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Understanding hospital activity and outcomes for people with multimorbidity using electronic health records

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As the prevalence of multimorbidity grows, provision of effective healthcare is more challenging. Both multimorbidity and complexity in healthcare delivery may be associated with worse outcomes. We studied consecutive, unique emergency non-surgical hospitalisations for patients over 50 years old to three hospitals in Scotland, UK between 2016 and 2024 using linked primary care and hospital records to define multimorbidity (2 + long-term conditions), and timestamped hospital electronic health record (EHR) contacts with nursing and rehabilitation providers to describe intensity of inpatient care. The primary outcome was emergency hospital readmission within 30 days of discharge, analysed using multivariable logistic regression. Across 98,242 consecutive admissions, 84% of the study population had multimorbidity, 50% had 4 + long-term conditions, and 37% had both physical and mental health conditions. Both higher condition count and contacts (nursing and rehabilitation) were independently associated with the primary outcome in fully adjusted models (example adjusted odds ratio [aOR] 1.62, 95% CI 1.52 to 1.73 for 4 + conditions compared to no multimorbidity, *p* < 0.001; aOR 1.35, 95% CI 1.28 to 1.42 for > 8 nursing contacts compared to 1–3, *p* < 0.001). While multimorbidity was associated with longer hospital stays with more nursing and rehabilitation contacts, the distribution of contacts and activity did not differ by multimorbidity or subsequent emergency readmission status. Higher count multimorbidity was associated with an increased risk of readmission, but we observed uniformity in care despite differential outcomes across multimorbidity groups. This may suggest that EHR data-driven approaches could inform person-centred care and improve hospital resource allocation.

Keywords Multimorbidity, Electronic health records, Readmission, Rehabilitation

Multimorbidity is highly prevalent. While associated with an ageing population, it is increasingly common in middle-age, particularly amongst the less affluent[1,2]. Similar to other countries, the number of people living with four or more long-term conditions (LTC) in the UK is projected to nearly double by 2035[3]. Multimorbidity has been associated with loss of functional independence[4,5], reduced economic activity[6], increased need for healthcare[7–9] with greater treatment burden[10,11], and increased risk of premature death[4,12]. With the majority of a hospitalised population now living with multimorbidity, identifying those with the greatest risk is often limited to a weighted or unweighted count of conditions, without an understanding of how individuals interact with services. Hospital performance reporting rarely accounts for casemix complexity driven by multimorbidity, instead relying on simple metrics like length of stay, inpatient complications and early unexpected readmission after discharge.

Up to a fifth of all hospital discharges are associated with a preventable adverse event[13] and early readmission rates are increasing[14]. In more dependent patient groups from care homes, over a third of transfers from hospital have been associated with adverse events such as medication errors, falls and infections[15]. Many causes of early

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readmission will be non-modifiable, but better understanding of inpatient activity to support improved discharge planning for the most complex patients with multimorbidity has the potential to improve patient outcomes and experience[16], and to minimise health or social care spending associated with 'failed discharges'.

Modern electronic health record (EHR) systems provide the opportunity to interrogate patterns of hospital care in much greater detail than previously possible. Every electronic contact of a health professional with the EHR generates a timestamped 'contact' that forms an event log of activity for each patient admission. Understanding the pattern and intensity of these contacts can reveal more information about hospital activity than traditional measures like total length of stay, and might better explain the likelihood of short-term discharge success. Our previous work has demonstrated how these data can reveal differences in patterns of rehabilitation delivery early in the COVID-19 pandemic[17]. Linking data from both primary care and hospital records also improves ascertainment of individual long-term conditions and of multimorbidity[18]. This may be particularly important for identifying people with combined physical and mental multimorbidity, who appear to be at particular risk of poorer healthcare experience and outcomes[2].

In this study, we aimed to use granular EHR data to understand associations between multimorbidity, patterns of contacts from hospital inpatient care providers and the risk of early unplanned readmission after discharge.

Methods

Study design and population

We conducted a retrospective cohort study including consecutive non-surgical admissions with a linked Emergency Department (ED) attendance to three acute hospitals in the Lothian region of Scotland between 1st April 2016 and 1st February 2024 for patients aged 50 years or older. Hospital admissions for which there was no transfer of care to another speciality (i.e. remained under ED care for brief observation), admissions under surgical services, or short admissions with no nursing or rehabilitation contacts were also excluded. To generate an analysis cohort, the first (index) eligible admission for each unique patient was included, and for the study of patterns of care provider contacts and readmission risk, only survivors to hospital discharge were included.

Care provider contacts

Contacts were extracted with an exact timestamp from the metadata generated when staff save data entries ('clinical notes') within the patient EHR hospital system, which is shared across the included hospitals (TrakCare, InterSystems, MA). These entries were classified by job role and were available for nursing and rehabilitation (physiotherapy, occupational therapy and speech and language therapy) staff. Contact with these care providers was assumed by the completion of a saved clinical note generating a timestamp, without any further knowledge of the content of that entry. Contacts from other care providers such as doctors or pharmacists were not available.

Multimorbidity status

Health conditions present before the index admission date were determined from both primary care (GP Read codes) and hospital records (ICD-10 codes). We used selected codelists produced by the CALIBER research study[19], published within the Health Data Research (HDR) UK phenotype library. To reduce redundancy and ensure focus on truly long-term health conditions, we selected 161 CALIBER phenotypes of interest after clinical review, and then grouped these into 25 high-level LTC, such as diabetes, ischaemic heart disease, depression and related disorders (see Tables S1 and S2). We categorised the LTC count into 0–1 conditions (no multimorbidity), 2–3 ('simple' multimorbidity) and four or more ('high-count' multimorbidity). We defined physical-mental multimorbidity as the presence of at least one mental health LTC and at least one physical LTC.

Linked data

All data from EHR and national registries were linked and de-identified by the DataLoch service (Edinburgh, United Kingdom) and analysed within their Secure Data Environment. The study was reviewed and received approval from Dataloch, under delegated authority from a regional National Health Service Research Ethics Committee (REC 22/NS/0093) and Caldicott Guardian, which also waived the need for obtaining informed consent. All methods were carried out in accordance with relevant guidelines and regulations. Consecutive hospital admissions and readmissions were determined using the Scottish Morbidity Record (SMR) 01, a national administrative dataset provided by Public Health Scotland. The SMR01 record was also used to determine ICD-10 coding for hospital-recorded LTC history, which was combined with GP data using the codelists described above. In addition to care provider contacts, the hospital EHR system (TrakCare) provided linked ED attendance and post-discharge reattendance data. The Scottish Index of Multiple Deprivation (SIMD) was used as a measure of relative socioeconomic deprivation based on postcode area for a patient's last registered address, with each person allocated to quintiles from 1 (most deprived) to 5 (least deprived)[20]. Finally, linkage with National Records of Scotland (NRS) mortality registration data was used to determine date of death.

Outcomes

The primary outcome was emergency readmission to hospital for any reason within 30 days of discharge for survivors of the index admission. Reattendance at ED within 30 days was a secondary outcome. For the care provider contacts analysis, total and rehabilitation-specific contact counts across an admission and averaged per day of admission were calculated.

Statistical analysis

Descriptive summary data for demographics, outcomes and care provider contacts were calculated across all index admissions and then stratified by multimorbidity group. The physical-mental multimorbidity group was separately reported and could include individuals with either simple or high-count multimorbidity. To explore the distribution of care provider contacts, each admission was divided into equal quintiles of time from admission to discharge to account for variations in length of stay between patients. Heat maps were generated to show the absolute and relative intensity of care contacts across these five time periods, stratified by the outcome of emergency readmission within 30 days of discharge.

A logistic regression model was used to determine the univariate associations of the following exposures for outcomes of emergency readmission and emergency reattendance within 30 days of discharge: age, sex, SIMD, index admission length of stay, multimorbidity group, and number of care provider contacts. To aid interpretability, SIMD was simplified into three groups: quintile 1 (most deprived), quintiles 2–4 and quintile 5 (least deprived) using the latter as a reference. Length of stay was considered as a continuous variable, and care provider contacts (separated as nursing and rehabilitation) were split into tertiles across the study population.

Multivariable regression was then conducted for the same outcomes. A base model (Model 1) consisted of age, sex and SIMD. Sequential addition included index admission length of stay (Model 2), multimorbidity group (Models 3 and 4), and number of care provider contacts (Models 5 and 6). The physical-mental multimorbidity grouping was handled in separate models (Models 4 and 6) to simple and high-count multimorbidity (Models 3 and 5) due to lack of independent patient assignment across these groups. Normally distributed variables are reported as mean ± SD, while non-normally distributed values are described as median [IQR] and differences tested using parametric or non-parametric methods, respectively. Odds ratios were calculated with associated 95% confidence intervals (95% CI). All analyses were conducted in Python (version 3.7), and significance was considered at $p < 0.05$.

Results

Study population

Following data cleaning, 208,477 consecutive, non-surgical hospital admissions that followed an ED attendance were identified between April 2016 and February 2024 (see Fig. 1). These occurred in 98,242 unique patients with their index (first) admission in the time period selected for analysis. The demographics and outcomes for this cohort, stratified by multimorbidity grouping are shown in Table 1. There were 16,053 patients (16%) with no multimorbidity (0 or 1 condition), 33,534 (34%) with simple multimorbidity (2–3 conditions) and 48,655 (50%) with high-count multimorbidity (4 + conditions). A total of 36,096 (37%) of the study population had physical-mental multimorbidity, of whom 25,969 (72%) also belonged to the high-count and 10,127 (28%) to the simple multimorbidity groups. Patients with high-count multimorbidity were the oldest group (74 ± 11 vs. 67 ± 12 years without multimorbidity, $p < 0.001$) and included the most women (53% vs. 48%, $p < 0.001$). The proportion of patients from the most deprived SIMD quintile was greatest in those with physical-mental multimorbidity (19% vs. 12% without multimorbidity).

Outcomes

The primary outcome of emergency readmission at 30 days after discharge occurred in 11,692 (13%) of those discharged alive. Risk was lowest in those without multimorbidity and highest in those with high-count burden (9% vs. 15% respectively, $p < 0.001$). Similar patterns were observed for emergency 30-day ED reattendance. Index admission length of stay was higher with multimorbidity, particularly in high-count and physical-mental groups. The highest risk of death during index admission and at 1-year was observed in the high-count multimorbidity group (8% and 26% respectively), with rates otherwise similar between multimorbidity groups, but higher than in those without multimorbidity.

Care provider contacts

Across the 92,149 index patient admissions there were 1,122,006 nursing and 575,629 rehabilitation care provider contacts recorded (Table 2). At least one nursing contact was recorded for 88,175 (96%) patients, but only 37,150 (40%) had contact with rehabilitation services. Total contacts were higher in those with multimorbidity and greatest in the high-count group (median 7 [3, 20] vs. 5 [2, 11] contacts without multimorbidity, $p < 0.001$) driven by more nursing contacts over longer admissions but at similar average daily intensity (median 2 nursing contacts per day in all groups). Rehabilitation was more common in patients with any classification of multimorbidity, and greatest in the high-count group (48% of patients vs. 26% without multimorbidity, $p < 0.001$). However, when limited to patients who received rehabilitation, the contact count, time to first contact and averaged number of contacts per day of admission did not differ between multimorbidity groups or those without multimorbidity. Patterns of nursing and rehabilitation contacts were similar between multimorbidity groups at the extremes of distribution when looking at the 90th and 95th percentiles of data (Table S3). The average number of nursing or rehabilitation contacts received by patients also appeared similar between the three acute hospital sites included (Table S4).

Distribution of care provider contacts

Patients with emergency 30-day readmission received more total nursing and rehabilitation provider contacts than those who were not readmitted (median 8 [3, 21] vs. 6 [3, 16] contacts respectively, $p < 0.001$). However, heat maps showing the distribution of contacts across time quintiles of the index admission did not reveal notable differences in this pattern across any multimorbidity or non-multimorbid group (Fig. 2A). When observing the relative proportion of contacts in each quintile to standardise for differences in total contact count, a clear trend was seen to higher activity early and late in admissions (Fig. 2B). These patterns were similar regardless of multimorbidity status or group, and also appeared similar between those readmitted or not within 30 days of discharge.

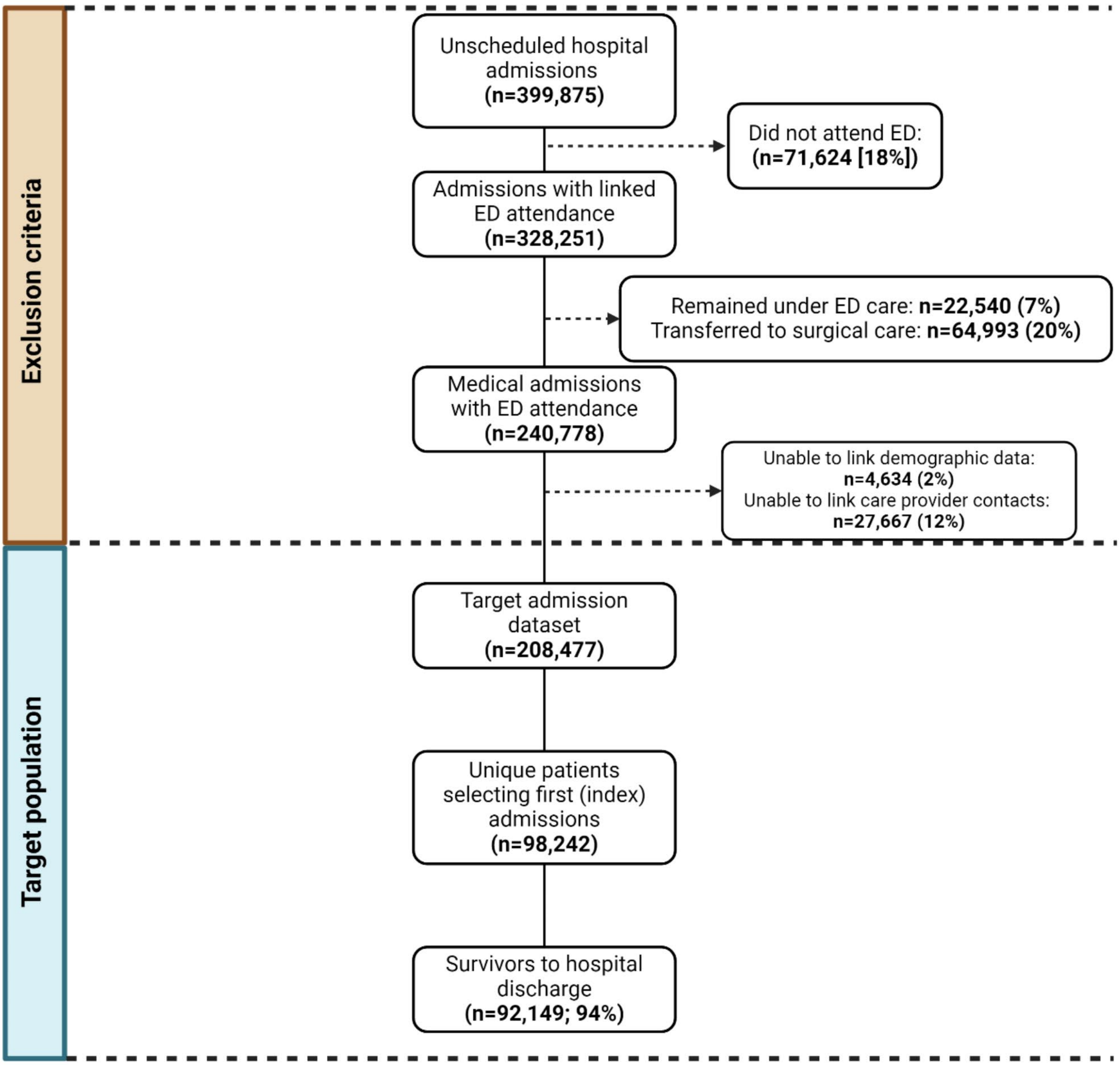

Fig. 1. Study flow diagram.

Associations with readmission and reattendance

Univariable logistic regression showed that older people and women were more likely to experience emergency 30-day readmission (Table 3). Patients from the most deprived SIMD quintile were at 8% higher risk of readmission than those in the least deprived group (OR 1.08, 95% CI 1.02 to 1.15, $p = 0.02$). Length of stay was also associated with a small but significant increased readmission risk per day of hospital admission. All multimorbidity groups were at higher risk of 30-day readmission than those without multimorbidity, with this association strongest in those with high-count multimorbidity (OR 1.80, 95% CI 1.69 to 1.91), followed by physical-mental (OR 1.58, 95% CI 1.49 to 1.69) and simple multimorbidity (OR 1.35, 95% CI 1.27 to 1.44). Increasing nursing contacts were associated with higher risk of readmission, with a 20% increase for those in the highest tertile with > 8 contacts in their index hospitalisation (OR 1.20, 95% CI 1.14 to 1.25). Findings for 30-day ED reattendance had a similar pattern, although there were no differences between men and women for this outcome. However, the highest risk of readmission was observed in the middle tertile of rehabilitation contacts (OR 1.20, 95% CI 1.15 to 1.26), with a smaller association in those receiving the most rehabilitation contacts (OR 1.11, 95% CI 1.06 to 1.17).

In multivariable analysis, age and deprivation were independently associated with readmission in all models, but sex differences in readmission risk were not associated once age and deprivation were accounted for (Table 4). Adjusted associations by multimorbidity group were largely unchanged by addition of age, sex, deprivation and length of stay with only minor attenuation of the magnitude, such as for high-count patients (aOR 1.66, 95% CI

	All	Multimorbidity group			
		None	Simple	High-count	Physical/mental
N (index admissions)	98,242	16,053	33,534	48,655	36,096
Age (mean, SD)	72 ± 12	67 ± 12	71 ± 12	74 ± 11	69 ± 11
Women	50,214 (51%)	7,647 (48%)	16,950 (51%)	25,617 (53%)	18,383 (51%)
SIMD quintiles					
1 (most deprived)	14,765 (15%)	1,932 (12%)	4,671 (14%)	8,162 (17%)	6,786 (19%)
2	23,437 (24%)	3,292 (21%)	7,615 (23%)	12,530 (26%)	9,513 (26%)
3	17,960 (18%)	3,102 (19%)	6,718 (18%)	8,680 (18%)	6,706 (19%)
4	17,181 (18%)	3,102 (19%)	5,948 (18%)	8,131 (17%)	5,593 (16%)
5 (least deprived)	24,899 (25%)	4,625 (29%)	9,122 (27%)	11,152 (23%)	7,498 (21%)
Index length of stay (days, IQR)	4 [1, 10]	2 [1, 6]	3 [1, 9]	4 [2, 12]	4 [1, 10]
Index admission death	6,093 (6%)	556 (4%)	1,830 (6%)	3,707 (8%)	2,016 (6%)
N (discharged alive)	92,149	15,497	31,704	44,948	34,080
ED reattendance at 30 days*	12,868 (14%)	1,609 (10%)	4,100 (13%)	7,159 (16%)	5,125 (15%)
Hospital readmission at 30 days*	11,692 (13%)	1,366 (9%)	3,666 (12%)	6,660 (15%)	4,521 (13%)
Death at 1 year*	20,548 (21%)	1,954 (12%)	6,094 (18%)	12,500 (26%)	7,148 (19%)

Table 1. Baseline demographics and outcomes by multimorbidity group. Data are presented as counts (%) unless otherwise stated. *Study population is those discharged alive.

	All	Multimorbidity group			
		None	Simple	High-count	Physical/mental
N (discharged alive)	92,149	15,497	31,704	44,948	34,080
Contacts per admission	6 [3, 17]	5 [2, 11]	6 [3, 16]	7 [3, 20]	6 [3, 17]
Contacts per admission day	2 [2, 4]	2 [2, 3]	2 [2, 3]	2 [2, 4]	2 [2, 4]
Nursing contacts per admission	5 [3, 12]	4 [2, 9]	5 [2, 11]	6 [3, 14]	5 [3, 12]
Nursing contacts per admission day	2 [2, 3]	2 [1, 2]	2 [1, 3]	2 [2, 3]	2 [2, 3]
Received any rehabilitation (n, %)	37,150 (40%)	4,032 (26%)	33,118 (43%)	21,340 (48%)	13,534 (40%)
Rehabilitation contacts per admission*	6 [2, 17]	5 [2, 15]	6 [2, 17]	6 [2, 17]	6 [2, 15]
Rehabilitation contacts per admission day*	2 [2, 4]	2 [2, 3]	2 [2, 4]	2 [2, 4]	2 [2, 3]
Time to first rehabilitation contact (hours)*	41 [19, 88]	42 [19, 90]	40 [19, 87]	42 [19, 89]	43 [19, 91]

Table 2. Summary of care provider contacts by multimorbidity group for survivors to index hospital discharge. Data are presented as median [IQR] unless stated otherwise. *Rehabilitation data were calculated only for those who received at least one rehabilitation contact (defined as physiotherapy, occupational therapy or speech and language therapy).

1.56 to 1.77). Increasing nursing contacts remained associated with readmission risk, with the highest tertile (> 8 contacts) independently associated with a 35% increased risk in both condition count (aOR 1.35, 95% CI 1.28 to 1.42) and physical-mental (aOR 1.35, 95% CI 1.28 to 1.42) multimorbidity models. For rehabilitation contacts, the middle tertile (1–5 contacts) was associated with an increased risk of readmission in both condition count (aOR 1.22, 95% CI 1.15 to 1.28) and physical-mental (aOR 1.23, 95% CI 1.17 to 1.29) multimorbidity models, but the highest tertile of rehabilitation contacts was not associated with a greater readmission risk than the lowest tertile (Table 4).

The variance inflation factor across all variables within these fully adjusted models remained below 5, suggesting no co-linearity between these measures (Table S5). Patterns were very similar for emergency ED reattendance, including for differences across both nursing and rehabilitation contacts (Table S6).

Discussion

We have described associations between healthcare activity and risk of early emergency hospital readmission across groups of patients with and without multimorbidity. It is striking that 86% of patients over 50 years old admitted through emergency medical pathways in our study were multimorbid, with half having at least four long-term conditions. More than one in every three patients with multimorbidity had a combination of physical and mental conditions, and this group were more likely to be living in areas of socioeconomic deprivation. A higher count of conditions was associated with a greater risk of in-hospital death and emergency reattendance or readmission after discharge. While multimorbidity was associated with longer hospital stays, more nursing contacts and greater need for rehabilitation, it was notable that contacts and the distribution of activity across the admission did not differ by multimorbidity or future readmission status. This observed uniformity in care

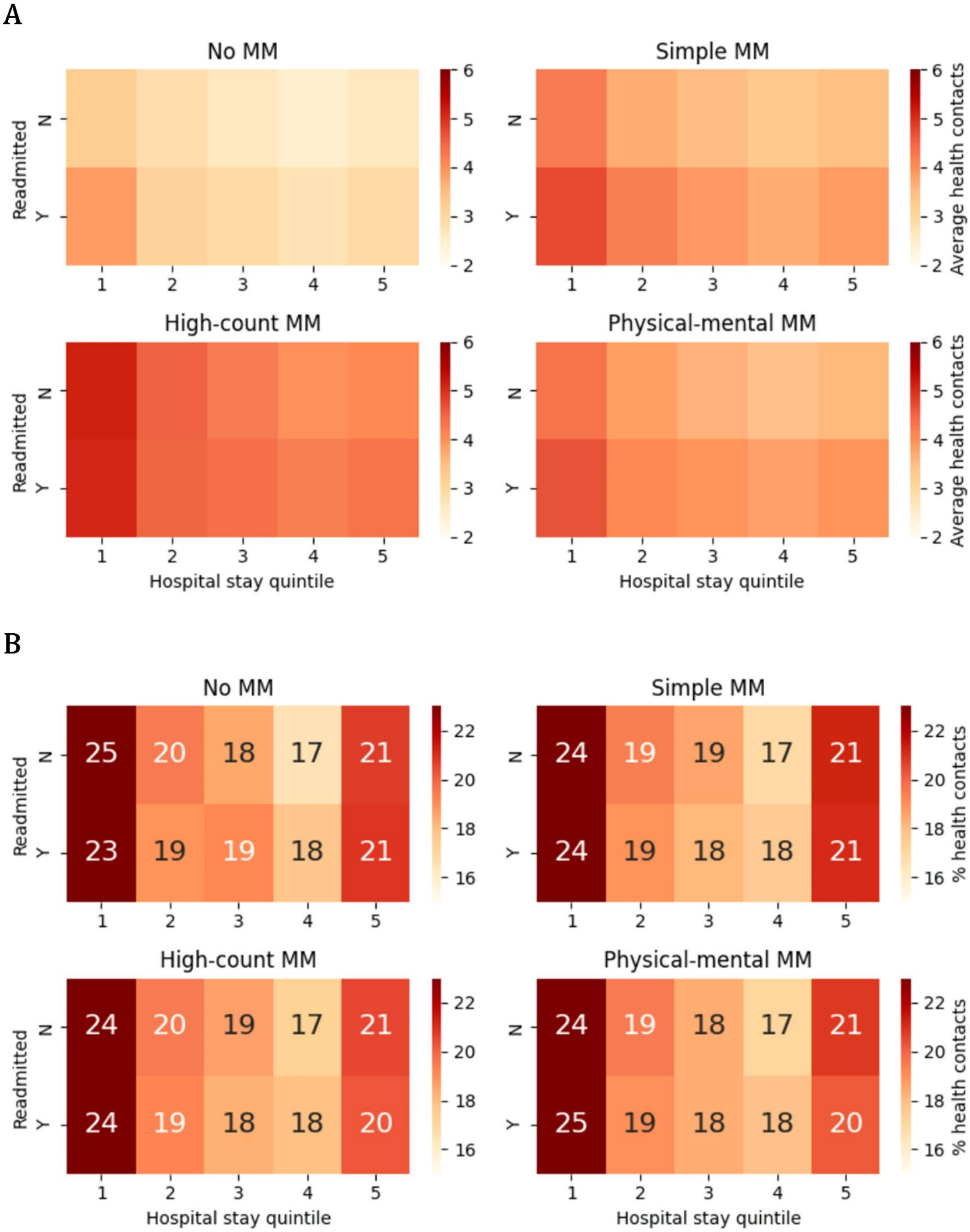

Fig. 2. Heat maps showing the average distribution of nursing and rehabilitation contacts across quintiles of duration of the index hospital admission, stratified by 30-day readmission. In (**A**) the absolute number of contacts averaged across each quintile of duration of admission are shown. In (**B**) the relative proportion of contacts for each patient in each quintile of duration of admission are shown, with mean percentages overlaid, such that an equal distribution would result in 20% of contacts in each quintile of duration of admission.

despite differential outcomes may suggest that data-driven targeting during hospital admissions could inform person-centred care and better resource allocation.

There are several strengths to our study. We used a consecutive patient approach across a large Scottish health region including three acute hospitals (~2,000 inpatient beds). Our ascertainment of LTCs and multimorbidity benefited from both GP and hospital data sources, which has been shown to enhance identification of disease burden[18]. We used EHR data to report nursing and rehabilitation interactions within a hospital admission, which adds information to less nuanced measures (e.g. total length of stay) that form the mainstay of hospital outcomes research. A potential limitation is the assumptions made around the meaning of a contact. For example, patients are likely to receive multiple nursing contacts outside of those documented within the EHR, and there is no way

Characteristic	30-day ED reattendance		30-day hospital readmission	
	Unadjusted OR (95% CI)	p	Unadjusted OR (95% CI)	p
Age				
50–59	1.000 (ref)		1.000 (ref)	
60–69	1.029 [0.970, 1.091]	0.34	1.168 [1.096, 1.245]	< 0.001
70–79	1.133 [1.072, 1.197]	< 0.001	1.384 [1.304, 1.468]	< 0.001
80–89	1.210 [1.144, 1.281]	< 0.001	1.493 [1.405, 1.586]	< 0.001
90 +	1.280 [1.174, 1.395]	< 0.001	1.579 [1.444, 1.727]	< 0.001
Sex				
Men	1.000 (ref)		1.000 (ref)	
Women	0.983 [0.947, 1.021]	0.37	1.054 [1.014, 1.096]	0.01
SIMD in quintiles				
1 (most deprived)	1.082 [1.021, 1.148]	0.01	1.083 [1.018, 1.152]	0.01
2–4	1.016 [0.971, 1.062]	0.49	1.074 [1.025, 1.125]	0.003
5 (least deprived)	1.000 (ref)		1.000 (ref)	
Length of hospital stay				
Per day	1.000 [0.999, 1.001]	0.88	1.001 [1.001, 1.002]	0.001
Multimorbidity group*				
None	1.000 (ref)		1.000 (ref)	
Simple	1.282 [1.206, 1.363]	< 0.001	1.353 [1.267, 1.444]	< 0.001
High-count	1.635 [1.544, 1.732]	< 0.001	1.799 [1.692, 1.913]	< 0.001
Physical-mental	1.528 [1.439, 1.621]	< 0.001	1.582 [1.485, 1.686]	< 0.001
Total care provider contacts during index admission**				
Nursing				
1–3	1.000 (ref)		1.000 (ref)	
4–8	1.143 [1.088, 1.201]	< 0.001	1.059 [1.011, 1.109]	0.02
> 8	1.412 [1.349, 1.479]	< 0.001	1.195 [1.144, 1.249]	< 0.001
Rehabilitation				
0	1.000 (ref)		1.000 (ref)	
1–5	1.395 [1.328, 1.465]	< 0.001	1.203 [1.146, 1.261]	< 0.001
> 5	1.302 [1.241, 1.366]	< 0.001	1.113 [1.062, 1.166]	< 0.001

Table 3. Univariate associations from logistic regression using emergency 30-day ED reattendance and 30-day hospital readmission as outcomes. Data are presented as odds ratios (OR) with 95% confidence intervals (CI). *Physical-mental multimorbidity modelled separately from count groups as no independent patient assignment. Reference in each case is no multimorbidity. **Dichotomisation was performed using quantile-based discretisation used to define three equally-sized buckets.

to understand the importance of an interaction from our data. However, it is at least plausible that patients with more EHR entries from a higher number of care providers are likely to be receiving more care than those with fewer entries. Our approach is also scalable, as we have used simple metadata collected for user interactions that should be similarly extractable regardless of EHR software provider. Unfortunately we were unable to include other care provider contacts in this work to fully represent the multidisciplinary nature of complex care, and including medical contacts might provide more context on illness acuity. As a focus of this work was the novel care contacts data, we used a relatively crude approach to multimorbidity classification to observe differences. It is likely that additional information could be gained from further analysis including individual disease data, patterns or clusters.

There are few examples where rehabilitation has been studied using routinely collected health records. This has usually been in outpatient settings, often using claims databases for insurance models[21–23]. Examples from hospital setttings have focussed on selected patient groups such those in intensive care[24] or following particular surgical procedures. For example, Walpitage et al.. reported that up to 12% of the variance in length of stay after a common elective spinal surgery procedure could be explained by the 'dose' and activity of interdisciplinary care revealed by timestamped contact data[25]. These examples demonstrate potential for increased explainability of healthcare activity using more granular records. Hospital system performance is often reported using simply defined metrics such as length of stay and emergency readmission. These are surrogates of a complex interaction between patient characteristics including multimorbidity, illness acuity, and the effectiveness of actual systems delivering healthcare. Length of stay is often also influenced by community context including the need for family or social support to facilitate discharge. In manual audits of 'value-added' inpatient activity, up to half of inpatient days for older patients may be considered low value in contribution towards discharge[26]. Deeper automated interrogation of care provider contacts data offers potential to understand these patterns and to support the test of new models of care to improve efficiency of inpatient bed utilisation.

Characteristic	Model 1		Model 2		Model 3		Model 4		Model 5⁺		Model 6⁺	
	aOR	p	aOR	p	aOR	p	aOR	p	aOR	p	aOR	p
Age at index admission												
Per year	1.014 [1.012, 1.015]	< 0.001	1.011 [1.009, 1.013]	< 0.001	1.008 [1.006, 1.010]	< 0.001	1.008 [1.006, 1.010]	< 0.001	1.008 [1.006, 1.009]	< 0.001	1.009 [1.007, 1.011]	< 0.001
Sex												
Men	1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)	
Women	1.019 [0.980, 1.060]	0.35	1.019 [0.980, 1.060]	0.35	1.014 [0.975, 1.055]	0.47	1.015 [0.976, 1.056]	0.45	1.007 [0.968, 1.048]	0.72	1.007 [0.968, 1.047]	0.73
SIMD quintiles												
1 (most deprived)	1.175 [1.104, 1.252]	< 0.001	1.176 [1.104, 1.252]	< 0.001	1.112 [1.044, 1.185]	< 0.001	1.139 [1.069, 1.214]	< 0.001	1.105 [1.037, 1.178]	0.002	1.131 [1.061, 1.205]	< 0.001
2–4	1.123 [1.071, 1.177]	< 0.001	1.123 [1.071, 1.177]	< 0.001	1.089 [1.039, 1.142]	< 0.001	1.105 [1.054, 1.158]	< 0.001	1.084 [1.034, 1.137]	< 0.001	1.099 [1.048, 1.153]	< 0.001
5 (least deprived)	1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)	
Length of stay												
Per admission			1.000 [1.000, 1.001]	0.34	1.000 [0.999, 1.001]	0.84	1.000 [0.999, 1.001]	0.64	0.998 [0.997, 0.999]	< 0.001	0.998 [0.997, 0.999]	< 0.001
Multimorbidity group												
None					1.000 (ref)		1.000 (ref)		1.000 (ref)		1.000 (ref)	
Simple					1.297 [1.215, 1.386]	< 0.001			1.282 [1.200, 1.369]	< 0.001		
High-count					1.660 [1.559, 1.768]	< 0.001			1.620 [1.521, 1.725]	< 0.001		
Physical-mental							1.520 [1.426, 1.621]	< 0.001			1.491 [1.398, 1.590]	< 0.001
Total care provider contacts during index admission												
Nursing												
1–3									1.000 (ref)		1.000 (ref)	
4–8									1.120 [1.066, 1.177]	< 0.001	1.120 [1.066, 1.177]	< 0.001
> 8									1.345 [1.276, 1.418]	< 0.001	1.350 [1.281, 1.423]	< 0.001
Rehabilitation												
0									1.000 (ref)		1.000 (ref)	
1–5									1.215 [1.154, 1.279]	< 0.001	1.227 [1.166, 1.292]	< 0.001
> 5									1.040 [0.978, 1.107]	0.21	1.046 [0.983, 1.113]	0.16

Table 4. Multivariable logistic regression for associations with emergency 30-day readmission. Data are presented as adjusted odds ratios (aOR) with 95% confidence intervals (CI). Sequential addition of variables from the base model of age, sex and SIMD (Model 1) to include length of stay (Model 2), multimorbidity group (Model 3 for count, Model 4 for physical-mental) and care provider contacts (Model 5 adding to multimorbidity count, Model 6 adding to physical-mental multimorbidity). ⁺Dichotomisation was performed using quantile-based discretisation used to define three equally-sized buckets.

An advantage of our hospitalised rehabiliation data is the equity of access outside of any fee-paying model for inpatient emergency care in the UK's National Health Service. Access to rehabilitation specialists is based on need, but may be constrained by scarcity of resources. Our data show that in those who received rehabilitation services, there was no difference in the time to first contact or number of additional contacts per day across multimorbidity groups for whom subsequent outcomes differed significantly. We can only speculate on whether this apparent equality of service delivery represents inequity in relation to need, or represents missed opportunities to prioritise available resources more efficiently and effectively. There is growing recognition of the potential benefits of person-centred rehabilitation programmes tailored around the needs and abilities of patients with multimorbidity. At least two feasibility trials have been conducted in this area, but definitive evidence to inform changes to existing models of care is lacking[27,28].

A recent Cochrane review of community interventions reported little to no change in subsequent health service use across 11 trials in people with multimorbidity[29]. Few of these studies specifically focussed on high-healthcare users and none included an intervention that specifically bridged hospital discharge back into community settings. There is evidence to support earlier initiation of more coordinated hospital discharge planning to reduce the risk of readmission for hospitalised older adults, many of whom will have multimorbidity[16]. It is perhaps surprising that in our multivariable models accounting for differences in demographics, length of stay and multimorbidity status, patients needing the most rehabilitation appeared at lower risk of readmission or reattendance than those in the middle tertile of contacts. This could reflect relative protection from readmission with higher quantities of rehabilitation, perhaps suggesting more comprehensively planned discharges. In contrast, increasing nursing contacts were consistently associated with reattendance and readmission risk, likely reflecting illness and disease burden.

In conclusion, we have described the high prevalence of multimorbidity in a large, consecutive and contemporary hospitalised population over 50 years old. We report consistent findings of increased healthcare utilisation and harms associated with multimorbidity, particularly amongst people with a high-count of conditions or combined physical and mental health problems. Our additional EHR contacts data reveals a significant burden of rehabilitation need amongst hospitalised patients with multimorbidity, but evidence that delivery of these services appears uniform rather than adapted by the risks observed in these data. Future data-driven models of care might offer more personalised approaches to target inpatient activity more effectively, such as by prediction of care needs early in a hospital admission.

Data availability

Data reported within this study were analysed through the DataLoch Secure Data Environment following the required approvals for access to unconsented, deidentified patient data. As such, these data cannot be made freely available, but researchers may independently apply for access (see https://dataloch.org/ for details). Furt her information or aggregate data may be made available upon reasonable request to the corresponding author.

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Author contributions

A.A. and K.G. conceived the study with review and refinement provided by J.M., S.D.S. and J.F. Additional data and interpretation review was provided by N.L., B.G. and J.A.J. Funding for this work was secured by A.A. and B.G. Application for data access was completed by K.G. with support from A.A. All authors reviewed and commented on the manuscript before submission.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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