

Outcomes in acute medicine - Evidence from extended observations on readmissions, hospital length of stay and mortality outcomes

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ABSTRACT

Background: The Acute Medical Admission Unit (AMAU) model of care has been widely deployed, we examine changes in hospital readmission rates, length of stay (LOS) and 30-day in-hospital mortality over 16 years.

Methods: All emergency medical admissions between 2002 and 2017 were examined. We assessed 30-day in-hospital mortality, readmission rates, and LOS using logistic regression and margins statistics modelled outcomes against predictor variables.

Results: There were 106,586 admissions in 54,928 patients over 16 years. Calculated per patient the 30-day in-hospital mortality was 8.9% (95%CI 8.6% to 9.2%) and showed a relative risk reduction (RRR) of 61.1% from 12.4% to 4.8% over the 16 years ($p = .001$). Calculated per admission the 30-day in-hospital mortality was 4.5% (95%CI 4.4% to 4.6%) with a RRR of 31.9% from 2002 to 2017. Over this extended period 48.7% of patients were readmitted at least once, 9.3% > 5 times and 20 patients > 50 times each. The median LOS was 5.9 days (IQR 2.4, 12.9) with no trend of change over time. Total readmissions increased as a time dependent function; early readmissions (< 4 weeks) fluctuated without time trend at 10.5% (95%CI 9.6 to 11.3). A logistic regression model described the hospital LOS as a linear function both of comorbidity and the utilisation of inpatient procedures and services.

Conclusion: 30-day in-hospital mortality showed a linear trend to reduce over time at unaltered LOS and readmission rates. LOS showed linear dependency on clinical complexity; interventions aimed at reducing LOS may not be appropriate beyond a certain point.

1. Introduction

Acute Medicine is that part of hospital medicine concerned with the immediate and early specialist management of adult patients suffering from a wide range of medical conditions requiring urgent or emergency care [1]. Increased life expectancy and increased time spent living with chronic disabling conditions has led to spiralling healthcare costs mandating increased service effectiveness [2]. The traditional pattern of the 'take' care delivery, whereby patients were admitted under the care of a rotating general physician from the Emergency Department (ED) to the next available general ward bed frequently resulted in patients widely dispersed around the hospital. Inefficiencies related to this process have been described that appear to result in longer hospital stays [3], and an increase in direct patient risk, sometimes resulting in avoidable death [4].

Acute Medicine evolved in the United Kingdom as a discipline as the result of changes in the demographic and clinical environment. The Acute Medical Admission Unit (AMAU) was the natural development of

this process and as such it represented as much a philosophy of care as being a physical entity. It propelled a large resource increase as evidenced by a 63% increase in the number of Acute Medicine consultants, with ultimately 92% of UK hospitals admitting sick medical patients via the AMAU concept [5]. AMAUs were also established in Australia and Ireland [6,7], and the Hospitalist movement has been gaining in popularity in North America [8]. Despite widespread adoption of the model, there is a paucity of data on the long-term outcomes and examination of the extent to which such system change could contribute to efficiency. The aim of this paper is to examine the 16 years of data from our AMAU in an attempt to separate patient and system determinants of hospital outcomes.

2. Methods

2.1. Setting

St James's Hospital, Dublin, serves as a secondary care centre for

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emergency admissions in a catchment area with a population of 270,000 adults. As a city centre hospital St James's admits persons resident elsewhere but working in the city in addition to tourists who became acutely ill. Emergency medical patients are admitted from the ED to a 59-bed AMAU; this was opened in 2003. The design philosophy was to retain the traditional team structure and continuity of care with a personal physician for each patient, but to underpin this with a nursing and allied support team dedicated to Acute Medicine. Patients remain under one of nine teams operating a 1:9 24 h 'on-call' roster and remain under the care of the same physician over the course of their admission. There were predicted logistic advantages of geographic location (proximity to the ED, intensive care and high dependency units, and radiology). Moreover, with the patients in one location, it was anticipated that the collaborative consultation process would be facilitated. The operation and outcome of the AMAU have been further described elsewhere [9–12].

2.2. Data collection

During any emergency hospital admission, core demographics are recorded on the Patient Administration System (PAS), ED presentation clinical observations and subsequent post-admission parameters (haematology, biochemical, blood culture or transfusion data) are entered into the electronic patient record; these data can then be collated and downloaded together with the National Hospital In-Patient enquiry (HIPE) scheme (ICD-10-CM codes or procedures). HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland [13]. HIPE initially utilised the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) for both diagnosis and procedure coding from 1990 to 2005 with ICD-10-CM used thereafter. In 2002 we implemented a database to prospectively capture this data to monitor the performance of the AMAU and it has been maintained and updated each year since. The downloaded data on our database is anonymised and consists of the unique hospital identifier, 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.

2.3. Acute illness severity score

Derangement of biochemical parameters may be utilised to predict clinical outcome. We derived an Acute Illness Severity Score (AISS) – this is an age adjusted 30-day in-hospital mortality risk estimator, derived from an aggregate laboratory score of admission parameters [14,15]. This AISS is exponentially related to the 30-day in-hospital mortality with a range of model adjusted mortality outcomes from 2.5% (2.3%–2.6%) to 32.1% (30.4%–33.8%). The AISS has been externally validated [16].

2.4. Morbidity score

Patient morbidity was assessed by a morbidity score [17] published in 2014, which was further adjusted by additional information collected by our information system since. To devise the score, we searched ICD9 hospital episode discharge codes (back-mapping ICD10 codes to ICD9 as appropriate) based on the definition for chronic physical or mental health disorders proposed by the US Department of Health and Human Services in Chapter III of their document "Private Payers Serving Individuals With Disabilities And Chronic Conditions" [18]. These ICD codes were similar to those proposed by the Canadian group for multimorbidity [19] and the work of Quan [20]. ICD codes that captured chronic physical or mental health disorders that limit people in activities that they generally would be expected to be able to perform were grouped according to the following ten systems: (i) cardiovascular, (ii) respiratory, (iii) neurological, (iv) gastrointestinal, (v) diabetes, (vi)

renal, (vii) neoplastic disease, (viii) others (including rheumatological disabilities), (ix) ventilatory assistance required and (x) transfusion requirement. In addition, we searched our hospital's other databases for evidence of diabetes (Diamond database) [21], respiratory insufficiency ($FEV1 < 2L$), troponin status (high sensitivity troponin $> 25\text{ ng/L}$) [22], low albumin ($< 35\text{ G/dL}$) and anaemia (haemoglobin levels $< 10\text{ G/dL}$) or chronic renal insufficiency - $MDRD < 60\text{ mL/min} \times 1.73\text{ m}^2$ [23]. Each component of the score was then weighted according to 30-day in-hospital mortality, Supplementary Table 1.

2.5. Statistical methods

Descriptive statistics were calculated for demographic data, including means/standard deviations (SD), medians/interquartile ranges (IQR), or percentages. We examined 30-day in-hospital mortality as the primary outcome. We performed comparisons between categorical variables and 30-day in-hospital mortality using chi-square tests; multiple comparisons were adjusted for multiplicity using Scheffe's comparison statistic. Logistic regression analysis was employed to examine significant outcome predictors ($p < .10$ by Wald test from the univariate analysis) of 30-day in hospital mortality to ensure that the model included all variables with predictive power. Adjusted Odds ratios (OR) and 95% confidence intervals (CI) were calculated for those significant model predictors. A stepwise logistic regression analysis examined the association between 30-day in-hospital mortality and the following predictor variables: AISS [14,15], Charlson Co-Morbidity Index [24], Sepsis status [25].

We used the margins command in Stata to estimate and interpret adjusted predictions for sub-groups, while controlling for other variables such as time, 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 logistic model 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. Statistical significance at $P < .05$ was assumed throughout. Stata v.15 (Stata Corporation, College Station, Texas) statistical software was used for analysis.

3. Results

3.1. Patient demographics

Over the 16-year study period from 2002 to 2017, there were a total of 106,586 admissions in 54,928 patients through the ED. These episodes represented all emergency medical admissions, including patients admitted directly into the Intensive Care Unit or High Dependency Unit. The proportion of males was 48.6%. The median (IQR) 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 number of admissions resident in the catchment area was 74.5%.

3.2. Mortality and hospital length of stay between 2002 and 2017

Mortality results have been presented either by admission (all admissions counted) or by patient (only one admission considered – last admission used if > 1); we present both as whether per admission or per patient mortality analysis is optimal is debated. 48.7% of patients were readmitted at least once, 9.3% > 5 times and 20 patients > 50 times over the course of the study. Calculated per patient 30-day in-hospital mortality over the 16 year period averaged 8.9% (95%CI 8.6% to 9.2%); there was a relative risk reduction (RRR) of 61.1% between 2002 and 2017, from 12.4% to 4.8% ($p = .001$) (Fig. 1). Calculated per admission 30-day in-hospital mortality over the 16 year period averaged 4.5% (95%CI 4.4% to 4.6%); there was a RRR of 31.9% between

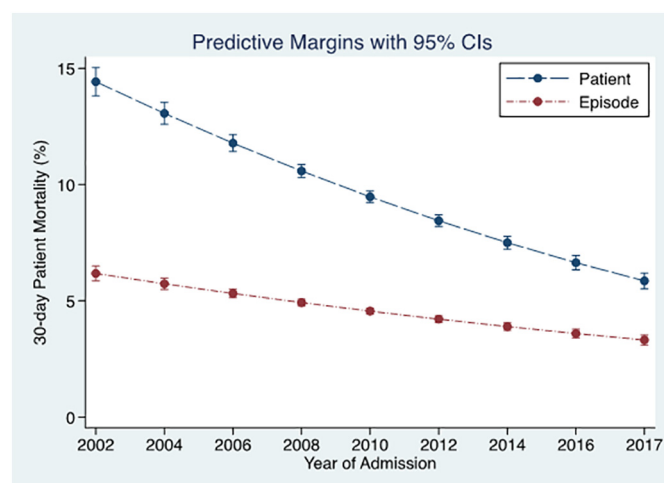


Fig. 1. 30-day in-hospital mortality calculated per admission episode and per patient from the multivariable logistic regression model. The predicted probabilities were derived from and plotted based on the model prediction.

2002 and 2017, from 5.5% to 3.7% ($p = .001$).

The median LOS was 5.9 days (IQR 2.4, 12.9); the median LOS for the three time periods 2002–06, 2007–11 and 2012–17 were 5.9 (IQR 2.4, 13.1), 5.9 (IQR 2.3, 13.0) and 5.9 (IQR 2.5, 12.9).

3.3. Readmission statistics between 2002 and 2017

Between 2002 and 2017, from a total of 106,568 admissions, 51,840 were readmissions, giving an overall 16 year readmission rate of 48.6%. The trend of readmission increased over time with respective calculated readmission rates at 1, 3, 5 and 10 years of 26.4%, 36.3%, 39.8% and 42.8%. The time to readmission progressively shortened (Fig. 2) from the time to the first 57.2 weeks (IQR 12, 165), third 36.4 weeks (IQR 8.9, 102), fifth 19.8 weeks (95% CI 5.5, 57.9), seventh 13.7 weeks (IQR 4.0, 40.4), and ninth 11.5 weeks (IQR 3.5, 30.4).

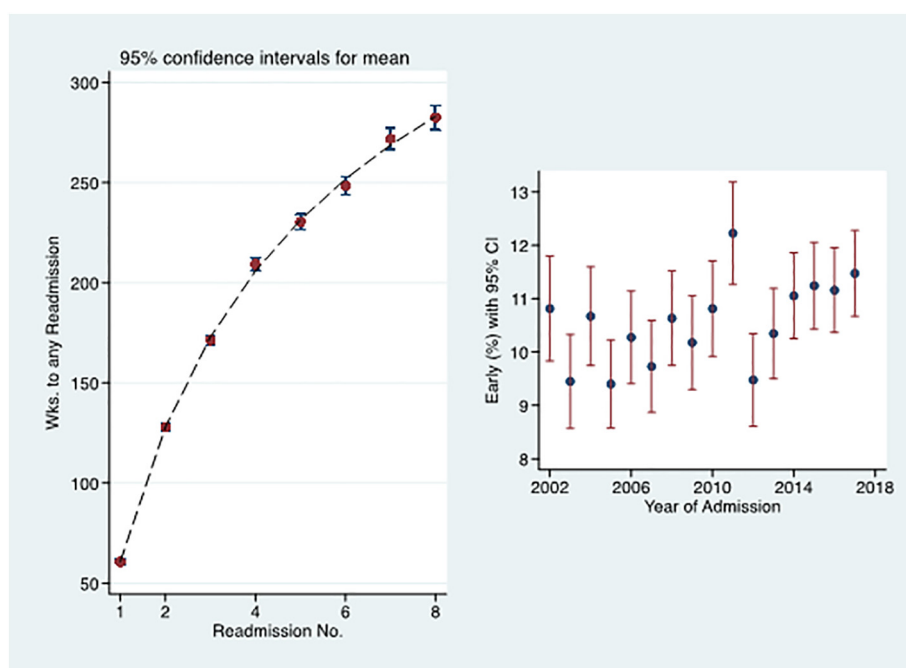


Fig. 2. Readmission rates between 2002 and 2017. Plotted are time to any readmission or rate of an early readmission (within 28 days) from the multivariable logistic regression model. Total readmissions increased as a function of time; there was no trend of change in the frequency of early readmissions between 2012 and 2017.

The total number of readmissions was a predictable function of time; the model prediction was for counts (i.e. predicated readmission number) to increase from 2.8 (95%CI 2.8 to 2.9) at 1 year to 18.7 (95%CI 17.9 to 19.6) by 16 years. The early readmissions within 4 weeks were unchanged over time with an average rate of 10.5% (95%CI 9.6, 11.3).

3.4. Relationship between comorbidity burden and length of hospital stay

The constraints on the ability for an early discharge were examined by examining the relationship between the Morbidity Score and the hospital LOS. The median (IQR) for the Morbidity Score was 5.2 (IQR 2.7, 2.9) with the 90% cut value at 10.4 and the maximum recorded patient score of 23 points. The model, adjusted for other predictors of LOS, predicted at a score of 6 points a LOS of 7.3 days (IQR 7.2, 7.3), a score of 12 points a LOS of 9.3 days (IQR 9.2, 9.4) and finally at a score of 18 points a LOS of 11.8 days (IQR 11.5, 12.2). Overall the relationship was linear (Fig. 3a).

3.5. Relationship between services & procedure utilisation and length of hospital stay

We examined the relationship between services and procedures utilised for patients during their admission and LOS. During an admission, patients could require services allied to medicine such as physiotherapy, occupational therapy, dietetics, speech therapy, psychology, social work or procedures including bronchoscopy, upper GI endoscopy, colonoscopy, coronary angiography, dialysis, ventilation, and blood transfusion. Analysis of these services and procedures revealed that the median was 1, with the 75th and 90th centiles at 2 and 3 and the maximum recorded at 6 units.

The demographic characteristics (Table 1), below or above the median number of procedures has been tabulated by AISS [14,26], Morbidity Score, Charlson Co-morbidity Index [24] and Sepsis status [25]. Those requiring more than the median were older at 74.8 years (IQR 59.3, 83.7) vs. 57.4 years (IQR 38.7, 74.0), had a longer LOS of 9.5 days (IQR 5.7, 15.7) vs. 3.8 days (IQR 1.6, 7.1) and a higher 30-day

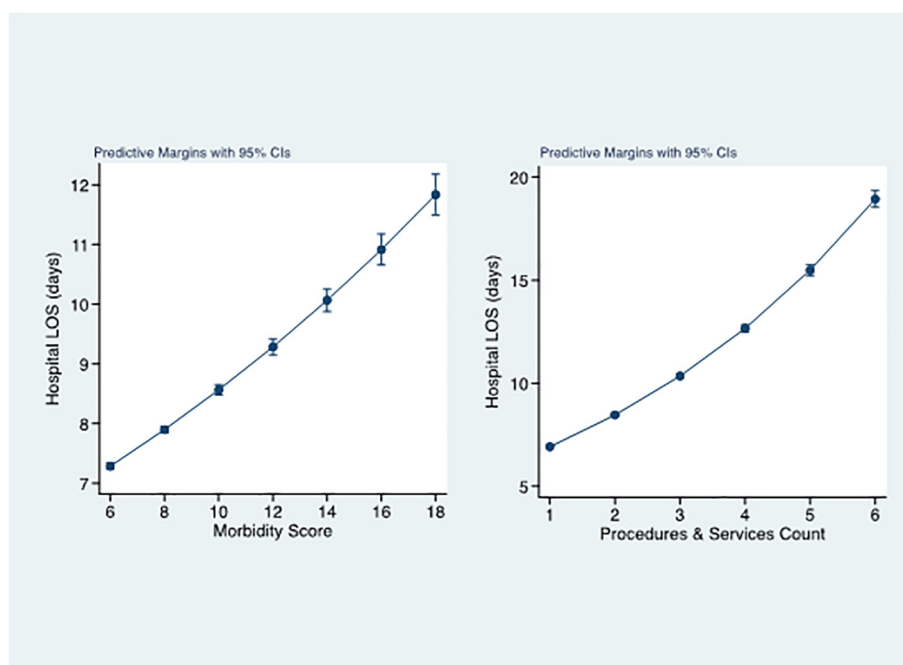


Fig. 3. Relationship between Morbidity Score and service/procedure utilisation and LOS. The LOS showed linear dependency on the underlying Morbidity Score and the number of services/procedures utilised.

Table 1
Demographics of emergency medical admissions by median service/procedure utilisation.

	≤ 1 (N = 57,573)	> 1 (N = 22,492)	p-value
Age (years)			
Mean (SD)	56.3 (20.57)	70.1 (17.61)	< 0.001
Median (IQR)	57.4 (38.7, 74.0)	74.8 (59.3, 83.7)	
Length of stay (days)			
Mean (SD)	5.34 (5.41)	11.18 (7.13)	< 0.001
Median (IQR)	3.8 (1.6, 7.1)	9.5 (5.7, 15.7)	
Gender			
Male	28,480 (49.5%)	10,727 (47.7%)	< 0.001
Female	29,093 (50.5%)	11,765 (52.3%)	
30-day In-hospital mortality			
Alive	55,894 (97.1%)	20,722 (92.1%)	< 0.001
Dead	1679 (2.9%)	1770 (7.9%)	
Acute illness severity score			
1	2414 (4.7%)	159 (0.7%)	< 0.001
2	5105 (9.9%)	475 (2.2%)	
3	7992 (15.5%)	1173 (5.5%)	
4	9691 (18.8%)	2447 (11.4%)	
5	9869 (19.2%)	4100 (19.1%)	
6	16,451 (31.9%)	13,122 (61.1%)	
Morbidity score			
< 6	33,567 (58.3%)	7000 (31.2%)	< 0.001
6	19,050 (33.1%)	10,256 (45.7%)	
10	4044 (7.0%)	3701 (16.5%)	
13	686 (1.2%)	1029 (4.6%)	
16	218 (0.4%)	468 (2.1%)	
Charlson index			
0	30,793 (53.6%)	7186 (32.0%)	< 0.001
1	15,883 (27.7%)	7400 (33.0%)	
2	10,765 (18.7%)	7852 (35.0%)	
Sepsis group			
1	45,921 (79.8%)	16,385 (72.8%)	< 0.001
2	10,130 (17.6%)	5065 (22.5%)	
3	1522 (2.6%)	1042 (4.6%)	

in-hospital mortality of 7.9% vs. 2.9%. Heavy users of these services were clearly at higher risk as evidenced by higher levels of AISS, Morbidity Score, Charlson Co-morbidity Index and sepsis status. They

had higher AISS (> Gr 4: 80.2% vs. 51.1%), Co-Morbidity Scores (≥ 10 points – 23.2% vs. 8.6%), a higher Charlson Co-morbidity Index (Grade 2–35.0% vs. 18.7%) and sepsis status (Culture positive 4.6% vs. 2.6%).

The LOS was a linear function of the service/procedure utilisation; from the average LOS at one service/procedure of 6.9 days, utilisations of 2, 3 and 6 services/procedures would increase the predicted median LOS to 8.5, 10.4 and 18.9 days respectively.

4. Discussion

Our analysis demonstrated continuing improvements in 30-day in-hospital mortality over the 16-year study period. This was essentially a linear trend over time; this occurred at unaltered early and total readmission rates and LOS. Over the 16 years there was a reduction in 30-day in-hospital mortality by admission of 31.9% from 5.5% to 3.7% and by patient of 61.1% from 12.4% to 4.8%. The fall in mortality was not due to a change in admission policy or lower risk categories, but represented the outcome figure adjusted for major risk factors [26]. LOS was linearly dependent on clinical complexity and did not reduce over the course of the study. We believe our data supports the theory that a pre-specified LOS may be an intrinsic part of the medical condition affecting these patients and is not amenable to intervention. In this scenario, the investment of considerable resources in trying to further reduce LOS is neither appropriate nor has the possibility of being successful.

There has been much debate about the value of reform of acute care delivery [6,7]. The fall in mortality over time we have demonstrated in our study has been described elsewhere and the extent to which UK and Ireland hospital system alterations, healthcare innovation, or general patient factors are responsible cannot be established with certainty. Laudicella et al. [27] reported that UK mortality rates fell between 2003 and 2008 from 14.9% to 11.4%; our comparable per patients figures were from 12.3% to 9.5%. Aragon & Chalkley [28] estimated that per admission mortality fell between 2002 and 2014 from 5.7% to 3.9%; our comparable admission statistics were from 5.5% to 3.8%. Thus our use of historical control data has limitations should one attempt to relate the AMAU initiative to any of the outcomes in terms of its specific design features and objectives [12] – rather the data suggests that the

temporal reduction in mortality was a general UK and Ireland healthcare system finding and not specific to a particular structural or system delivery reform.

Our data demonstrates that following an emergency medical admission, the risk of a readmission was high initially but rapidly declined with a long tail [29]. On average the early readmission rate within 28 days averaged 10.5% without an overall time trend. Blunt et al. [30] estimated that early readmissions over a 6 year period were equivalent to 7.0% of hospital discharges. For the period 2003–08, Laudicella et al. [27] reported UK hospital risk-adjusted early readmission rates; the median rate was 15.9% with the upper and lower 10% values at 19.4% and 12.2%. In this context, our readmission rates appear below the 10th centile of the UK at that period. Overall for readmissions, as might be expected there is a trend to increase over time with the longest interval in time to the first readmission and progressive shortening in this interval with each consecutive admission. The extent to which it is realistic to selectively alter the tail of a statistical distribution has been long argued. Geoffrey Rose focused on this issue in a classic paper [31]; he argued personally with us that it was unlikely that one could alter part of a distribution selectively. Or as he aptly put it, the distribution was the way it is for complex reasons that one might not comprehend, and it would resist well-meaning but simplistic attempts at selective intervention. However, such theoretical arguments have not detracted from opinions that an early hospital readmission reflects inferior hospital care; a meta-analysis of 16 studies [32] suggested that the risk of early readmission was increased by 55% when care was of relatively low quality. Furthermore a systematic review by Ashton et al. indicated that on average, substandard care increased the risk of early readmission by 24% [33]. The proportion of all readmissions assessed as preventable varies from 9 to 59% [34]. Randomized prospective trials have shown that 12% to 75% of all readmissions can be prevented by patient education, pre-discharge assessment, and domiciliary aftercare. However, when Des Harnais et al. [35] ranked 300 hospitals on 3 risk adjusted indices of hospital quality, mortality, readmissions and complications, there was no relationship between a hospital's ranking on any one of these indices and its ranking on the other two. On balance the evidence suggests that readmission rates, uncorrected for confounding medical, social and hospital factors, are a poor guide to quality of care. Notwithstanding this ongoing debate, the data of Laudicella et al. [27] on UK hospital risk-adjusted early readmission rates showed variations that are quite hard to comprehend, much less justify.

One of the major strengths of our study is that since the inception of our AMAU information on patients and outcomes has been collected and recorded prospectively in “real time”, thereby maximising accuracy and reducing the bias associated with retrospective data collection. As with any study and methodology there are limitations to our work. As we have noted above there have been improvements in mortality over time in the population as a whole. This mortality improvement has coincided with the development of the AMAU model of care, this association may not be causative; indeed as we have discussed previously the evidence would suggest otherwise. Although we have adjusted for multiple confounding variables in our multivariable model, there remains the possibility that unmeasured confounding variables are responsible for some of the changes we have observed. Mortality improvements for hospital admissions may result from improved care, alternatively they may equally result from either increasing admissions of patients who are unlikely to die or from decreasing admissions of patients who are more likely to die (eg those receiving palliative care). We believe these scenarios are unlikely to be responsible for our findings for a number of reasons. Firstly, our findings remained consistent when adjusting for acute illness severity and co-morbidity. Secondly, the 16 year study period we report on coincided with a significant recession in the Irish economy accompanied by reduced health care spending; in this environment community palliative care services have not expanded significantly and there has been no expansion in resources to facilitate the admission of less sick patients through the ED.

There has been limited institution of ambulatory care services in the Irish healthcare system, it is possible and perhaps even likely that introduction of these services may reduce LOS beyond the level in our study. As our study is a single centre study, the external validity will require confirmation in other institutions and populations. The median age of the patients in our study is younger than in some other populations, as we have previously described this is a reflection of the high deprivation in our local catchment area [36–39]. Our data does not allow us to adjust readmission rates for mortality, however as deaths occur in 4.5% of admissions we believe the potential overall effect of this is limited. Finally, there is ongoing debate as to whether per patient or per admission calculations are the optimum method to evaluate outcome measures in acute medical admissions. We present both sets of calculations in order that readers are fully informed of outcomes in our population. It is reassuring that the trends in both sets of calculations parallel one another in both directions and magnitude.

In conclusion our study demonstrated a sustained linear reduction in 30-day in-hospital mortality over time. In contrast LOS and readmission rates did not materially alter over the same time period. LOS showed linear dependency on clinical complexity suggesting that a certain minimum LOS may be an intractable part of the underlying disease process.

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ejim.2019.06.001>.

Conflict of interests

None.

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