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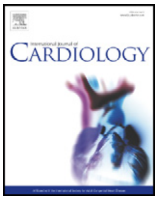

Provider profiling models for acute coronary syndrome mortality using administrative data☆,☆☆

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ABSTRACT

Background: Administrative data have been used to construct risk-adjustment models for provider profiling to benchmark hospital performance for acute myocardial infarction (AMI), but much less for acute coronary syndrome (ACS). We assess the impact on risk model performance and hospital-level mortality rate ratios (SMRs) of three key issues: comorbidity measurement methods, inter-hospital transfers and post-discharge deaths.
Methods: Logistic regression models for 30-day total mortality used three years of national public hospital emergency (unplanned) admissions data for England for ACS ($n = 329{,}369$) linked to death registrations. We compared using the Charlson comorbidity index with modelling previous admissions.
Results: Prior admission for various conditions such as cancer and renal failure was associated with higher post-ACS mortality, whereas previous AMIs, PCI and unstable angina admissions were associated with lower mortality. The Charlson comorbidity index performed better than one- and five-year admission histories. Discrimination ($c = 0.81$) was comparable with that from clinical databases. Adjusted 30-day total mortality rates ranged between hospitals from 6.3% to 13.3%.
Median differences in SMRs between the comorbidity-adjustment methods were small. Although SMRs and outlier status could change, a hospital's 'qualitative' mortality rating (low, average or high) was not affected. In contrast, a sizeable minority of SMRs changed by ≥ 10 points if transfers were excluded or post-discharge deaths ignored. Model choice occasionally affected funnel plot outlier status.
Conclusions: Models for comparing hospitals' ACS mortality can be constructed with good discrimination using English administrative hospital data. Adjusting for transfers in and capturing post-discharge deaths are more important than the choice of comorbidity adjustment.

1. Introduction

Death is a key outcome for acute myocardial infarction, AMI [1]. Clinical data sets have been used to predict the risk of death in AMI [2,3] and acute coronary syndromes (ACS) as a whole [4–6]. These incorporate physiological measurements lacking in most administrative datasets. Nonetheless, administrative databases have many important predictors of mortality [7]. For AMI, Krumholz et al. [8] were able to use administrative data to build a model for profiling hospital performance that correlated well with a clinical one despite a moderate c statistic of 0.71; Ross et al. [9] reported a c statistic of 0.79 for US Veterans Association patients. For ACS as a whole, however, little has been done with administrative data. Since all acute coronary syndromes are managed in a similar manner by cardiologists within a particular unit, considering ACS as a whole is in principle a valid approach to benchmarking that unit's performance. It has the additional benefit of having greater statistical power over using AMI alone and increasing clinical importance as care of all patients with ACS advances.

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☆☆ *Ethics*: We hold Section 251 (formerly Section 60) National Information Governance Board for Health and Social Care permission to hold these data for research purposes. We hold South East Local Research Ethics Committee approval to analyse the data.

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There are various issues when using administrative data. For comorbidity adjustment, some studies have used comorbidity information such as the Charlson scores [10] or sets of codes tailored for use with the target group, e.g. AMI [11]. Some use secondary diagnoses in the index record whereas others [5,6,12] link records for each patient in the year before the index record to obtain the cardiovascular and other history. Secondly, inter-hospital transfers are common. Cram et al. [13] examined the potential impact of inappropriate transfer of critically ill patients to avoid in-hospital deaths, and others have found that it affects a hospital's Standardised Mortality Ratio, SMR [14,15]. In the Centers for Medicare and Medicaid Services' National Quality Forum-endorsed AMI mortality measure [see AHRQ http://www.qualitymeasures.ahrq.gov/content.aspx?id=16299] patients who are transferred from another acute care or Veterans hospital are excluded because the death is attributed to the hospital where the patient was initially admitted. However, some data sets in the USA and the Netherlands, for example, cannot link the pre- and post-transfer stays. Thirdly, hospital data commonly cannot capture post-discharge deaths, and the necessary linkage with death certification information often incurs a significant time lag.

Our aim was to construct a model suitable for benchmarking hospitals rather than predicting risk in individual patients. We compared the model performance and resulting hospital-level SMRs from various models handling these three issues in different ways using data for all public English hospitals. We tested the relative importance of these issues with this guiding question in mind: how much important information is lost when considering only in-hospital deaths and information from only the ACS record?

2. Methods

2.1. Data and outcome measures

We took emergency (unplanned) admissions for ACS (primary diagnosis of ICD10 I200, I21 or I22) in all English NHS (public) hospitals for 2006/7 to 2008/9 from Hospital Episode Statistics (HES), an England-wide administrative record-based system. Each record, or ‘finished consultant episode’, contains one primary and now up to 19 secondary diagnoses coded to the International Classification of Disease, 10th revision (ICD10). Episodes belonging to the same patient admission were linked together into ‘spells’ in HES terminology. For admissions with multiple episodes, we took the primary diagnosis from the first episode (or the second if the first episode merely contained a symptom code). Spells ending in transfer to another NHS hospital were linked together to form ‘superspells’. We will refer to all admissions, whether involving transfers or not, as ‘admissions’ throughout.

HES does not include the cause of death, but we obtained death certificate data, including date and underlying cause of death, linked to the HES records from the Office for National Statistics. We calculated 30-day in-hospital and 30-day total mortality. The latter includes deaths in and out of hospital and is our focus for the modelling.

2.2. Comorbidity and patient history variables

For each ACS admission, we tracked back five years via deterministic matching on patients' date of birth, sex and postcode. 0.1% of ACSs had an invalid postcode (some of these were homeless or from overseas) and were therefore not linked; these were assigned to the ‘sixth’ Carstairs population-weighted area-level deprivation quintile [16]. The Carstairs index is calculated at small-area level using census data on factors including unemployment and overcrowding. To summarise patients' admission histories, we began with the groups used in Krumholz et al. [8] defined using ICD9. ICD10 codes for these were initially taken from where there was overlap from the Charlson index with some England-specific modifications [17]. Other diagnosis groups were based on a review of the literature on factors predicting mortality following AMI [11] and clinical knowledge (see Appendix for codes). Previous PCIs or CABGs were taken from any of the 12 procedure fields. We constructed a set of 0/1 flags to indicate admission for a given diagnosis in the previous one and five years. We also calculated the Charlson index from secondary diagnoses in the index ACS admission, which requires no linkage.

2.3. Statistical methods

2.3.1. Validation of the basic model

We first define what we will refer to as the basic model. This contained age group (0–39, 40–44 and in five-year bands up to 90+), sex, deprivation quintile, source of admission (admitted from patient's own home, or other/unknown place), ethnicity (white, non-white, or other/unknown), presence of palliative care codes (either the specialty code in any episode or the ICD10 code Z515 in any diagnosis field), financial year and whether admission was for AMI or unstable angina. The three years of data were divided into two, giving 2006/7 and 2007/8 as a ‘training’ set and 2008/9 as a ‘validation’ set [18], and the basic model fitted to each. As model performance was similar for each set, all analyses were run using the three years combined.

The basic model was constructed ignoring the clustering of patients within hospitals. A random effects two-level hierarchical model was then implemented (using PROC GLIMMIX in SAS v9.2).

2.3.2. Comparison of methods for handling comorbidities and transfers

We fitted three sets of logistic regression models. The first set compared each of the four following additions to the basic model described above: i) Charlson index (using our general purpose published weights [17]); ii) Charlson index (using weights derived for all ACS patients in this study), iii) one-year admission variables; and iv) five-year admission variables. One- and five-year ‘lookback’ periods represent two extremes in terms of data linkage and likely availability.

The second set all used the basic model and compared the following four ways of dealing with transfers: i) include all transferred patients and adjust for whether they were transferred in; ii) exclude transfers in; iii) exclude patients transferred in or out; and iv) count transfers as separate admissions, without adjustment for fact of transfer (i.e. ignoring transfer information).

The third set of models compared the best performing model from the first set against a model containing the same set of variables but: i) using 30-day in-hospital deaths, and ii) using 30-day in-hospital deaths and counting transfers as separate admissions, without adjustment for fact of transfer.

2.3.3. Assessing model performance and impact of model choice on hospital-level outcomes

For each model, we derived the area under the ROC curve (c statistic, a common measure of a model's ability to discriminate between deaths and survivors), the Hosmer–Lemeshow calibration statistic and Akaike's Information Criterion (AIC). A model is often said to have satisfactory discrimination if $0.7 \leq c \leq 0.79$ and good if $c \geq 0.80$.

To obtain Standardised Mortality Ratios (SMRs) for each hospital from a given model, we divided the observed number of deaths by the sum of the patient-level predicted risk of death and multiplied by 100 (for the hierarchical model, predicted risks were derived from the fixed effects part). An average hospital would therefore have an SMR of 100. We compared the sets of SMRs obtained from the different models in terms of the absolute difference in SMRs and the number of statistical outliers using 99.8% funnel plot control limits, which takes into account hospital size.

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3. Results

In the three years 2006/7 to 2008/9, there were 329,369 ACS admissions recorded in 288,550 patients in 146 acute, non-specialist hospitals, with 11.7% having more than one ACS admission during this time, up to a maximum of ten. Of these 329,369 admissions, 11.7% were to patients who had had at least one ACS admission during the previous year (19.6% during the previous five years). Of the 29,369 total 30-day deaths (for a case fatality rate of 8.9%), 24,839 (84.6% of the total) occurred in hospital. Crude total 30-day death rates by hospital ranged from 4.0% to 14.1%.

65.3% of the causes of 30-day total deaths admitted with ACS were given as AMI and only 2 (0.01%) as unstable angina. After AMI, the next commonest recorded causes of death were other CHD (11.3%), pneumonia (2.9%), cancer (2.5%) and stroke (2.1%). We used all-cause mortality throughout.

Table 1 shows the patient characteristics. 14.3% of ACS admissions had a LOS of <2 days (including any transfer) and survived; for AMI, this proportion was just 2.1%. Mortality for unstable angina was 2.6%. For AMI it varied by site, from 8.3% for subendocardial to 15.3% for unspecified site; as the latter made up some 53.7% of the AMIs, we did not adjust for site of infarct in any of the regression models.

17.8% of ACS involved transfers from or to other hospitals: 21.2% for AMI and 12.3% for unstable angina. 22.2% of the ACS admissions had revascularisation, ranging from 5.8% to 55.0% between hospitals; of these, 49% had the procedure following transfer. In line with the principles of risk adjustment rather than risk prediction, we did not include in any model the use of percutaneous coronary intervention (PCI) or CABG during in the index admission as this is part of the treatment, despite large differences: the 30-day total death rate was 2.3% in patients having PCI (19.4% of admissions), 3.9% in patients