al*[17]	Institution-specific prediction model	0.74 (hospital 2) 0.64 (at admission) 0.72 (after discharge)						
	LACE (validation)	0.55 (hospital 2)						
Baillie *et al*[18]	Prediction model	Retrospective: 0.62			40	85	31	89
		Prospective: 0.61			39	84	30	89
Choudhry *et al*[12]	ACC Admission Model	Derivation data set: 0.76 Internal validation: 0.75 Average (500 simulations in derivation data set): 0.76 External validation data set with recalibration: 0.76	Derivation data set: 36.0 (p<0.001) Internal validation data set: 23.5 (p=0.0027) External validation with recalibration: 6.1 (p=0.641)	11	70	71		
	ACC Discharge Model	Derivation data set: 0.78 Internal validation: 0.77 Average: 0.78 External validation data set with recalibration: 0.78	Derivation: 31.1 (p<0.001) Internal validation: 19.9 (p=0.01) External validation with recalibration: 14.3 (p=0.074)	11	70	71		
Gildersleeve and Cooper[19]	Risk of readmission score (RRS)	Derivation cohort: 0.74	21.6 (p=0.006)	14	74.9	54.4	22.2	92.6
		Validation cohort: 0.70			79.2	55.4	22.6	94.2
Kruse *et al*[20]	Unnamed	Derivation set: 0.668 Validation set: 0.657						
Richmond[21]	Unnamed	0.60			47	78		
Shulan *et al*[22]	Unnamed	Derivation cohort: 0.80 Validation cohort: 0.70						
van Walraven *et al*[23]	LACE+ (extension of a validated index)	0.768 (1 hospitalisation per patient) 0.730 (all hospitalisations)	H–L χ^2 50.3 H–L χ^2 10 972					
Cotter *et al*[13]	LACE index (validation)	0.55						
	Regression model	0.57		47	54	47		

Continued

Table 2 Continued

Reference	Model name	Discrimination (ROC)	Calibration (H&L)	Threshold (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
All-cause UHRs (14)								
Khan *et al*[24]	Rehospitalisation risk score			19	97	28	19	98
				21	58	63	21	90
				27	42	81	27	89
Lee[25]	Unnamed	ROC was graphically illustrated, but no actual number was reported						
van Walraven *et al*[26]	CMG Score	0.637	p=0.0079					
	LACE index (validation)	0.72	P<0.0001					
	Combined CMG Score and LACE	0.743	p<0.0001					
van Walraven *et al*[27]	LACE+ (validation)	0.743						
	LACE+ with CMG score	0.753						
Cardiovascular disease-related UHRs including pneumonia (11)								
Hebert *et al*[15]	CHF model	Derivation cohort: 0.64–0.73;	p>0.05					
	PNA model	Historical validation: 0.61–0.68;						
	AMI model	Random sample combined:						
	Combined model	0.63–0.76						
Iannuzzi *et al*[28]	Vascular surgery readmission risk score	Derivation dataset: 0.67	0.09					
		Validation dataset: 0.64	0.66					
Keyhani *et al*[29]	CMS-based model	0.636	0.866					
	CMS-based model plus social risk factors	0.646	0.462					
	CMS-based model plus social risk and clinical factors	0.661	0.856					
Rana *et al*[30]	EMR model	0.78		5	65	78	21	83.6
	HOSPITAL score (validation)	0.60			62	50	13	78.9
	Comorbidities (validation)	0.53				65	45	
Shahian *et al*[31]	Unnamed	0.648						
Shams *et al*[32]	Potentially avoidable readmission (PAR)	Retrospective cohort: 0.836			91.95	97.65	86.61	98.65
		Validation internal: 0.818/external: 0.809						
	CMS endorsed model (validation)	0.63						

Continued

Table 2 Continued

Reference	Model name	Discrimination (ROC)	Calibration (H&L)	Threshold (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
Cardiovascular disease-related UHRs including pneumonia (11)								
Sharif *et al*[33]	Unnamed (basic model vs final model)	Basic model (patient characteristics only): 0.677; final model (additional provider-level and system-level factors) Derivation set: 0.717 Validation set: 0.73						
Wallmann *et al*[35]	Unnamed	0.75		4	66	70	10	98
Wasfy *et al*[36]	Risk score for 30-day readmission after PCI (parsimonious)	Validation data set: 0.67		>24				
Lucas *et al*[34]	Complex all-variable model	Derivation data set: 0.721 Validation data set: 0.724						
	Parsimonious readmission score	Derivation data set: 0.696 Validation data set: 0.702		1.2	100	0	8	/
				2.4	99	6	8	99
				4.7	92	28	10	98
				8	77	52	12	97
				11.8	55	73	15	95
				14.6	37	85	17	94
				17.2	21	92	19	93
				20.3	9	97	21	93
				22.2	2	100	22	92
				40	0	100	40	92
Krumholz *et al*[37]	Claims model	Derivation cohort: 0.63 Validation cohort: 0.62–0.63						
	Medical record model	Derivation cohort: 0.58 Validation cohort: 0.59						
Cardiovascular disease-related UHRs including pneumonia—heart failure only (11)								
Betihavas *et al*[38]	Unnamed	0.8						
Di Tano *et al*[39]	Unnamed	0.695						
Huynh *et al*[40]	The non-clinical model	0.66						
	The clinical model	0.72						
	The combined model	0.76						
Raposeiras-Roubin *et al*[41]	The GRACE risk score	0.79	p=0.83	37.9	82.5	62.8	5.6	99.1

Continued

Table 2 Continued

Reference	Model name	Discrimination (ROC)	Calibration (H&L)	Threshold (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
Sudhakar *et al*[42]	Readmission Risk (RR)	All age group—0.61		≥29	33	80	47	69
USA	Score	≥65 years—0.59						
		Random selection—0.58						
				≥24	61	52	41	71
				≥21	83	27	38	75
Fleming *et al*[43]	Unnamed	Derivation cohort: 0.69						
		Validation cohort: 0.66						
Wang *et al*[44]	LACE index (validation)			≥10				
Eapen *et al*[45]		Derivation cohort: 0.59						
		Validation cohort: 0.59						
Zai *et al*[46]	The telemonitoring-based readmission model	0.21			50	81	61	72
	The psychosocial model (validation)	0.67			87	32	44	80
Au *et al*[47]	Five administrative data-based models	0.57–0.61						
Watson *et al*[48]	The psychosocial readmission model	0.67						
Cardiovascular disease-related UHRs including pneumonia—pneumonia only (2)								
Mather *et al*[49]	Hartford Hospital model	Derivation data set: 0.71	p=0.96					
		Validation data set: 0.67						
Lindenauer *et al*[50]	Administrative claims model	0.63						
	CMS medical record model	0.59						
General medical condition-related UHRs (10)								
Shadmi *et al*[51]	PREADM	Derivation data set: 0.70						
		Validation data set: 0.69						
Tsui *et al*[52]	Unnamed	Derivation data set: 0.819	p<0.05					
		Validation data set: 0.824						
Donzé *et al*[53]	Unnamed	0.85						

Continued

Table 2 Continued

Reference	Model name		Discrimination (ROC)			Calibration (H&L)	Threshold (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
General medical condition-related UHRs (10)											
He *et al*[54]	Unnamed	Medical patient	Validation								
			Within site	CV on JHH	0.75		21	50	84	29	93
				CV on BMC	0.79		30	50	88	28	95
			Across site	Test on BMC	0.81		9	47	88	27	95%
				Test on JHH	0.78		30	58	76	24	93
		CP	Within site	CV on JHH	0.71		21	50	68	34	84
				CV on BMC	0.65		30	56	79	20	955
			Across site	Test on BMC	0.65		9	85	41	11	97
				Test on JHH	0.73		30	60	71	27	91
Taha *et al*[55]	Readmission Risk Score						12			18	95
							16			18	90
							20			20	89
							24			21	86
							28			28	85
							32			38	84
Donzé *et al* (2013)[14]	HOSPITAL score		Derivation data set: 0.69 Validation data set: 0.71			Derivation data set: p=0.28 Validation data set: p=0.15	5.2–18.4				
Tan *et al*[56]	LACE index (validation)		0.70			13.1 (p=0.107)	16				
Billings *et al*[11]	PARR-30		0.70				50	5.4	99.5	59.2	
Zapatero *et al*[57]	SEMI INDEX		0.876			*Derivation cohort* p=0.247 (≤50 years group) p=0.1 (51–70 years group) p=0.182 (71–90 years group) p=0.227 (>90 years group) *Validation cohort* p=0.350 (≤50 years group) p=0.1 (51–70 years group) p=0.246 (71–90 years group) p=0.617 (>90 years group)	7.4–22				
Gruneir *et al*[58]	LACE index (validation)						16				

Continued

Table 2 Continued

Reference	Model name	Discrimination (ROC)	Calibration (H&L)	Threshold (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
Medical condition UHRs—cirrhosis only (2)								
Singal *et al*[59]	Unnamed	Derivation cohort: 0.68 Validation cohort: 0.66						
Volk *et al*[60]	Cirrhosis readmission prediction model	0.65						
Medical condition UHRs—chronic kidney disease only (1)								
Perkins *et al*[61]	Unnamed	0.792		20 50 80	69 28.5 1.7	73.4 97.1 99.8	38.3 70.2 66.7	90.9 85 19.1
Medical condition UHRs—HIV only (1)								
Nijhawan *et al*[62]	Unnamed	Derivation: 0.72 Validation: 0.70						
Medical condition UHRs—acute pancreatitis (1)								
Whitlock *et al*[63]	Unnamed	Derivation cohort: 0.88 Validation cohort: 0.83						
Surgical condition-related UHRs (6)								
Taber *et al*[64] USA	30DRA with fixed variable	0.63	p=0.061	10			57.7	63.8
	30DRA with fixed variable and dynamic clinical data	0.731	p=0.603	10			62.8	73.3
Lawson *et al*[65]	Unnamed	0.728						
Iannuzzi *et al*[66]	Endocrine surgery Readmission risk score	Derivation cohort: 0.676 Validation cohort: 0.646	p=0.083 p=0.592					
Mesko *et al*[67]	Unnamed	Derivation data set: 0.59 Validation data set: 0.59						
Moore *et al*[68]	Unnamed	0.651	Intercept, slope 0.000370; 1.0001					
Graboyes *et al*[69]	Unnamed	0.85						
Mental health condition-related UHRs (1)								
Vigod *et al*[70]	READMIT	Derivation data set: 0.631 Validation data set: 0.63	p=0.868					

NPV, negative predictive value; PPV, positive predictive value; ROC, receiver operating characteristic.

Table 3 Summary of significant variables included in the predictive models for unplanned hospital readmissions (UHRs)

Reference	Model name	Admitting diagnosis	Admitting ward	Blood transfusion	BMI	Comorbidities	Complications before discharge	Daily living score	Demographic/social	Discharge disposition	Discharge hour	Environment	General anaesthesia	Health insurance \hskip1ex	Index type of admission	Injury severity score	Laboratory tests	Length of stay	Physical examinations	Postoperative complications	Medications	Number of previous admission	Number of previous ED presentations	Overall prognosis	Procedures at index admission	Substances usage	Symptoms	Use of outpatient clinic	Vital signs
All-cause UHRs (14)																													
Escobar *et al*[16]	ED 30 and Discharge 30					✓				✓							✓	✓				✓							
	LACE index (validation)					✓									✓			✓					✓						
Yu *et al*[17]	Institution-specific prediction model	✓				✓			✓	✓					✓			✓				✓	✓						
	LACE index (validation)					✓									✓			✓					✓						
Baillie *et al*[18]	Prediction model																					✓							
Choudhry *et al*[12]	ACC Admission and Discharge Model					✓			✓	✓		✓					✓	✓			✓	✓			✓				
Gildersleeve and Cooper[19]	Risk of Readmission Score (RRS)					✓			✓					✓	✓			✓			✓	✓	✓						
Kruse *et al*[20]	Unnamed						✓										✓	✓			✓	✓			✓				
Richmond[21]	Unnamed	✓				✓			✓												✓	✓		✓					
Shulan *et al*[22]	Unnamed					✓			✓									✓											
van Walraven *et al*[23]	LACE+ (validation)	✓				✓			✓						✓			✓				✓	✓		✓				
Cotter *et al*[13]	LACE index (validation)					✓									✓			✓					✓						
	Regression model																						✓						
Khan *et al*[24]	Rehospitalisation Risk Score	✓				✓		✓	✓					✓								✓							
Lee[25]	Unnamed	✓	✓												✓			✓											
All-cause UHRs (14)																													
van Walraven *et al*[26]	CMG score	✓																											
	LACE (validation)																												
	Combined CMG and LACE	✓				✓									✓			✓					✓						
van Walraven *et al*[27]	LACE+ (validation)																												
	Combined CMG and LACE+	✓				✓			✓						✓			✓				✓	✓		✓				
Cardiovascular disease-related UHRs including pneumonia (11)																													
Hebert *et al*[15]	CHF model					✓												✓			✓	✓	✓			✓			
	PNA model					✓											✓				✓	✓			✓				
	AMI model					✓			✓								✓				✓	✓							
	Combined model					✓			✓								✓	✓			✓	✓	✓						
Iannuzzi *et al*[28]	Vascular surgery readmission risk score					✓			✓	✓					✓						✓				✓				
Keyhani *et al*[29]	CMS-based Model					✓			✓																				
	CMS-based Model plus social risk factors					✓			✓																	✓			
	CMS-based model plus social risk and clinical factors	✓				✓		✓	✓																	✓			
Rana *et al*[30]	EMR Model	✓				✓			✓									✓											
Shahian *et al*[31]	Unnamed					✓			✓																				
Shams *et al*[32]	PARs					✓			✓						✓			✓				✓							
	CMS endorsed model (validation)																												
Sharif *et al*[33]	Unnamed					✓			✓									✓			✓							✓	
Lucas *et al*[34]	Complex all-variable model				✓		✓	✓	✓	✓					✓		✓	✓			✓				✓				
	Parsimonious readmission score																	✓							✓				
Wallmann *et al*[35]	Unnamed					✓			✓													✓			✓				
Wasfy *et al*[36]	Risk score after PCI (parsimonious)					✓			✓					✓	✓			✓							✓				
Krumholz *et al*[37]	Claims model (administrative)					✓			✓																				
	Medical record model					✓			✓								✓		✓								✓			✓

Continued

Table 3 Continued

Reference	Model name	Admitting diagnosis	Admitting ward	Blood transfusion	BMI	Comorbidities	Complications before discharge	Daily living score	Demographic/social	Discharge disposition	Discharge hour	Environment	General anaesthesia	Health insurance \hskip1ex	Index type of admission	Injury severity score	Laboratory tests	Length of stay	Physical examinations	Postoperative complications	Medications	Number of previous admission	Number of previous ED presentations	Overall prognosis	Procedures at index admission	Substances usage	Symptoms	Use of outpatient clinic	Vital signs
Cardiovascular disease-related UHRs including pneumonia—heart failure only (11)																													
Betihavas *et al*[38]	Unnamed					✓			✓																				
Di Tano *et al*[39]	Unnamed																	✓			✓						✓		
Huynh *et al*[40]	Non-clinical model					✓			✓		✓							✓											
	Clinical model																✓		✓		✓								✓
	Combined model								✓		✓						✓		✓		✓								✓
Raposeiras-Roubin *et al*[41]	The GRACE Risk Score					✓			✓								✓								✓				✓
Sudhakar *et al*[42]	Readmission Risk Score					✓			✓								✓		✓						✓				✓
USA																													
Fleming *et al*[43]	Unnamed								✓		✓						✓					✓							
Wang *et al*[44]	LACE index (validation)																												
Eapen *et al*[45]	Unnamed					✓			✓					✓	✓			✓			✓	✓	✓						
Zai *et al*[46]	The telemonitoring based readmission model																				✓						✓		
	The psychosocial readmission model (validation)																												
Au *et al*[47]	Charlson (validation)					✓			✓																				
	CMS Krumholz (validation)																												
	Keenan (validation)					✓			✓								✓												
	LACE (validation)																												
	LACE+ (validation)																												
Watson *et al*[48]	The psychosocial readmission model					✓																						✓	
Cardiovascular disease-related UHRs including pneumonia—pneumonia only (2)																													
Mather *et al*[49]	Hartford Hospital Model					✓	✓		✓								✓					✓							
	CMS Model (validation)																												
Lindenauer *et al*[50]	Claims model (administrative)					✓			✓																	✓			
	Medical record model					✓			✓								✓				✓					✓			✓
General medical condition UHRs (10)																													
Shadmi *et al*[51]	PREADM				✓	✓			✓									✓				✓						✓	
Tsui *et al*[52]	Unnamed					✓			✓													✓	✓					✓	
Donzé *et al* (2014)[53]	Unnamed	✓				✓															✓	✓							
He *et al*[54]	Unnamed																✓					✓			✓				
Taha *et al*[55]	Readmission Risk Score (RRS)	✓				✓			✓												✓	✓							
Donzé *et al* (2013)[14]	HOSPITAL score														✓		✓	✓				✓			✓				
Tan *et al*[56]	LACE index (validation)																												
Billings *et al*[11]	PARR-30					✓			✓						✓								✓						
Zapatero *et al*[57]	SEMI INDEX					✓			✓									✓											
Gruneir *et al*[58]	LACE index (validation)																												
Medical condition UHRs—cirrhosis only (2)																													
Singal *et al*[59]	Unnamed								✓					✓			✓					✓							
Volk *et al*[60]	Cirrhosis readmission prediction model																✓				✓			✓					
Medical condition UHRs—chronic kidney disease (1)																													
Perkins *et al*[61]	Unnamed					✓				✓					✓		✓	✓			✓							✓	✓

Continued

Table 3 Continued

Reference	Model name	Admitting diagnosis	Admitting ward	Blood transfusion	BMI	Comorbidities	Complications before discharge	Daily living score	Demographic/social	Discharge disposition	Discharge hour	Environment	General anaesthesia	Health insurance \Skip1ex	Index type of admission	Injury severity score	Laboratory tests	Length of stay	Physical examinations	Postoperative complications	Medications	Number of previous admission	Number of previous ED presentations	Overall prognosis	Procedures at index admission	Substances usage	Symptoms	Use of outpatient clinic	Vital signs
Medical condition UHRs—HIV (1)																												
Nijhawan *et al*[62]	Unnamed	✓													✓		✓					✓							
Medical condition UHRs—acute pancreatitis (1)																													
Whitlock *et al*[63]	Unnamed					✓															✓					✓			
Surgical condition UHRs (6)																													
Taber *et al*[64]	30DRA with fixed variable					✓			✓											✓									
	30DRA with fixed variable and dynamic clinical data					✓	✓		✓						✓					✓									✓
Lawson *et al*[65]	Unnamed	✓			✓	✓		✓																					
Iannuzzi *et al*[66]	Endocrine surgery Readmission Risk Score	✓				✓						✓	✓				✓	✓											
Mesko *et al*[67]	Unnamed			✓		✓				✓																			
Moore *et al*[68]	Unnamed					✓			✓							✓						✓					✓		
Graboyes *et al*[69]	Unnamed					✓	✓			✓															✓	✓			
Mental health condition UHRs (1)																													
Vigod *et al*[70]	READMIT	✓				✓									✓			✓				✓						✓	

BMI, body mass index; ED, emergency department.

included studies were qualitatively synthesised and presented in narrative form.

RESULTS

Literature search result

The initial electronic database search produced 7310 records. After removal of 1798 duplicates, a total of 5512 references of potential relevance to this systematic review remained. Titles and abstracts were then appraised and excluded 5333 records due to irrelevance. Of the remaining 179 relevant references, 98 were excluded as they were conference abstracts. A total of 81 references were reviewed as full text and a further 21 were excluded against selection criteria. A total of 18 of the 21 excluded studies developed and/or validated risk predictive models for the 48-hour[73] or 72-hour[74] intensive care unit readmissions or the 3-month to 1-year unplanned hospital readmissions.[75–90] One study focused on participants who were discharged to a hospital in the home–hospital programme receiving intravenous antibiotics.[91] The other study,[92] which had been included in the previous systematic review,[10] was also excluded. It was also found that the same result was published in two articles;[32] therefore, the later year article[32] was excluded. A hand search of reference list of the remaining 60 articles was also conducted and no additional studies were identified. Finally, a total of 60 studies were included in this systematic review. Figure 1 is a flow chart as per the Preferred Reporting Items for Systematic Reviews and Meta-Analyses of the screening process of the database search results. The overall risk of bias of the 60 studies was low when evaluated against the six domains of potential bias. All studies described the population of interest adequately for key characteristics, the response rate information was clearly stated, adequate proportion of the study population had complete data on all independent variables, the outcome variable readmission was measured with sufficient accuracy and the method of statistical analysis was appropriate for the design of the study.[72]

Study characteristics

Table 1 summarises the characteristics of the final included studies of this systematic review. The 60 studies were conducted in several countries: USA (n=41), Canada (n=7), Australia (n=3), Spain (n=3), and one from Hong Kong, Korea, Israel, Italy, Singapore and the UK. Of the included studies, the majority employed retrospective data except two. One study[18] used retrospective and prospective data and the other[39] collected prospective data. Fifty-seven included studies accessed healthcare data of either tertiary hospital, centralised or national health information databases. The remaining three studies used community hospital data.[19 44 54] The duration of retrieved data source ranged from 1 single day across 10 hospitals[24] to 10 years[47] of four healthcare databases. All included studies were based on adult

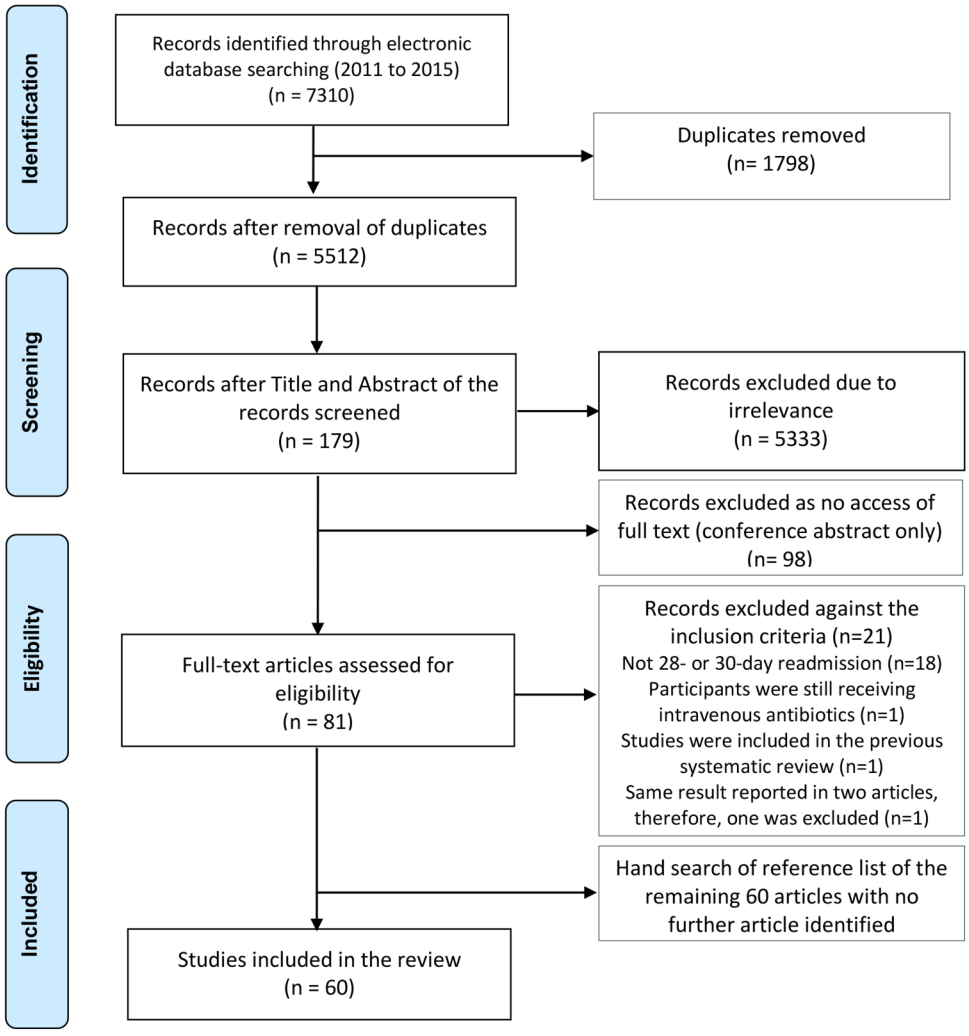

Figure 1 Flow chart for the search and study selection process (PRISMA). PRISMA, preferred reporting items for systematic reviews and meta-analyses.

patients' (aged ≥18 years) healthcare data and the mean age, if reported, ranged from 43 to 85 years.

The 60 included studies reported unique 73 predictive models for 28-day or 30-day unplanned hospital readmissions. A total of 68 of the unique 73 predictive models were developed between 2011and 2015 and 5 were existing models, which were further validated or applied to compare with other developed/existing models. The model utilisation outcome included all-cause admissions (14 studies),[12 13 16–27] cardiovascular-related disease including pneumonia (24 studies,[15 28–50] of which 11 studies focused on heart failure only), medical/internal medicine conditions (15 studies),[11 14 51–63] surgical conditions (6 studies)[64–69] and mental health conditions.[70] A total of 17 models were based on administrative data and the remaining models were derived or validated using administrative and/or clinical/medical records data. The sample size varied from 100 patients[46] to nearly a million[57] patients. The unplanned hospital readmission rate ranged from 2.8%[66] (n=34 046) to 38%[46] (n=100).

Performance of predictive models for 28-day or 30-day unplanned hospital readmissions

Table 2 displays the measures of all included predictive models. Multivariable logistic regression model was used in all included studies. In logistic regression, the outcome variable is the log of the odds of the event (probability of readmission/(1−probability of readmission)). Once the final model is determined, the multivariable logistic regression allows for the calculation of probability of readmission for cohort studies. The predicted probabilities of the final multivariable logistic model are also used for computing the receiver operating characteristic (ROC) curve and the calculation of the ROC, a measure of model discrimination.

Overall, 56 of the 60 included studies reported model discriminative ability (C-statistic), ranging from 0.21[46] to 0.88.[63] The area under curve for validation studies ranged from 0.53[30] to 0.83,[63] being slightly lower than those for the derivation study, 0.21[46] to 0.88.[63] For all-cause unplanned hospital readmission models, the C-statistic was reported by 14 studies ranging from 0.55[13]

to 0.80.[22] Among 16 developed models and 2 existing models, 8 new models and 2 existing models had a C-statistic value >0.70.[12 16 17 19 22 23 26 27]

Regarding cardiovascular disease-related readmissions (24 studies), the C-statistic ranged from 0.21[46] to 0.836[32] across 32 developed models and 5 existing models. Of those, only nine developed models had a C-statistic value >0.70.[30 32 34 35 38 40 41 49 50] In particular, 13 of the 17 models (12 developed and 5 existing) from 11 studies with the special focus on heart failure-related readmissions were presented with C-statistic <0.70.[39 40 42–48] For surgical-related readmissions (6 studies), the C-statistic ranged from 0.59[67] to 0.85[69] among 7 developed models. Three of the seven models showed moderate-to-high discrimination ability.[64 65 69] Patients with heart failure in the telemonitoring program were less likely to be admitted, with the reported C-statistic being 0.21.[46] This indicates that the telemonitoring program was effective in identifying and intervening in patients who were reporting symptoms and thus reduced the likelihood of readmission.

However, 10 of 13 developed models and 1 existing model for medical condition-related readmissions (15 studies) were found to have consistent moderate discrimination ability. Four developed models also demonstrated high discrimination ability with C-statistic exceeding 0.80.[53 52 57 63]

This updated systematic review also identified one study on mental health condition-related unplanned hospital readmission. A predictive model, READMIT <(R) Repeat admissions; (E) Emergent admissions; (D) Diagnoses, and unplanned Discharge; (M) Medical comorbidity; (I) prior service use Intensity; and (T) Time in hospital>, was derived and validated using a 3-year Canadian National Health Database with a C-statistic of 0.63.

One existing predictive model, the LACE index, although validated by eight studies, demonstrated inconsistent model performance. The LACE index was first developed by van Walraven *et al*[93] in 2010 to predict the risk of unplanned readmission or death within 30 days after hospital discharge in medical and surgical patients. The model was derived and validated based on administrative data with a C-statistic of 0.684. The model includes the length of hospitalisation stay (L), acuity of the admission (A), comorbidities of patients (C) and number of emergency department visits in the 6 months before admission (E). Five studies validated the LACE index model using healthcare data of Canada, Singapore, the UK and the USA to predict all-cause readmission (4),[13 16 17 26] heart failure readmission (1)[44] and general medical condition-related readmission (2).[58 56] The discriminative ability of the model (C-statistic), reported by six studies, varied from 0.51 to 0.72.[13 16 17 26 56 58]

An extension of the LACE index to predict early death or all-cause 30-day urgent hospital readmission was further derived using administrative healthcare data and named as LACE+ index by van Walraven *et al*[27] in 2012. The LACE+ index, in addition to four predictive variables, included patient age and sex, teaching status of the discharging hospital, acute diagnoses and procedures performed during the index admission, number of days on alternative level of care during the index admission and number of elective and urgent admissions to hospital in the year before the index admission. The LACE+ index had a C-statistic of 0.771, which exceeded the performance of LACE index. The LACE+ index was further validated by two large Canadian retrospective studies. The performance of the model was 0.61[47] for patients with heart failure and 0.73[23] for patients with all-cause hospital readmissions.

A Canadian study compared the performance of different models within the same population for 30-day readmission or death due to heart failure. A total of 59 652 patients' admission information was retrieved from four health databases over a 10-year period. Five models were examined in the study,[47] namely Charlson, CMS Krumholz, Keenan, LACE index and LACE+. The five models had the C-statistic of 0.57–0.61. In terms of types of data sources used to develop or validate the 73 unique predictive models, administrative healthcare data were used for 17 models but were found/identified with inconsistent discriminative ability. A total of 13 of the 17 models reported C-statistic between 0.55 and 0.7, and the remaining four models reported C-statistic between 0.7 and 0.876. Similarly, the performance of the remaining 56 models using clinical/medical data varied between 0.21 and 0.88 (C-statistic).

Only two models[32 53] were developed targeting the potentially avoidable/preventable unplanned hospital readmissions. The outcome measure of the models focused on the end-of-life patients[53] and pneumonia, heart failure, acute myocardial infarction and chronic obstructive pulmonary disease.[32] Both models had C-statistic >0.8 (0.85 and 0.83, respectively).

Sensitivity and specificity were calculated by 16 of the 60 included studies. The sensitivity of the predictive model ranged from 5.4% (PARR-30 model, Patients at Risk of Re-admission within 30 days)[11] to 91.95% (potentially avoidable readmission (PAR) model),[32] while specificity values were between 22% (Rehospitalisation Risk Score)[24] and 99.5% (PARR-30 model).[11]

A total of 14 of the 60 included studies reported the PPV (5.6[41]–86.61%[32]) and NPV (19.1[61]–99.1%[41]) of the readmission risk predictive model. Similarly, only 17 studies calibrated the developed predictive models and mostly presented as p value, except one study[68] that reported the model calibration as the value of intercept and slope.

Predictive risk of readmission was assessed in all included studies, but only 14 of the included 60 studies specified thresholds for risk categories. Thresholds ranged from 4%[35] to 80%.[61]

Key variables included in the readmission risk predictive model

A total of 28 types of significant variables were extracted from the 73 unique predictive models for unplanned hospital readmissions as shown in table 3. Overall, the top 10 significant variables included in the 73 risk predictive models are comorbidities (n=54), demographic/social (n=45), length of stay (n=29), number of previous admissions (n=29), laboratory tests (n=25), medications (n=21), index type of admission (n=17), procedures at index admission (n=16), admitting diagnosis (n=14) and number of previous emergency department presentations (n=14) (refer to figure 2). The key demographic/social variables consisted of age (n=26), gender (n=25), living arrangement (n=12), race (n=8) and marital status (n=6).

The variables 'comorbidities', 'length of stay' and 'number of previous admissions' remained as the most frequently cited predictive risk variables against all utilisation outcomes. However, the variables 'laboratory tests' and 'medication' were more commonly included in the predictive models for cardiovascular disease-related and medical condition-related unplanned hospital readmissions compared with all-cause, mental health and surgical condition-related unplanned hospital readmissions.

DISCUSSION

A total of 60 studies with 73 unique risk predictive models for 28-day or 30-day unplanned hospital readmissions were included in this systematic review. The discrimination ability (C-statistic) of the 73 models varied largely from 0.21 to 0.88. Inconsistent performances were found among models for all-cause readmission, cardiovascular disease-related readmission and surgical-related readmission. However, most of the predictive models for the general medical condition-related readmission exceeded C-statistic of 0.7. In comparison, Kansagara *et al*[10] included 26 models with the focus of adult medical patients only. A total of 13 predictive models measured 30-day readmissions; of these, 10 models performed poorly and only 3 models reported C-statistic >0.70. The outcome measures of the other 13 models ranged from 41-day to 4-year unplanned hospital readmission; as a result of the vast difference in the time frame, the C-statistic also varied from 0.53 to 0.75.

This updated systematic review has certain limitations. The studies included in this systematic review were limited compared with studies that were published in English with full-text access. The outcomes of the predictive models included in this systematic review were also restricted to 28-day or 30-day unplanned hospital readmission. A meta-analysis is not permitted in this systematic review as the included studies were heterogeneous due to diversity of cohort of population, duration of retrieved data source, sample sizes and geographical locations. It was noted that the sample size was reported in different units, that is, (index) admission/hospitalisation, cases, patients or discharges, as shown in table 1. The lack of standardised calculation could also

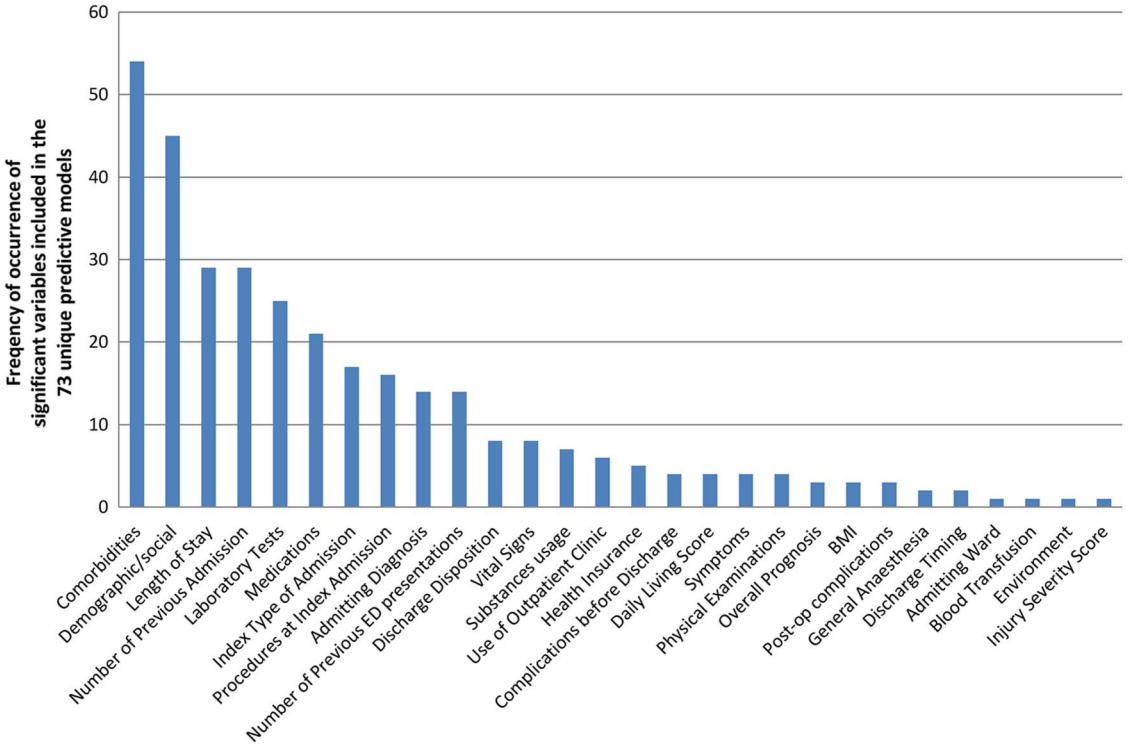

Figure 2 Pareto chart of significant variables included in the predictive models. BMI, body mass index; ED, emergency department.

contribute to the broad range of readmission rates (2.8–38%); thus, the results were not comparable. This systematic review also found the sample size is not associated with the model predictive ability. Of the included 73 unique models, Zai *et al*[46] derived a model based on the selected 100 readmitted patients with heart failure and scored the lowest C-statistic of 0.21. In contrast, Whitlock *et al*[63] retrieved around 200 readmitted patients with acute pancreatitis and developed a model with the highest discrimination ability (C-statistic=0.88).

There has been increased recognition that some unplanned hospital readmissions are associated with the diagnosis of the initial hospitalisation and could be potentially prevented or avoided through systematic discharge process. In 2006, a Swiss study[94] compared three models (non-clinical model, Charlson-based model and SQLape model, A patient classification system, also designed to adjust for costs and other outcomes) to identify potentially preventable readmission risk on over 60 000 medical patients. The C-statistics of the three models were 0.67, 0.69 and 0.72, respectively, which indicated poor-to-reasonable discrimination ability. In contrast, this systematic review identified two high-performance models[32 53] for potentially avoidable/preventable readmissions with C-statistic >0.8. The PAR model[32] was also high in other predictive model performance indicators, such as sensitivity (91.95%), specificity (97.65%), PPV (86.61%) and NPV (98.65%). However, the two models were developed based on comparatively smaller sample size of 5600[32] and 10 275[53] using American healthcare data collected over a 12-month period. Overall, the number of potentially preventable readmissions remains unclear due to lack of standardised identification process.[95–98]

Compared with the previous systematic review,[10] there were more studies in this review using clinical medical record data to develop disease-specific predictive models. However, the debate whether a predictive model should be developed using administrative data or clinical/medical records data remains inconclusive. Three key variables extracted from the 73 unique models, 'comorbidity', 'length of stay' and 'previous admissions', were based on administrative data and were consistent with the findings of a previous systematic review.[10] The latest evidence has shown that variables based on clinical medical data, that is, 'laboratory tests' and 'medications', were also valued in models for predicting cardiovascular-related and medical condition-related readmissions. Of note, ineffective communication in transitions of care is reported as a major contributing factor to adverse events that directly risk patient safety.[99 100] Poor communication at discharge also leads to preventable unplanned readmissions and frequent problems with the continuity of medication management.[101–103] None of the examined 73 models cited the comprehensiveness of discharge information as a predictor to unplanned hospital readmissions.

All included studies in this systematic review were based on adult population. To date, only two paediatric predictive models were identified and both were based on American paediatric populations. One retrospective multicentre study[104] retrieved 12-month administrative data from 38 children's hospitals. A model was developed and internally validated with a high discrimination ability (C-statistic=0.81). However, the model outcome measure was 12-month all-cause readmissions. In comparison, a 30-day hospital readmission model[105] was developed based on 5376 paediatric patients following plastic surgery procedures. The study accessed prospective medical records, and the model had moderate discrimination ability of C-statistic 0.784.

The performance of the 73 unique predictive models in this review was assessed using a variety of statistical measures. Inconsistency of reported statistical measures was noted in the included 60 studies, of which 2 studies[44 58] reported threshold as the only model performance measurement. A US framework for assessing the performance of predictive models[106] argued the importance of reporting discrimination and calibration for a risk predictive model. In all included 60 studies, the most reported measure of the risk predictive model is the ROC (C-statistic). The interpretation of the risk predictive model discriminative ability (C-statistic) was inconsistent. For instance, a study[47] examined five predictive models and concluded that the models had moderate discrimination ability based on the C-statistic of 0.57–0.6; whereas models are typically considered reasonable when the C-statistic is higher than 0.7 by Hosmer and Lemeshow.[71]

CONCLUSION

The risk predictive models which focused on general medical conditions in relation to unplanned hospital readmissions reported moderate discriminative ability. Two models[32 53] for potentially preventable/avoidable readmissions showed high discriminative ability. This systematic review, however, found inconsistent performance across the included unique 73 risk predictive models for unplanned hospital readmissions.

The variables 'comorbidities', 'length of stay' and 'previous admissions' were frequently cited across the examined unique 73 models, and 'laboratory tests' and 'medication' variables had more weight in the models for cardiovascular disease and medical conditions in relation to readmissions. However, comprehensiveness of discharge information was not included in any of the examined models.

This review highlighted the need for rigorous validation of the risk predictive models with moderate-to-high discriminative ability be undertaken, especially the two models[32 53] for the potentially avoidable hospital readmissions. There is a need to review and update predictive models. Specifically this is essential for paediatric 28-day all-cause unplanned hospital readmissions as limited evidence was found.

Findings from this updated systematic review revealed an increasing number of developed risk predictive

models for specific disease-related unplanned hospital readmission using clinical/medical records data. Findings from this systematic review also confirm the limited applicability of hospital readmission risk predictive models. The performance of the applied existing models was inconsistent. It is, therefore, essential to clearly define utilisation outcomes and the type of accessible data sources prior to determining which risk predictive model to use. For example, most of the models were developed based on healthcare data from the USA, which might not be applicable to patients from other settings.

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