Identifying patients at high risk of emergency hospital admissions: a logistic regression analysis

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SUMMARY

Objective To use routine data to identify patients at high risk of future emergency hospital admissions.

Design Descriptive analysis of inpatient hospital episode statistics. Predictive model developed using multiple logistic regression.

Setting National Health Service hospital trusts in England.

Participants All patients with an emergency admission to an NHS hospital between 1 April 2000 and 31 March 2001.

Main outcome measures 'High-impact users' were defined as patients who had at least one emergency inpatient admission and who then went on to have at least two further emergency hospital admissions in the 12 months following the start date of that index admission.

Results 2 895 234 patients were admitted as emergencies in 2000/2001, of whom 147 725 (5.1%) did not survive their first spell. Of the 2 747 509 surviving patients, 269 686 (9.8%) subsequently had at least two or more emergency admissions within 365 days of the index date of admission. A further 236 779 (8.6%) died during this period. Risk factors for becoming a high-impact user included the number of emergencies in the 36 months before index spell, comorbidity, age, an admission for an ambulatory care sensitive condition, ethnicity, area-level socio-economic data, local admission rates, the number of episodes in the index spell, sex and the source of admission. The predictive model based on all emergency admissions produced a receiver operating characteristic curve score of 0.72.

Conclusions Routine hospital episode statistics can be used to identify patients who are at high risk of suffering future multiple emergency hospital admissions. The potential cost savings in preventing a proportion of these subsequent admissions need to be compared with the costs of case management of these patients.

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INTRODUCTION

Emergency hospital admissions have been rising in the UK's National Health Service, and in several other developed countries, for many years.[1,2] As well as raising questions about how the NHS manages patients at risk of emergency admissions, this increase has also contributed to the financial pressures on hospitals and on national health care budgets. [3] In recent years, we have therefore seen the introduction of initiatives to improve the out-of-hospital management of patients at risk of emergency admission.[4,5] These initiatives have included the 'case management' approach in which patients with long-term conditions that might place them at risk of hospital admission are offered additional support in the community, coordinated by a specially trained case manager.[6] More recently, the 2006 White Paper on community services proposed an expansion of case management,[7] as well as of other initiatives such as self-care and integrated care plans. These initiatives will be supported by increased resources for community health services and could lead to radical changes in the organization and provision of health services in England.

One group of patients at which case management approaches will need to be targeted is those at high risk of emergency hospital admission, particularly from ambulatory care-sensitive conditions (disorders such as asthma where improved management in the community might be expected to improve the patient's well being and quality of life, and reduce their risk of hospital admission). Previous attempts to identify such patients using age and prior history of emergency admission have not been successful: with emergency admission rates in the group of patients identified as 'high-risk' approaching, over time, those of the general population.[8] Improved methods are therefore needed to identify patients who might benefit from more intensive and carefully monitored treatment in primary and secondary care.

In this study, we evaluated the use of routine hospital data to identify patients at high risk of emergency admission. We defined this group of 'high-impact users' as patients who have had at least one emergency admission, and who then went on to have at least two further emergency hospital admissions in the 12 months following the start date of their index admission. We aimed to identify the size of this group of patients, the impact these patients had on the use of healthcare resources, and to evaluate the effectiveness of using admissions data to identify them before they had any further emergency hospital admissions.

METHODS

Hospital Episode Statistics (HES) data cover all admissions to NHS hospitals in England and contain a field that allows separate admission spells by the same patient to be linked. Data were extracted for the years April 1999–March 2000 to April 2003–March 2004. All emergency admissions in 2000/2001 were sorted by patient and dates of admission, and the first admission for each patient taken as the 'index spell'. Patients who died at the end of this first admission were excluded. The number of further emergency admissions, first between 0 and 365 days and, secondly, between 366 days and 36 months from the date of admission of the index spell was counted for each patient. High-impact users were defined as those patients with at least two further emergencies within a year (i.e. three or more emergency admissions in a 12-month period).

The number of emergencies in the 365 days before the index spell was also calculated and added to the data set. Other variables added to the data set included:

- the Charlson index of comorbidity (originally developed for predicting 1-year mortality, giving various weights to the presence of conditions such as diabetes and malignancy) based on ICD10 diagnosis codes,[9] age, ethnicity, whether the main diagnosis was an ambulatory care sensitive condition (these are listed in Table 1)
- two area-level socio-economic indices: MOSAIC type[10] and the Index of Multiple Deprivation 2004 score with areas grouped into fifths with equal population[11]
- the log-transformed age–sex standardized emergency admission ratio of the patient's electoral ward of residence
- the number of consultant episodes in the index spell, the sex of the patient and the source of the hospital admission (Box 1).

The patients were then randomly divided into two groups of equal size to give a 'training' dataset from which to develop a model to predict the likelihood of patients becoming high-impact users and a 'validation' dataset to test the model. Parameter estimates from the two halves of the data were compared and model fit assessed by inspecting residuals as usual.[12] For patients in the training data set, logistic regression models were developed with high-impact user status as the outcome and the variables listed in Box 1 (in descending order of importance to the model fit). Ambulatory care sensitive conditions were included in the model as these are thought to be amenable to intervention at primary care level.[13]

Box 1 **Covariates used to predict high impact user status in descending order of importance in explaining the variation**

Covariate	***Comments***
Number of emergencies in 365 days before index spell	Modelled as a continuous variable
Number of emergencies between 366 days and 36 months before index spell	Modelled as a continuous variable
Charlson index of comorbidity	Was devised originally to predict death. Capped at an upper limit of 6 (few patients had scores above this)
Age	Five-year age bands up to 90+
Ambulatory care sensitive condition	Conditions considered most amenable to case management. 19 groups as per Table 1, plus a 'group 0' for all other conditions
Ethnicity	Six groups: white, black, Indian sub-continent, Chinese, 'unknown' and 'other'
Standardized admission ratio (SAR) (log-transformed)	SAR adjusted for age and sex for all emergencies for the ward of residence for 2000/2001 to 2002/2003 combined
Area-level lifestyle group	Postcodes were allocated to one of 61 groups based on various lifestyle factors using the MOSAIC classification
Source of admission	Home, nursing home, other hospital, etc.
Area-level deprivation	2004 Index of Multiple Deprivation for the patient's area of residence, divided into fifths
Number of consultant episodes in index spell	Modelled as a continuous variable
Sex	Male or female

Table 1 **Subsequent emergency spells and deaths in 3 years of follow-up by factor relating to index spell in 2000/2001**

Factor	***Patients admitted as an emergency in 2000/2001***	***Patients who become high-impact users (%)***	***Subsequent spells per patient in first year***	***Subsequent spells per patient in second year***	***Subsequent spells per patient in third year***	***Death rate within 1 year (%)***	***Death rate within 2 years (%)***	***Death rate within 3 years (%)***
Age								
All	2 747 509	269 849 (9.8)	0.46	0.27	0.23	8.8	13.2	16.8
0–4	277 413	20 700 (7.5)	0.38	0.18	0.12	0.4	0.5	0.5
5–44	1 006 961	65 885 (6.5)	0.33	0.20	0.18	0.8	1.3	1.7
45–64	518 500	53 265 (10.3)	0.47	0.28	0.25	7.1	10.1	12.4
65–74	345 257	46 435 (13.4)	0.60	0.36	0.31	14.9	21.8	27.4
75–84	384 195	54 794 (14.3)	0.63	0.38	0.32	21.1	32.3	41.9
85+	215 183	28 770 (13.4)	0.61	0.35	0.25	29.3	45.0	57.6
Deprivation fifth								
1 (least deprived)	410 553	33 087 (8.1)	0.39	0.21	0.17	9.6	14.2	17.9
2	465 972	41 423 (8.9)	0.42	0.23	0.20	9.6	14.3	18.1
3	514 095	49 095 (9.5)	0.45	0.26	0.21	9.3	14.0	17.8
4	581 732	59 790 (10.3)	0.48	0.29	0.24	8.8	13.2	16.9
5 (most deprived)	727 251	84 742 (11.7)	0.54	0.33	0.28	7.9	12.0	15.4
Unknown	47 906	1 712 (3.6)	0.18	0.10	0.08	3.1	4.5	5.7
Spells in previous year								
0	2 399 496	190 094 (7.9)	0.38	0.22	0.19	7.7	11.7	15.0
1	237 500	41 454 (17.5)	0.75	0.46	0.37	14.8	22.0	27.6
2	65 721	17 945 (27.3)	1.13	0.68	0.53	18.2	26.9	33.4
3+	44 792	20 356 (45.4)	2.21	1.34	0.99	20.3	29.4	36.0

Continued

Table 1 **Subsequent emergency spells and deaths in 3 years of follow-up by factor relating to index spell in 2000/2001 *(Continued)***

Factor	***Patients admitted as an emergency in 2000/2001***	***Patients who become high-impact users (%)***	***Subsequent spells per patient in first year***	***Subsequent spells per patient in second year***	***Subsequent spells per patient in third year***	***Death rate within 1 year (%)***	***Death rate within 2 years (%)***	***Death rate within 3 years (%)***
ACS condition								
COPD	48 821	13 298 (27.2)	1.16	0.75	0.59	22.7	36.2	46.9
Diabetes with complications	10 479	2 338 (22.3)	0.98	0.69	0.61	9.3	15.5	20.6
Congestive heart failure	36, 22	7 559 (20.6)	0.87	0.46	0.33	29.5	43.9	54.7
Angina (without major procedure)	62 012	10 462 (16.9)	0.74	0.49	0.44	7.3	12.5	17.5
Convulsions and epilepsy	39 526	5 728 (14.5)	0.66	0.42	0.34	5.1	8.4	11.1
Gangrene	2 239	301 (13.4)	0.62	0.31	0.25	25.9	35.5	44.1
Iron-deficiency anaemia	5 727	738 (12.9)	0.58	0.36	0.29	17.3	27.2	35.4
Asthma	42 969	4 804 (11.2)	0.53	0.38	0.33	1.8	3.2	4.5
Vaccine-preventable conditions	1 644	179 (10.9)	0.50	0.25	0.25	5.2	7.0	8.3
Flu and pneumonia (>2 months old)	27 405	2 843 (10.4)	0.49	0.28	0.24	13.6	20.6	26.1
Non-ACS	2 324 215	211 759 (9.1)	0.43	0.25	0.21	8.6	12.8	16.2
Dehydration and gastroenteritis	35 045	2 818 (8.0)	0.39	0.23	0.20	7.9	11.4	14.4
Hypertension	4 443	327 (7.4)	0.36	0.26	0.24	4.9	8.9	13.4
Cellulitis (without major procedure)	30 636	2 219 (7.2)	0.36	0.24	0.22	6.4	11.0	15.3
Pelvic inflammatory disease	4 756	338 (7.1)	0.34	0.24	0.21	0.5	0.8	1.0
Perforated/bleeding ulcer	5 808	384 (6.6)	0.35	0.21	0.19	10.3	16.5	22.2
Ear, nose and throat infections	54 355	3 270 (6.0)	0.31	0.16	0.12	0.6	0.9	1.2
Pyelonephritis	6 106	355 (5.8)	0.30	0.20	0.19	1.6	2.4	3.5
Nutritional deficiencies	35	2 (5.7)	0.29	0.17	0.09	14.3	22.9	34.3
Dental conditions	4 666	127 (2.7)	0.17	0.13	0.12	2.3	3.5	4.6

ACS, ambulatory care sensitive (those considered most amenable to case management); COPD, chronic obstructive pulmonary disease

We calculated the standardized admission ratio for all emergencies between 2001/2002 and 2003/2004 for the patient's electoral ward of residence, standardizing by age and sex, to try to adjust for differing admission thresholds in patients' local hospitals. Two other area-level variables were added, based on the patient's postcode of residence (lifestyle group and deprivation fifth). In addition, age, sex, ethnicity and where the patient was admitted from were included in the model.

We defined this model as model A and created two further models in addition to this. The first of these additional models (model B) restricted the analysis to index spells where the main diagnosis was for a condition most amenable to case management, again aiming to predict at least two further emergency admissions in the subsequent year. The covariates used were the same as in model A.

The third model (C) was the same as model A with the important difference that it aimed to predict patients having at least two further emergency admissions within 365 days of the index admission but who did not die during this period. To ensure that all deaths were included, and not just those taking place in hospital, we used a linked mortality file, which assigns a date of death to each patient record, based on a linkage with Office for National Statistics death registrations. Patients were followed up for 3 years using HES and the linked mortality file for 2000/2001 to 2003/2004 to obtain the number of subsequent emergency admissions, both total and for conditions most amenable to case management, and whether they died or not during this period. The total tariff for each admission was derived using the Healthcare Resource Group (HRG, the basis of remuneration to the hospital for the cost of the admission) for that admission and 2005 tariffs, adjusting for the hospital-specific market forces factor and assigning to those HRGs not yet covered by the tariff a value equal to the average for admissions for the HRGs that are covered.

For patients in the validation data set, we compared the actual high impact user status, i.e. whether each patient went on to have two or more emergencies within a year, with whether their predicted probability of being a high impact user from the logistic models derived from the training data set exceeded one of three threshold values. We calculated 2×2 tables for each threshold with statistics for sensitivity, specificity and positive predictive value, based on the total number of index spells. This is analogous to comparing a potential new screening test for a disease with a gold standard; here, the 'gold standard' is the actual high-impact user status and the new 'test' is whether the patient's modelled probability exceeds a given threshold value. The receiver operating characteristic (ROC) c statistic is widely used to summarize a model's ability to correctly discriminate between outcomes such as whether the patient died. A value of 0.5 suggests that the model is no better than chance in predicting death. A value of 1.0 suggests perfect discrimination. In general, values less than 0.7 are considered to show poor discrimination, whereas values above 0.8 suggest very good discrimination.

Any level of probability threshold chosen would be arbitrary, but for illustration we chose three thresholds that resulted in the identification ('flagging') of England totals of 250 000, 150 000 and 50 000 patients at high risk of becoming high-impact users. We chose the figure of 250 000 because the Department of Health for England has entered into a public service agreement with the Treasury to reduce emergency bed use by 5% in 2008; this has led to an emphasis on case management of 250 000 'very high intensive users'.[14] With 303 current primary care trusts in England, this corresponds to an average of around 825 patients per primary care trust. Our other chosen totals correspond to around 500 and 165 patients per primary care trust, respectively, and might represent more manageable caseloads for community health services and primary healthcare professionals.

RESULTS

There were 2 895 234 patients admitted as emergencies in 2000/2001, of whom 147 725 (5.1%) did not survive their first spell, leaving 2 747 509 patients with index spells; 423 294 (15.4%) of these patients were admitted for a condition most amenable to case management. Of the 2 747 509 patients, 269 686 (9.8%) subsequently had at least two or more emergency admissions within 365 days of the index date of admission; 236 779 (8.6%) patients died during this period.

Table 1 shows the proportion of patients who became high-impact users, the cumulative death rates within 1, 2 and 3 years of the index spell by age, condition most amenable to case management, and the number of spells in the previous 365 days, together with the mean number of spells per patient in each subsequent year. As expected, subsequent admission and death rates generally increase with age, with the exception of the under-5s, who are readmitted more often than the 5–44-year-olds. The proportion of the total index spells increases with deprivation fifth, as does the number of subsequent emergency spells per patient and the proportion who go on to become high-impact users. The death rate, however, falls with increasing deprivation status of the patient.

There is a strong relation between high-impact user status and previous admission history. Nearly half of all patients who had three or more emergency admissions in the previous year went on to become high-impact users and more than a third (36%) had died within 3 years of the index admission. Of the conditions most amenable to case management, chronic obstructive pulmonary disease

(COPD), congestive heart failure and the smaller gangrene group had the highest mortality rates, with the COPD patients having more subsequent spells on average than patients with any other condition examined.

We assessed the performance of the models in predicting high-impact user status using sensitivity (the proportion of all patients who went on to have two or more admissions in the following 12 months who were correctly identified by the model); specificity (the proportion of patients who went on to have fewer than two spells who were correctly identified); and positive predictive value (the proportion of flagged patients who actually went on to be admitted two or more times in 12 months). These measures are given in Table 2 for the three chosen thresholds. Very similar results were obtained from both the training and validation datasets.

As the number of flagged patients falls, the proportion of all high-impact users who are correctly flagged (sensitivity) also falls. Sensitivities for model B are highest because it only considers patients with an index spell for a condition most amenable to case management and therefore the denominator is much smaller than when considering all index spells (as in models A and C). This smaller denominator also explains why model B has the best discrimination (highest ROC c statistic) but the lowest positive predictive value.

Model A has a greater positive predictive value than model C because the outcome it aims to predict (high-impact user status irrespective of whether the patient survives one year) is more common than that for model C (Table 1 shows that 8.8% of all patients who survive their first spell die within a year). Again using the analogy of screening for a disease, it is well known that the prevalence of the disease being tested for shows a positive correlation with the positive predictive value of the test, so this observation is to be expected.

Table 3 shows the actual number of subsequent admissions within a year of the index spell, including how many were for conditions most amenable to case management, together with the estimated costs. Again, figures are given for each of the three thresholds considered and for each of the three models. Model A had the highest death rate but its flagged patients have very similar number of total spells and spells for conditions most amenable to case management to those flagged using model C. The 3-year death rates of flagged patients were between 47% and 48% for model A. Model C tries to predict 1-year survival and for 50 000 patients flagged has the lowest death rate of the three. However, despite more of the flagged patients surviving for model C, the total tariff of the subsequent spells was greater for model A.

Model B only considers patients with an index spell for conditions most amenable to case management, which is why its flagged patients have a higher number of mean subsequent spells for conditions most amenable to case management. The total tariff of such spells in the year after the 50 000 model B patients were flagged was £111m, or £2217 per patient, their mean total tariff for all spells was £3929 each.

Table 2 **Comparison of the performance of the three regression models**

No. of flagged patients		***Model***		
	Measure	***A***	***B***	***C***
250 000	Sensitivity	27.4%	85.7%	27.3%
	Specificity	92.9%	45.1%	92.4%
	PPV	29.6%	19.9%	23.4%
150 000	Sensitivity	19.5%	65.9%	19.7%
	Specificity	96.1%	69.5%	95.7%
	PPV	35.1%	25.6%	28.2%
50 000	Sensitivity	9.1%	32.7%	9.4%
	Specificity	99.0%	91.7%	98.8%
	PPV	48.8%	38.4%	40.6%
	ROC 'c' statistic	0.72	0.75	0.70

PPV, positive predictive value; model A, all index spells, adjusting for conditions most amenable to case management, predicting 2+ further spells in next 365 days; model B, index spells for only conditions most amenable to case management, predicting 2+ further spells in next 365 days; model C, all index spells, predicting 2+ further spells and survival in next 365 days; ROC, receiver operating characteristic (see methods section)

DISCUSSION

We have shown that it is possible to use routine hospital episode statistics to identify patients at risk of becoming high-impact users (i.e. suffering two or more further emergency admissions in the 12 months following the index emergency admission). The sensitivity and specificity of the models varies depending on the model used and the number of patients flagged for follow-up. Confining the models to patients admitted with an index admission for a condition most amenable to case management results in the highest sensitivity. As these patients may be the group that can benefit most from primary care management of their medical disorders, they may be very suitable for targeting by case management programmes. The total tariffs of the flagged patients in the next year varies from £196 million (50 000 patients flagged using model B) to £792 million (250 000 patients flagged using model A). Hence, even for the lowest cost scenario, these patients will utilize considerable NHS hospital funds in the year following their

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Table 3 **One-year follow-up of patients flagged by each model for three different thresholds in 2000/2001**

No. of patients flagged	***Model***	***Deaths within 365 days***	***Death rate within 365 days***	***Total spells within 365 days***	***Mean total spells per flagged patient within 365 days***	***Total tariff for those spells (£)***	***ACS spells within 365 days***	***Mean ACS spells per flagged patient within 365 days***	***Total tariff for those spells (£)***
250 000	A	65 281	26.2	318 500	1.28	792 472 178	103 331	0.41	249 779 717
	B	37 938	15.2	216 315	0.86	513 893 374	110 557	0.44	247 695 869
	C	45 648	18.3	319 262	1.28	740 406 354	106 102	0.42	239 201 135
150 000	A	39 521	26.3	229 193	1.53	556 400 391	78 117	0.52	186 770 480
	B	29 646	19.8	163 033	1.09	401 823 700	87 489	0.58	206 500 895
	C	29 029	19.3	231 918	1.55	529 087 006	79 756	0.53	179 562 694
50 000	A	12 755	25.4	113 805	2.26	258 087 832	40 650	0.81	92 876 647
	B	11 911	24.1	81 032	1.64	196 457 208	47 069	0.95	110 867 264
	C	9 837	19.9	115 203	2.33	247 929 721	40 881	0.83	88 709 597

ACS, spells with an ambulatory care sensitive condition (those most amenable to case management) recorded in one or more diagnosis field; model A, all index spells, adjusting for condition most amenable to case management, predicting 2+ further spells in next 365 days; model B, index spells for only conditions most amenable to case management, predicting 2+ further spells in next 365 days; model C, all index spells, predicting 2+ further spells and survival in next 365 days index admission. Patients with other conditions may also benefit from greater monitoring in primary care—for example, by arranging an appropriate elective outpatient referral. Not all flagged patients would necessarily enter a case management programme if, after consideration of factors not recorded in routine data, the general practitioner may decide that some patients are not suitable or would not benefit, either in terms of reduction in future admissions or in other outcomes. We routinely combine all spells belonging to the same patient to form an admission history, with key details such as date, age, sex, primary diagnosis and length of stay, which would assist the GP in the patient selection process.

A key strength of this study is that it is based on all emergency admissions to NHS hospitals over a 5-year period. All patients in the UK are entitled to free care under the NHS and relatively few patients are admitted as emergencies to private hospitals (which are largely used for elective care). Hence, selection bias is unlikely to have occurred and the findings should be applicable throughout the NHS. We were also able to link hospital episodes statistics with other data sets, for example, deprivation measures to incorporate patients' socio-economic status and Office for National Statistics mortality files to include deaths that occurred outside hospital.

One weakness of the study is that, as it used HES, we did not have access to the primary care records of these patients, and so cannot include any diagnoses not recorded in the HES database. These data have had a poor reputation for accuracy in the past, but the quality has much improved in recent years.[15] Nor could we examine the impact of out-of-hospital care (for example, appropriate prescribing for conditions most amenable to case management) on the risk of further emergency admissions. In the longer term, the NHS Information Technology Programme (Connecting for Health) aims to provide data sets through its secondary user service that combine information from primary, community and hospital services.[16] These data sets will allow for the development of more sophisticated models for predicting the likelihood of patients becoming high-impact users of emergency hospital care.

There have been few prior similar studies published. Roland *et al*. examined a cohort of elderly patients admitted as emergencies and found that their emergency admission rate approached that of the general elderly population.[7] By contrast, the groups we flagged as potential high-impact users remained, on average, high users of emergency hospital care in subsequent years—probably because we used a more sophisticated strategy to identify these patients. Other studies have used cross-sectional designs to examine factors associated with emergency admissions.[17,18,19] Because they did not include a longitudinal analysis, these studies were not able to provide information that might help predict the future likelihood of emergency admissions in the populations studied.

In conclusion, we have shown that routine HES can be used to identify patients at high risk of suffering future multiple emergency hospital admissions. The cost of these admissions is large, but it is not known what proportion of them is preventable via case management. Any potential savings need to be compared with the costs of case management, which we have not considered. For the time being, however, primary care and acute trusts could consider using these models to identify patients who may benefit from more intensive case management. In the future, developments in the NHS may allow even more sophisticated predictive models to be developed, incorporating information from health records in outpatient departments and in primary care. The efficacy of the models in reducing emergency medical admissions does, however, need testing in prospective studies—with suitable control groups—that incorporate clinical and economic outcome measures, as well as measures of patient satisfaction.

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Ethical approval We have Section 60 approval from the Security and Confidentiality Advisory Group (SCAG) to hold confidential data and analyse them for research purposes. We also have approval from St Mary's Local Research Ethics Committee.

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