Risk Prediction Models to Predict Emergency Hospital Admission in Community-dwelling Adults

A Systematic Review

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Background: Risk prediction models have been developed to identify those at increased risk for emergency admissions, which could facilitate targeted interventions in primary care to prevent these events.

Objective: Systematic review of validated risk prediction models for predicting emergency hospital admissions in community-dwelling adults.

Methods: A systematic literature review and narrative analysis was conducted. Inclusion criteria were as follows; Population: community-dwelling adults (aged 18 years and above); Risk: risk prediction models, not contingent on an index hospital admission, with a derivation and ≥ 1 validation cohort; Primary outcome: emergency hospital admission (defined as unplanned overnight stay in hospital); Study design: retrospective or prospective cohort studies.

Results: Of 18,983 records reviewed, 27 unique risk prediction models met the inclusion criteria. Eleven were developed in the United States, 11 in the United Kingdom, 3 in Italy, 1 in Spain, and 1 in Canada. Nine models were derived using self-report data, and the remainder (n = 18) used routine administrative or clinical record data. Total study sample sizes ranged from 96 to 4.7 million participants. Predictor variables most frequently included in models were: (1) named medical diagnoses (n = 23); (2) age (n = 23); (3) prior emergency admission (n = 22); and (4) sex (n = 18). Eleven models included nonmedical factors, such as functional status and social supports. Regarding predictive accuracy, models developed using administrative or clinical record data tended to perform better than those developed using self-report data (*c* statistics 0.63–0.83 vs. 0.61–0.74, respectively). Six models reported *c* statistics of >0.8, indicating good performance. All 6 included variables for prior health care utilization, multimorbidity or polypharmacy, and named medical diagnoses or prescribed medications. Three predicted admissions regarded as being ambulatory care sensitive.

Conclusions: This study suggests that risk models developed using administrative or clinical record data tend to perform better. In applying a risk prediction model to a new population, careful consideration needs to be given to the purpose of its use and local factors.

Key Words: risk prediction model, emergency hospital admission, community-dwelling adults

(*Med Care* 2014;52: 751–765)

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The authors declare no conflict of interest.

Funded by the Health Research Board (HRB) of Ireland by the Research Training Fellowship for Healthcare Professionals award under Grant HPF/2012/20 and conducted as part of the HRB PhD Scholars Programme in Health Services Research Grant No. PHD/2007/16.

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Supplemental Digital Content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's Website, www.lww-medicalcare.com.

ISSN: 0025-7079/14/5208-0751

In the United States, rehospitalizations alone are estimated to cost €12 billion each year.[1] Emergency or unplanned admissions account for approximately 35% of all hospitalizations in the United Kingdom (UK) costing an average of £11 billion annually.[2] As a result of this escalating expenditure, reducing emergency admissions is a priority for health care policy-makers.[3] For patients, unplanned hospitalizations may be distressing, and older people in particular are at risk of related adverse events such as hospital-acquired infections, loss of functional independence, and falls.[4]

One way of reducing emergency admissions is to identify people at higher risk who can then be prioritized for an intervention, such as case management.[5] Risk prediction models developed for this purpose and not contingent on recent hospitalization have the advantage of broader applicability and can include a wider range of predictor variables. It has also been argued that focusing on specific high-risk groups, such as those discharged from a hospital, may not be the best approach to take in targeting emergency admissions. This is due, in part, to the concept of "regression to the mean," which means that patients with a history of multiple admissions will on average have fewer admissions in the future than they had in the past.[6,7]

Three main types of data sources are utilized to derive risk models for predicting emergency admission.[3] The first is self-report data collected through patient questionnaire or interview with the advantage of being able to include non-medical variables such as functional status and social supports. The second is routine data collected for the purposes of administrative databases or population registries. The third incorporates data collated from the clinical record or other primary data sources with the advantage of being able to test larger number of variables and without the response biases associated with self-report.

The aim of this study is to perform a systematic review of validated risk prediction models for predicting emergency hospital admission in community-dwelling adults. Specific objectives were: (1) To examine the variables included in risk prediction models; (2) to summarize the performance of risk prediction models in derivation and validation cohorts; and (3) to compare the predictive accuracy of risk models externally validated in the same setting.

METHODS

The protocol for this systematic review has been published on PROSPERO (PROSPERO2013:CRD42013004390) and is available at http://www.crd.york.ac.uk/PROSPERO/display_record.asp?ID=CRD42013004390.

The PRISMA guidelines for the conduct and reporting of systematic reviews were utilized in undertaking this systematic review.[8]

Search Strategy

A systematic literature search was carried out in September 2013 and updated in February 2014 of the following search engines: PubMed, EMBASE, CINAHL, the Cochrane Library, and Google scholar. Additional databases were also searched: the US Agency for Healthcare Research and Quality (AHRQ), the John Hopkins Adjusted Clinical Groupings (ACG) publications, the UK Nuffield Trust, and the King's fund. The search was supplemented by hand searching references of relevant articles and contacting study authors when necessary. No restrictions were placed on language or year of publication.

A combination of MeSH terms and keywords were used to capture studies of interest (Appendix 1, Supplemental Digital Content 1, http://links.lww.com/MLR/A747).

Study Selection

Studies were included if they met the following criteria:

(1) Population: Community-dwelling adults (aged ≥ 18 y).
(2) Risk: Risk prediction models, which were not contingent on an index hospital admission, with a derivation and at least 1 validation (either internal or external) cohort. Models were subdivided according to the data used to develop the model as follows: (i) Self-report; (ii) Administrative or clinical record data.
(3) Outcome: Primary outcome of emergency hospital admission (defined as unplanned overnight stay in hospital). Studies that had emergency admission as part of their outcome of interest (e.g. combined endpoints) were also included.
(4) Study design: Retrospective or prospective cohort studies.

The following studies were excluded:

Primary population of interest focused on pediatrics, obstetrics, surgery, mental illness, or patients enrolled in managed care programs; readmission risk prediction models (models contingent on an index hospital admission); models in which the primary outcome of interest was elective hospital admissions, models developed for use in emergency rooms (ERs), for specific diagnoses, for example, congestive heart failure, for a different primary outcome, e.g., mortality and risk adjustment models (models to compare provider performance with inform pay and health care financing). Studies that reported risk factors only and did not develop a model were also excluded.

Data Extraction

Two reviewers (E.W., E.S.) read the titles and/or abstracts of the identified records in duplicate and eliminated irrelevant studies. Studies that were considered eligible for inclusion were read fully in duplicate and their suitability for inclusion determined. Disagreements were managed by consensus and if consensus could not be reached then by third review (S.M.S.). Additional data were sought from authors when necessary. Data were extracted using a standardized data extraction form.

Statistical Analysis

Meta-analysis was not possible because of risk prediction model heterogeneity, so we narratively summarized each unique risk prediction model under the following headings:

- The model's derivation cohort study setting, participants and population studied.
- Type of validation cohort, that is, internal or external.
- Type of data used to derive the model.
- Model discrimination was assessed using the *c* statistic with 95% confidence intervals when available. A *c* statistic of 0.5 indicates that the model performs no better than chance, a score of 0.7–0.8 indicates acceptable discrimination, whereas a score of >0.8 indicates good discrimination.[9] In cases in which the *c* statistic was not presented, we present positive predictive values, sensitivity, and specificity.
- Variables evaluated and considered for inclusion.
- Variables included in the final model.

Methodological Quality Assessment

Methodological quality assessment of included studies was independently performed in duplicate (E.S., N.V.) using the McGinn checklist for the methodological assessment of clinical prediction rule studies[10] (Appendix 2, Supplemental Digital Content 2, http://links.lww.com/MLR/A748). The McGinn criteria include a total of 8 criteria to assess the internal and external validity of derivation articles. For validation studies, a total of 5 criteria were used. Detailed guidance notes were also developed in-house to accompany the derivation and validation methodological criteria. Disagreements were solved by consensus or by adjudicating third review (E.W.).

RESULTS

Study Identification

A flow diagram of the search strategy is presented in Figure 1. The electronic databases search strategy yielded 20,666 papers. A further 20 articles were retrieved from searches of other resources. After removal of duplicates, a total of 18,983 articles were screened by title and abstract, of which 163 studies were reviewed in full text; 27 unique risk prediction models met all inclusion criteria.

Description of Included Risk Prediction Models

Of the 27 unique models included, 11 were developed in the UK, 11 in the US, 3 in Italy, 1 in Spain, and 1 in Canada. Nine models were developed using self-report data or a combination of self-report and administrative or routine data (Table 1) and the remainder (n = 18) utilized routine or primary data alone (Table 2). A total of 13 models were developed specifically for use in older people (60 y and above). Total sample sizes ranged from 96 to 4.7 million participants. The majority of models (18 of 27) were developed to predict emergency hospital admission at 12-month follow-up (range, 90 d–4 y). Of these, 3 models focused on emergency admissions for chronic disease or conditions amenable to primary care management as a primary outcome measure.[27,31,38] Two models predicted any hospitalization and 2 predicted occupied bed days over specific time periods.[17,26,32,38] A further 3 models used the endpoint of emergency admission or ER visit and 2 used combined hospitalization/death.[11,19,21,35,37]

Data Sources Used to Develop Risk Prediction Models

The 9 models developed with self-report data included literature reviews; medical record review and questionnaire pilot in the development of their models (Table 1). Of the 18 models developed using routine or clinical record data, 10 were developed using a combination of administrative and clinical record data.[22–24,26–30,35,39] A further 8 were developed using administrative data alone.[17,25,32–34,36–38] Eleven models included general practice (GP)/family practice clinical record data in their final model.[22–24,26–30,35,39]

Risk Prediction Model Variables

Each of the variables considered and included in each of the 27 models are presented in Table 3. Seven studies presented their final risk model only and not all variables considered for inclusion, and 1 study uses locally available data to create a risk prediction model specifically for a named population so variables considered for inclusion vary.[23–25,27,28,31,34,37] The most frequently included predictor variables in final risk models were: (1) named medical diagnoses (23 models); (2) age (23 models); (3) prior emergency admission (22 models); and (4) sex (18 models). Other health care utilization variables commonly included were prior ER and outpatient department (OPD) visits (14 and 13 models, respectively). Twelve models included measures of multimorbidity (the presence of 2 or more chronic medical conditions in an individual), most commonly the Charlson index and simple disease counts.[19,23,24,29–33,36–39] One model considered multimorbidity for inclusion and then excluded it after evaluation.[17] Polypharmacy was considered as a predictor variable in 14 models and included in 11 final models.[11,18,19,21,23,24,28–30,37,39] Five models included a specific measure of socioeconomic group (SEG) and a further 3 used either employment history or income as proxy measures for SEG.[17,21–23,25,28,29,31]

Overall, a smaller number of models (n = 11) included nonmedical factors.[11,13–15,17,20–22,24,31,37] These variables were largely included in self-report data models (Table 1). Of those that included functional status as a predictor variable, most considered either activities of daily living, mobility, and/or a history of falls.[11,13,17,20–22,24,31] Four questionnaires included measures of self-rated health and 1 included health-related quality of life.[13–15,17,18] Two questionnaires included the social support measure of caregiver availability.[15,21] Three models developed using administrative or clinical record data included nonmedical variables; these included a history of falls as a predictor variable, social supports and living arrangements, and a disability rating variable respectively.[22,31,37]

Predictive Accuracy of Risk Prediction Models

Eighteen models presented *c* statistics for the outcome of emergency admission ranging from 0.61 to 0.83. Six models reported *c* statistics of >0.8, indicating good model discrimination.[27,28,31–33,38] Some similarities were noted among these models; all included prior health care utilization variables, multimorbidity or polypharmacy measures, and named medical diagnoses or named prescribed medications variables. Three of these 6 models utilized emergency admissions for chronic disease or conditions amenable to primary care management as a primary outcome measure.[27,31,38] A further 7 risk prediction models reported *c* statistics of between 0.7 and 0.8 representing acceptable model performance.[18,22–24,35–37,39] Of 9 models developed using self-report data primarily, 8 were designed for use in older people. In contrast, only 5 of the 18 models developed using administrative or clinical record data were derived specifically for use in older people. The remainder were developed for use in general populations aged over 18 years. Overall, models developed primarily using administrative or clinical record data performed better than those developed using self-report data, with reported *c* statistics ranging from 0.68 to 0.83 versus 0.61 to 0.74, respectively.

Comparison of Performance of Risk Prediction Models Within and Across Populations

Three studies developed several prediction models in 1 population, using different datasets and then compared their performance. Billings et al[23] developed 4 models in the United Kingdom using: (1) inpatient data alone; (2) combined inpatient and ER data; (3) combined inpatient, ER, and OPD data; and (4) combined inpatient/ER/OPD/GP/family practice data. This was undertaken to determine whether the addition of GP/family practice data improved overall model performance. In the test sample of >1.8 million people, the OPD/ER/GP/inpatient model performed best (*c* statistic 0.78

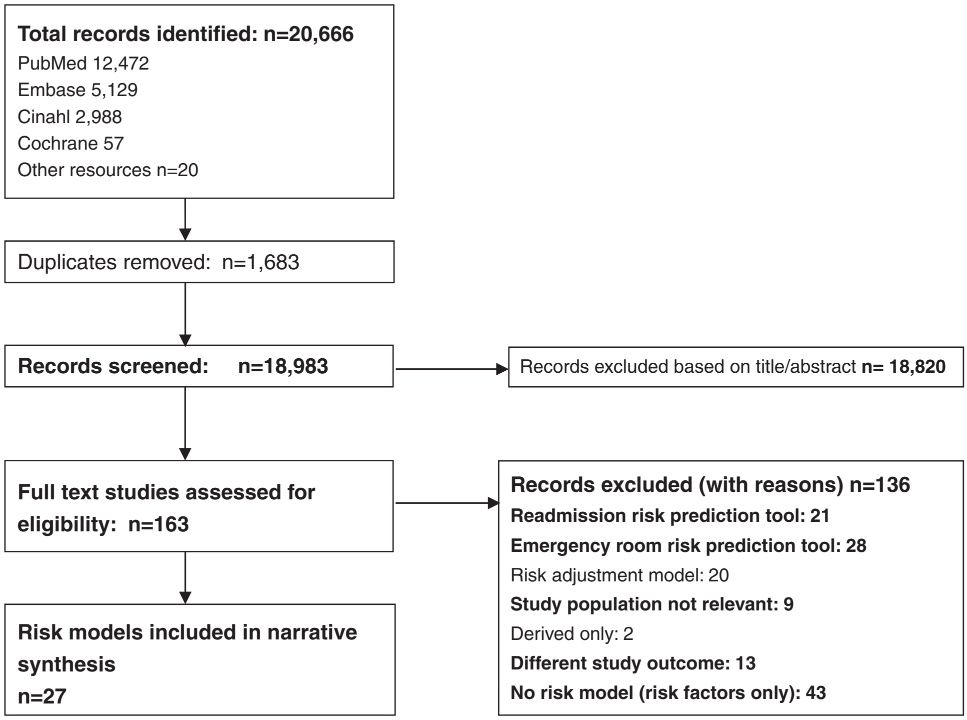

FIGURE 1. PRISMA flow diagram of included risk prediction models.

vs. 0.73 for inpatient model).[23] Similarly, Lemke and colleagues in the United States examined various models using the ACG classification and compared these with models using prior hospitalization only using a data source of 4.7 million medical insurance claims. The model using ACG groupings plus prior health care utilization performed best overall (*c* statistic 0.8 vs. 0.75).[33] Reuben and colleagues compared models developed using prior admission only, self-report data only, and a model using a combination of self-report variables and laboratory values. The model with greatest predictive accuracy used a combination of self-report and laboratory variables (*c* statistic 0.69).[17]

Two studies directly compared different validated models in the same population. The UK Combined Predictive Model (CPM) was developed to be nationally representative.[30] It was compared with 2 other UK risk models, the Wales predictive model and the Devon predictive model.[24,29] In primary care the Wales model was found to have superior predictive ability when compared with the CPM in correctly identifying those who were subsequently admitted. The Devon predictive model included many of the same variables as the CPM but also local data variables and was found to have greater predictive accuracy when compared with the CPM. The authors argued that the addition of local factors, for example, the participant's duration of family practitioner registration as a proxy for continuity of care, was integral to improved performance.

Methodological Quality Assessment of Included Studies

Overall, the methodological quality of included studies was good. For derivation, the majority of studies reported all checklist items with the exception of items pertaining to blinding of outcome assessors, blinding of those assessing the presence of predictors, and reporting of the proportion of the population with important predictors. For validation the majority of studies reported all checklist items with underreporting of blinding of those assessing the outcome event (Figs. 2A, B).

DISCUSSION

Summary of Findings

This systematic review identified 27 unique risk models for predicting hospital admission. Less than half were developed specifically for older people, with the rest designed for use in an adult population. Overall, models developed using administrative or clinical record data and developed on large datasets tended to have greater predictive ability than self-report questionnaires. Risk prediction models that examined the added benefit of GP/family practice clinical record data in increasing predictive accuracy reported improved performance when this data source was included.

Variables Included in Risk Prediction Models

Overall, almost all risk models in this review included age, prior hospitalization, and specified medical diagnoses, and the majority included sex. However, less than half considered a specific measurement of multimorbidity, which is surprising considering the impact the presence of multiple conditions has been shown to have on health care utilization.[40,41] Similarly, less than half of models considered polypharmacy and only 8 included a measure for SEG in

TABLE 1. Risk Prediction Models Developed Using Self-report Data Primarily (n = 9)

Reference, Risk Model Name	Population and Setting	Derivation (n)	Validation (n)	Data Used to Develop Final Model	Outcome*	No. Admissions (%)	*c* Statistic (Confidence Interval)†
United Kingdom							
Walker,[11] Sherbrooke questionnaire (derivation) Daniels,[12] Sherbrooke questionnaire (validation)	Aged ≥ 75, general practice, London, UK, 2000–2002 Aged ≥ 70, general practice, Netherlands, 2008–2010	2307	532	Postal questionnaire, 6 items: (1) Living alone (2) Takes ≥ 3 medications (3) Uses a walking aid (4) Problem with sight (5) Problem with hearing (6) Problem with memory	24 mo (ER visit or emergency admission) 12 mo (emergency admission)	Derivation: 342 (15.5%) Validation: 75 (17%) (430 participants included in final analysis)	Derivation: NR Validation: 0.60 (0.53–0.67)
Lyon,[13] EARLI	Patients aged ≥ 75 y UK general practice, 2002–2003	3032	500 (bootstrap and split samples)	Pilot study and review of literature to identify predictor variables. Final model: Postal questionnaire with 6 yes/no items: (1) Heart problems. (2) Leg ulcers. (3) Problems with memory and get confused. (4) Go out of the house without help. (5) Admitted to hospital as an emergency in the last 12 mo. (6) Rate general state of health as good	12 mo	696 (23%) ≥ 1 emergency admission	Derivation = 0.695 (0.671–0719). Validation: Bootstrap = 0.690 (no CIs) Split sample = 0.669 (0.630–0.709)
United States							
Roos et al[14]	Community-dwelling insured participants aged ≥ 65 y, Manitoba, Canada, 1970–1973	1518	1518 (split sample)	Three models compared in same population: (1) Administrative data only (2) Interview data only (3) Both administrative and interview data Six interview questions included: (1) Living with spouse. (2) Self-rated health fair, poor, or bad (3) Basic disabilities ≥ 1%. (4) Reported conditions of arthritis, diabetes, chest. (5) Reported undergoing treatment for ≥ 1 conditions. (6) Amount of time spent in hospital in last year	12 mo	NR	NR
Boult et al,[15] Probability of repeated admission (Pra) (derivation) Wallace et al[16]	Patients aged ≥ 70 y US Community dwelling, 1984–1990	2942	2827 (split sample) External validation: 11 cohorts (9 studies) Range 306–17,469	Data from longitudinal study of aging Final model: Postal questionnaire with 8 items: (1) Age (2) Sex (3) Self-rated health (4) Availability of an informal	≥ 2 emergency admissions within 4 y Validated for 12 mo	669 (24%)	Derivation = 0.61 Validation studies: Meta-analysis of 5 cohorts (n = 8843), pooled *c* statistic 0.69, pooled sensitivity 12% (10.5–13.6%), pooled specificity 96% (95.8–96.7%)

(*Continued*)

TABLE 1. Risk Prediction Models Developed Using Self-report Data Primarily (n = 9) (*continued*)

Reference, Risk Model Name	Population and Setting	Derivation (n)	Validation (n)	Data Used to Develop Final Model	Outcome*	No. Admissions (%)	*c* Statistic (Confidence Interval)†
(Systematic review of Pra validation studies)				caregiver. (5) Diagnosis of coronary artery disease. (6) Diagnosis of diabetes. (7) Hospital admission in previous year. (8) ≥ 6 physician visits in the previous year			
Reuben et al[17]	Patients aged ≥ 71 y US Medicare community dwelling, 1988–1992	5138 [50% of total sample (split sample) used for derivation, ie, 2569]	5138 (50% of total sample used for validation, ie, 2569)	Data Epidemiologic Studies of the Elderly-1988 wave for East Boston, New Haven and Iowa used as baseline Three models developed: (1) Prior hospitalization only (2) Self-report items only (3) Self-report and physical examination and laboratory values 10 self-report variables: (1) Sex (2) Self-rated health (3) Infrequent religious participation. (4) Help needed bathing. (5) Ability to walk 0.5 miles. (6) Diagnosis of diabetes. (7) Taking loop diuretics. (8) Not working (9) Hospitalization in previous year. (10) Hospitalization in year before that	11 or more hospital days within 36 mo	1243 (24.2%)	Self-report variables model; 0.68 for ≥ 2 admissions over 3 y
Damush et al[18]	Patients aged ≥ 50 with prespecified chronic medical conditions and all aged ≥ 75 y US academic primary care (1 practice)	1041	1000 (bootstrap sample)	Data included from literature review, medical record review, and patient interviews Final model: Questionnaire (through interview) 5 self-report items and 2 physical examination/laboratory items Self-report items: (1) Diagnosis of congestive heart failure. (2) Diagnosis of diabetes mellitus. (3) Number of medications. (4) Health-related quality of life (physical functioning). (5) ER visits in the previous year	12 mo	216 (20.7%) ≥ 1 emergency admission	Derivation = 0.73 Validation = 0.74
Shelton et al,[19] Community Assessment Risk Screen (CARS)	Aged ≥ 65 y US Medicare with ≥ 1 defined comorbidities and psychosocial factors, 1993–1995	411	1054	Data included from telephone interview and postal questionnaire Final model: Postal questionnaire, 3 items:	12 mo (admission or ER visit)	Derivation = 89 (22%) Validation = 180 (17%)	CARS score ≥ 4 = 0.67 for composite endpoint NR for admissions only

				(1) ≥ 2 comorbidities of a predefined list of conditions (heart disease, diabetes, myocardial infarction, stroke, COPD, cancer). (2) Taking ≥ 5 medications. (3) Hospitalization or ER encounter in previous 12 mo			
Freedman[20]	Aged ≥ 81 y in Colorado, US primary care (Kaiser Permanente health plan members), 1993	1873	1872 (random split sample)	Postal questionnaire informed by literature and new items (148 questions) Final Model: Postal questionnaire, 4 items; (1) Presence of heart disease. (2) Presence of diabetes. (3) Need help preparing meals. (4) Require help of person or mechanical aid to get around	4.5 mo	NR	Derivation = 0.69 Validation = 0.63
Italy							
Mazzaglia et al[21]	Primary care in Florence, Italy, aged ≥ 65 y, 2003–2004	2470	2926	Questionnaire (7 items) as screening test then local registry data (administrative). Self-report items: (1) Activities of daily living (ADLs). (2) Instrumental ADLs. (3) Poor vision (4) Poor hearing (5) Recent unintentional weight loss (6) Use of homecare services (7) Income	15 mo (emergency hospitalization or death)	Derivation: 445/2470 (18%) Validation: 509/2926 (17%)	Derivation: 0.68 (0.66–0.71) Validation: 0.67 (0.65–0.70)

*Outcome is emergency hospital admission unless otherwise stated.
†If *c* statistics are not presented then positive predictive values (PPVs), sensitivity, and specificity (when available) are recorded.
NR indicates not recorded.

TABLE 2. Risk Prediction Models Developed Using Administrative or Clinical Record Data (n = 18)

Reference, Risk Model Name	Study Population and Setting	Derivation (n)	Validation (n)	Data Used to Develop Model	Outcome(s)*	N (%) Admitted to Hospital	c Statistic (Confidence Intervals)†
United Kingdom Hippisley-Cox and Coupland,[22] Qadmissions	Aged ≥ 18–100 y registered in UK general practice, 2010–2011	2,849,381	Two validation cohorts: Qresearch 1.3million CPRD 2.4 million	Developed using linked computerized GP and hospital inpatient data; final model 30 variables	24 mo (first emergency admission)	265,573 (9%) derivation cohort Qresearch validation 132,723 (10%) CPRD validation 234,204 (9%)	Qresearch validation 0.773 (0.771–0.774) women 0.776 (0.774–0.778) men CPRD validation 0.771 (0.770–0.773) women 0.772 (0.771–0.774) men
Billings et al[23]	Aged ≥ 18 y registered in UK general practice (5 primary care teams), 2007–2010, compared 4 models within same population	1,836,099	Not recorded (NR)	Four prediction models developed to compare advantage of addition of different datasets: (1) Inpatient (Inpt) only (2) Inpt/A+E (3) Inpt/A+E/OPD (4) Inpt/A+E/OPD/GP	12 mo	Risk threshold 50%+; Inpt only 52.9%, Inpt/A+E 53.1%, Inpt/A+E/OPD 52.3%, Inpt/A+E/OPD/GP53.8% Risk threshold top 1%; Inpt/A+E/OPD 45.8%, Inpt/A+E/OPD/GP 47.5%	Risk threshold = 50%; Inpt/A+E/OPD/GP model; 0.780 Inpt only model; 0.731
Chenore et al,[24] Devon Predictive Model	Patients aged ≥ 65 y, UK General practice in Devon, (105 practices), 2007–2011	80% of total sample 722,383, ie, 577,906	20% of total sample 722,383, ie, 144,477	NHS Secondary Uses Service database-inpt, OPD, ER Local GP practice data in Devon (combined CPM variables with local variables), computerized 89 variable model	12 mo	65,892 (9.1%)	Risk threshold = 50% 0.781 (0.778–0.783)
NHS/Information Services Division Scotland,[25] Scottish Patients At Risk of Re-Admission (SPARRA)-Version 3	Patients aged ≥ 16 y in population in Scotland 2006–2010	3,506,796	NR	Three different models: (1) Frail elderly aged >75 (2) Long-term conditions, aged 16–74 (3) Younger ED, aged 16–55 with ≥ 1 ED visit in last year Hospital inpatient admissions data, community dispensed prescriptions, ED attendances, new outpatient attendances, psychiatric inpatient admissions	12 mo	309,783 (8.8%)	Risk thresholds; 30%-PPV 59.8%, 40%-PPV 52.2%, 50%-PPV 59.8% Sensitivity at threshold 50% = 10.5%
Baker et al[26]	Patients aged 40–98 y registered to Lodgehill clinic general practice in Nairn, Scotland‡	96‡	96‡	Data from 1 general practice in Nairn, Scotland and inpatient	Occupied bed days over 12 mo‡	105 (54.7%)	Derivation: 0.794

				data (NHS Highland Patient Administration System)			
Sussex Key Events Predictor tool[27]	All ages in the population of East Sussex and Brighton, UK‡	Total sample = 823,000 80% derivation‡	Total sample = 823,000 20% validation‡	Inpatient, outpatient, ER and community data‡	12 mo Emergency chronic admission (any of: COPD, asthma, diabetes, dementia, ischemic heart disease, respiratory disease or stroke)‡	NR	0.82‡
Donnan et al,[28] PEONY	Patients aged ≥40 y in general practice in Tayside, Scotland, 1996–2004	90,522	90,879	Computerized model data from all general practices in Tayside, Scotland used record linked primary and secondary data via unique patient ID numbers of medications (includes all health encounters)-previous admissions, number bed days, LOS mean, demographics, receipt of drugs and number. Final model contains 35 variables.	12 mo	6793 (7.5%) in derivation cohort	Derivation: 0.80 Validation: 0.79
Health Dialog UK, 2008, Welsh Predictive Model (WPM)[29]	All ages (0–100 y) in general practice in Wales (51 practices), 2004–2007 (n = 10,247 were aged <15 y)	Total sample 298,077 Split three ways, 50% derivation, 25% validation of variables and 25% predictive testing Derivation cohort 149,038	74,114	Used GP data from 51 Welsh general practices, Welsh index of multiple deprivation, hospital records and GP data (no ER visit data), compared accuracy with CPM in same population. Compared Combined Predictive Model vs. Wales model in same population	12 mo	NR	Risk thresholds; Top 1%; PPV = 44.3%, Sensitivity 6.6%, Top 5%; PPV = 28.0%, Sensitivity = 20.7%
Health Dialog UK, 2006, Combined Predictive Model (CPM)[30]	All ages (0–100 y) in 2 UK primary care teams, 2002–2005	280,000 (random split sample)	280,000, (random split sample)	Data from 2 primary care trusts-includes inpt, OPD and ER data) plus primary care data (lab, diagnosis, and encounter information). Limited pharmacy and social services data. Top 0.5% considered very high risk	12 mo	NR	Risk threshold top 1%; PPV 40.5%, sensitivity 6% (recorded in WPM report, NR in CPM report)
United States and Canada							
Gao et al[31]	Adult Veterans Association (VA) patients treated in fiscal years 2011 and 2012 for any ambulatory care sensitive condition (ACSC). Prevention Quality indicators (Agency for Healthcare Research and Quality) used to specify ACSCs	Total sample 2,987,052 Split sample Derivation sample 50% of total 1,493,526	Total sample 2,987,052 Split sample Validation sample 50% of total 1,493,526	VA centralized National Patient Care Database. The following files were utilized (1) Patient treatment file (inpatient care) (2) Outpatient care file (3) Extended care file (long-term care) (4) Contract hospital file (5) Fee file. Four models developed and compared for outcome of 90 d admissions.	(1) 90 d ACSC admission (2) 12 mo ACSC admission	21,873 (0.7%) 90 d admission 71,425 (2.4%) 12 mo admissions	*90 d admission* Final full model; Derivation 0.856 (0.853–0.860) Validation 0.856 (0.852–0.860) *12 mo admission* Final full model Derivation 0.835 (0.31–0.837) Validation 0.833 (0.830–0.837)

(*Continued*)

TABLE 2. Risk Prediction Models Developed Using Administrative or Clinical Record Data (n = 18) (*continued*)

Reference, Risk Model Name	Study Population and Setting	Derivation (n)	Validation (n)	Data Used to Develop Model	Outcome(s)*	N (%) Admitted to Hospital	*c* Statistic (Confidence Intervals)†
				Final full model then applied to predict admission at 12 mo			
Wang et al[32]	Aged $\geq$ 18 y in population in US, 2009–2011	2.7 million (Random 60% of 4.5 million participants)	1.8 million (Random 40% of 4.5 million)	Prediction model developed using Veterans Health Administration primary care data	First occurrence of hospital admission; death without hospitalization; combined event of hospital admission or death within 90 d and 12 mo	123,927 (2.7%) 90 d 378,863 (8.2%) 12 mo	*90 d outcomes;* 0.833 (0.832–0.834) Hospital admission only; 0.81 (0.810–0.812) Hospital admission or death *12 mo outcomes;* 0.809 (0.808–0.810) Hospital admission only; 0.787 (0.786–0.787) Hospital admission or death
Lemke,[33] Adjusted Clinical Groupings (ACG)	Aged <65 y in employer health plans, $\geq$ 65 y in managed care plans in US insurance databases, 2005–2007, compared 3 models in same population	4.63 million	4.7 million	US Health Plan insurance claims administrative database Several models developed and compared: (1) Prior hospitalization model (2) Charlson comorbidity hospitalization model (Combined model of hospitalization, other health care utilization and Charlson comorbitity index) (3) Four ACG models	(1) Acute hospitalization within 12 mo (2) ICU/CCU admission within 12 mo (3) Extended inpatient care for $\geq$ 12 d within 12 mo	150,417 (3.2%) Derivation 149,843 (3.2%) Validation	Validation cohorts; (1) Prior hospitalization = 0.75 (2) Charlson hospitalization model = 0.78 (3) ACG inpatient hospitalization = 0.80
Versisk Health,[34] DxCG Likelihood of Hospitalization	All ages in 1 US insurance database (Versisk Health)	NR	NR	Demographics and administrative claims data from OPD and inpatient	6 mo	NR	Risk threshold; Top 1% PPV 24.2%
Crane et al,[35] Elders Risk Assessment Index	Patients aged $\geq$ 60 y, US primary care clinics in 1 hospital, 2003–2006	12,650	450 (bootstrap samples)	Electronic medical record and administrative databases from primary care clinics in 1 hospital, computerized model,10 items, scored as 5 quartiles, >16 highest risk	24 mo (admissions or ER visits)	5785 (45.7%) admitted or ER visit	Combined admission/ ER visit 0.678 Admission only 0.705
Inouye et al[36]	Patients aged $\geq$ 70 y in 2 US primary care clinics, 2003–2005	1932	1987	Computerized model Administrative database, inpatient and OPD visits, demographics, billing diagnoses, radiologic procedures, and lab results. No EMR data. 5 item score, $\geq$ 3 = high risk	12 mo	299 (15%)	Derivation: 0.72 Validation: 0.73

Italy							
Falasca et al,[37] MoSaiCO	Patients aged ≥ 18 y from population in Ravenna, Italy, 2006–2008	146,949	147,654	Computerized model developed using data from Ravenna population registry, record links inpt, ER, OPD, medications, demographics and social and mental health services	12 mo (emergency admission or mortality) note includes medical and involuntary mental health admissions	9691 (6.59%) derivation 9850 (6.7%) validation	Validation cohort: 0.77
Louis et al[38]	Aged ≥ 18 y in the population of the Emilia-Romanga region, Italy, 2002–2007	200,000‡	Internal validation 50,000 External validation 3.3 million	Model developed using a longitudinal administrative database, linked demographic, hospital, OPD pharmacy, and referral data	12 mo (hospitalisation or death for problems that are amenable to disease management)	6% for internal validation cohort	Internal validation: 0.82
Spain							
Lopez-Aguila et al[39]	Primary care in Catalonia, Spain aged ≥ 65 y 2006–2009	28,430	NR	Model developed using computerized retrospective primary care, pharmacy, and hospital database data.	12 mo	Derivation: 2103 (7.4%)	Derivation: 0.78 Validation: 0.76

*Outcome is emergency hospital admission unless otherwise stated.
†If *c* statistics are not presented then positive predictive values (PPVs), sensitivity, and specificity (when available) are recorded.
‡Author correspondence.

TABLE 3. Predictor Variables in Risk Prediction Models (n = 26*) for Predicting Emergency Hospital Admissions

Predictor Variable	Included in Final Model (n)	Excluded After Evaluation (n)†
Medical history		
Specific medical diagnoses	23[13–15,17–20,22–26,29–39]	0
Multimorbidity	12[19,23,24,29–33,36–39]	1[17]
Ambulatory care sensitive (ACS) conditions	2[23,33]	1[18]
Mental illness	12[22,23,25,26,29–34,37,38]	5[13,14,17–19]
Cognitive impairment	7[11,13,23,25,32,35,37]	3[15,17,29]
Alcohol or substance misuse	7[22–25,30,32,33]	2[17,20]
Clinical and laboratory findings		
Clinical examination findings	3[18,23,32]	6[17,22,24,30,38]
Laboratory findings	7[17,18,22–24,30,32]	3[29,36,38]
Medications		
Prescribed specific medications	9[22–25,28–30,32,38]	0
Polypharmacy	11[11,18,19,21,23,24,28–30,37,39]	3[13,20,38]
Potentially inappropriate prescription	1[38]	0
Health care utilization		
Prior emergency admission	22[13–15,17,19,21–26,28–37,39]	4[11,18,20,38]
Prior elective admission	3[23,29,39]	0
Prior ACS admission	2[24,30]	1[14]
Prior ER visits	14[18,19,22–25,29–34,37,39]	2[11,20]
Prior OPD visits	13[14,15,23–26,29–34,39]	4[18,20,36,38]
Prior GP visits	8[14,15,23,31–33,36,39]	2[29,38]
Duration of GP registration	3[23–25]	0
No. previous bed days	5[14,25,28,32,35]	1[15]
Demographics		
Age	23[11,13–15,18,21–26,28–39]	3[17,19,20]
Sex	18[11,13–15,17,21–24,26,28–33,37,39]	5[18,19,35,36,38]
Race/ethnicity	2[22,37]	5[15,18,19,35,36]
Marital status	6[14,31,32,35–37]	4[17–19,29]
Socioeconomic group (SEG) or proxy measure	8[17,21–23,25,28,29,31]	3[15,18,38]
Health insurance	2[14,31]	2[18,36]
Functional status		
Activities of daily living	4[17,20,21,31]	3[13,15,19]
Mobility	5[11,13,17,20,21]	2[14,32]
History of falls or hip fracture	2[22,24]	5[11,13,15,20,35]
Self-rated health	4[13–15,17]	3[18–20]
Health-related quality of life	1[18]	0
Social supports		
Lives alone	3[11,21,37]	7[13–15,17–20]
Caregiver availability	2[15,21]	2[13,18]
Community nurse visits	4[21,23,33,39]	1[15]
Use of other social supports	2[21,37]	1[17]
Other		
Recent stressful life event	0	2[13,20]

*One risk model (The Sussex Key Events Predictor tool) creates customized models using a combination of inpatient, outpatient, ER, and community data relevant to the population of interest.
†Seven models presented the final model only and did not present all variables considered for inclusion.

their development. In this review the 6 risk prediction models that demonstrated greatest predictive accuracy (based on reported *c* statistics) included similar variables, namely, prior health care utilization, multimorbidity or polypharmacy measures, and named medical diagnoses or named prescribed medications predictor variables. Three of the 6 focused on ambulatory care sensitive conditions (ACSCs) admissions.

Overall, nonmedical factors such as functional status, social supports, and self-rated health were included in approximately one third of risk models. These factors have been highlighted as potentially contributing to emergency hospitalization. One US study of qualitative interviews with patients identified by a risk prediction model as high risk found that the majority had poor self-rated health, precarious housing status, lived alone, and reported high levels of social isolation.[42]

Performance of Risk Prediction Models in New Settings

In 2 studies a nationally developed risk prediction model was applied to new populations in the same country and its performance compared with adapted models, which included local factors.[24,29] In both studies the locally adapted models performed better at predicting future emergency hospitalization. One UK risk score developer designs customized risk models for a specified population using locally available data to ensure that the model created is fit for purpose.[27] This approach seems sensible as local factors may well differ within countries and differences in population demographics may mean that a risk model should be applied differently.

Comparison With Previous Research

To our knowledge this is the first systematic review of risk prediction models for emergency admission in

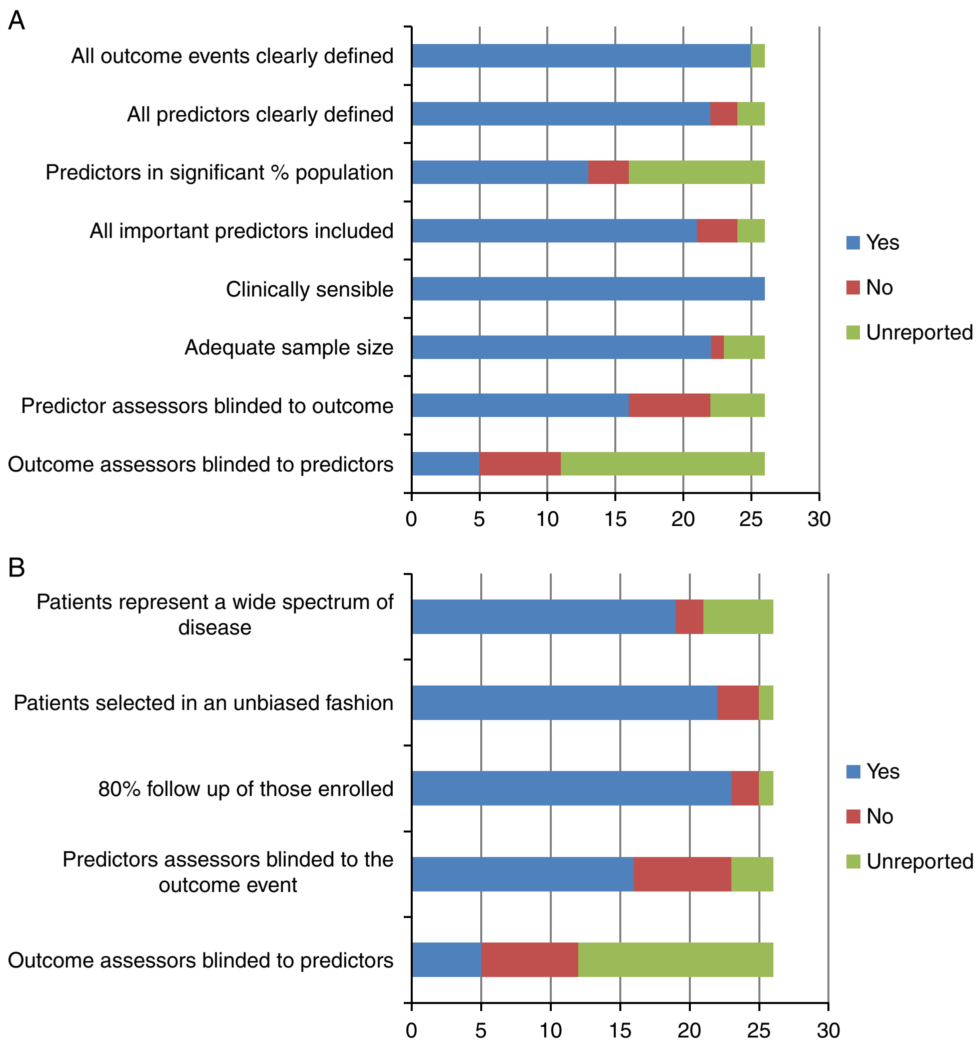

FIGURE 2. Methodological quality assessment of included risk prediction models (n = 26, n = 1, model customized depending on the population it is intended for). A, Derivation studies. B, Validation studies. Colour code: Blue: item done and reported; Red: item not done and reported; Green: item unreported.

community-dwelling adults. Previous systematic reviews have focused on readmission risk models and risk factors for emergency admission. Kansagara et al[43] found that of 26 retrieved readmission risk models only 6 reported a *c* statistic >0.7. They concluded that most readmission models perform poorly and suggested that the additional variables available through the medical record or patient self-report may improve performance. Our review supports this suggestion with models developed using clinical record data demonstrating improved predictive accuracy overall.

García-Pérez et al[44] reported that the risk factors of chronic disease status and functional disability were the most important predictors, followed by prior health care utilization. Whereas medical diagnoses and prior health care utilization were included in almost all risk prediction models in this review, far fewer included functional status. This may be related to the type of data available in the development phase, especially those that utilize administrative or clinical record data only. Functional status variables have tended to be included in self-report questionnaires, which may be more prone to response bias for the reporting of other important predictors such as medical diagnoses and previous health care utilization. Future research needs to consider how best to capture nonmedical factors to determine whether their inclusion into predictive models improves performance.

Clinical and Research Implications

In 2011, a US-based heritage provider group offered a $3 million prize to any group that could develop a risk prediction model to identify people at higher risk for admission so that resources could be directed at reducing their risk.[45] However, to date, the evidence for case management for higher-risk community-dwelling people is mixed and has not reduced emergency admissions.[46] For instance, the Guided Care model aims to provide primary care that includes comprehensive geriatric assessment, case management, self-management support, and caregiver support provided by a team that includes a specially trained nurse who acts as care coordinator. Patients were targeted using age and multimorbidity as risk stratification criteria. In a 32-center randomized control trial, this intervention was found to improve participants' chronic care and reduce caregiver strain and resulted in high levels of health care professional satisfaction.[47] However, apart from 1 subgroup, compared with usual care, participants utilized similar levels of health care at 20-month follow-up, with the exception of home health care, which was significantly reduced.[48]

Overall, it is difficult to know whether case management has not achieved anticipated reductions in emergency admissions because of the intervention used or the case finding mechanism utilized. Studies to date have chosen relatively blunt measures of risk stratification to target patients for their respective interventions.[48,49] Perhaps intensifying efforts in the choice of model for risk stratification may provide dividends for future studies. Further, focusing case management on interventions that prioritize components relating to multimorbidity and polypharmacy may have a role to play.[50]

Another consideration relates to the choice of outcome measure. Most risk models in this review used emergency admission for any cause as their primary outcome. Only 3 chose emergency admissions due to ACSCs as an endpoint. A further 3 models considered ACSCs in their development process. This is interesting as a proportion of all emergency admissions will not be preventable even with intensified care.[51] ACSCs are chronic conditions for which it is possible to prevent acute exacerbations, therefore reducing the need for hospital admission through management in primary care.[52,53] In the United Kingdom, it is estimated that approximately 16% of all emergency admissions for all age groups occur as a result of these conditions and up to 30% of admissions for those aged over 75 years.[52] Community-based interventions should target conditions for which upscaling primary care management can really impact on preventing subsequent admissions. In the United States, risk prediction model developers are testing models that aim to focus resources not necessarily on patients at highest risk for emergency admission, but those with conditions or characteristics (such as prior treatment adherence) most likely to benefit from increased preventative care.[54] In this way resources can be focused where impact is more likely to be realized.

Strengths and Limitations

This review is timely considering the increased interest in risk stratification to identify community-dwelling people at higher risk for future admission. However, there are some limitations. Risk prediction models developed in one population or health care setting may not be transferable to another and care must be taken in comparing models. Further, risk prediction models need frequent updating to remain relevant, and some of the older models described in this review are now obsolete. Seven of the included models presented their final risk model only and not all variables considered for inclusion, so the data presented in Table 3 is limited by this.

CONCLUSIONS

Choosing a robust method of risk stratification is an essential first step in attempting to reduce emergency hospital admissions. This review identified 27 validated risk prediction models developed for use in the community. Local factors and choice of outcome are important considerations in choosing a model. Capturing nonmedical factors may have a role in improving predictive accuracy.

ACKNOWLEDGMENTS

The authors thank the following authors who provided additional data: Dr Adrian Baker, Dr Paul Shelton, Prof. Peter Donnan, and Colin Styles.

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