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Predicting unplanned readmission after myocardial infarction from routinely collected administrative hospital data

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Abstract

Objective. Readmission rates are high following acute myocardial infarction (AMI), but risk stratification has proved difficult because known risk factors are only weakly predictive. In the present study, we applied hospital data to identify the risk of unplanned admission following AMI hospitalisations.

Methods. The study included 1660 consecutive AMI admissions. Predictive models were derived from 1107 randomly selected records and tested on the remaining 553 records. The electronic medical record (EMR) model was compared with a seven-factor predictive score known as the HOSPITAL score and a model derived from Elixhauser comorbidities. All models were evaluated for the ability to identify patients at high risk of 30-day ischaemic heart disease readmission and those at risk of all-cause readmission within 12 months following the initial AMI hospitalisation.

Results. The EMR model has higher discrimination than other models in predicting ischaemic heart disease readmissions (area under the curve (AUC) 0.78; 95% confidence interval (CI) 0.71–0.85 for 30-day readmission). The positive predictive value was significantly higher with the EMR model, which identifies cohorts that were up to threefold more likely to be readmitted. Factors associated with readmission included emergency department attendances, cardiac diagnoses and procedures, renal impairment and electrolyte disturbances. The EMR model also performed better than other models (AUC 0.72; 95% CI 0.66–0.78), and with greater positive predictive value, in identifying 12-month risk of all-cause readmission.

Conclusions. Routine hospital data can help identify patients at high risk of readmission following AMI. This could lead to decreased readmission rates by identifying patients suitable for targeted clinical interventions.

What is known about the topic? Many clinical and demographic risk factors are known for hospital readmissions following acute myocardial infarction, including multivessel disease, high baseline heart rate, hypertension, diabetes, obesity, chronic obstructive pulmonary disease and psychiatric morbidity. However, combining these risk factors into indices for predicting readmission had limited success. A recent study reported a C-statistic of 0.73 for predicting 30-day readmissions. In a recent American study, a simple seven-factor score was shown to predict hospital readmissions among medical patients.

What does this paper add? This paper presents a way to predict readmissions following myocardial infarction using routinely collected administrative data. The model performed better than the recently described HOSPITAL score and a model derived from Elixhauser comorbidities. Moreover, the model uses only data generally available in most hospitals.

What are the implications for practitioners? Routine hospital data available at discharges can be used to tailor preventative care for AMI patients, to improve institutional performance and to decrease the cost burden associated with AMI.

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Introduction

Nearly one patient in every five admitted to hospital with acute myocardial infarction (AMI) is readmitted within 30 days of discharge.[1–3] Many of these readmissions are unplanned and avoidable. The high rate of unplanned readmissions detracts from the quality of patient care and institutional performance, and adds to the cost of managing AMI patients. Reducing unplanned readmissions requires identification of patients at high risk of readmission during their initial presentation, and tailored and targeted interventions on these patients.

To date, reliable risk stratification of AMI patients admitted has proved challenging despite several well-documented risk factors,[4] including severe heart failure,[4] multivessel disease,[5] living alone,[6] ethnic background,[7] psychological comorbidities[8,9] and socioeconomic factors.[10] As with many clinical prediction problems, the known risk factors for readmission after AMI individually have only weak predictive ability.

Institutions that have adopted the electronic medical record (EMR) have access to a wealth of clinical and administrative data that, if used appropriately, could improve clinical care and institutional performance.[11–13] In the present study we examined all the available administrative hospital factors associated with readmission in a cohort of patients admitted with AMI to a large regional hospital in Geelong (Vic., Australia). We used data from the EMR to derive and internally validate a model to predict unplanned ischaemic heart disease (IHD) readmissions over a 30-day period and all-cause readmission over 12 months after an admission with AMI. We defined an admission to be unplanned if the patient was admitted through the emergency department (ED). The EMR model was compared with the model derived from Elixhauser comorbidities and a recently described[14] simple predictive scoring system (HOSPITAL) that was developed to predict unplanned admissions in patients admitted with acute medical conditions.

Methods

Datasets

The present study is a retrospective study using EMR of inpatient admissions and ED visits at Barwon Health, a regional health service in Australia. As the only public tertiary hospital in Greater Geelong, a catchment area with more than 350 000 residents, the hospital's patient database provides a single point of access for information on hospitalisations, ED visits, medications and treatments. Detailed records of patient interactions with the hospital system are available through the EMR. This includes International Classification of Disease 10 (ICD-10),[15] procedure and diagnosis-related Group (DRG)[16] codes of each admission and ED visit; details of procedures; and departments involved in the patient's care. Other information includes demographic data (age, gender and postcode) and details of access to primary care facilities. Ethics approval was obtained from the Hospital and Research Ethics Committee at Barwon Health (no. 12/83). Deakin University has reciprocal ethics authorisation with Barwon Health.

The patient cohort consisted of 1660 patients with a confirmed diagnosis of AMI admitted between January 2009 and December 2011. An AMI admission was defined by ICD-10 codes I21 (Acute myocardial infarction) or I22 (Subsequent myocardial infarction) in discharge diagnoses (either primary or secondary).[17] In Australia, cardiac troponin (cTn)[18] is the primary biomarker for AMI diagnosis.

For each patient, the index admission was defined to be the AMI admission of the patient starting from 1 January 2009. Readmission predictions were made (retrospectively) at the end of the index admission. Patient records before the index admission were used to construct independent variables. Two dependent variables were considered: (1) unplanned IHD readmissions in 30 days; and (2) unplanned all-cause admissions in 12 months following the index admission. An IHD readmission was defined as a readmission with a discharge diagnosis (either primary or secondary) within the ICD-10 code segment I20–I25 (as specified in the Australian Coding Standards[19]).

Comparators

A logistic regression model built upon Elixhauser comorbidities was chosen for comparison because the Elixhauser index has been shown to be more discriminatory than other comorbidity indices.[20] The Elixhauser index consists of 31 comorbidities that can be mapped from ICD-10 codes.[21] Diagnosis codes from the previous year were used to construct the comorbidities. The second baseline is the recently introduced predictive scoring system HOSPITAL,[14] which has been shown to perform moderately well in predicting readmissions.

Derivation of the readmission prediction model

Through unrestricted randomisation, the cohort of 1660 patients was divided into a derivation set consisting of two-thirds, whereas the remaining one-third was used for validation. Figure 1 illustrates the process used to derive a prediction model. For each unit of observation, potential risk factors were extracted from the derivation cohort before the index admission. We considered all available administrative hospital data including static information (age, gender, occupation, insurance types) and time-stamped events associated with changes of postcode, emergency visits, hospitalisations, laboratory tests, length of stay, emergency attendance time, transfers after emergency, primary and secondary diagnoses, rare diagnoses, DRG codes, procedures, operations, theatre types and Elixhauser comorbidities. Age was coded as a binary variable in one of 10-year intervals. Occupation was a binary of value 1 if it was either pensioner, retired or home duties and 0 otherwise.

Time-stamped events were aggregated over six periods of time before the index admission: 1, 3, 6, 12, 12–24 and 24–36 months. This procedure resulted in a list of 4471 independent variables with specific timing. These include 23 variables on demographics, 344 variables on laboratory test results, 36 variables on past hospitalisations and ED visits, 2460 variables on diagnoses, 582 variables on procedures, 792 variables on DRG codes and 48 variables on theatre use. The dependent variables were the presence or absence of readmissions in periods following the index admission.

The derivation cohort was used to build a logistic regression with lasso[22] in the first step of variable screening. Bootstraps were used to estimate probability that a variable was stably selected against data variations.[23] Variables with >70% chance of selection were then used to build a second logistic regression

model. This model generated prediction of subsequent readmission in the validation cohort.

Let T be the length of prediction (e.g. 6 months). The model to predict the readmission probability in time T following an AMI hospitalisation takes the form below:

$$\text{logit}(p_T) = \beta_0 + \sum_{i=0}^{N} \beta_i X_i$$

where X_i are $N = 4471$ independent variables and p_T is the probability of readmission in time T following an AMI admission. To fit the model, lasso penalise below was used:

$$\sum_{i=0}^{N} |\beta_i| < c$$

where c is a positive threshold selected through cross-validation.

Note that the logistic model was used to predict the readmission probability, not to estimate the effect size of independent variables. Therefore the size of each β_i should not be interpreted as in regression with a relatively few number of independent variables.

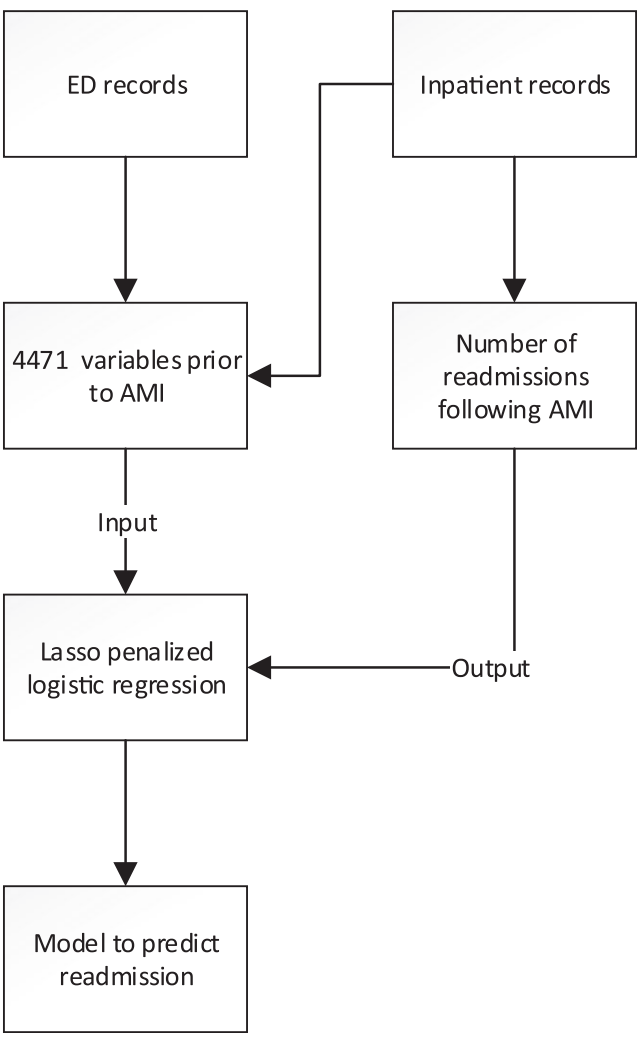

Fig. 1. Derivation of predictive models. ED, emergency department; AMI, acute myocardial infarction.

Results

Patient characteristics

The study included 1660 patients admitted between January 2009 and December 2011. Patient readmissions during the 12 months following the index admission were measured. Only the first index admission during the study period was considered for analysis. Characteristics of the patients are given in Table 1. In-patient mortality was low in this cohort at 2.6%.

Readmission rates are as follows: 105 patients (6.3%) had an unplanned IHD readmission within 30 days. This increased to 149 (9.0%), 191 (11.5%) and 245 (14.8%) at 3, 6 and 12 months respectively. The all-cause admission rates were higher: 212 (12.7%) at 30 days, 316 (19.0%) at 3 months, 419 (25.2%) at 6 months and 518 (31.2%) at 12 months. Although non-cardiac admissions were more common than cardiac admissions at all time points studied, the five most common single causes for readmission were still cardiac diagnoses (chest pain, angina, AMI, heart failure and atrial fibrillation) at 12 months. Other common causes for readmission were other cardiac conditions (rhythm disturbances and valvular disorders; 9.4% of all readmissions), as well as respiratory (9.4%), gastrointestinal (7.6%) and circulatory (arterial and venous, 4.3%) disorders.

Prediction of 30-day IHD readmission

Characteristics of the derivation and validation cohorts are given in Table 2. In all respects, the two cohorts had very similar

Table 1. Clinical and demographic characteristics

Unless indicated otherwise, data show the number of patients in each group, with percentages in parentheses. AMI, acute myocardial infarction; STEMI, ST segment elevation myocardial infarction

No. patients	1660
No. men	1107 (66.7%)
No. women	553 (33.3%)
Mean (range) age (years)	67.9 (24–102)
AMI type	
STEMI	568 (34.2%)
Non-STEMI	1092 (65.8%)
Length of stay (Days)	
1–4	751 (45.2%)
≥5	909 (54.8%)
In-patient mortality	43 (2.6%)
Coronary angiogram	1291 (77.8%)
Comorbidities	
Hypertension	998 (60.1%)
Diabetes mellitus	285 (17.2%)
Hyperlipidaemia	194 (11.7%)
Cardiac failure	262 (15.8%)
Pathology tests	
Admission glucose 7.8–11.0 mM	68 (4.1%)
Admission glucose >11.0 mM	29 (1.8%)
Peak troponin ≥0.5 μg L^{-1}	1046 (63%)
Predischarge sodium <130 mM	26 (1.6%)
Predischarge haemoglobin <120 g dL^{-1}	461 (27.8%)

characteristics. The derivation set of 1107 was used to generate a model to predict 30-day IHD readmissions. The performance of this EMR model was compared against the HOSPITAL score and with a model built on the Elixhauser comorbidities, using data from the testing group. The performance of the three models is given in Table 3. The EMR model performed better than the other models, with greater sensitivity and specificity. The area under the curve (AUC) was 0.78 (95% confidence interval (CI) 0.71–0.85). The major predictive factors (selected automatically) used by this model are listed in Table 4. Previous attendances with chest pain, diabetes, electrolyte abnormalities, use of preventative drugs and a history of cardiac investigations were all predictive of a subsequent IHD readmission.

To illustrate what use of the EMR model may mean in practice, we examined the comparative positive predictive value (PPV) of the three predictive models. The PPV of the three models was examined for the 5%, 10% and 20% of patients identified as being at highest risk of readmission. In each instance, the PPV of the EMR model was higher than that of the other three models (e.g. for the patients estimated to be the highest 5% risk of readmission, the EMR model had a PPV of 0.21 (negative predictive value (NPV) = 0.836) compared with 0.13 for the HOSPITAL score (NPV = 0.789)). Thus, 21% of those judged to be at high-risk of admission were actually readmitted. The overall 30-day IHD readmission rate in the present study was approximately 6.3%. Thus, the EMR model could identify patients who were more than threefold more likely to require readmission than the cohort as a whole. Using the model at different thresholds (e.g. 10% or 20% highest risk of readmission) would lead to loss of PPV but would identify a larger number of patients at risk of readmission.

Table 2. Derivation and validation cohorts

Unless indicated otherwise, data show the number of patients in each group, with percentages in parentheses. AMI, acute myocardial infarction; STEMI, ST segment elevation myocardial infarction

	Derivation number (%)	Validation number (%)
No. patients	1107	553
Gender		
No. men	741 (66.9%)	360 (66.1%)
No. women	366 (33.1%)	187 (34.3%)
Mean age (years)	67.8	68.4
AMI type		
STEMI	391 (35.3%)	177 (32.0%)
Non-STEMI	724 (64.7%)	376 (68.0%)
Length of stay (days)		
1–4	512 (46.4%)	239 (43.2%)
≥5	595 (53.6%)	314 (56.8%)
Comorbidities		
Hypertension	659 (59.5%)	339 (61.3%)
Diabetes mellitus	199 (18.0%)	86 (15.6%)
Hyperlipidaemia	139 (12.6%)	55 (10.0%)
Cardiac failure	184 (16.6%)	78 (14.1%)

Table 3. Prediction of 30-day ischaemic heart disease readmissions

EMR, electronic medical records; AUC, area under the curve; CI, confidence interval

Method	AUC (95% CI)	Sensitivity	Specificity
HOSPITAL score	0.60 (0.47–0.73)	0.62	0.50
Comorbidities	0.53 (0.42–0.65)	0.65	0.45
EMR model	0.78 (0.71–0.85)	0.65	0.78

Prediction of 12-month all-cause readmission

The same derivation and validation procedures were performed for 12-month all-cause readmission. The AUCs for the three predictive methods (EMR, HOSPITAL and Elixhauser) on the testing group are given in Table 5. The EMR model performed better than the other two models, with an AUC of 0.72 (95% CI 0.66–0.78). Cardiac predictors predominate, even as predictors for non-cardiac admissions. Again, electrolyte disturbances and renal disease are major predictive factors. From the PPV of the three predictive models in identifying the 5%, 10% and 20% of patients estimated to be at highest risk of readmission, the EMR model again had greater PPV than the other three models. For example, the EMR model had a PPV of 0.42, meaning that 42% of patients placed in this risk category were readmitted within 1 year.

Discussion

We have described a model for predicting readmission after AMI using administrative hospital data from EMRs. The model performed moderately well on the validation dataset and outperformed a model derived from Elixhauser comorbidities and the recently introduced HOSPITAL score.[14] This approach has considerable potential to tailor preventative care for AMI patients, to improve institutional performance and to decrease the cost burden associated with AMI.

The considerable burden that unplanned readmissions after AMI places on the healthcare system[1–3] could be decreased if we could identify patients at high risk of readmission and institute, or intensify, measures to prevent a further coronary event. Attempts to predict readmission after AMI have relied

Table 4. Selected predictors for 30-day cardiac readmission

Administrative data	Total time spent in emergency, number of emergencies and number of emergency-to-ward transfers
Recent emergency attendances	Unstable angina, chest pain
Diagnosis in the previous month	Sepsis, hyperkalaemia, hypokalaemia, fluid overload, acute kidney failure, unspecified, urinary tract infection, long-term use of anticoagulants
Diagnosis in the previous 3 months	Sepsis, disorders of magnesium metabolism, hypokalaemia, left ventricular failure, acute kidney failure, presence of cardiac device
Diagnosis in the previous 12 months	Hypokalaemia
Investigations	Invasive coronary investigations undertaken in the past year, debridement of skin and subcutaneous tissue

Table 5. Prediction of 12-month all-cause readmission
EMR, electronic medical records; AUC, area under the curve; CI, confidence interval

Method	AUC (95% CI)
HOSPITAL score	0.59 (0.51–0.68)
Comorbidities	0.54 (0.47–0.62)
EMR model	0.72 (0.66–0.78)

on biomarkers, the use of known clinical risk factors and comorbidity indices. Although several biomarkers[24–28] are known to predict readmission after a coronary event, none is measured routinely in clinical practice at present and we do not know which biomarker or combination will yield the best prediction. There are several known clinical and demographic risk factors for readmission after AMI,[5–8,29] but their individual predictive power is relatively low and models derived from such factors have performed poorly.[4] Not surprisingly, the presence of comorbidities such as vascular disorders, hypertension, diabetes and other cardiorespiratory conditions increases the risk of readmission after AMI, and combining these into indices results in modest predictive power.[30,31] We document here that Elixhauser comorbidities do have predictive power for readmission, but do not perform as well as the EMR model. The readmission rate after AMI in the present study was comparable to that in other recent studies.[1,3,32]

The use of data in the EMR to predict readmission is attractive for a variety of reasons. Data are routinely collected, forming a comprehensive overview of the patient's health; data are updated continuously and the derived models can adapt in real time; and the EMR covers comorbidities and biomedical markers known to be predictive. The use of the EMR has considerable potential to improve institutional performance, including decreasing the readmission rate for prevalent conditions such as AMI.[11–13] Because EMRs are widely adopted, predictive models that exploit these resources could be seamlessly integrated into clinical pathways, offering an inexpensive tool to assist clinicians in assessing risk. However, the dataset in a comprehensive EMR is complex and unless methods are developed to interpret and present data, the full benefit of the EMR may not be realised. Thus, having an EMR available in an institution does not automatically improve institutional performance.[33,34]

As demonstrated in the present study, modern statistical techniques such as lasso[22] and stability selection[23,35] are effective at screening a large number of potential risk factors in EMR, many of which could have been overlooked if a small number of hypotheses were tested.[4] Such methods can be used as a fast screening tool to identify risk factors and subjects for further investigation.[36]

For ischaemic heart disease, algorithms have been developed for surveillance of acute events[37,38] and drug safety surveillance[39] using the EMR. To date, there has been no comprehensive study of predicting readmissions in AMI patients using EMR data. One recent study,[40] using only 11 data items, showed that using routinely collected administrative data has considerable potential. Our EMR model performed better than the recently described HOSPITAL score.[14] The latter has not been validated in individual medical conditions and may be of less use in AMI because two of the seven items used in HOSPITAL are invalid in this instance: only 1.6% of discharges were from an oncology service and all admissions were acute. The comprehensive EMR model also outperformed the model based solely on comorbidities. In fact, the top predictive variables also include prior emergency attendances or hospitalisations for both 30-day ischaemic heart disease readmission and 12-month all-cause readmission, and these agree with a recent finding.[41]

There are several limitations of the present study. First, the study was performed in a single centre and the EMR model has not been independently and externally validated. We did not track readmissions to other hospitals. However, we believe the effect was minimal because the institution under study is the only public hospital in the region (although the data may be biased due to patient migration to urban centres for better-quality care). The present study was based on administrative and clinical data routinely stored in hospital databases. Although such data have the advantage of being readily available, the do not cover the known risk factors for cardiac events, such as metabolic syndrome and waist circumference.

Competing interests

None declared.

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