



Original Article

Factors predicting the hospital episode costs of emergency medical admissions



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ABSTRACT

Background: Important outcome predictor variables for emergency medical admissions are the Manchester Triage Category, Acute Illness Severity, Chronic Disabling Disease and Sepsis Status. We have examined whether these are also predictors of hospital episode costs.

Methods: All patients admitted as medical emergencies between January 2008 and December 2012 were studied. Costs per case were adjusted by reference to the relative cost weight of each diagnosis related group (DRG) but included all pay costs, non-pay costs and infra-structural costs. We used a multi-variate logistic regression with generalized estimating equations (GEE), adjusted for correlated observations, to model the prediction of outcome (30-day in-hospital mortality) and hospital costs above or below the median. We used quantile regression to model total episode cost prediction over the predictor distribution (quantiles 0.25, 0.5 and 0.75).

Results: The multivariate model, using the above predictor variables, was highly predictive of an in-hospital death-AUROC of 0.91 (95% CI: 0.90, 0.92). Variables predicting outcome similarly predicted hospital episode cost; however predicting costs above or below the median yielded a lower AUROC of 0.73 (95% CI: 0.73, 0.74). Quantile regression analysis showed that hospital episode costs increased disproportionately over the predictor distribution; ordinary regression estimates of hospital episode costs over estimated the costs for low risk and under estimated those for high-risk patients.

Conclusion: Predictors of outcome also predict costs for emergency medical admissions; however, due to costing data heteroskedasticity and the non-linear relationship between dependant and predictor variables, the hospital episode costs are not as easy to predict based on presentation status.

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1. Introduction

Finance has become an increasingly important aspect of the modern medical landscape. Spiralling general healthcare costs coupled with new and effective but increasingly expensive treatments has driven the cost of healthcare provision to ever increasing heights [1]. The global financial crisis of recent years has given rise to a reevaluation of healthcare spending [2]. While understandably emotive and often criticised these assessments of value are essential to the future of sustainable healthcare [3]. The estimation of costs is well developed in certain areas such as medication use [4]; however, in the prediction of cost of acute medical care it is less well defined. Identification of the key factors predicting the cost of hospital admissions is essential to enable appropriate targeting of cost reductions.

An Acute Medical Admission Unit (AMAU) was established in our institution in 2003. We have previously evaluated the outcomes of the AMAU [5–7] with a 60% reduction in in-hospital mortality witnessed over this 10-year period from 14.5% to 5.7% [6]. Much of the academic effort has focused on understanding factors impacting inpatient outcomes following an emergency medical admission and the modification of these factors to improve care. Major mortality outcome predictors identified include Acute Illness Severity Score [8–13], Chronic Disabling Disease Score [14–16], Charlson Co-Morbidity Index [17], Manchester Triage Category [18], and Sepsis Status.

A recent innovation for hospital practice in the Republic of Ireland is the proposal that Money Follows the Patient (MFTP), by the use of a case based funding model, weighted for Diagnosed Related Groups (DRG's). This initiative gives access, from 2008 onwards, to hospital in-patient costs by episode. With the increased focus on costs, consequent on the austerity imposed by financial circumstances, we have investigated the extent to which the factors predicting clinical outcomes might also drive hospital episode costs. We have utilised a large database detailing

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all emergency medical admissions to determine whether predictors of outcome would also predict episode cost.

2. Methods

2.1. Study setting

St James's Hospital (SJH) serves as a secondary care centre for emergency admissions for its local catchment area of 270,000 adults, operating a continuous sectorized acute general 'take' with patients directed towards surgical or medical specialties. Emergency medical patients are admitted from the ED to an AMAU; its 59-bed capacity is such that up to 70% of all admissions could be predicted to receive their entire hospital care within the maximum permitted stay of 5 days in AMAU. Patients are not triaged to specialties or dispersed towards until their acute illness has been stabilised. The operation and outcome of the AMAU [5,6] have been previously reported.

2.2. Data collection

An anonymous patient database has been created assembling core episodic information from the patient administration system, the national hospital in-patient enquiry (HIPE) scheme, the patient electronic record and other laboratory IT systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland [19] having used the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) from 1990 to 2005 and ICD-10-CM since. The database includes the unique hospital number, admitting consultant, date of birth, gender, area of residence by county, principal diagnosis, up to nine additional secondary diagnoses, procedures and admission and discharge dates. Additional information cross-linked and available for analyses includes physiological, haematological and biochemical parameters. The HIPE dataset has up to six fields of coded diseases recorded at time of discharge/death, together with procedures and investigations undertaken during the hospital stay. Data was related to all emergency medical patients admitted between January 1st 2008 and 31st December 2012, including patients admitted to the Intensive Care Unit (ICU) or High Dependency Unit (HDU) but excluding patients with acute ischaemic coronary disease, admitted directly under a specialist cardiology team.

We used the Clinical Classifications Software (CCS) for ICD-9-CM – a diagnosis and procedure categorization scheme – to collapse the (> 14,000 diagnosis codes) ICD-9-CM's multitude of codes into a smaller number (approx 240) of clinically meaningful categories that are more useful for presenting descriptive statistics than are individual ICD-9-CM codes. For example, CCS can be used to identify populations for disease- or procedure-specific studies or to develop statistical reports providing information (such as charges and length of stay) about relatively specific conditions.

2.3. Outcome predictors

Disturbance of haemodynamic and physiological admission parameters may be utilised to predict a clinical outcome [8–11]. We have previously derived an Acute Illness Severity Score, an age adjusted risk estimate, representing an aggregate laboratory score based on the admission serum sodium, serum potassium, serum urea, red cell distribution width, white blood cell count, serum albumin and troponin values [12,13]. The score derives from the principle of physiological homeostasis, with the expectation of maintenance of a stable internal milieu and deviation from the normal equilibrium indicating the expected risk of adverse outcome [13]. Blood culture requests were recorded along with a result. An urgent blood culture was one performed within 48 h of admission. Sepsis was defined by three categories 1) no request during the admission 2) request but blood culture report negative and 3) culture request and positive result.

While life expectancy has increased by 4.0 and 2.6 years for males and females respectively between 1970 and 2010, the time spent with 'disabling' conditions has increased by 9.2 and 9.4 years, respectively, over this period [14]. This is based on a definition of 'chronic disabling condition' as proposed by the US Department of Health and Human Services [15] defined as an impairment of an individual's ability to function during routine daily tasks. While quantity of life has increased full quality of life during these extended years cannot be assumed [16]. The Chronic Disabling Disease Score allocated one point for any single code in separate categories of cardiovascular, neurological, gastrointestinal, diabetes, renal, neoplastic or other coded diseases; the scores were summed. Disabling disease is frequently present in our emergency admissions with ICD9/ICD10 discharge codes of 1, 2, 3 or 4 separate systems in 23.3%, 28.7%, 21.9% and 15.5% of episodes, respectively. The calculated univariate risk, of an in-hospital death by day 30, gave OR's of 3.1, 4.8, 7.7 and 14.0 with 1, 2, 3 and 4 disabling codes respectively.

Comorbidity was measured using the Charlson Comorbidity Index [17]. At time of presentation to the ED, patients were categorised using the Manchester Triage System [18]: these were Category 1 (resuscitation), Category 2 (very urgent), Category 3 (urgent), Category 4 (standard) and Category 5 (non-emergency).

2.4. Hospital costings

The Republic of Ireland proposes to introduce a MFTP system, a case-based funding model with DRG's, comparing hospital costs, quality and efficiency. The calculation of costs per case is adjusted by reference to the relative cost weight of each DRG and encompasses all costs appropriately associated with the delivery of that care including: 1) Pay costs, 2) non-pay costs – such as drugs, blood, medical and surgical supplies, radiology, laboratory equipment and supplies, heat, light & power and 3) costs of diagnostics, medical services, theatres, laboratories, wards and overhead allocations as appropriate.

The hospital uses a number of standard accounting costing methodologies. The predominant approaches used in this exercise were Activity Based Costing and Absorption Costing [20,21]. Both methods are used in parallel to cost individual patient episodes of care by directly linking cost to patient clinical data (e.g. laboratory and radiology tests, inpatient beds, day). The accuracy of the costing is greatly enhanced because the hospital has utilised a robust devolved accounting and budgetary framework since 2004. The financial data is validated by externally audited annual Financial Statements; in addition strong relationships between costing and clinical risk profile/outcomes data suggest that the financial calculations provide a realistic view of the costs of care provision.

2.5. Statistical methods

Descriptive statistics were calculated for background demographic data, including means/standard deviations (SD), medians/interquartile ranges (IQR), or percentages. Comparisons between categorical variables and mortality were made using chi-square tests. Significant predictors from the univariate analyses were entered into a multivariable logistic regression model, using fractional polynomials for all continuous measures, for examining non-linear associations. The method proposed by Sauerbrei [22] was applied, to investigate non-linear functional relationships based on fractional polynomials and the combination of linear and non-linear predictor variables with backward elimination. We used the Hosmer and Lemeshow test for goodness-of-fit where non-significant departures between observed and predicted outcomes ($p > 0.05$) indicate an acceptable model fit (Hosmer–Lemeshow χ^2 (10) 8.5; $p = 0.58$). For mortality and including all episodes, we employed a generalized estimating equations (GEE) logistic model to allow for correlated observations (readmissions). Taking account of clustering in the data allows better characterization of the variability of covariates; robust standard errors, in the GEE model, are derived using the

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