Readmissions – can they be predicted on admission?

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This paper looks at the development of logistic regression models to predict readmissions for medical patients on their initial admission to hospital. The design of our study was a retrospective analysis of a large dataset drawn from a range of secondary sources – medical, nursing, therapy and social care records. Three northern hospitals and related community health districts and social care organizations in the UK participated. Records of 1,192 patients discharged from medical wards during the period April 1992–March 1995 were analysed. Readmission within six weeks of discharge was the main outcome measure.

Four logistic regression equations were produced. Three individual site equations were calculated and classification levels for readmission of 17–22 per cent were achieved. Component factors that differed in importance were age, GP contact, social services contact, marital status and living status. The weakest equation was the equation that encompassed patients from all three sites, which classified 7 per cent of readmissions. It is possible to develop equations that will predict explain readmission for a fifth of medical patients on admission to individual hospitals. Further exploratory work needs to be undertaken to explore reasons for differences between districts and develop more generalizable predictive equations.

Keywords
predicting, readmission, delayed, hospital, discharge, integrating large datasets

INTRODUCTION

More than 8 million people in England are admitted to hospital every year [1]. For many, discharge home will be a straightforward and desired outcome. For some, however, discharge home can be a difficult and unsettling process exacerbated by poor co-ordination between hospital and community-based services [2][3][4][5]. The study on which this paper is based was designed to identify predictor indicators for readmission and delayed discharge for patients admitted to general medical wards in three hospitals in the north of England. This paper describes the development of predictive equations and reviews the strengths and limitations of developing predictive equations for readmission, for both research and service management. The concept of delayed discharge is explored elsewhere, highlighting problems with measuring delayed discharge identified during the course of this study [6].

Despite a considerable literature examining hospital discharge processes, no consensus exists as to what are appropriate outcome indicators for measuring successful discharge. The following have been used: readmission rates, incidence and magnitude of delays in discharge, length of stay and demand on post-discharge service [7][8][9][10][11][12][13][14][15]. Within the literature readmission rates appear to be one of the most frequently used measures for determining the level of successful discharge [7][8][9][10][11].

A number of studies have begun to investigate methods for predicting those patients at greatest risk of unsuccessful discharge. These have demonstrated some limited success at predicting problematic discharge, variously defined as delayed discharge, admission to a nursing home or readmission or death within 12 months [14][15][16].

These studies have demonstrated the potential for identifying patients at risk of unsuccessful discharge. They are, however, limited, targeting a particular group of patients be it the elderly or those with a specific diagnosis, or confined to success in one particular hospital. It is difficult, therefore, to generalize to a wider group of patients. The aims of this study were to investigate factors that are associated with readmission and/or delayed discharge and to develop predictive equations that could determine the risk of readmission and/or delayed discharge for patients on admission to hospital, using patients admitted to general medical wards at three different hospitals.

BACKGROUND

The research was conducted within three health authorities in the north of England. Study site A is a hospital which serves as a regional centre for healthcare, meeting the local health needs of an urban population and the regional health needs of both an urban and rural population. Study site B is a district general hospital situated in an urban, non-teaching authority. Study site C is a hospital situated in a geographically large area with a widely dispersed, mainly rural, population.

The divergent arrangements for discharge from each of the three sites enabled a comparative approach to be taken to the analysis of the data, allowing the generalizability of the results to be examined.

METHODS

Following ethical approval, the Regional Information Service (RIS) provided anonymized Körner data on approximately 46,000 medical discharges from the three acute hospital trusts for the period April 1993 to March1995. Table 1 lists the items collected. From this Körner data, 9,000 records were excluded as they failed to meet the study criteria (that is: the patient lived outside the health authority area, was a day patient or was not classified as a medical patient). This left a study population of approximately 37,000. After removing repeat admissions and retaining only the first admission in the study period for each patient, a study population of 20,925 remained. Ninety-seven per cent of admissions were emergency admissions so all patients were included in the sampling frame as this represents a profile of general medical wards and the numbers of planned admissions is too small to allow separate analysis. This study population was classified in the three hospital trusts and 500 patients randomly selected from each (see Figure 1).

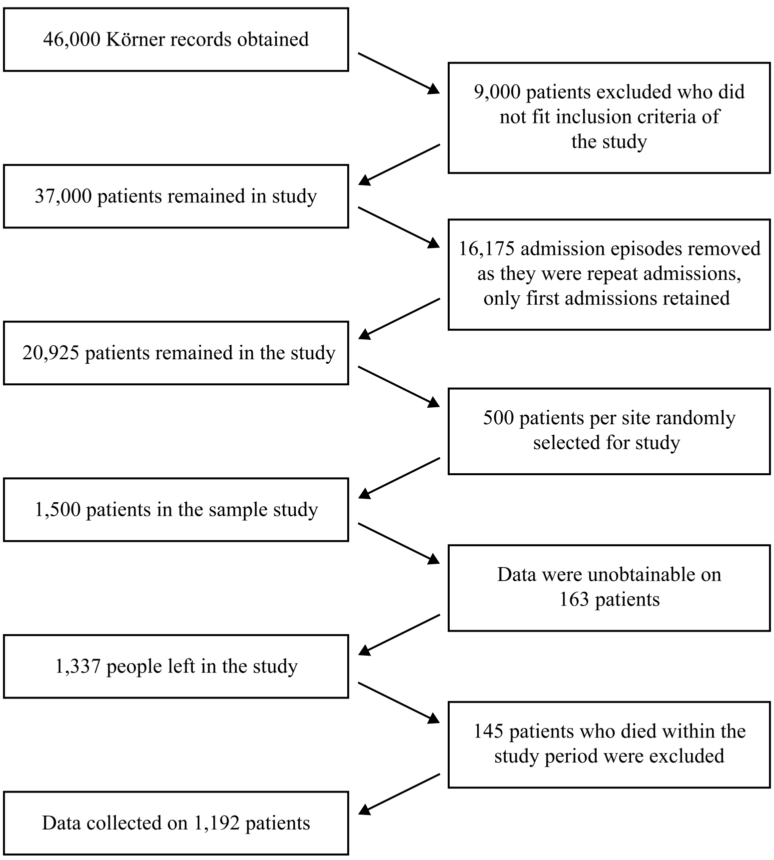

Fig. 1 Flowchart depicting derivation of the sample

Additionally, data on the ID case note number and postcode (see Table 1) were requested from RIS and used to match the 1,500 patients sampled from the Körner dataset. Social work data held on Social Services Client Information System (SOSCIS) were obtained as a dataset for the patients identified in each health authority area. Community nursing data held on the community nursing activity database (COMCARE) were also obtained as an additional dataset. Cases were then matched on postcode, date of birth and sex, and the datasets merged.

Data were collected for a period from six weeks prior to the first admission episode recorded in the Körner dataset to six weeks post discharge on all sets of notes. All the computerized data for the sample were transferred to laptop computers. Further information was collected manually from the hospital medical records, nursing records, therapy records and GP records of each patient sampled. Discrepancies between the different datasets were noted by the data collectors collecting the manual data and bought back to the research team for further investigation.

The note-based data from each source were entered on to a menu-driven program specifically designed for the project using visual Dbase 5.5 [17]. Data were available and collected for 1,337 people. Attrition was due to a combination of missing records and the time constraints of the study. Patients who died in hospital or within the six-week post-discharge period were also excluded, which left a study population of 1,192 patients (see Figure 1). However, these problems were anticipated in calculating the initial sample size which was inflated. The overall response rate was 79 per cent and is in line with that recommended by Bland (1995) of between 70–80 per cent. For the individual hospitals the response rates were also adequate: Hospital A (80 per cent) Hospital B (85 per cent) and Hospital C (74 per cent). Consequently, the final sample size did allow sufficient statistical power to enable robust statistical analysis. Although the sample was longitudinal rather than cross-sectional, once the sample was obtained standard statistical procedures were used to analyse the data as described below.

ANALYSIS

Statistical analysis utilized univariate and multi-variate techniques. Univariate methods

Table 1 Körner collected on all general medical admissions April 1993–March 1995. Enhanced data collected from casenotes on first admission episode of the study population

Körner data	Hospital medical notes	Hospital nursing notes
Speciality code District of residence Date of admission to episode Date of discharge from episode Destination at discharge from episode Method of discharge (e.g. self-discharge) Diagnosis (ICD-9) (up to six) Procedures ID (casenote number)* Date of birth Sex Postcode* Marital status Consultant (GMC code) Ward code	Length of stay Readmission within 6 weeks Gender Living status Marital status Destination on discharge Diagnosis (up to 6) Occupation Source of admission Change of discharge date Medication changes pre- and post-admission Contact with GP pre- and post-admission Outpatient appointment Yes/no	Problems identified post-discharge by hospital nurses **Physiotherapy, occupational therapy and speech and language therapy notes if applicable** Source of referral Assessment Interventions Discharge status **GP notes (pre- and post-discharge)** Type of visit Reason for visit Letters sent/received Medication prescribed Verify Körner data

*Additional items of data April 1993–March 1995

included independent t-tests for parametric data and Mann–Whitney and Chi-square tests for non-parametric data. Multiple logistic regression was used to identify the most important factors for predicting readmission. In order to facilitate use of the equations in subsequent work, data used in this analysis were restricted to data available on admission. Independent variables derived from the Körner dataset were: age at admission; sex; marital status; living status; locality (by postcode district) and disease group (e.g., ischaemic heart disease, cerebrovascular disease). Independent variables as derived from the enhanced dataset included contact with the GP or social services in the six weeks prior to admission. A p-value of <0.05 was considered to indicate statistical significance. All statistical analyses were performed on SPSS for Windows (Version 9).

RESULTS

Table 2 shows a descriptive summary of the key factors investigated for the overall dataset and for each individual site.

The overall readmission rate was 17.8 per cent (95 per cent CI:15.6–20.0 per cent). Comparing the readmission rates between the study sites, there was a significant difference between the three hospitals ($\chi^2(2) = 13.5$, $p = 0.001$). Hospital C had the lowest readmission rate (12.8 per cent, 95 per cent CI: 9.4–16.2 per cent) and Site A with the highest readmission rate (22.9 per cent, 95 per cent CI: 18.7–27.0 per cent).

For the overall dataset there was a significant difference in readmission rates by age ($t(1190) = 3.2$, $p < 0.001$). For the individual study sites there was a significant difference at Hospitals B ($t(424) = 3.5$, $p = 0.001$) and C ($t(366) = 2.2$, $p = 0.033$), but not for Hospital A ($t(396) = 1.0$, $p = 0.306$).

For the overall dataset there was no difference in readmission rates by living status ($\chi^2(4)=8.3$, $p = 0.081$), nor for the individual study sites (Hospital A ($\chi^2(4) = 1.8$, $p = 0.771$), Hospital B ($\chi^2(4) = 7.5$, $p = 0.114$), Hospital C ($\chi^2(4) = 8.9$, $p = 0.062$).

For the overall dataset there was no difference in readmission rates by sex ($\chi^2(1) = 0.235$, $p = 0.628$), nor for the individual study sites (Hospital A ($\chi^2(1) = 0.003$, $p = 0.954$), Hospital B ($\chi^2(1) = 0.002$, $p = 0.965$), Hospital C ($\chi^2(1)=962$, $p = 0.327$).

For the overall dataset there was no difference in readmission rates by marital status ($\chi^2(2) = 2.064$, $p = 0.356$), nor for the individual study sites (Hospital A ($\chi^2(2) = 0.556$, $p = 0.757$), Hospital B ($\chi^2(2) = 4.464$, $p = 0.107$), Hospital C ($\chi^2(2) = 4.381$, $p = 0.112$).

For the overall dataset there was no difference in readmission rates by contact with the GP pre-admission ($\chi^2(1) = 1.511$, $p = 0.219$). For the individual study sites there was a difference at Hospital A ($\chi^2(1) = 4.391$, $p = 0.036$), but not at Hospital B ($\chi^2(1) = 0.003$, $p = 0.955$) or Hospital C ($\chi^2(1) = 0.004$, $p = 0.950$).

For the overall dataset there was a difference in readmission rates by contact with social services pre-admission ($\chi^2(1) = 13.323$, $p < 0.001$). Similarly there was a significant difference at Hospital B ($\chi^2(1)=17.196$,

Table 2 Descriptive summary of key factors

	Total (N = 1192)		Hospital A (N = 398)		Hospital B (N = 426)		Hospital C (N = 368)	
	R/N	% R	R/N	% R	R/N	% R	R/N	% R
Readmission	212/1192	17.8%	91/398	22.9%	74/426	17.4%	47/368	12.8%
Age	61.9 (19.9)	66.5 (16.6)***	62.1 (21.6)	64.5 (19.1)	62.8 (18.5)	69.0 (12.9)**	60.7 (19.8)	66.5 (16.6)*
Marital status								
Single	28/193	14.5%	19/81	23.5%	5/57	8.8%	4/55	7.3%
Married	168/897	18.7%	64/276	23.2%	63/336	18.8%	41/285	14.4%
Divorced	10/62	16.1%	4/24	16.7%	6/23	26.1%	0/15	0.0%
Living status								
Home alone	50/290	17.2%	25/106	23.6%	15/96	15.6%	10/88	11.4%
Home not alone (with carer, spouse or other)	113/676	16.7%	45/187	24.1%	42/264	15.9%	26/225	11.6%
Residential	9/67	13.4%	2/15	13.3%	5/29	17.2%	2/23	8.7%
Sheltered	15/65	23.1%	5/31	16.1%	6/22	27.3%	4/12	33.3%
Other	23/84	27.4%	12/51	23.5%	6/15	40.0%	5/18	27.8%
Sex								
Male	106/578	18.3%	43/187	23.0%	37/212	17.5%	26/179	14.5%
Female	106/614	17.3%	48/211	22.7%	37/214	17.3%	21/189	11.1%
Diagnosis								
Other forms of heart disease	24/176	13.6%	3/176	1.7%	8/176	4.5%	13/176	7.4%
Ischaemic heart disease	35/221	15.8%	6/221	2.7%	10/221	4.5%	8/221	3.6%
Symptoms	86/493	17.4%	5/493	1.0%	12/493	2.4%	18/493	3.7%
COAD	8/44	18.2%	3/44	6.8%	9/44	20.5%	4/44	9.1%
Pneumonia and influenza	5/25	20.0%	0/25	0.0%	2/25	8.0%	3/25	12.0%
Other	14/69	20.3%	23/69	33.3%	23/69	33.3%	40/69	58.0%
Cerebrovascular disease	16/77	20.8%	5/77	6.5%	6/77	7.8%	3/77	3.9%
Other forms of respiratory disease	24/87	27.6%	2/87	2.3%	4/87	4.6%	2/87	2.3%
GP contact pre-admission								
Yes	135/728	18.5%	56/211	26.5%*	53/307	17.3%	26/210	12.4%
No	34/227	15.0%	17/106	16.0%	6/34	17.6%	11/87	12.6%
Social services pre-admission								
Yes	51/188	27.1%***	15/44	34.1%	30/95	31.6%***	6/49	12.2%
No	161/1004	16.0%	76/294	21.5%	44/331	13.3%	41/319	12.9%
Distance (km) from hospital Mean (SD)	7.4 (9.5)	8.3 (12.7)	11.7 (12.8)	19.6 (21.0)***	4.3 (3.9)	3.2 (2.0)*	6.4 (8.2)	6.6 (7.6)

Key: R = Readmitted, N = Number, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

$p < 0.001$) but not at Hospital A ($\chi^2(1) = 3.535$, $p = 0.060$) and Hospital C ($\chi^2(1) = 0.014$, $p = 0.906$).

For the overall dataset there was no difference in readmission rates and distance the patient lived from the hospital of admission ($t(1187) = 1.154$, $p = 0.249$). There was a significant difference at Hospital A ($t(366) = 3.551$, $p < 0.001$) and at Hospital B ($t(424) = 2.247$, $p = 0.025$) but not at Hospital C ($t(393) = 0.143$, $p = 0.887$).

For the overall dataset there was no difference in readmission rates by diagnosis ($\chi^2(7) = 9.257$, df = 7, $p = 0.235$), nor for the individual study sites (Hospital A ($\chi^2(7)= 8.389$, $p = 0.300$), Hospital B ($\chi^2(7)= 10.049$, $p = 0.186$), Hospital C ($\chi^2(7)= 6.283$, $p = 0.507$).

Logistic regression was performed to investigate the factors that were significant in explaining readmission. All factors shown in Table 2 were included in the regression. Table 3 shows the results of the logistic regression analysis for the overall dataset. After deletion of 279 patients with missing values, 912 patients were available for analysis. As can be seen according to the Wald criterion the only significant factors in predicting readmission were age, social service contact, preadmission and living status. The Hosmer–Lemeshow goodness-of-fit test was not significant ($\chi^2(8) = 4.11$, $p = 8467$). The model classification was good at categorizing those not readmitted (98.9 per cent), but poor at categorizing those readmitted (6.8 per cent), with an overall success rate of 82.5 per cent.

Table 4 shows the results of the logistic regression for Hospital A. After deletion of 103 patients with missing values, 295 patients were available for analysis. As can be seen the according to the Wald criterion the only significant factors in predicting readmission was GP contact preadmission. The Hosmer–Lemeshow goodness-of-fit test was not significant ($\chi^2(8) = 2.22$, $p = 0.9735$). The model classification was good at categorizing those not readmitted (97.4 per cent), and moderate at categorizing those readmitted (22.1 per cent), with an overall success rate of 80 per cent. For Hospital B (Table 5), after deletion of 95 patients with missing values, 331 patients were available for analysis. As can be seen according to the Wald criterion the only

Table 3 Logistic regression: overall dataset

Variable	n	B	Wald	P-value	Odds ratio	Confidence Interval Lower	Upper
Age	912	0.02	**5.12**	**0.02**	**1.02**	**1.01**	**1.03**
Sex			0.69	0.41			
Male	439	0.16			1.17	0.81	1.71
Female	473				1.00		
Marital status			0.75	0.69			
Single	145	–0.03	0.00	0.95	0.97	0.36	2.58
Married/widowed	715	0.23	0.24	0.62	1.26	0.51	3.12
Divorced	52						
Living status			**18.16**	**0.00**			
Home alone	217	–0.25	1.00	0.32	0.78	0.49	1.27
Other	57	1.31	11.87	0.00	**3.71**	**1.76**	**7.83**
Residential	48	–0.62	1.70	0.19	0.54	0.21	1.37
Sheltered	53	–0.50	1.35	0.25	0.60	0.26	1.14
Home not alone	537						
Diagnosis			8.00	0.33			
Other	379	0.26	0.89	0.35	1.29	0.76	2.20
Ischaemic HD	140	–0.23	0.43	0.51	0.79	0.40	1.58
Other forms of heart disease	68	0.73	3.68	0.06	2.05	0.98	4.28
Cerebrovascular	47	0.45	1.01	0.31	1.57	0.65	3.75
Pneumonia and influenza	17	–0.36	0.19	0.66	0.70	0.14	3.44
COAD	65	0.43	1.17	0.28	1.53	0.71	3.32
Other forms of respiratory	28	0.11	0.04	0.85	1.11	0.38	3.24
symptoms	168				1.00		
GP contact pre-admission			2.19	0.14			
Yes	698	0.35			1.43	0.89	2.28
No	214				1.00		
Social services pre-admission			**12.92**	**0.00**			
Yes	144	0.89			**2.42**	**1.50**	**3.94**
No	768				1.00		
Distance from hospital	912	<0.0001	0.06	0.81	1.00	0.99	1.01
Postcode district	912		28.04	0.94			
Constant		–9.32	0.26	0.61			

significant factors in predicting readmission were age, marital status and social services pre-admission. The Hosmer–Lemeshow goodness-of-fit test was not significant ($\chi^2(8) = 2.69$, $p = 0.9524$). The model classification was good at categorizing those not readmitted (96.7 per cent), and again moderate at categorizing those readmitted (18.6 per cent), with an overall success rate of 82.8 per cent. For Hospital C (Table 6), after deletion of 82 patients with missing values, 286 patients were available for analysis. As can be seen according to the Wald criterion the only significant factor in predicting readmission was living status. The Hosmer–Lemeshow goodness-of-fit test was not significant ($\chi^2(8) = 12.28, p = 0.1391$). The model classification was good at categorizing those not readmitted (99.6 per cent), but moderate at categorizing those readmitted (16.7 per cent), with an overall success rate of 89.2 per cent. All four equations were good at classifying non-readmissions (all greater than 95 per cent). The overall equation was poor at classifying readmissions, whereas the individual hospital equations were more successful.

Although postcode district was not significant in the equations, Figure 2 indicates that for selected postcode districts, there are observable differences in readmission rates. Including postcode districts in the equation was therefore important to increase the sensitivity of the logistic regression in classifying patients as at risk of readmission.

The euclidian distance between the centroid of each postcode sector boundary and each of the three hospitals was calculated in metres. Table 2 displays the mean and SD of these distances in kilometres for each hospital. The postcode sectors closest in distance to the hospitals were found to have the greatest rate of readmission (Figure 3). These are absolute values of patients readmitted. There was a statistically significant difference in these distances for readmitted patients compared with non-readmitted patients for Hospitals A and B, but after controlling for all the other factors it was not a significant factor in the logistic regression.

DISCUSSION

This paper has demonstrated that equations classifying patients at risk of readmission for

Table 4 Logistic regression: Hospital A

Variable	n	B	Wald	P-value	Odds ratio	Confidence Interval Lower	Upper
Age	295	0.02	1.78	0.18	1.01	0.99	1.04
Sex			0.01	0.91			
Male	140	–0.04	0.01	0.91	0.96	0.50	1.85
Female	155				1.00		
Marital status			2.66	0.27			
Single	53				4.08	0.69	24.30
Married/widowed	221				2.27	0.41	12.89
Divorced	21				1.00		
Living status			5.60	0.23			
Home alone	78	–0.42	1.04	0.31	0.66	0.29	1.47
Other	34	0.05	0.01	0.93	1.05	0.33	3.40
Residential	11	–1.76	2.06	0.15	0.17	0.02	1.90
Sheltered	26	–1.40	4.07	0.04	0.25	0.06	0.96
Home not alone	146				1.00		
Diagnosis			7.03	0.43			
Other	134	0.17	0.15	0.70	1.19	0.05	2.80
Ischaemic HD	41	–0.37	0.38	0.54	0.69	0.21	0.24
Other forms of heart disease	26	0.86	2.14	0.14	2.35	0.75	7.40
Cerebrovascular	18	–0.18	1.61	0.21	0.31	0.05	1.91
Pneumonia and influenza	6	–0.46	0.14	0.70	0.63	0.06	6.77
COAD	18	0.12	0.03	0.87	1.13	0.27	4.67
Other forms of respiratory	6	–0.82	0.44	0.51	0.44	0.04	4.91
symptoms	56				1.00		
GP contact pre-admission							
Yes	197	0.98	**6.81**	**0.01**	**2.67**	**1.28**	**5.59**
No	98				1.00		
Social services pre-admission							
Yes	33	0.79	2.34	0.13	2.19	0.80	6.01
No	262				1.00		
Distance from hospital	295	<0.0001	0.00	0.97	1.00	0.99	1.01
Postcode district	295		9.21	1.00			
Constant		–10.67	0.10	0.76			

general medical patients can be developed using factors available for collection on admission. The individual hospital equations were much stronger at predicting readmission, with accuracy ranging between 17–22 per cent, compared with the equation for the overall dataset (6.8 per cent). This may be a result of the fact that different factors were important between sites; for instance, for the overall equation age, living status and contact with social services were the only significant factors. For Hospital A, which had the highest level of classification, the only significant factor was contact with a GP prior to admission, which was not included in the overall equation. For Hospital B, age and social services contact were significant: these were both significant factors in the overall equation, but the level of classification at Hospital B was much greater. At Hospital C only living status was a factor; this was a factor in the overall equation, but again the classification at Hospital C was much greater.

The research team required the equation to be able to identify patients at risk of readmission within the first 72 hours of admission. This enabled the team, in a subsequent stage of the research, to identify patients at risk of readmission and to interview them and, with their consent, their relatives, as soon after admission as possible. Consequently, certain data such as length of stay were (known only at

(Reference line represents the overall readmission rate of 17.8 per cent)

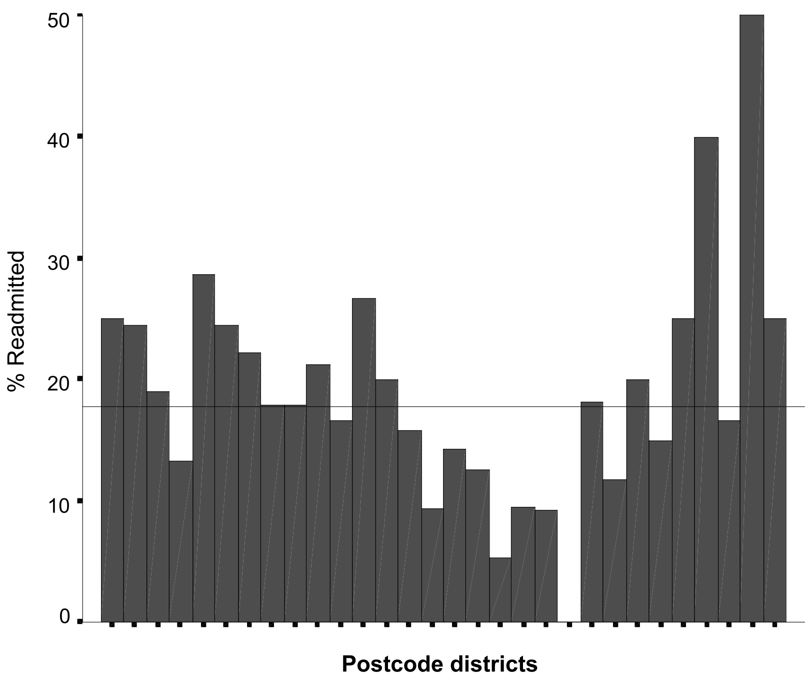

Fig. 2 Readmission rates by postcode district

Table 5 Logistic regression: Hospital B

Variable	n	B	Wald	P-value	Odds ratio	Confidence Interval Lower	Upper
Age	331	0.35	**5.58**	**0.02**	**1.04**	**0.01**	**0.07**
Sex							
Male	168	0.04	1.10	0.29	1.45	0.73	2.89
Female	163						
Marital status			**7.38**	**0.03**			
Single	45	−2.51	**6.95**	**0.01**	**0.08**	**0.01**	**0.53**
Married/widowed	268		**5.14**	**0.02**	**0.19**	**0.04**	**0.80**
Divorced	18				1.00		
Living status			6.32	0.18			
Home alone	68	−0.18	0.16	0.69	0.08	0.35	1.99
Other	9	2.18	4.94	0.03	8.89	1.30	60.62
Residential	20	0.11	0.03	0.87	1.12	0.29	4.30
Sheltered	16	−0.63	0.60	0.44	0.53	1.08	2.62
Home not alone	218				1.00		
Diagnosis			8.09	0.32			
Other	125	−0.23	0.23	0.63	0.80	0.31	20.33
Ischaemic HD	59	−0.65	1.24	0.27	0.72	0.16	1.64
Other forms of heart disease	21	0.56	0.70	0.40	1.75	0.47	6.50
Cerebrovascular	14	1.01	1.66	0.20	0.75	0.59	12.85
Pneumonia and influenza	5	1.00	0.64	0.43	2.71	0.23	31.55
COAD	30	0.64	1.10	0.30	1.90	0.57	6.36
Other forms of respiratory	14	0.22	0.85	0.77	1.25	0.28	5.52
Symptoms	63				1.00		
GP contact pre-admission							
Yes	298	−0.02	0.00	0.97	0.98	0.29	3.26
No	33						
Social services pre-admission							
Yes	71	1.20	**10.56**	**0.00**	**3.32**	**1.61**	**6.83**
No	260				1.00		
Distance from hospital	331	0.00	0.23	0.63	1.00	1.00	1.00
Postcode district	331		5.82	1.00			
Constant		6.36	0.00	0.95			

discharge) excluded as a variable for predicting readmission. This approach had the advantage of producing equations that could potentially be used on admission by hospital staff to identify patients at risk of readmission, as information on the factors included would also be available to hospital staff at the time of admission.

Another possible indicator of readmissions could be the number of previous admissions within a given time period. However, as we were using the first admission in the Körner dataset, we did not have access to this information. It may have been available from hospital notes, but the reliability of this data

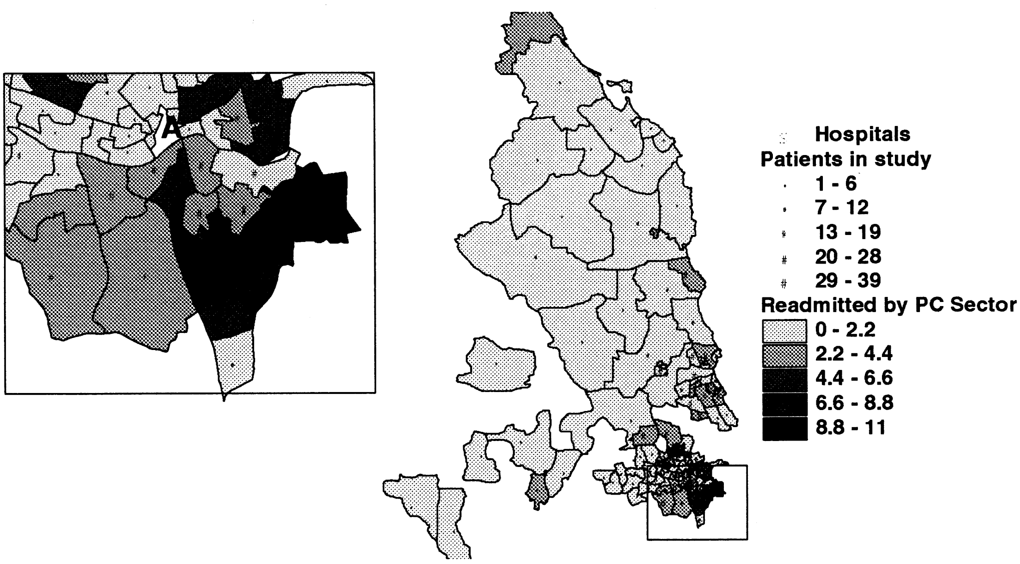

Fig. 3 Distribution of patients by postcode sector

Table 6 Logistic regression: Hospital C

Variable	n	B	Wald	P-value	Odds ratio	Confidence Interval Lower	Upper
Age	286	0.02	1.62	0.20	1.02	0.99	0.01
Sex							
Male	131	0.64	2.07	0.15	0.89	0.76	4.52
Female	155				1.00		
Marital status			1.34	0.51			
Single	47	7.06	0.07	0.79	1116.37	<0.001	
Married/widowed	226	7.88	0.09	0.77	2643.68	<0.001	
Divorced	13				1.00		
Living status			**13.77**	**0.01**			
Home alone	71	–0.32	0.28	0.60	**0.73**	**0.22**	**2.38**
Other	14	0.90	9.62	0.00	**18.11**	**2.93**	**113.00**
Residential	17	–1.03	0.73	0.39	0.36	0.03	3.76
Sheltered	11	1.29	1.91	0.17	3.62	0.58	22.45
Home not alone	173				1.00		
Diagnosis			4.83	0.68			
Other	130	0.69	0.94	0.33	2.00	0.49	8.13
Ischaemic HD	40	0.28	0.12	0.73	1.33	0.27	6.48
Other forms of heart disease	21	–0.49	0.21	0.65	0.61	0.07	5.07
Cerebrovascular	15	1.40	2.10	0.15	4.06	0.61	27.11
Pneumonia and influenza	6	–6.95	0.25	0.87	0.00	<0.001	
COAD	17	–0.18	0.02	0.88	0.84	0.09	7.78
Other forms of respiratory	8	–0.39	0.09	0.77	0.68	0.05	8.97
Symptoms	49				1.00		
GP contact pre-admission							
Yes	203	0.09	0.04	0.85	1.09	0.45	2.67
No	83				1.00		
Social services pre-admission							
Yes	40	0.46	0.49	0.48	1.59	0.44	5.78
No	246				1.00		
Distance from hospital	286	<0.001	0.00	0.96	1.00	1.00	1.00
Postcode district	286		0.98	0.96			
Constant		–18.64	0.03	0.86			

source appeared poor. Further work needs to be undertaken to determine if replacing the patient's postcode by a measure of deprivation such as the Townsend score would increase the predictive power of the equation, given that the distance from the hospital wasn't a significant factor.

In the UK hospital readmission is currently being used as a high-level performance indicator for medical and surgical patients [18]. Readmissions can, however, be planned. This may represent a more appropriate service for the patient. Any equation designed to predict readmissions would need to differentiate between planned and emergency readmissions. However, our data indicate that there are very few planned admissions on general medical wards.

Much of the literature on discharge planning attributes unsuccessful discharge to a failure to plan for and provide an appropriate level of health and social service support following discharge [19][20]. Findings from this research contradict these interpretations of unsuccessful discharge processes. In the overall dataset and for Hospital B those patients at risk of readmission were significantly more likely to be receiving social service support prior to admission than patients not at risk of readmission. In Hospital A, the one with the highest readmission rate, patients who were seen by a GP prior to admission were significantly more likely to be readmitted than those not seen by a GP prior to admission. These statistical associations raise interesting questions as to whether readmission can be attributed primarily to a lack of primary healthcare and social service support. Instead they highlight the complex circumstances frequently being experienced by patients at risk of readmission and their carers and the need for individualized responses which address these complexities.

CONCLUSION

Prediction of unsuccessful discharge may enable more effective targeting of scarce and expensive resources. The study presented in this paper indicates that it is possible to produce indicators for readmission for general medical wards, but so far we have only been able to produce equations for individual hospitals.

In the absence of a method for accurately identifying those patients at risk of unsuccessful discharge, discharge protocols designed to produce an effective discharge from hospital have to be comprehensively applied or rely on professional judgement for referral to a specialist service if it is available. Further work needs to be undertaken to compare the accuracy of predictive equations such as those produced here, with that of professional judgement. Consideration also needs to be given to definitions of successful discharge, readmission may be one indicator of unsuccessful discharge; however other indicators such as use of emergency GP services or severe and/or prolonged disruption to families may be other less obvious indicators. A thorough investigation of the relative costs of reducing readmission and improving functional ability has yet to be carried out. In particular there seems to be a dearth of studies that look at the costs for community provision and families of meeting the expectations of policy planners in effecting a well-planned discharge in which the patient and their family receive the levels of support deemed to be appropriate to their needs.

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