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Prediction of 30-day cardiac-related-emergency-readmissions using simple administrative hospital data

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ABSTRACT

Background: Control and reduction of cardiovascular-disease-related readmissions is clinically, logistically and politically challenging. Recent strategies focus on 30-day readmissions. A screening tool for the detection of potential cases is necessary to make further case management more efficient.
Methods: Cohort study. Hospital administrative data were analyzed in order to obtain information about cardiac-related hospitalizations from 2003 to 2009 at a Spanish academic tertiary care center. Predictor-variables of admissions that presented or did not present 30-day cardiac-related readmission were compared. A prediction model was constructed and tested on a validation sample. Model performance was assessed for all cardiac diseases and for 24 main-cardiac-disease-sets.
Results: The study sample was 35 531 hospital-admissions. The model included 11 predictors: number of previous emergency admission in 180 days, residence out of area, no procedure applied during hospitalization, major or minor therapeutic procedure applied during hospitalization, anemia, hypertensive disease, acute coronary syndrome, congestive heart failure, diabetes and renal disease.
The performance indicators applied on all cardiac diseases were: C-statistic = 0.75, Sensitivity = 0.66, Specificity = 0.70, Positive predictive value = 0.10, Negative predictive value = 0.98, Positive likelihood ratio = 2.21 and Negative likelihood ratio = 0.48. Diseases for discriminative prediction are: stenting, circulatory disorders, acute myocardial infarction and defibrillator and pacemaker implantation.
Conclusions: This study provides a prediction model for 30-day cardiac-related diseases based on available administrative data ready to be integrated as a screening tool. It has reasonable validity and can be used to increase the efficiency of case management.

1. Introduction

Rehospitalization is a frequent, costly and sometimes life-threatening event associated with gaps in follow-up care. Cardiovascular diseases and procedures, such as heart failure and cardiac-stent-placement have the highest 30-day rehospitalization rates [1].

That is why clinicians, payers and policy makers are seeking to promote efficiency and quality in health care by targeting hospital readmission rates [1,2]. Policy makers in Great Britain are lately introducing financial penalties for hospitals which discharge patients before they are fully fit in an attempt to reduce the rising number of emergency readmissions [3].

Although it seems to be clear that rehospitalization is a big issue, there is still no clear evidence that strategies like focused case-management can improve health outcomes or reduce hospital-bed-utilization and healthcare expenditure [4,5,2,6–10].

An essential component of any strategy to make focused case-management more efficient and to improve care and services for these patients is the development of a case finding mechanism to identify high risk patients accurately [11]. Interventions to reduce follow-up-gaps could be applied before readmission gets necessary, health status could be improved and costs reduced. An effective case finding mechanism identifies as many patients at high risk of readmission as possible without including a too large number of patients who will not be actually readmitted.

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Up till now, several efforts have been done to identify high-risk-patients in hospital settings. However, risk stratification is still challenging for patients with cardiovascular diseases [12,13].

1.1. Objective

With this study we wanted to create a prediction-model able to identify high-risk-of-readmission-patients with cardiac related disease. This prediction-model should become an integrated part of a screening-test in every day hospital life and be used for a more efficient case-management in order to avoid unnecessary readmissions.

2. Methods

2.1. Study design

This cohort study was conducted at the Marqués de Valdecilla University Hospital in Santander in Northern Spain (900 beds). The hospital is the reference hospital for the whole area of the autonomous community of Cantabria with about 592 000 habitants.

2.2. Data source

As data source, we used hospital administrative data which contains the demographic characteristics of the patients, the principal and up to 12 secondary diagnosis and the procedures performed. Diagnosis and procedures are based on International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codification. We applied Diagnostic grouping to obtain Diagnostic related groups (DRG) and Major Diagnostic Categories (MDC).

2.3. Study samples

Data was extracted for the period between January 2003 and December 2009. We included all the patients' hospitalization episodes whose DRG corresponded to the Major Diagnostic Category 5 (MDC-5). MDC-5 contains all those patients whose diagnosis at discharge is associated with diseases of the circulatory system. We excluded those patient episodes that ended up with the death of the patient, as well as same day readmissions.

2.4. Variables

A variable that identifies hospital admissions that were followed within 30 days of discharge by an emergency admission of the same MDC-5 was created. This is the main outcome variable of our study. Next a comparison was established between the predictor variables of these admissions that presented readmission and those that did not.

As potentially important and generally available predictors we explored 52 variables. They represent values of four fields of measurement: demographic measures (3 variables), hospital utilization measures (10 variables), comorbidities (24 variables) and process of care (5 variables).

Demographic measures were sex, age and rurality (as a marker of accessibility to hospital care). We defined as rural those patients who live in a municipality with less than 10,000 inhabitants within Cantabria and urban those who live in cities with more than 10,000 inhabitants. The third category for this variable includes all patients who do not have residence within the hospital's area of influence (Cantabria).

Hospital utilization measures include Hospital length of stay and number of prior episodes. We calculated the number of previous admissions (either emergency, programmed or both type of admissions) that took place in the 90, 180 or 365 days before. We put no diagnostic restriction on them so that preceded admissions might be of any MDC. In order to obtain preadmission-data for the 2003-episodes, we matched them with data from 2002.

Comorbidities were determined for each patient by searching the principal and secondary diagnosis codes. We used Deyo's coding algorithms [14] to define Charlson index of comorbidity [15] and 17 comorbidities in administrative data [16]. Additionally we scanned the diagnosis fields for 6 further comorbity-groups as we found them relevant in other studies: anemia (ICD-9-CM: 285.x), cardiac arrhythmias (426.x, 427.x), hypertensive disease (401.x, 402.x, 403.x, 404.x, 405.x), acute coronary syndrome (428.x), chronic rheumatic heart disease (393.x, 394.x, 395.x, 396.x, 397.x, 398.x) and alcohol dependency (303.x). The total number of comorbidity-variables was 23.

To obtain process of care measures we categorized procedure codes into one of four broad categories: minor diagnostic, minor therapeutic, major diagnostic, and major therapeutic. The Procedures–Classes–Tool developed by the Agency of Healthcare Research and Quality was used [17]. For each admission we assessed if there had occurred at least one procedure in each category or no procedure at all during the whole time of hospitalization.

2.5. Statistical analysis

The predictive model was developed using logistic regression on a 70% derivation sample selected at random and later validated on the remaining 30% sample. This cut point was chosen in recognition of the large number of candidate variables being evaluated while developing the model.

The predictor measures were first evaluated within their natural classes to minimize co-linearity and to prevent a large number of conceptually similar measures from saturating the model. For example, the prior utilization variables were entered into a regression model as a group and the best subset of them was identified using the selection methods proposed by Hosmer and Lemeshow [18]. The other measures were identified in a similar way. These subsets were then combined and further backward elimination was applied to identify the most parsimonious model. We retained variables that remained significant at p-value < 0.10. Significant categorical and nominal variables were retained in a complete form — that is, all levels of the variable were retained in the model.

The regression coefficients were used to calculate the probability-of-readmission-index for each admission in the validation sample by using the formula:

$$\textit{Probability of readmission}(i) = \frac{e^{\beta 0 + \beta i \times Xi}}{\left(1 + e^{\beta 0 + \beta i \times Xi}\right)}.$$

Then we used these index-values to define thresholds to differ between positive or negative test results as either above or below the threshold. We calculated the Youden-index (Sensitivity + Specificity − 1) [19] for different thresholds and selected the threshold where the Youden-index was highest.

2.6. Model-performance measurement

The main diagnostic-test-indices to measure the discriminatory performance (ability to classify admissions that will present readmission versus those which do not) of the model in the validation sample were computed. We calculated the area under the receiver operating characteristic curves (AUC), Sensitivity (Se) and Specificity(Sp), Positive predictive values (PPV), Negative predictive values (NPV) and Positive and Negative Likelihood Ratios (LR+/−) [20].

We report the performance of the model on all-cardiac-disease-admissions as well as those applied on several diagnostic related groups of disease (DRG-set). Therefore we summarized all DRGs in 24 sets of cardiac diseases to get a clinical useable format (Table 1). To fit the model best on each DRG-set we repeated threshold selection for each set separately. Findings from the validation sample are reported here.

3. Results

Between 2003 and 2009, 37,381 hospitalizations with cardiac related disease were identified. 1821 episodes ended up in death and

Table 1
Composition of DRG-sets.

DRG*-set	DRG-codes
Stenting	854, 853, 550, 852
Circulatory disorder	543, 124, 125
Acute myocardial infarction	122, 121, 808
Defibrillator and pacemaker implantation	116, 118, 549, 851, 115, 548, 850, 117, 849
Vascular procedure	479, 797, 111, 796, 110, 478
Peripheral vascular disorders	131, 130
Arrhythmias	139, 138
Heart failure	127, 544
Angina pectoris	140
Heart valve procedure	105, 545, 104
By-pass	107, 109, 546, 106
Percutaneous cardiovascular procedures	112
Complications with device or cardiac procedure	812
Chest pain	143
Atherosclerosis	133, 132
Amputation	113, 114
Other circulatory system diagnoses	145
Syncope and collapse	142, 141
Other circulatory diagnoses	144
Congenital and valvular heart disease	136, 135, 137
Endocarditis	126
Hypertension	134
Other procedures	108, 120, 119, 547, 809, 811
Thrombophlebitis	128

* Diagnosis-related group (DRG).