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Emergency Medical Admission Outcomes-Improved Survival Evidenced by Risk Score Comparator

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Abstract

Background: Improved mortality as evidence of quality improvement is difficult to establish. We investigate whether improved 30-day survival following an emergency medical admission is due to improved outcomes at equivalent risk rather than a reduction in risk profile over time.

Methods: For emergency medical admissions (96,526 episodes in 50,731 patients) between 2002 and 2016, the relationship between 30-day in-hospital mortality and Risk Score was determined using logistic regression and margins statistics. Risk Score was obtained by summing the individual patient illness acuity and complexity.

Results: A 17 point Risk Score was constructed by summing the laboratory admission data (Illness Severity), the Charlson Comorbidity, the Chronic Disabling Disease Score and the Sepsis status. This had a curvilinear relationship to 30-day in-hospital mortality with an AUROC of 0.84 (95% CI: 0.83, 0.85). The range of predicted 30-day mortality was 3.7% (10 points) to 54.7% (15-17 points). The 30-day in-hospital mortality between 2002- 2016 averaged 4.6% (95% CI 4.4% to 4.7%) if calculated by episode, or 8.9% (95% CI 8.6% to 9.1%) if calculated by unique patient. The corresponding relative risk reductions (RRR) from 2002-2016 were 30.4% and 60.9% by episode and patient. Comparing the early and later phases of the 15 year period, at the same risk score, there was an overall 7% mortality reduction (RRR 0.93 - 95% CI: 0.92, 0.94) with greatest impact for those at the highest risk scores.

Conclusion: A Risk Score can be constructed to predict hospital mortality following an emergency medical admission. Its utility includes risk profiling admissions to infer quality improvement by relating outcomes to specific risk profiles.

Keywords: Emergency medical admissions; Mortality; Quality improvement

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Introduction

Emergency medical admissions require immediate and specialist management in urgent care situations - this is the domain of Acute Medicine [1]. Structural reform and standardization in respect of medical management for such acute conditions, for example stroke and myocardial infarction, have been investigated [2,3]. Changes to care delivery via the establishment of acute medical admissions units (AMAU) [4-6], and the implementation of other structural changes [7,8] with the increased presence of senior consultant staff [9], have improved clinical outcomes. At St. James' Hospital Dublin, as part of this Acute Medicine Movement, an Acute Admission Unit was established in 2003; all emergency medical admissions from the Emergency Department were initially treated here irrespective, of their specialty profile, unless they required immediate Intensive Care. The operation and outcome of this initiative has been previously described [5,10]. In a major teaching hospital our expectation was that this re-organization would result in efficiency gains (reduced length of stay) with unaltered outcomes. Paradoxically substantial reductions in 30-day hospital mortality occurred [5,10] without altered hospital length of stay. The substantive question then, is whether reduced mortality reflected quality improvement in care, or simply a falling patient risk profile?

The essential problem is how to benchmark the clinical outcomes objectively or quantitatively. In this paper we investigate the construction of an individual patient Risk Profile and then use this methodology as a risk adjustor to compare outcomes at different times but at the same level of risk. We have previously described an Acute Illness Severity Score [11] for predicting in-hospital mortality relied on admission laboratory tests (i.e. serum sodium (Na), serum potassium (K), serum urea, hematocrit or RDW and white blood cells count (WBC). This used a multivariate fractional polynomial method [12]. Laboratory data scores for predicting in-hospital mortality are not new but vary in the components included in the model and the relative weight applied to each; models have been used on different occasions with predictive accuracy (AUROC) reported at 0.78 [13], 0.89 [14] and 0.84 [15]. Our full model proved predictive of a 30-day in hospital death with an AUROC of 0.90 (95% CI: 0.89, 0.90) [11]. The relative performance of risk scoring models has been well described [16]. To extend the laboratory data model, we can add further information from both discharge codes (ICD9/ICD10) and laboratory blood culture inpatient data to calculate the Charlson Comorbidity index [17], the Chronic Disabling Score [18] and the Sepsis Status [19]. This allows the construction of an overall risk profile for each patient. In this paper:

1. We deploy the validated Risk Score to demonstrate its robustness
2. We then describe how the 30-day in-hospital mortality for all medical admission patients admitted via the emergency department of our centre has changed over time.
3. We then adjust changing mortality outcomes to the constructed risk profile, by categorizing patients into increasing risk groups, and relating their clinical outcomes to two consecutive time intervals (2000-2009 and 2009-2015) but at equivalent risk score levels.

The hypothesis being tested is whether quality improvement, as evidenced by improved survival, is due to either improved survival at equivalent risk scores, or alternatively, is due to the admission of a lower risk cohort with time.

Methods

Background: St. James's Hospital, Dublin serves as a secondary care centre for emergency admissions in a catchment area with a population of 270,000 adults. All emergency medical admissions were admitted from the ED to an Acute Medical Admission Unit, the operation and outcome of which have been described elsewhere [5,10].

Data collection: An anonymous patient database was employed, collating core information of clinical episodes from the Patient

Administration System (PAS), the national hospital in-patient enquiry (HIPE) scheme, the patient electronic record, the emergency room and laboratory systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland [19,20]. International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) has been used for both diagnosis and procedure coding from 1990 to 2005 with ICD-10-CM used since then. Data included parameters such as the unique hospital number, admitting consultant, date of birth, gender, area of residence, principal and up to nine additional secondary diagnoses, principal and up to nine additional secondary procedures, and admission and discharge dates. Additional information cross-linked and automatically uploaded to the database includes physiological, hematological and biochemical parameters.

Risk score: Derangement of biochemical parameters may be utilized to predict clinical outcome. We derived an Acute Illness Severity Score-this is an age adjusted 30-day in-hospital mortality risk estimator, representing an aggregate laboratory score based on the admission serum sodium (Na), serum potassium (K), serum urea, red cell distribution width (RDW), white blood cell count (WCC), serum albumin and troponin values at admission and applied as an Acute Illness Severity score [11,21]; the score predicts 30-day in-hospital mortality from the biochemical parameters recorded in the Emergency Department [22]. Candidate variables from univariate analysis were entered into a multivariable logistic regression model, using fractional polynomials for all continuous measures with the exception of age. The Illness Severity score has six risk subgroups (I–VI) and initial cut-offs (set at 1, 2, 4, 8 and ≥16% 30-day mortality) were such as to describe groups with a progressive doubling of risk versus the previous. We supplemented the Illness Severity score with data from the ICD 9/10 discharge codes to compute Co-Morbidity (as per the Charlson Index [16]) and chronic disabling disease [17] status. The Charlson Co-Morbidity has three and the chronic disabling disease five categories. In addition, sepsis status was described, based on blood culture status with possible states of 1) No Culture requested 2) Culture request but Negative and 3) Culture request and Positive were included (3 groups). For each of these four predictors we have previously described the relationship between status and the outcomes [11,17,18,21]. Therefore, the maximum possible risk score for any one patient, from the allocation of one point to each predictor and subcategories (Illness Severity 6, Charlson 3, Disabling Disease 5 and sepsis 3) was 17 points (range 4-17).

Statistical methods: Descriptive statistics were calculated for background demographic data, including means/standard deviations (SD), medians/Inter-quartile ranges (IQR), or percentages. Comparisons between categorical variables and mortality were made using chi-square tests.

We assessed the prediction of outcome (30-day in-hospital mortality considering only one admission per patient - last if >1 admission) with the previously described predictor variables that included age, acute Illness Severity score [11,22], the Charlson Comorbidity index [17], the Chronic Disabling Score [18] and Sepsis Status [19]. We employed a logistic model with robust estimate to allow for clustering; the correlation matrix thereby reflected the average dependence among the specified correlated observations [11]. Logistic regression analysis identified potential mortality predictors and then tested those that proved to be significant univariate predictors ($p<0.01$ by Wald test). The Hanley and McNeil method was used to estimate AUROC statistics [24].

We used the margins command in Stata 13.1 to estimate and interpret adjusted predictions for sub-groups, while controlling for other variables such as the year of admission, using computations of average marginal effects. Margins are statistics calculated from predictions of a previously fitted model at fixed values of some covariates and averaging or otherwise over the remaining covariates. In the multivariable model (logistic), we adjusted univariate estimates of effect, using the previously described outcome predictor variables. The model parameters were stored; post-estimation intra-model and cross-model

hypotheses could thereby be tested.Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated for those predictors that significantly entered the model ($p<0.10$). Statistical significance at $P<0.05$ was assumed throughout Stata v.13.1 (Stata Corporation, College Station, Texas) statistical software was used for analysis.

Results

Patient demographics: A total of 96,526 episodes in 50,731 unique patients were admitted as medical emergencies from the hospital catchment area over the 15-year study period (2002-2016). These episodes represented all emergency medical admissions, including patients admitted directly into the Intensive Care Unit or High Dependency Unit, respectively. Patients who stayed > 30 days (10.2%) were not included in the formal analysis; these in the main were waiting for placement in long-term care facilities. The proportion of males was 48.6%. The median (IQR) length of stay (LOS) was 4.4 (1.8, 8.9) days. The median (IQR) age was 58.7 (38.0, 76.2) years, with the upper 10% boundary at 84.9 years.

The demographic characteristics (Table 1) of the admission profile by the Risk Score are of interest; this is tabulated with cut-offs set at <10, 10=13 and ≥13 points so that one can appreciate how the underlying characteristics alter with increasing score. Clearly as the Risk Score increased there were many older patients (41.4 years (29.5, 55.6) to 73.8 years (59.2, 82.2) with increasing length of hospital stay 3.2 days (1.4, 6.3) to 6.3 days (2.6, 12.1). Mortality by episode was far higher in the highest risk group 0.4% *vs.* 9.2%. There were large increases over the score range in those with high Illness Severity (2.5% to 81.6%), Charlson Comorbidity score (1.5% to 53.8%) and Sepsis Positivity (0.9% to 6.1%).

Factor	Level	<10	10<13	≥13	p-value
N		26052	26851	33680	
Gender	MA	13312 (51.1%)	13353 (49.7%)	15668 (46.5%)	<0.001
	Female	12740 (48.9%)	13498 (50.3%)	18012 (53.5%)	
Outcome	Alive	25959 (99.6%)	26059 (97.1%)	30595 (90.8%)	<0.001
	Died	93 (0.4%)	792 (2.9%)	3085 (9.2%)	
Age (yr)*		41.4 (29.5, 55.6)	67.1 (52.0, 78.4)	73.8 (59.2, 82.2)	<0.001
LOS (days)		3.2 (1.4, 6.3)	5.9 (2.9, 10.7)	6.3 (2.6, 12.1)	<0.001
Acute Illness Severity	1	2480 (9.5%)	28 (0.1%)	5 (<1%)	<0.001
	2	5583 (21.4%)	231 (0.9%)	18 (0.1%)	
	3	8048 (30.9%)	1723 (6.4%)	48 (0.2%)	
	4	6806 (26.1%)	5698 (21.2%)	714 (2.8%)	
	5	2494 (9.6%)	9043 (33.7%)	3936 (15.4%)	
	6	641 (2.5%)	10128 (37.7%)	20906 (81.6%)	
Charlson Index	0	21649 (83.1%)	11413 (42.5%)	6686 (19.9%)	<0.001
	1	4021 (15.4%)	11075 (41.2%)	8804 (26.3%)	
	2	382 (1.5%)	4363 (16.2%)	18028 (53.8%)	

Table 1: Characteristics of Emergency Medical Admissions by Risk Score (2002-2016).

Impact on mortality: Hospital mortality can be calculated by episode or by patient. Between 2002 and 2016 only 34.5% of episodes were the first and only admission. Mortality is a fixed numerator but episodes inflate the denominator - lowering the calculated mortality figure. By episode, the 30-day in-hospital mortality over the 15 year period averaged 4.6% (95% CI 4.4%

to 4.7%); there was a relative risk reduction (RRR) of 30.4% between 2002 and 2016, from 5.5% to 3.8% (p = 0.001), with a number needed to treat (NNT) calculation of 60.1 (Figure 1). By patient, the 30-day in-hospital mortality averaged 8.9% (95%CI 8.6% to 9.1%); there was a RRR of 60.9% between 2002 and 2016, from 12.2% to 4.8% (p=0.001) with a calculated NNT of 13.5.

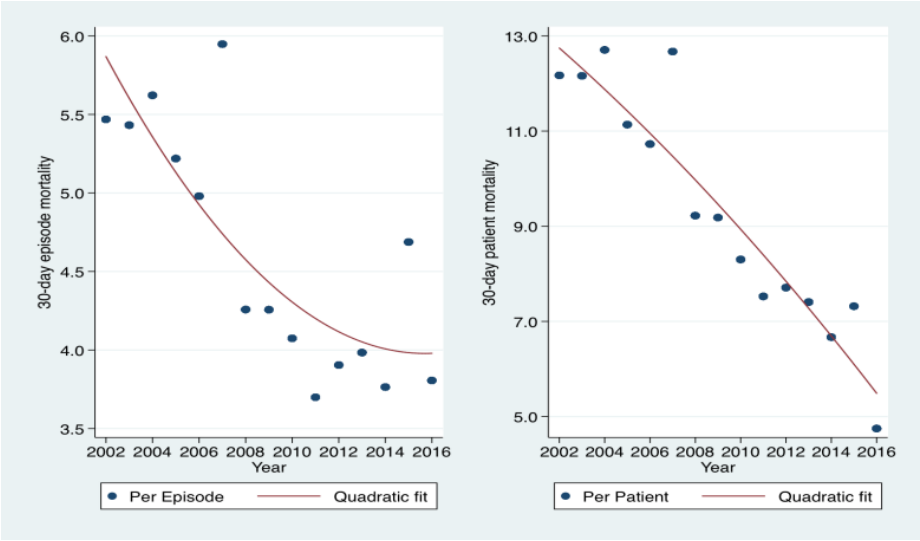

Figure 1: Hospital 30-day mortality by episodes averaged 4.6% with a relative risk reduction (RRR) of 30.4% between 2002 and 2016. By patient mortality averaged 8.9% with a RRR of 60.9%.

Risk predictors combined to compute an overall risk score: The admission laboratory data calculated an Acute Illness Severity Score. Based on the 30 day mortality outcomes (each patient counted once only, last admission if >1 admission), six risk groups were defined with 30-day mortality rates of Group I- 0.2%, II- 0.1%, III- 0.6%, IV- 1.8%, V- 4.6% and VI- 25.2%. We added additional risk categories from ICD 9/10 discharge codes calculating the Charlson Comorbidity index (17) and the Chronic Disabling Score [18]; Sepsis Status was derived from laboratory blood culture data (19). The 30-day mortality rates for Charlson Co-Morbidity groups were: Group 0 - 2.9%, Group I - 9.4% and Group II- 22.8%. For Chronic Disabling Score, the 30-day mortality rates were Gr 0 - 1.0%, I- 3.5%, III- 7.8%, IV- 14.3% and V- 28.4%. By Sepsis Status, the 30-day mortality rates were: no blood culture request - 5.5%, blood culture request but culture negative -17.7%, and blood culture request and a positive result 31.6%.

Summing these risk computations gave a maximum Risk Score of 17 points (Figure 2). The full model was curvilinear and predictive with an AUROC of 0.84 (95% CI: 0.83, 0.85). The predicted 30-day mortality at a score of 10 points was 3.7% (95% CI: 3.4, 4.0), at 11 points 6.4% (95% CI: 6.0, 6.8), at 13 points 17.8% (95% CI: 17.1, 17.4), at 14 points 27.7% (95% CI: 26.8, 28.6) and > 15 points - 54.7% (95% CI: 52.8, 56.4). Below a score of 10 included 40.7% of patients, with an approximate 8% increase in numbers within each score point category thereafter. The cumulative 50% was at a score of 10, 70% at score 12 and 90% at score 14.

Risk Score and 30-day hospital mortality by time of admission: We examined the relationship between the Risk Score and the 30-day hospital mortality for two consecutive periods- 2002-2008 and 2009-2016. As one would expect, the 30-day mortality increased progressively with risk score; however mortality was consistently lower, at any equivalent risk score level, for patients admitted in the second period. The interaction effect (between score impact and time) showed an overall 7% mortality reduction (RRR 0.93 - 95% CI: 0.92, 0.94).

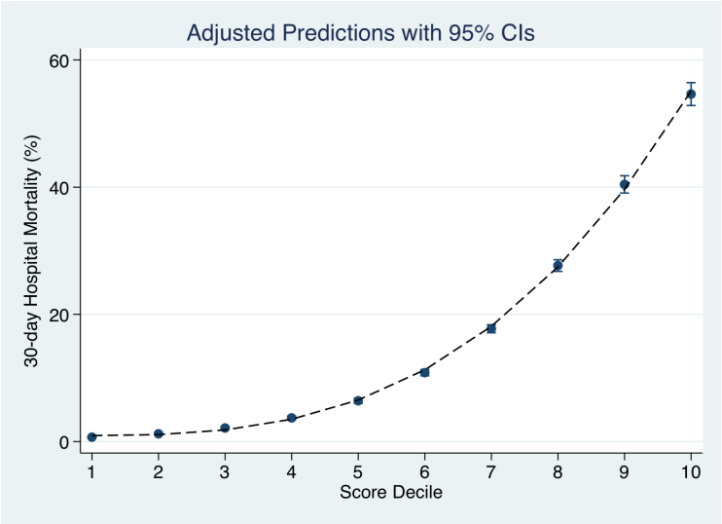

Figure 2: The 30-day in hospital mortality was related to the underlying Risk Score. The decile of each predictor variable was related to the 30-day mortality rate; the risk estimate was derived from the logistic regression model and was the sum of the Illness Severity, Charlson Co-Morbidity, Chronic Disabling Disease and Sepsis Scores. The cut points for deciles were (7-15).

The benefits appeared greater at the higher risk scores for example at score 10-1.7% (95%CI: 1.6, 1.9) *vs*. 1.5% (95% CI: 1.3, 1.6), 12 - 6.1% (95% CI: 5.8, 6.5) vs. 4.6% (95% CI: 4.3, 4.9), 14-19.7% (95% CI: 18.8, 20.5) *vs*. 13.5% (95% CI: 12.9, 14.1) and >15-47.8% (95% CI: 46.1, 49.6) *vs*. 33.4% (95% CI: 31.9, 34.9) (Figure 3).

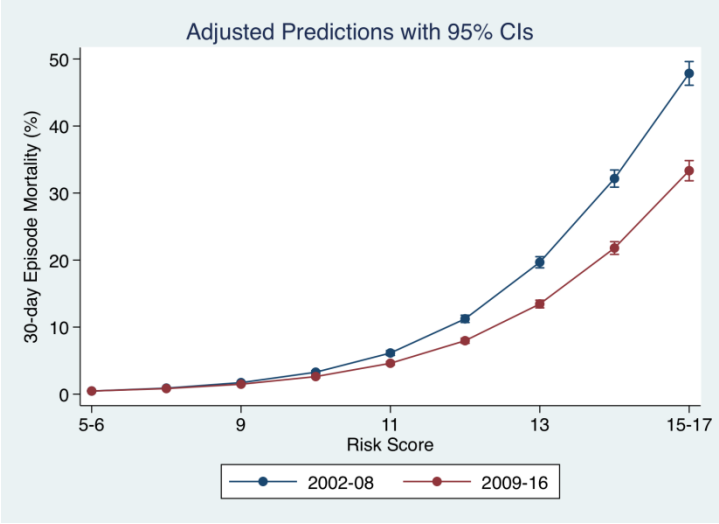

Figure 3: The 30-day in hospital mortality related Risk Score by calculated value to the 30-day in-hospital mortality comparing the time periods 2002-08 and 2009-16. We used margins to estimate the average marginal effect. As Risk Score increased, the 30-day mortality progressively increased but it was statistically lower at a given score for the second period ($p<0.001$).

Discussion

These data demonstrate that between 2002 and 2016 there was a substantial improvement in survival (30-day in-hospital mortality decline) following an emergency medical admission; by episode there was a relative risk reduction (RRR) of 30.4%

from 5.5% to 3.8% and per unique patient a RRR of 60.9% from 12.2% to 4.8%. The Risk Score distinguished between groups with a very wide difference in outcomes from a low 30-day mortality risk of 3.7% to an extremely high risk group of 54.7%. Comparing the early and later phases of the 15 years period, at the same risk score, there was an overall 7% mortality reduction (RRR 0.93- 95% CI: 0.92, 0.94) with greatest impact for those at the highest risk scores. Therefore, these data suggested that patients who formerly would have died (based on a risk score projection) were more likely to survive. Our AMAU was established in 2002 and the system of care, operational pathways, and institutional experience and memory embedded and over the extended time period. The USA National Hospital Discharge Survey (NHDS) data from 2000 through 2010 reported that inpatient hospital deaths decreased 8% from 2000 to 2010 [25] - an effect size comparable with the outcome improvement reported here.

There has been much debate about how best to improve clinical outcomes of emergency medical admissions with focus variously on the structure of care delivery such as the acute medical admissions unit (AMAU) [4-6,26] or with other structural reforms including staff rostering and specialty triage [7,8] or the presence of senior consultant interventions [9]. Of course most of these discussions cannot adjust for other variables such as radiological imaging and diagnostic innovations or improved therapeutic interventions; thus the explanation of the improvement is difficult to define precisely. The problem with a falling trend of mortality or one of improved survival is to rebut the challenge of reduced mortality being ascribed to a lower bar to admission from the Emergency Department.

The laboratory data score methodology has evolved over time. Prytherch et al. [13] suggested a logistic regression model that predicted death very early after admission AUROC 0.78. Froom and Shimoni [14] used similar methodology with improved in-hospital mortality prediction with an AUROC of 0.89. Another model combining clinical and laboratory data including age, vital signs, phosphate and albumin levels reported an AUROC of 0.84 [15]. Our Risk Score is numbers and combines laboratory and discharge code analyses of Co-morbidity and Chronic Disabling Disease but also incorporates sepsis status (based on blood culture results). Sepsis data is of course a major determinant of short and longer term outcomes [27,28]. Survival in our patient groups, considering sepsis in isolation clearly was better where no blood culture was requested (5.5%) compared with a culture negative (17.7%) or culture positive request (31.6%); Holt et al. [27] reported sepsis in-hospital mortality of 27.7% and Winters et al. [28] reported a figure of 20% from a large meta-analysis . Our Risk Score therefore attempts to build an objective measure of clinical complexity and to capture acute illness severity (laboratory profile and sepsis status) on a backdrop of complexity (comorbidity plus disabling disease). It offers a method of relating clinical outcome to the individual status.

Of course the question is what exactly has an altering hospital mortality to do with a hospitals performance? The hospital standardized mortality ratio (HSMR) is developed to evaluate and improve hospital quality but its application to compare hospitals, is controversial [29]. It may seem peculiar to question as to whether the hospital mortality rate can be an absolute number or merely an estimate. It is clearly a ratio to the number of deaths in a time period to some admitted population. The longer the time sample the more the denominator will inflate - as one can only die once but can be admitted many times. A consequence of deprivation is that subjects from a disadvantaged background are much more likely to be readmitted [30]. Between 2002 and 2016, only 34.5% of episodes were the first and only admission and this value could be even lower as the number of our population admitted to other institutions is unknown. Using a common approach of comparing outcomes between institutions using a Standardized Mortality Rate takes the denominator as an estimate of the number of deaths that would have been expected, adjusted for age, demographics (social circumstances), gender and co-morbidities [29]. Of course the computer model can be constructed in different ways altering the perceived outcome and indirect standardization may interact with the case-mix to produce differing SHMR's between hospitals providing the same quality of care [31]. Our approach would obviate

some of these difficulties allowing a more robust assessment of the complexity of the clinical presentation. The importance of the laboratory data and sepsis status can be judged from the Odds Ratios computed in the logistic model; for the Risk Score overall 1.8 (95% CI: 1.7, 1.8) but for Illness Severity 4.1 (95% CI: 3.8, 4.4) and for sepsis state 2.3 (95% CI: 2.2, 2.4). Not having this information will greatly reduce the likelihood of being able to relate clinical outcomes to the patient risk profile. This would be particularly useful when interpreting the effect of quality improvement initiatives. These endeavors can occur across asynchronous time periods and are vulnerable to the 'narrative fallacy' phenomenon [32]. By ensuring that a robust risk profiling system is in place one can have more confidence in the interpretation of the effect of any intervention- particularly one that may represent a fundamental shift in practice.

As with any study, this work has both strengths and limitations. The strengths lie in the comprehensive nature of the data available collated over a 15-year period. Further, our aggregate score used routine laboratory tests which are often collected and available during the course of an emergency medical admission. Laboratory tests are regarded as accurate, unbiased, and are routinely available within a short period following admission. Whilst it could be argued that different laboratories may use different methodologies and have different normal ranges, these are unlikely to be significantly different for many routine determinations, such as the full blood count, urea and electrolyte determinations. However, given that this is a single centre study, the contribution of each parameter would need to be established for different hospitals.

Conclusion

This paper has demonstrated that a Risk Score can be constructed to predict hospital mortality following an emergency medical admission. Its utility includes risk profiling admissions to infer quality improvement by relating outcomes to specific risk profiles. This approach may have utility across the clinical and quality improvement domains.

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