Consumer segmentation and time interval between types of hospital admission: A clinical linkage database study

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Abstract

Background – Healthcare policies target unplanned hospital admissions and 30-day re-admission as key measures of efficiency, but do not focus on factors that influence trajectories of different types of admissions in the same patient over time.

Objectives – To investigate the influence of consumer segmentation and patient factors on the time intervals between different types of hospital admission.

Research design, subjects and measures – A cohort design was applied to an anonymised linkage database for adults aged 40 years and over (N=58,857). Measures included Mosaic segmentation, multimorbidity defined on six chronic condition registers, and hospital admissions over a 27-month time period.

Results – The shortest mean time intervals between two consecutive planned admissions were: 90 years and over (160 days (95% Confidence Interval 146-175)), Mosaic groups 'Twilight subsistence' (171 days (164-179)) or 'Welfare borderline' & 'Municipal dependency' (177 days (172-182)) compared to the reference Mosaic groups (186 days (180-193)), and multimorbidity count of four or more (137 days (130-145)).

Mosaic group 'Twilight subsistence' (Rate Ratio 1.22 (95% CI 1.08-1.36)) or 'Welfare borderline' & 'Municipal dependency' RR 1.20 (1.10-1.31) were significantly associated with higher rate to an unplanned admission following a planned event. However, associations between patient factors and unplanned admissions were diminished by adjustment for planned admissions.

Conclusions – Specific consumer segmentation and patient factors were associated with shorter time intervals between different types of admissions. The findings support innovation in public health approaches to prevention by a focus on long-term trajectories of hospital admissions, which include planned activity.

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Background

There is an enduring international policy interest in reducing the rising costs of hospital admissions and re-admissions by implementing timely and earlier care interventions based in the community.[1,2,3] Potential interventions could be targeted at any point including from the first hospital admission or for those patients who have recurrent admissions over time or targeting factors relating to the patient or clinical status and location of care.[4,5] Healthcare policy initiatives have targeted the reduction of unplanned hospital admissions through a focus on reducing 30-day re-admissions,[6,7] and prevention approaches have either tried to use social, clinical or healthcare indicators to target patients at higher risk of unplanned hospital admission.[4,8,9] However there is little current evidence on effective interventions to prevent unplanned hospital admissions. Developing effective interventions is likely to include (i) clear identification of the population at risk, (ii) identifying the appropriate teams co-ordinating the respective clinical pathway, and (ii) on-going assessment of interventions in preventing or reducing the risk of future hospital admissions.

Currently clinical and healthcare data identifies patients at risk but these could also be considerably enhanced by detailed consumer segmentation methods. An example, is the Mosaic geodemographic segmentation which has been used to profile populations in consumer marketing.[10] It is a broader area-based classification which uses residential postcodes to create profiles based on census, lifestyle, socio-economic and socio-cultural behaviour indicators. These are more likely to capture important determinants of health and lifestyles and with further stratification by clinical factors could provide novel methods for identification and new tailored interventions in preventing unplanned hospital admissions.

Hospital provision includes planned and unplanned activity, and recurrent admissions in a patient provide a window on the on-going potential impact of any interventions and longer-term outcomes. For example, the diabetes pathway care provision includes outpatient assessments, hospital reviews and elective admissions. The diabetic patient will also engage with community services, so developing broader interventions could integrate planned hospital care with community-based markers of patients at-risk of an unplanned admission.

Using a large anonymised database linking the Mosaic segmentation measure, socio-demographic data and six specified Long-Term Conditions (LTCs) to hospital admissions, we investigated how such factors influenced the time intervals between different types of consecutive hospital admissions. Specific factors influence the risk of unplanned hospital admission[4,8,9], but by investigating time intervals between repeated planned or unplanned admissions provides the opportunity for more detailed characterisation of the risk of admission. The null hypothesis then was that all consumer segmentation would have the same time intervals between different types of consecutive admissions and alternative hypothesis that planned hospital admission will increase the time or rate to an unplanned admission compared to two unplanned admissions.

Methods

Design

A cohort design nested in an anonymised clinical linkage database was used to investigate the population aged 40 years and over (N=58,857), with data available for a 27-month time-period to 31st March 2009. The Long-Term Condition (LTCs) registers were drawn from 53 Stoke-on-Trent general practices and linked to hospital admissions covering the same time period. The 40 year age threshold was chosen as the selected LTCs are more common from this age group and when hospital activity and admission escalates above this age.[11]

The provision of the database was made under Clinical Commissioning Group and Public Health governance agreements to support and evaluate local quality improvement programmes focusing on Long-Term Conditions and their outcomes. Linkage of the Mosaic segmentation, socio-demographic patient factors and LTC registers to hospital admissions for the same time period was done using the unique NHS number allocated to an individual patient prior to the provision of the anonymised data set for analyses.

Long-Term Condition (LTC) registers

The general practices had participated in national quality outcomes framework[12] and local quality improvement frameworks for specific LTCs, including hypertension, diabetes, ischaemic heart disease, chronic obstructive airways disease, chronic heart failure and chronic kidney disease to develop registers for their population. The standard UK Read classification[13] was used by clinicians to code the actual consultation, providing the individual LTC status for each patient, and this set of six conditions also identified patients with multimorbidity of two or more conditions.

Consumer segmentation

The Mosaic segmentation measure is based on individual patient residential post codes and relates to approximately 15 households, with individuals living in these households assigned the same Mosaic profiling category according to their 'average' characteristics.[10] The profiling is drawn from the 2011 UK census, lifestyle survey, consumer credit databases, the electoral roll, shareholder registers, land registry data, council tax information, the British Crime Survey, Expenditure and Food Survey and other sources. There are 61 distinct 'lifestyle types' which are aggregated into a main set of 11 lifestyle groups to describe the socio-economic and likely socio-cultural behaviours of populations.

Linked hospital admission data

Admissions were based on Hospital Episode Statistics (HES) in England, which contain records for all NHS admissions to any hospitals in each financial year. The data are means by which purchasing commissioning organisations arrange payment to the acute hospital providers[14] and linking these clinical databases allows the possible tracking of healthcare patterns of patient populations. Overall admissions types are either planned or unplanned and data included the date of admission and discharge allowing for the determination of time intervals between repeated consecutive admissions. There were in total 65,298 admissions in the study time window.

Statistical analyses

The overall study population is first described by age categorised as 40-49; 50-59; 60-69; 70-79; 80-89; and 90 years and over, gender, the 11 Mosaic groups, gender, six LTCs and up to six multimorbidity counts for admissions defined by planned only, unplanned only and patients who had both types of admissions.

For regression analysis, the 11 Mosaic groups were categorised into six ordinal groups because some were small in number. Re-categorisation was done by cross-tabulating with the mean Index of Multiple Deprivation score[15] for each of the 11 groups resulting in six ordinal groups starting from most affluent as follows: *(i)* A (symbols of success), B (happy families), C (suburban comfort) & K (rural isolation) as the most 'affluent' group; *(ii)* J (grey perspectives) as a single group; *(iii)* D (ties of community) as a single group; *(iv)* E (urban intelligence) & H (blue collar enterprise); *(v)* I (twilight subsistence) as a single group; and *(vi)* F (welfare borderline) & G (municipal dependency) as the most deprived group.

Multimorbidity was defined as four count categories of the six study LTCs (1, 2, 3 and 4 or more). Individual LTCs were excluded from regression analyses as they would correlate with the multimorbidity categories.

Cox regression was used to present associations between individual factors and hospital admissions in unadjusted analyses and then adjusting for the stated co-variates (age, gender, Mosaic groups and multimorbidity counts). These analyses included censored observations which is the time between the occurrence of the last event (a planned or unplanned admission) and the end of the study, and were adjusted to take account of possible multiple intervals for the same patient.[16]

The three nested structure analyses with time interval expressed as rate were as follows: (i) between two planned admissions, (ii) between two unplanned admissions and (iii) planned to unplanned admission, with rates adjusted for co-variates. Additional adjustment by the number of planned admissions was used to test the hypothesis that any planned care can impact on two unplanned admissions. Means and confidence intervals adjusted for possible multiple observations on the same patients are presented where there were at least two admissions. Rate ratios are presented with two-tailed significance level testing at 5% using Stata 13 and no adjustments were made for multiple testing.

Results

Overall type of admissions

In the ‘youngest’ age group 40 to 49 years, 15% had planned hospital admissions only but 9% an unplanned admission only (**Table 1**). The respective planned admissions only and ‘both types’ figures for 80 to 89 years were 10% and 17%, and for 90 years and over 3% and 10%. The respective figures for men and women were similar. The Mosaic groups with the highest proportion of planned hospital admissions only were ‘suburban comfort’ (group C - 18%) and ‘symbols of success’ (group A - 17%) with figures for ‘both type’ of admissions at 11% and 9% respectively. The Mosaic groups with the lowest proportion of planned admissions only were ‘welfare borderline’ (group F- 14%) and ‘twilight subsistence’ (group I - 15%) with figures for ‘both type’ of admissions at 13% and 16% respectively.

Coronary heart disease (CHD) group had the highest proportion of planned admissions only (17%) and the figure for ‘both’ type of admissions was 17%. Chronic heart failure (CHF) had the lowest proportion of planned admissions only (10%) and the figure for ‘both’ type of admission was 21%. CHF and Chronic Obstructive Pulmonary Disease (COPD) had the highest levels of unplanned admissions (19%). The proportion of planned admissions only decreased with increasing multimorbidity count but the proportion with ‘both’ type of admissions in contrast increased (**Table 1**). For the group with a single count of the study specified LTCs, the proportion with planned hospital admissions only was 16% and 9% who also had unplanned admissions only, and the respective figures for the multimorbid group with 5 counts were 10% and 25%.

Study factors and time intervals

Increasing age was associated with decreased time intervals between two planned admissions, with a mean time interval of 200 days (95% confidence intervals 190 to 210 days) for the 40 to 49 year age group compared to 160 days (95% CI 146-175) for the age group 90 years and over (**Table 2**). The mean time intervals for women and men were similar. Compared to most 'affluent' Mosaic groups, all other groups with the exception of E & H had shorter mean time intervals between two planned hospital admissions. The respective mean time intervals for the 'most' deprived Mosaic groups I or F&G were 171 days (95% confidence intervals 164-179) and 177 days (172-182) respectively compared to the reference group of 186 days (180-193). The mean time interval for the multimorbidity count group 4 or more was 137 days (130-145) compared to reference group of one at 192 days (187-196).

The time intervals for two unplanned (**Table 3**) and planned to unplanned admissions (**Table 4**) were respectively as follows: a mean time interval of 102 *vs* 133 days for the 40 to 49 year age group compared to 89 *vs* 143 days for the age group 90 years and over; 94 *vs* 136 days for women and 93 *vs* 124 days for men; 88 *vs* 140 days for Mosaic group I and 94 *vs* 130 days for F&G compared to the reference group of 88 *vs* 127 days. The respective figures for the multimorbidity count group 4 or more were 81 *vs* 116 days respectively.

Associations between study factors and time intervals

After adjusting for age, gender, Mosaic groups and multimorbidity counts, the associations between age and higher rate of two unplanned hospital admissions were significant for the age groups 70 to 79 years (Rate Ratio 1.42 (95% CI 1.21-1.68)), 80 to 89 years (2.55 (2.04-3.18)) and 90 years and over (2.54 (2.04-3.18)) compared to the reference youngest age group (**Table 3**). There were no significant differences for gender. All five study-defined

Mosaic groups were significantly associated with higher rate of two unplanned hospital admissions compared to the reference group. The associations between Mosaic groups I ('Twilight subsistence') or F&G ('Welfare borderline' & 'Municipal dependency') and rate of two unplanned hospital admissions compared to the reference category were respectively RR 1.73 (95% confidence interval 1.52-1.98) and 1.56 (1.39-1.75). All multimorbid groups compared to the single morbidity group were significantly associated with shorter time intervals between two unplanned admissions. The adjusted estimates of associations were: 2 multimorbid counts (1.37, 1.25-1.49), 3 counts (1.89, 1.71-2.08) and 4 counts or more (RR 2.88 (2.55-3.26).

The adjusted associations between age and rate of an admission from planned to unplanned admissions were significant for the age groups 60 to 69 years (RR 1.17 (1.04-1.32)), 70 to 79 years (1.46, 1.30-1.64) and 80 to 89 years (1.50, 1.33-1.71) (**Table 4**). Women were significantly more likely to have a longer time interval between a planned and an unplanned admission than men (0.92, 0.86-0.97). Of the Mosaic groups, the only significant associations were for the 'most' deprived Mosaic groups I (1.22, 1.08-1.36) and F&G (1.20, 1.10-1.31) with a higher rate from a planned to an unplanned admission compared to the reference category. All multimorbid groups compared to the single morbidity group were significantly associated with shorter time intervals. The adjusted estimates of associations were: 2 multimorbid counts (1.32, 1.23-1.42), 3 counts (1.83, 1.68-1.99) and counts 4 or more (RR 2.34 (2.10-2.60)). After adjustment for any number of planned admissions the strengths of these associations diminished but remained statistically significant, with exception of Mosaic group J (**Supplementary Table**).

Discussion

Main findings of this study

This large population-based study over the two and half year time-period showed that older age, deprived Mosaic status and higher multimorbidity were associated with a lower proportion of planned admissions and higher proportion of planned and unplanned hospital admissions. 'Welfare borderline' and 'Twilight subsistence' group had the highest proportion of both planned and unplanned hospital admissions. The LTC population type showed different hospital admission types, with CHD populations showing more planned hospital admission whereas CHF and COPD populations experiencing more unplanned hospital admissions.

When the time interval between two planned admissions was measured, the range was from 5 months for the oldest age group to 7 months for the youngest age group. The average time interval was 6 months when stratified by Mosaic groups. The time interval ranged from 4 months for the multimorbid group with a count of four or more, to 6 months for a count of one condition. Time intervals by gender were similar.

Older age and specific Mosaic groups were significantly associated with an increased rate of two unplanned hospital admissions. The average time interval between unplanned admissions was 3 months, with around 15 days difference between youngest and oldest age group, around 1 week between different Mosaic groups, but almost 2 weeks between the highest and lowest multimorbidity count group. The time interval for women and men was similar. Older age and specific Mosaic groups were significantly associated with an increased rate of consecutive planned to unplanned hospital admission. The average time interval between was over 4 months, with around 10 days difference between youngest and oldest age group, around 3 weeks between different Mosaic groups, and 2 weeks between the highest and lowest multimorbidity count group. Men also had a time interval 2 weeks shorter than women.

What is already known on this topic

Older age, deprivation and long-term conditions (LTCs) including ambulatory care sensitive conditions[17] and healthcare indicators such as different types or frequency of contact have been shown to increase the risk of unplanned admission.[18,19] These indicators are being combined as risk stratification scores to identify populations at risk.[20] However, the impact of these approaches is modest and critical gaps in better identification and tailoring interventions remains to be established.[21] These novel segmentation measures provide the potential routes to both identification and implementation of tailored interventions through profiles of a person's 'consumer behaviour'.

What this study adds

The healthcare implications of the findings are three fold. First, the results highlight the potential of consumer segmentation to identify patients at higher risk of a subsequent hospital admission, especially unplanned admissions, and adjusting for other factors. Whilst the current focus on risk stratification methods which incorporate social, clinical and healthcare factors[8,10] is likely to remain important, the addition of segmentation measure offers the potential interventions through targeting of behaviours and 'consuming' lifestyle.[22,23,24] Such interventions have been used in United States approaches to improve exercise activity and reduce smoking levels.[25] Second, linking time intervals between planned and unplanned admission status offers an alternative to the focus on 30-day re-admission. Whilst the 30-day interval offers a convenient target from a hospital perspective, our method provides the longer-term perspective on linked hospital admissions. Hospital engagement, especially unplanned activity, requires pro-active longer-term engagement and co-ordination of the different pathways (community, interface and hospital) rather than short-term intensive interventions, which have little impact on the rise in admissions.[26,27] Third, our study shows that higher multimorbidity was associated with shorter time intervals between admissions, less planned activity, but more unplanned admissions. Combined with segmentation, the type and nature of multimorbidity may provide additional approaches for clinically-specific interventions.[28,29]

Limitations of this study

The strength of the study is in linking the richness of socio-demographic profiles to LTCs derived from Quality Outcomes Framework registers, to hospital admissions data, for a large regional population. The socio-demographic profiles were based on an internationally used classification, the recording of LTCs in primary care is almost fully recorded, and since hospitals are paid by episodes, the simple descriptors of 'planned' and 'unplanned' is likely to be accurate. We had to group individual Mosaic segments into groups due to sample size considerations and ranked by deprivation, however, the study showcases the usefulness of segmentation for translating into individual segments for fuller consumer profiles. Additionally, our analyses did not incorporate general practice-level measures such as access and continuity of care which may also explain variations in admissions.[30] The limitation of interpretation in time intervals is the precise nature of planned admissions and how or whether it links to subsequent type of unplanned admissions. However, the current analyses show the potential utility of linking such information. We employed a relatively simple approach in this study which sampled defined time windows in each patient as a basis of outcome measurement and further work needs to address the fact patients may have multiple planned and unplanned admissions. Finally, such linkage approaches in clinical practice are becoming routine, so that it will be feasible to develop better interventions to reduce unplanned hospital admission or re-admission.[31,32]

Conclusions

Our study shows that deprived segmentation profiles were associated with shorter time interval between two consecutive unplanned hospital admissions and also between planned to unplanned hospital admissions compared to the affluent Mosaic groups. Older age, specific LTC multimorbidity also showed similar outcomes in terms of shorter time intervals.

The potential of this work is in terms of developing innovative public health approaches to admission prevention, shifting the target from 30-day re-admission to time intervals in long-term care, and developing interventions at the point of planned hospital admission.

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Table 1: Socio-demographic characteristics of the study population and hospital admissions

Groups	Number	None (%) n=34,810	Hospital admissions Planned only (%) n=9635	Unplanned only (%) n=7385	Both (%) n=7027
Age (years)					
40-49	7017	4730 (67.4)	1052 (15.0)	636 (9.1)	599 (8.5)
50-59	12961	8489 (65.5)	2264 (17.5)	1119 (8.6)	1089 (8.4)
60-69	15880	9608 (60.5)	3041 (19.1)	1489 (9.4)	1742 (11.0)
70-79	14238	7439 (52.2)	2479 (17.4)	2123 (14.9)	2197 (15.4)
80-89	7690	3862 (50.2)	769 (10.0)	1761 (22.9)	1298 (16.9)
90+	1071	682 (63.7)	30 (2.8)	257 (24.0)	102 (9.5)
Gender					
Men	28015	16802 (60.0)	4525 (16.2)	3362 (12.0)	3326 (11.9)
Women	30842	18008 (58.4)	5110 (16.6)	4023 (13.0)	3701 (12.0)
Mosaic segmentation					
Symbols of success (A)	1132	728 (64.3)	194 (17.1)	105 (9.3)	105 (9.3)
Happy families (B)	2987	1913 (64.0)	498 (16.7)	259 (8.7)	317 (10.6)
Suburban comfort (C)	6517	3980 (61.1)	1201 (18.4)	630 (9.7)	706 (10.8)
Ties of community (D)	19486	11937 (61.3)	3145 (16.1)	2286 (11.7)	2118 (10.9)
Urban intelligence (E)	300	184 (61.3)	48 (16.0)	33 (11.0)	35 (11.7)
Welfare borderline (F)	1516	865 (57.1)	209 (13.8)	239 (15.8)	203 (13.4)
Municipal dependency (G)	13160	7389 (56.1)	2122 (16.1)	1836 (14.0)	1813 (13.8)
Blue collar enterprise (H)	6372	3760 (59.0)	1064 (16.7)	822 (12.9)	726 (11.4)
Twilight subsistence (I)	3705	1855 (50.1)	569 (15.4)	678 (18.3)	603 (16.3)
Grey perspectives (J)	2553	1496 (58.6)	409 (16.0)	359 (14.1)	289 (11.3)
Rural isolation (K)	1129	703 (62.3)	176 (15.6)	138 (12.2)	112 (9.9)
Long-Term conditions					
Hypertension	46433	27818 (59.9)	7712 (16.6)	5584 (12.0)	5319 (11.5)
Diabetes	13741	7756 (56.4)	2316 (16.9)	1785 (13.0)	1884 (13.7)
Coronary Heart Disease	13708	6654 (48.5)	2327 (17.0)	2337 (17.0)	2390 (17.4)
COPD	6774	3302 (48.7)	987 (14.6)	1285 (19.0)	1200 (17.7)
CHF	3262	1541 (47.2)	327 (10.0)	709 (21.7)	685 (21.0)
CKD	11754	6056 (51.5)	1733 (14.7)	2005 (17.1)	1960 (16.7)

Multimorbidity count					
1	33433	21527 (64.4)	5457 (16.3)	3397 (10.2)	3052 (9.1)
2	16817	9393 (55.9)	2897 (17.2)	2318 (13.8)	2210 (13.1)
3	6316	2944 (46.6)	1017 (16.1)	1132 (17.9)	1223 (19.4)
4	1845	771 (41.8)	223 (12.1)	424 (23.0)	427 (23.1)
5	399	156 (39.1)	38 (9.5)	104 (26.1)	101 (25.3)
6	47	20 (42.6)	3 (6.4)	10 (21.3)	14 (29.8)

Table 2: Study factors associations with time intervals between any two planned admissions

Factors	Categories (n)	Time Interval (days)		Rate Ratio	Rate Ratio
		Days (SE)	**95% CI**	**Unadjusted (95% CI)**	**Adjusted‡ (95%CI)**
Age groups (years)	40-49 (599)	200 (5.3)	190-210	1.0	1.0
	50-59 (1089)	194 (3.8)	187-202	1.09 (1.01-1.12)	1.04 (0.99-1.09)
	60-69 (1742)	180 (2.8)	174-185	1.32 (1.23-1.41)	1.18 (1.13-1.24)
	70-79 (2197)	176 (2.3)	171-180	1.55 (1.45-1.65)	1.46 (1.39-1.54)
	80-89 (1298)	171 (2.5)	166-175	1.56 (1.47-1.67)	1.61 (1.52-1.70)
	90+ (102)	160 (7.2)	146-175	1.27 (1.13-1.41)	1.22 (1.09-1.37)
Gender	Men (3326)	178 (2.0)	174-182	1.0	1.0
	Women (3701)	184 (1.8)	180-187	0.97 (0.94-1.00)	0.98 (0.96-1.00)
Mosaic Groups*	A, B, C, K (1240)	186 (3.3)	180-193	1.0	1.0
	J (289)	181 (6.7)	168-194	1.08 (0.99-1.18)	1.04 (0.98-1.12)
	D (2118)	180 (2.5)	176-185	1.06 (1.00-1.11)	1.03 (0.99-1.07)
	E, H (761)	190 (4.4)	182-199	1.04 (0.98-1.11)	1.08 (1.02-1.13)
	I (603)	171 (3.8)	164-179	1.34 (1.26-1.42)	1.29 (1.21-1.36)
	F, G (2016)	177 (2.4)	172-182	1.20 (1.15-1.26)	1.17 (1.12-1.21)
Multimorbidity Count	1 (3052)	192 (2.2)	187-196	1.0	1.0
	2 (2210)	183 (2.4)	178-188	1.24 (1.20-1.29)	1.24 (1.20-1.28)
	3 (1223)	166 (2.9)	160-172	1.58 (1.52-1.65)	1.58 (1.52-1.65)
	4 or more (542)	137 (3.7)	130-145	1.97 (1.86-2.08)	1.91 (1.80-2.03)

‡Adjusted for other co-variates; *Mosaic group ordered with category A, B, C, K most affluent; total number of defined intervals = 17,486

Table 3: Study factors associations with time intervals between two unplanned admissions

Factor	Category (n)	Time Interval (days)		Rate Ratios	Rate Ratios
		Days (SE)	95% CI	Unadjusted (95% CI)	Adjusted[‡] (95%CI)
Age groups (years)	40-49 (807)	102 (6.1)	90-114	1.0	1.0
	50-59 (1309)	95 (4.4)	86-104	0.86 (0.72-1.03)	0.81 (.67-0.97)
	60-69 (2215)	98 (3.6)	90-105	1.12 (0.94-1.32)	0.96 (0.81-1.13)
	70-79 (3781)	94 (2.4)	89-98	1.89 (1.61-2.21)	1.42 (1.21-1.68)
	80-89 (3270)	88 (2.4)	83-93	2.91 (2.49-3.40)	2.55 (2.04-3.18)
	90+ (427)	89 (6.8)	76-102	3.22 (2.60-3.98)	2.54 (2.04-3.18)
Gender	Men (5368)	93 (2.1)	89-97	1.0	1.0
	Women (6441)	94 (1.9)	90-97	1.06 (0.99-1.14)	0.94 (0.88-1.01)
Mosaic Groups*	A, B, C, K (1597)	88 (3.6)	81-95	1.0	1.0
	J (555)	97 (6.0)	86-109	1.55 (1.31-1.83)	1.26 (1.07-1.48)
	D (3466)	96 (2.5)	91-101	1.29 (1.15-1.45)	1.26 (1.12-1.41)
	E, H (1207)	97 (4.0)	89-105	1.29 (1.13-1.48)	1.20 (1.05-1.37)
	I (1375)	88 (3.7)	81-95	2.39 (2.09-2.73)	1.73 (1.52-1.98)
	F, G (3609)	94 (2.8)	88-99	1.71 (1.52-1.92)	1.56 (1.39-1.75)
Multimorbidity Count	1 (4304)	96 (2.3)	91-100	1.0	1.0
	2 (3658)	95 (2.5)	90-100	1.57 (1.44-1.71)	1.37 (1.25-1.49)
	3 (2347)	94 (3.1)	88-100	2.44 (2.23-2.68)	1.89 (1.71-2.08)
	4 or more (1500)	81 (3.7)	73-88	3.97 (3.53-4.46)	2.88 (2.55-3.26)

[‡]Adjusted for other co-variates; *Mosaic group ordered with category A, B, C, K most affluent; total number of defined intervals = 11,809

Table 4: Study factors association with time intervals between planned to unplanned admissions

Factor	Category (n)	Time Interval (days)		Rate Ratios	Rate Ratios
		Days (SE)	95% CI	Unadjusted (95% CI)	Adjusted‡ (95%CI)
Age groups (years)	40-49 (448)	133 (7.8)	118-149	1.0	1.0
	50-59 (841)	134 (5.5)	123-145	1.00 (0.88-1.14)	0.95 (0.84-1.08)
	60-69 (1441)	118 (4.2)	110-125	1.33 (1.18-1.50)	1.17 (1.04-1.32)
	70-79 (1865)	132 (3.7)	125-139	1.81 (1.61-2.02)	1.46 (1.30-1.64)
	80-89 (1064)	139 (5.0)	129-149	1.90 (1.69-2.15)	1.50 (1.33-1.71)
	90+ (82)	143 (20.7)	103-184	1.26 (0.98-1.63)	1.06 (0.82-1.37)
Gender	Men (2785)	124 (2.9)	118-130	1.0	1.0
	Women (2956)	136 (3.1)	130-142	0.95 (0.90-1.01)	0.92 (0.86-0.97)
Mosaic Groups*	A, B, C, K (982)	127 (5.0)	117-137	1.0	1.0
	J (217)	120 (10.0)	100-139	1.01 (0.85-1.19)	0.91 (0.77-1.07)
	D (1797)	132 (3.9)	125-140	1.10 (1.01-1.20)	1.08 (0.99-1.18)
	E, H (598)	125 (5.9)	113-136	1.04 (0.93-1.16)	0.99 (0.89-1.11)
	I (502)	140 (8.1)	124-156	1.49 (1.32-1.68)	1.22 (1.08-1.36)
	F, G (1645)	130 (3.9)	122-138	1.28 (1.18-1.40)	1.20 (1.10-1.31)
Multimorbidity Count	1 (2329)	132 (3.4)	125-139	1.0	1.0
	2 (1783)	133 (3.9)	125-140	1.43 (1.34-1.53)	1.32 (1.23-1.42)
	3 (1076)	130 (4.6)	121-139	2.10 (1.94-2.27)	1.83 (1.68-1.99)
	4 or more (553)	116 (6.0)	104-128	2.79 (2.53-3.09)	2.34 (2.10-2.60)

‡Adjusted for other co-variates; *Mosaic group ordered with category A, B, C, K most affluent; total number of defined intervals = 5,741

Supplementary Table: Study factors and two unplanned admissions adjusting for planned admissions

Factor	Category (n)	Time Interval (days)		Rate Ratios	Rate Ratios
		Days (SE)	95% CI	Adjusted‡ (95%CI)	Adjusted‡‡ (95%CI)
Age groups (years)	40-49	621	609-633	1.0	1.0
	50-59	628	619-637	0.92 (0.84-1.00)	0.94 (0.87-1.00)
	60-69	583	575-592	1.07 (0.99-1.16)	1.02 (0.95-1.01)
	70-79	495	488-503	1.45 (1.34-1.57)	1.22 (1.14-1.30)
	80-89	450	441-458	1.71 (1.57-1.85)	1.41 (1.32-1.51)
	90+	517	493-542	1.39 (1.22-1.58)	1.31 (1.17-1.47)
Gender	Men	552	547-558	1.0	1.0
	Women	540	534-545	0.98 (0.94-1.01)	1.00 (0.98-1.04)
Mosaic Groups*	A, B, C, K	593	584-602	1.0	1.0
	J	539	521-557	1.10 (1.01-1.21)	1.07 (0.99-1.16)
	D	565	558-572	1.12 (1.06-1.18)	1.06 (1.01-1.12)
	E, H	555	544-566	1.12 (1.05-1.20)	1.06 (1.00-1.12)
	I	456	442-469	1.44 (1.34-1.55)	1.23 (1.16-1.31)
	F, G	514	507-523	1.32 (1.25-1.40)	1.18 (1.12-1.24)
Multimorbidity Count	1	647	641-652	1.0	1.0
	2	562	553-571	1.36 (1.30-1.43)	1.15 (1.11-1.20)
	3	457	445-470	1.87 (1.77-1.98)	1.31 (1.26-1.38)
	4 or more	356	338-375	2.52 (2.34-2.71)	1.54 (1.45-1.64)

‡Adjusted for other co-variates; ‡‡Adjusted additionally for number of planned admissions; *Mosaic group ordered with category A, B, C, K most affluent

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