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Effectiveness of a population-based integrated care model in reducing hospital activity: an interrupted time series analysis

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ABSTRACT

Objectives First impact assessment analysis of an integrated care model (ICM) to reduce hospital activity in the London Borough of Hillingdon, UK.

Methods We evaluated a population-based ICM consisting of multiple interventions based on self-management, multidisciplinary teams, case management and discharge management. The sample included 331 330 registered Hillingdon residents (at the time of data extraction) between October 2018 and July 2020. Longitudinal data was extracted from the Whole Systems Integrated Care database. Interrupted time series Poisson and Negative binomial regressions were used to examine changes in non-elective hospital admissions (NEL admissions), accident and emergency visits (A&E) and length of stay (LoS) at the hospital. Multiple imputations were used to replace missing data. Subgroup analysis of various groups with and without long-term conditions (LTC) was also conducted using the same models.

Results In the whole registered population of Hillingdon at the time of data collection, gradual decline over time in NEL admissions (RR 0.91, 95% CI 0.90 to 0.92), A&E visits (RR 0.94, 95% CI 0.93 to 0.95) and LoS (RR 0.93, 95% CI 0.92 to 0.94) following an immediate increase during the first months of implementation in the three outcomes was observed. Subgroup analysis across different groups, including those with and without LTCs, showed similar effects. Sensitivity analysis did not show a notable change compared with the original analysis.

Conclusion The Hillingdon ICM showed effectiveness in reducing NEL admissions, A&E visits and LoS. However, further investigations and analyses could confirm the results of this study and rule out the potential effects of some confounding events, such as the emergence of COVID-19 pandemic.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ In many countries, including England, integrated care models (ICMs) have become the cornerstone of policy responses to growing pressure on health services, especially hospital activities.
⇒ The tendency has been towards broader population-based approaches to implement different models across the entire population rather than individual or disease-specific models.
⇒ New population-based ICMs in England implemented under the 'vanguard' initiative showed promising results in slowing non-elective hospital admissions.

WHAT THIS STUDY ADDS

⇒ Population-based ICMs could effectively reduce hospital activity in a general population and across different groups with various conditions.
⇒ ICMs should not be expected to work straight after implementation.
⇒ Accident and emergency visits could be considered an outcome of interest while evaluating such models.
⇒ Assessing the effects of such models on populations with various conditions could examine the requirement of implementing additional condition-specific models to increase effectiveness.
⇒ COVID-19 might be considered a significant factor contributing to changes in hospital utilisation outcomes.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ This evaluation can provide insights into the short-term effectiveness of population-based ICMs delivered to general populations, particularly in Hillingdon.
⇒ This study can assist in informing and improving future evaluations of population-based ICMs in Hillingdon and provide an epitome for other contexts.

INTRODUCTION

The increasing number of older populations with multiple long-term conditions (LTCs) imposes significant pressure on most health services across England, including the London borough of Hillingdon.[1] According to the latest data from the office for national statistics in England, 13.3% of the population of Hillingdon are over 65 years of age and this was estimated to increase by 19% in 2024.[2] Hillingdon has a higher prevalence of multiple LTCs compared with London

as a whole. For example, hypertension and diabetes in 2018 were 12.52% and 7.43%, around 2.50% and 1% higher than London's, respectively.[3] Approximately 34 000 (15%) of the population in Hillingdon have a life-limiting or long-term illness, with around 6417 individuals accounting for 50% of all non-elective hospital admissions (NEL admissions).[4]

According to internal unpublished data reported by Hillingdon Health and Care Partners (HCPP), within this cohort, at least 21% of these admissions were in some way sensitive to ambulatory care and, therefore, potentially avoidable. In line with the same data, unplanned admissions for adults with chronic ambulatory care sensitive conditions is above the England average and 46% higher than the best five clinical commission groups (CCGs) nationally. Also, individuals with such characteristics have higher rates of accident and emergency (A&E) attendances[5] and more extended stays at hospitals.[6] Because of the pressures mentioned above, Hillingdon providers and commissioners reported that the health and social care system is becoming increasingly unsustainable. If working practices do not change, the financial situation will deteriorate to a £151 million deficit by 2023/2024 if no action is taken.

Reducing hospital activity could relieve the pressure on services quickly approaching their maximum limits.[1] Accordingly, integrated care models (ICMs) have become the cornerstone of the policy response in many countries, including England.[1 7 8] ICMs facilitate more contact with patients in primary care, community or even in their homes. ICMs aim to deliver the proper care and improve patients' experience through better coordination between and across settings.[9] Consequently, providing patients with person-centred and integrated quality of care in different settings, including their homes, could relieve the pressure on health services and reduce hospital activity.[8]

New ICMs are inclined toward focusing on single-disease management models with case management (CM) approaches.[10] However, those approaches had minor effects on utilisation.[11] More lately, the tendency has been towards broader population-based approaches to implement different models across the whole population.[12] Such approaches tend to focus on scaling up patient-centred and prevention-based approaches, and a recent evaluation of such ICMs in England showed promising results.[13] Besides, evidence suggests that combining multiple integrated care interventions (ICIs) could produce better results. For example, more positive results were seen when self-management (SM) was incorporated into multidisciplinary teams (MDTs) care or individualised patient education was included in discharge planning.[8] While most interventions are inclined toward targeting patients with specific LTCs,[8 14–16] there is currently a lack of evidence on whether combining various interventions in one ICM will achieve the intended outcomes in general populations.

In this connection, we conducted an interrupted time series (ITS) analysis to evaluate a new population-based ICM combining multiple ICIs for effectiveness in reducing hospital activity. The HCPP implemented the model in October 2019. Outcomes assessed included: NEL admissions, A&E attendances and length of stay (LoS) at hospitals.

DATA AND METHODS
Description of the intervention
The HCPP ICM consists of two main models, including the Neighbourhood Teams and Intermediate Tier (IT) (figure 1). This model consists of eight neighbourhoods with several general practitioner (GP) surgeries in each neighbourhoods. The model is designed for GPs to work holistically with different teams, including MDTs and care connection teams (CCTs). MDTs consist of multiple HCPs, including pharmacists, mental health practitioners and social workers, working together with CCTs. These teams are responsible for proactively identifying individuals at high risk of A&E attendance and/or hospital admission, providing long-term care, assessing their needs and developing personalised care plans with the goal of enabling patients to manage their own conditions.

The IT model aims to provide a range of time-limited (up to 6 weeks) integrated health and social care services. Those services can be divided into two main categories, including home/community-based ((1) intermediate home-based services, (2) home from hospital (HFH) (3) (GP visiting) and intermediate community bed based) and hospital based ((1) ambulatory emergency care unit (AECU), (2) rapid assessment medical unit (RAMU) and (3) frailty unit). Most services aim for discharge management (DM), providing early discharge support for people recovering from an illness. Other services, including hospital based, aim to streamline intermediate care and hospital 'front door' and 'back door' services into a coherent service.

Lastly, the model includes A 24/7 single point of coordination (SPoC) accessible through a medical information system or by direct dial is proposed to assist health and social care professionals arrange the proper care for all urgent and non-urgent referrals. The SPoC should facilitate better communication between MDTs and GPs across different settings to manage patients with LTCs in the community at the neighbourhood level.

The HCPP ICM is designed to target three primary outcomes, including NEL admissions, A&E visits and LoS at the hospital. The model is expected to reduce these outcomes by providing personalised care plans (MDT, SM and CM) to increase the quality of care to patients, especially those at high risk of unplanned admissions. Besides, the model is also expected to provide hospital and home-based integrated health and social care services (DM) to promote faster recovery from illness, prevent unnecessary acute hospital admission and reduce the LoS at the hospital.
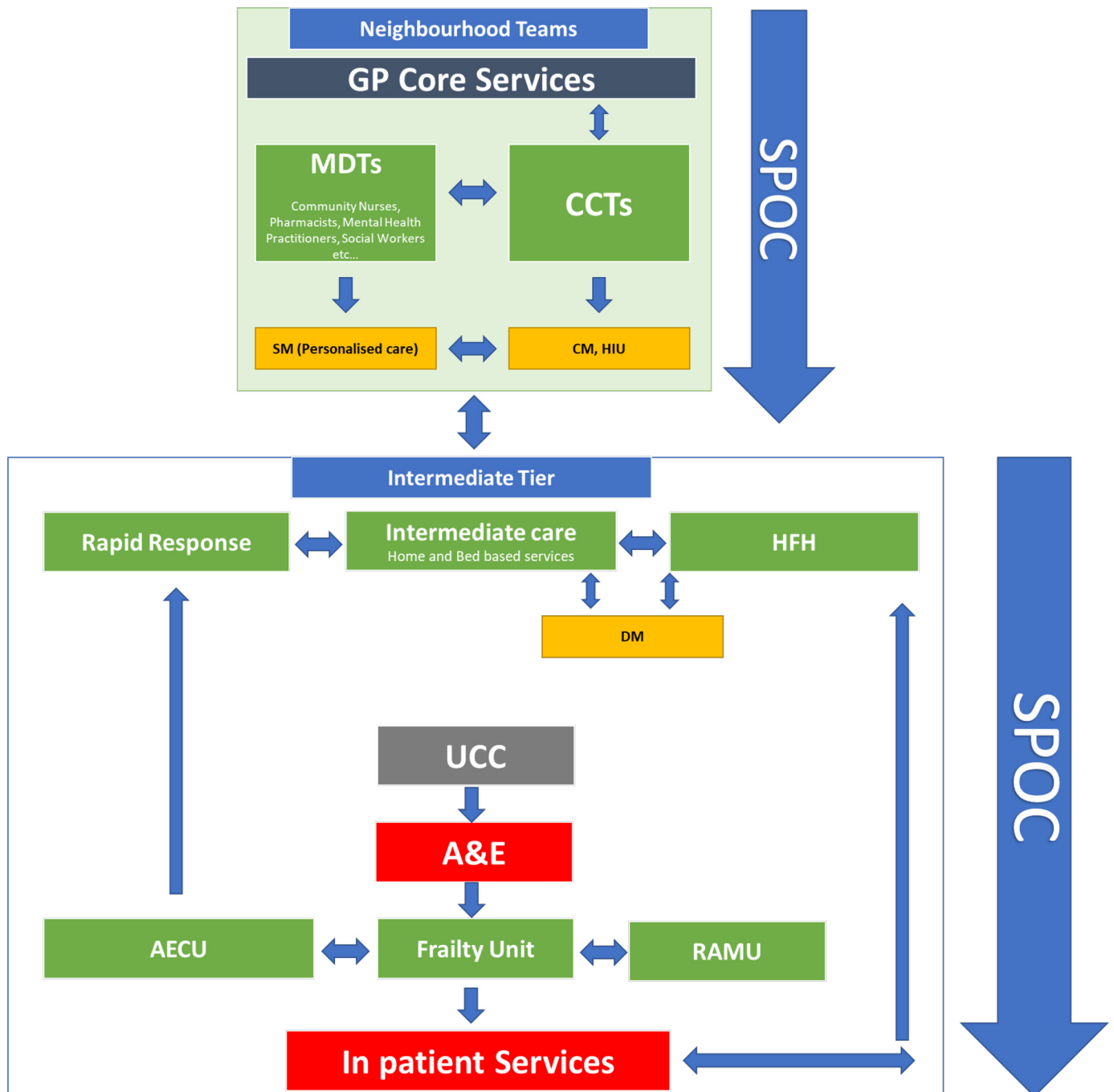
Figure 1 The Hillingdon Health and Care Partners (HCPP) integrated care model. List of Abbreviations: GP, general practitioner; A&E accident and emergency; AECU ambulatory emergency care unit; CCTs, care connection teams; CM, case management; DM, discharge management; HFH, hospital from home; HIU, high-intensity user; MDTs, multidisciplinary teams; RAMU, rapid assessment medical unit; SM, self-management; SPOC, single point of coordination; UCC, urgent care centre.

Data

Data used came from the Whole Systems Integrated Care (WSIC) database (Discover Now Project[17]) provided by the North-West London CCG business intelligence team from October 2018 to July 2020. Structured Query Language algorithms were adopted to extract the data. The data also included demographic characteristics of patients, including age, gender and ethnicity. Data was provided as an individual-level panel dataset and was analysed as so to prevent aggregation bias.[18 19] However, data was also analysed in its aggregative form to plot predicted regression curves.

Patient and public involvement

The data was analysed in a deidentified environment (WSIC servers). Only the first (MHHM) and the third authors (MB) had access to the server. Patients were given pseudo-IDs, and there was no risk of identification neither in the dataset nor the analysis outcomes. The

details of our assessment were shared with Hillingdon policy-makers in many meetings.

Statistical analysis

The analysis was performed in Stata: Software for Statistics and Data Science. Data integrity was checked, and missing data were identified. Multiple imputations (MI) (n=5) by chained equations were used to replace missing data.[20] Imputation models used ordinal logistic regression to predict missing values in LTC and ethnicity based on the three dependent variables (outcomes) separately, including NEL admissions, A&E visits and LoS at the hospital.

ITS Poisson and Negative binomial models (Only for LoS),[21] with random effects estimator, predicted the change in the outcomes adjusting for gender, age, ethnicity and LTC. Robust standard errors (Huber-White) were obtained for the regression parameters to account for potential serial correlation and overdispersion check. We used periodic functions to control potential seasonality and long-term trends.[22] The choice of the models for each outcome was informed by the robust SE estimators in addition to means and variances (see online supplemental table 5). Generalised linear models (ITS) with Poisson and Negative binomial extensions were adopted for plotting regression curves and analysing data in its aggregative form.

To achieve the ITS model, the following segmented regression model was used:

$$Y_t = \beta_0 + \beta_1 T + \beta_2 X_t + \beta_3 TX_t$$

We defined independent variables T_t (from October 2018 to July 2020) as the time elapsed from the start until the end of the study and X_t as a dummy variable to indicate the preintervention period ($X_t = 0$) or the postintervention period ($X_t = 1$). $T_t = 13$ (October 2019) was defined as the time of implementation of the intervention. Also, the variable T_t represented the change in rate over each month. The β_2 coefficient was defined as the level of change following the intervention and represented the immediate effect (IE) (using $\beta_2 X_t$). Using the interaction between T_t and X_t (TX_t), the β_3 coefficient was defined as the level of change following the intervention and represented the effect over time.

We undertook further subgroup analysis to examine the effect of the intervention on the outcomes within diverse populations, with or without LTCs. Groups were defined as: with LTC, without LTC, cardiovascular disease (CVD), hypertension, asthma, chronic obstructive pulmonary diseases (COPD), diabetes, cancer, multimorbid (more than one condition) and other conditions (eg, rheumatoid arthritis, neurological disorders and thyroid conditions).

Sensitivity analysis examined the effect of missing data replacement by comparing raw and imputed datasets. Also, we examined the effect of potential confounders by removing them from the model. The coefficients estimated for the GLM analysis were also compared with the preliminary modelling results. See online supplemental material for sensitivity analysis output.

RESULTS

Description of the sample

We analysed a sample of n=331 330 individuals registered in the London borough of Hillingdon (UK) when the data was extracted (online supplemental table 7). Most individuals were under 65 years of age (84%). Men were more than women by 2%. The population was predominantly white with 46%, followed by Asian (28%) and black (7%). Only 1% of the data in this category was missing. Overall, 36% of the population had one or more LTC. Patients with multimorbidity accounted for 14% of the population. Like ethnicity, this category also included missing data (6%). MI was used to replace missing data in both categories. Demographic data were the same after implementing the intervention compared with before implementation suggesting the absence of lose to follow-up.

Description of the outcomes by the sample

The total number of NEL admissions from the start until the end of the study was 43 680. Patients with LTCs accounted for most admissions (66%) (table 1). Also, patients with multimorbidies accounted for most admissions with 37% (55% of patients with LTC). The total number of A&E visits was 212 180. Individuals with no LTCs accounted for most attendances (53%). Similarly, individuals with multimorbidies accounted for most visits with 25% (47% of patients with LTC). Finally, patients spent a total of 178 784 days at the hospital from October 2018 to July 2020. Patients with LTCs spent around 68% more days at the hospital compared with individuals with no history of LTCs. Patients with multimorbidies were also the most in spending time at the hospital overall, with 44% (approximately 53% compared with other LTC groups). In general, outcomes across all groups were lower in number after implementing the intervention than before implementation.

Effects on outcomes

Figure 2 summarises the change in rates before and after the intervention on a monthly basis, together with the predicted regression curves. We observed a gradual decline over time in the three outcomes' rates following an immediate increase in the first month of implementation. The immediate increase in the three outcomes rates, as in rate ratios (RR), was not statistically significant when the data was analysed in its aggregative form (online supplemental table 4). However, this was not the case for the original regression analysis undertaken on the individual level panel dataset.

Table 2 summarises the ITS segmented regression model results, which were fitted to the individual level panel data to predict the change in outcomes during and before implementing the Hillingdon ICM model. Among the whole population of Hillingdon, and during the first

Table 1 Outcome characteristics by sample(s) group

Condition	Non-elective admissions		Accident and emergency visits		Length of stay (days)	
	N	%	N	%	N	%
Total						
Total	43 680	100	212 180	100	178 784	100
No LTCs	14 625	33.5	112 081	52.8	29 003	16.2
With LTCs	29 055	66.5	99 486	46.9	149 781	83.8
CVD	1236	2.8	2185	1.0	9766	5.5
Diabetes	508	1.2	2232	1.1	1675	0.9
COPD	188	0.4	511	0.2	737	0.4
Asthma	877	2.0	5596	2.6	1446	0.8
Hypertension	1467	3.4	5956	2.8	5902	3.3
Cancer	415	1.0	974	0.5	1403	0.8
Multimorbid	16 183	37.0	52 520	24.8	78 646	44.0
Other	4419	10.1	21 008	9.9	20 142	11.3
Missing/unknown	3688	8.4	8504	4.0	30 064	16.8
Before intervention						
Total	28 883	66.1	140 035	66.0	113 384	63.4
No LTCs	10 028	23.0	75 642	35.6	19 116	10.7
With LTCs	18 855	43.2	64 393	30.3	94 268	52.7
CVD	953	2.2	1680	0.8	7589	4.2
Diabetes	324	0.7	1438	0.7	1005	0.6
COPD	147	0.3	382	0.2	549	0.3
Asthma	658	1.5	3885	1.8	1061	0.6
Hypertension	949	2.2	3924	1.8	3517	2.0
Cancer	288	0.7	679	0.3	904	0.5
Multimorbid	10 699	24.5	34 885	16.4	50 467	28.2
Other	2993	6.9	13 268	6.3	14 144	7.9
Missing/unknown	1844	4.2	4252	2.0	15 032	8.4
After intervention						
Total	14 797	33.9	72 145	34.0	65 400	36.6
No LTCs	4597	10.5	36 439	17.2	9887	5.5
With LTCs	10 200	23.4	35 093	16.5	55 513	31.1
CVD	283	0.6	505	0.2	2177	1.2
Diabetes	184	0.4	794	0.4	670	0.4
COPD	41	0.1	129	0.1	188	0.1
Asthma	219	0.5	1711	0.8	385	0.2
Hypertension	518	1.2	2032	1.0	2385	1.3
Cancer	127	0.3	295	0.1	499	0.3
Multimorbid	5484	12.6	17 635	8.3	28 179	15.8
Other	1426	3.3	7740	3.6	5998	3.4
Missing/unknown	1844	4.2	4252	2.0	15 032	8.4

CDV, cardiovascular disease; COPD, chronic obstructive pulmonary diseases; LTCs, long-term conditions.

month of implementation, there was an increase of 15% in NEL admissions (RR 1.15, 95% CI 1.07 to 1.24). Similarly, the other outcomes showed a statistically significant increase during the first month of implementation (table 2, IE (RR)).
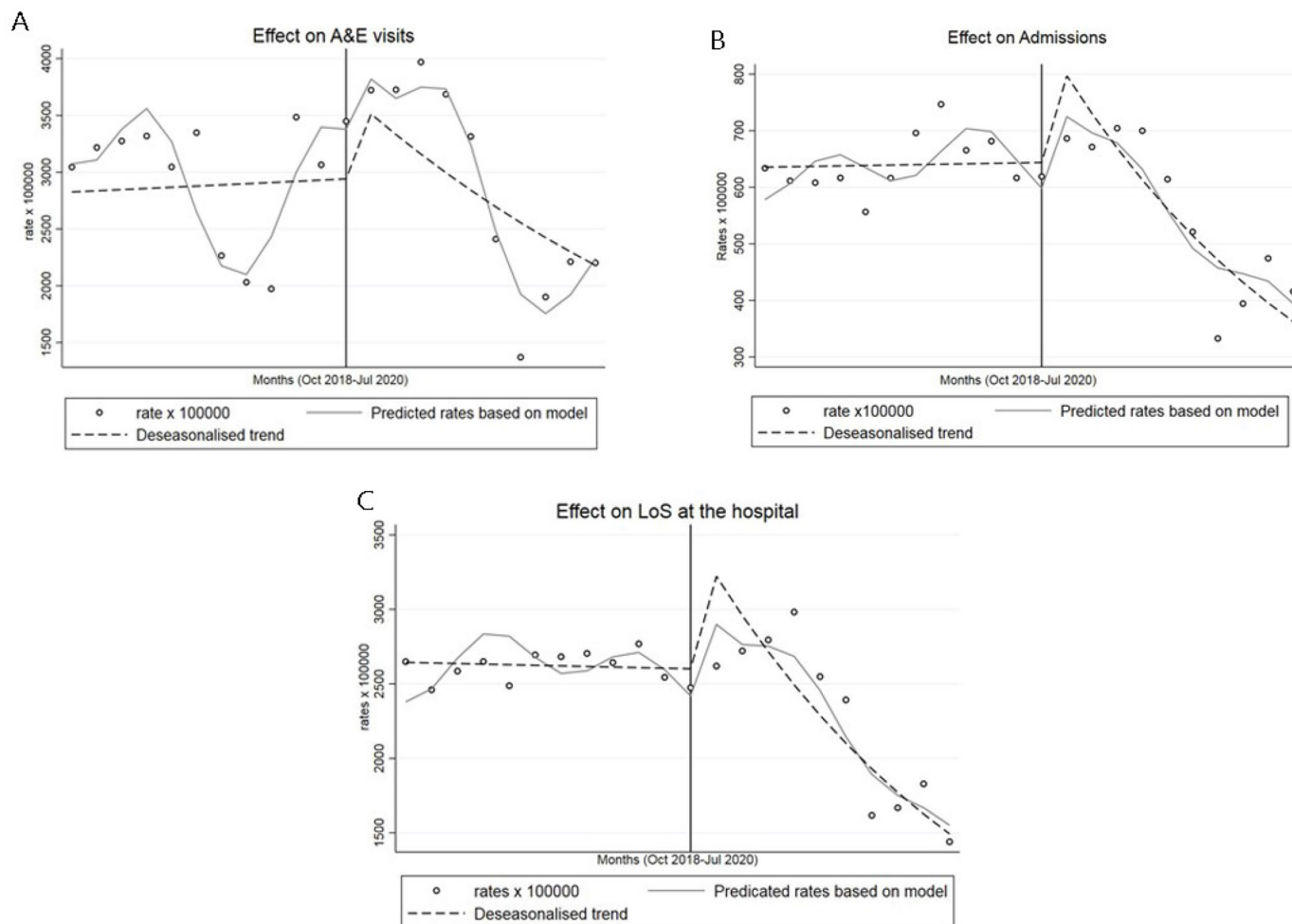
Figure 2 Effect of the intervention on outcomes (A): A&E visits, (B): NEL Admissions, and (B) LoS at the hospital, during the period of the study. Circles and solid lines represent the observed and the predicted rates, respectively. The dashed lines represent the deseasonalised trend of the three outcomes before and after the intervention. A&E, accident and emergency; LoS, length of stay.

Following the first month of implementation, we found a gradual effect (decrease in rates) on the three outcomes with a change in the underlying trend in NEL admissions, A&E visits, and LoS at the hospital among the whole population. The rates of admissions showed a gradual effect of a decrease of 9% per month (RR=0.91,

95% CI 0.90 to 0.92), whereas the rates of A&E visits and LoS decreased significantly by 6% and 7%, respectively (table 2, effect over time (EO) (RR)). Effects on other outcomes were similar, with a slight difference in magnitudes. Moreover, no statistically significant IE was

Table 2 Rates of outcomes of interest during the intervention compared with the preintervention period

Outcomes	NEL admissions		A&E visits		LoS	
Effect	IE (adRR) 95% CI	EO (adRR) 95% CI	IE (adRR) 95% CI	EO (adRR) 95% CI	IE (adRR) 95% CI	EO adRR) 95% CI
Hillingdon pop	**1.15*** 1.07 to 1.24	**0.91*** 0.90 to 0.92	**1.07*** 1.03 to 1.10	**0.94*** 0.93 to 0.95	**1.13*** 1.04 to 1.22	**0.93*** 0.92 to 0.94
With LTCs	**1.13*** 1.04 to 1.24	**0.92*** 0.90 to 0.93	0.99 0.94 to 1.05	**0.95*** 0.94 to 0.96	**1.12*** 1.02 to 1.24	**0.93*** 0.92 to 0.94
Without LTCs	**1.19*** 1.05 to 1.34	**0.90*** 0.88 to 0.91	**1.12*** 1.07 to 1.18	**0.93*** 0.92 to 0.94	1.11 0.96 to 1.30	**0.91*** 0.89 to 0.93

*Bold : Significant
adRR, adjusted rate ratio; A&E, accident and emergency; EO, effect over time (gradual effect); IE, immediate effect; LoS, length of stay; LTCs, long-term conditions; NEL, none-elective.

Table 3 Rates of outcomes of interest during the intervention compared with the preintervention period among different groups with various LTCs

Outcomes	NEL admissions		A&E visits		LoS	
Effect	IE (adRR) 95% CI	EO (adRR) 95% CI	IE (adRR) 95% CI	EO (adRR) 95% CI	IE (adRR) 95% CI	EO (adRR) 95% CI
CVD	1.11 0.55 to 2.26	0.97 0.89 to 1.06	1.31 0.94 to 1.84	**0.88*** 0.84 to 0.93	1.05 0.69 to 1.59	**0.87*** 0.82 to 0.92
Diabetes	1.23 0.65 to 2.36	0.94 0.87 to 1.01	0.89 0.63 to 1.28	1.00 0.95 to 1.04	0.91 0.42 to 1.95	1.02 0.94 to 1.11
COPD	1.09 0.39 to 3.03	0.90 0.78 to 1.04	1.21 0.54 to 2.69	0.97 0.88 to 1.07	0.63 0.19 to 1.99	0.98 0.85 to 1.14
Asthma	**2.15*** 1.31 to 3.52	**0.89*** 0.83 to 0.95	1.23 0.99 to 1.53	**0.93*** 0.91 to 0.96	**3.38*** 1.66 to 6.88	**0.91*** 0.84 to 0.98
Hypertension	1.18 0.78 to 1.78	**0.88*** 0.84 to 0.92	1.20 0.95 to 1.51	**0.95*** 0.92 to 0.97	1.41 0.89 to 2.23	**0.90*** 0.86 to 0.95
Cancer	1.11 0.55 to 2.24	0.97 0.89 to 1.06	0.95 0.55 to 1.63	1.03 0.97 to 1.10	1.00 0.43 to 2.26	0.99 0.90 to 1.08
Multimorbid	1.08 0.96 to 1.22	**0.92*** 0.91 to 0.93	0.96 0.89 to 1.45	**0.96*** 0.95 to 0.97	1.05 0.93 to 1.20	**0.95*** 0.93 to 0.96
Other	1.06 0.84 to 1.33	**0.90*** 0.88 to 0.93	0.91 0.80 to 1.03	**0.96*** 0.95 to 0.98	1.16 0.90 to 1.50	**0.92*** 0.89 to 0.94

*Bold: Significant
adRR, adjusted rate ratio; A&E, accident and emergency; COPD, chronic obstructive pulmonary diseases; CVD, cardiovascular disease; EO, effect over time; IE, immediate effect; LoS, length of stay; NEL, non-elective.

observed on A&E visits (In patients with LTC) and LoS (In patients without LTC).

Effects on outcomes by LTC groups

We conducted a subgroup analysis for patients with different LTCs to examine the effect of the model in reducing the three outcomes of interest across these groups. The results of the analysis are summarised in table 3.

The IE and EO effects varied in terms of significance and magnetite between groups. The overall pattern of effects was consistent with the analysis of the whole population, with an increase in rates during the first month of implementation, followed by a gradual decrease over time. However, in most groups, this immediate increase was not significant. The model did not significantly affect patients with diabetes, COPD and cancer. Although, patients with CVD showed a 12% and 13% significant decrease over time in A&E visits and LoS only. However, this was not the case for other groups. In the three outcomes, patients with asthma and hypertension showed a significant decrease ranging between 5% and 12%. The other groups, including patients with multimorbidies, showed a significant decrease over time in the three outcomes that ranged between 4% and 10% (table 3).

Sensitivity analysis did not show a notable change in findings across all groups assessed, including the general population. We found no discernible effects of missing data or non-time varying confounders that we controlled for on the analysis results. There was no change in statistical significance in all effect sizes across all outcomes and

groups except for CVD (change in IE NEL admissions with no imputations—online supplemental table 2). In terms of magnitude, the difference was negligible across all assessments.

DISCUSSION

Principal findings

We evaluated a population-based ICM in Hillingdon and found evidence of a reduction in hospital activity following an immediate increase after implementation. It is well known that ICMs are complex systems rather than comparable to clinical interventions.[23] Consequently, these models are not straightforward and are not expected to work straight away after implementation. The increase in three outcomes observed during the first month of implementation does not necessarily indicate a lack of effectiveness of the model. This is related to the increase followed by a significant decrease that continued over time (figure 2). This continuation might indicate that the model could have effectively achieved its aims, at least to a certain extent. Although, the high immediate increase during the first month might indicate that the implementation was not fully achieved, or the model was not fully operational across all the interventions. As a result, the need for an implementation assessment and evaluation of the HCPP ICM during this study and beyond is emphasised.

Although this study did not specify which populations used which compartment of the model, we can still gain

some insight into the model's overall effectiveness in reducing those outcomes. This is because any compartment of the model could generally improve patients' conditions or the way they manage them, thereby improving any of the three outcomes. For example, SM may improve patient knowledge to manage their conditions, avoid the need for hospital care, such as an NEL admission or a visit to the A&E, or at least reduce their stay at the hospital. On the other hand, DM services may help to reduce readmission. Furthermore, services such as RAMU or AECU could help with preinpatient care, reducing LoS at the hospital after admission. In other words, the model aims to improve patient self-care and, by extension, their health, hence; decreasing any of the three outcomes, including LoS (e.g. better health=less need to stay at the hospital).

The differential analysis of individuals with and without LTCs separately showed similar trends compared with the whole population. For example, A&E visits among individuals with no LTCs during the study period were 33 828 per 100 000 (around 6% higher than the patients with LTC). Our results showed a gradual decrease of 7% in rates per month in this group (around 2368 per 100 000) with similar trends in other outcomes. These findings might indicate the importance of implementing population-based ICMs rather than models that focus on patients with LTC alone. While the A&E visits among individuals with no LTCs were higher than patients with LTC, targeting those populations would be necessary. In addition, the findings summarised in table 2 show that individuals with no LTC might constitute a notable percentage of the total number of all three outcomes.

The Hillingdon ICM model also showed a noticeable effect on patients with LTC. Those patients accounted for most percentages of the total number of hospital admissions and LoS at the hospital. Patients with multimorbidity had the highest admissions rate during the study period (4825 per 100 000), and the analysis showed an 8% decrease over time (equivalent to around 430 per 100 000/month). This effect was similar in other groups except for patients with COPD, cancer, CVD and diabetes. However, the absence of effect might be explained statistically by the low sample sizes and frequency of outcomes across these groups (table 1). The non-significant IE among most groups could also raise the likelihood of this increase being due to chance or other factors rather than being linked to the model itself.

Nevertheless, the model did show a noticeable effect on patients with LTCs overall (table 3), who are considered the main targets of the model. This might indicate that the model might have effectively achieved its aims. In other words, if the model works on patients who are the most vulnerable to being admitted to or staying at the hospital, this might indicate that the model might have met its causal assumptions and the combination of multiple ICIs produced the intended effects. Although, this does not necessarily indicate that condition-specific models are not needed. For example, no effect over time

was observed in groups with different LTC. On the other hand, a high increased significant IE on NEL admissions and LoS was observed in patients with asthma. With this in mind, regardless of the factors that contributed to this increase, this might indicate that specific interventions or condition-specific models might be needed for better outcomes at this level and highlights the importance of assessing outcomes that relate to the different interactions of various parts of the model with different populations.

Comparison with existing evidence and meaning of the study

The findings of this study were partly consistent with recent evaluations of new ICMs in England piloted under the 'Vanguard' initiative.[13] These evaluations suggested a slowed rise in emergency admissions in Vanguard sites compared with a substantial increase in emergency admissions among non-Vanguard sites. The study evaluated two primary outcomes, including NEL admissions and LoS at hospitals (no reduction in total bed days (LoS) was reported). Our overall evaluation of the Hillingdon ICM found a substantial decrease in the same outcomes in addition to A&E visits compared with the preintervention period.

Our study had some strengths compared with the recent evaluations of the NHS vanguard programmes. Reducing A&E visits is an official objective of NHS England's new ICMs.[24] Besides, this outcome is known as an outcome of interest when evaluating ICMs.[8 11] Accordingly, considering this outcome in our evaluation is the first strength recognised. Second, assessing the effect of the Hillingdon ICM on different populations with various LTCs could also be considered a major strength of our study. Exploring effects on such groups might guide assessing the requirement of further interventions targeting such groups specifically. For example, implementing disease or condition-specific interventions as a part of population-based ICM might be required to achieve better outcomes in such groups. Third, to reduce confounding bias, our control for some potential confounders such as age, gender and ethnic category could be another strength to add. With this in mind, there is evidence on the effects of such factors on hospital utilisation in patients with different conditions.[25 26] Finally, the approach adopted in our analysis to treat missing values might be more accurate than discarding missing values and analysing balanced samples. Our sensitivity analysis could indicate the precision of our MI model and increase the precision of the estimates compared with the vanguard programme evaluation study. However, our study still has some weaknesses and limitations compared with other evaluations discussed in the next section.

Even after considering limitations with studies assessing the new ICM in England, either our evaluation or other assessments, these studies still have meanings in the context of the effectiveness of population-based ICMs. These evaluations might highlight the advantage of population-based ICMs on other models to achieve their

aim of reducing hospital utilisation. Compared with other models that showed minor effects on utilisation,[11] the findings of this study and those recent evaluations might suggest that population-based ICMs with a combination of different ICIs might provide better effects. This is related to the fact that such models aim toward a complete system integration which is considered the most ambitious. This form of integration usually combines a population-based and person-centred approach to integrated care. Thus, it focuses on delivering care (especially for the vulnerable groups), improving the population's health and preventing diseases through health promotion. To achieve this form of integration, an ICM should combine multiple ICIs to form a model of care that can be solely described as population based. Consequently, while new ICMs are inclined to focus on single disease management models with CM approaches,[10] population-based ICM might be considered a better model of choice to reduce care fragmentation and by extension, reduce hospital utilisation.

Policy implications, strength and limitations and future research

While ICMs have become the cornerstone of the policy response in different countries, including England, to relieve the pressure on health services, these models have become an important goal in the NHS long-term plan.[1] The plan is leaning towards creating Integrated Care Systems everywhere by the end of 2021, building on the progress already made. ITS design is considered a powerful tool for evaluating the impact of interventions implemented in healthcare settings.[27] Accordingly, an indication of the Hillingdon ICM short-term impact on the three outcomes of interest is a major strength of this study. The study may provide policy-makers in various CCGs with the first steps toward determining whether these models can deliver the expected benefits.

However, it is well known that evaluating ICMs is not straightforward and requires an understanding of the interactions between different parts of models.[24] Besides, ICMs should also be evaluated regarding patient-centred outcomes, including patients' knowledge of their conditions and their satisfaction with services. Also, ITS studies cannot exclude time-varying confounders, such as other interventions. As a result, including a control group could limit the biases resulting from such confounders.[28] However, it is worth mentioning that the study did consider other time-invariant and time-dependent confounders, and sensitivity analysis did not show a notable change in findings.

Nonetheless, we cannot rule out the possibility that other confounding events might have affected the results of this study. It remains possible that other coincident events, such as the emergence of the COVID-19 pandemic might have influenced our findings. In other words, we cannot tell if these drops in hospital utilisation outcomes were due to ICM implementation or COVID-19. As a result, while incorporating a control group cannot rule out the

possibility of a pandemic effect on these outcomes, it is still possible to obtain some insights by comparing other London boroughs covered by other CCGs with partially implemented models (e.g. London Borough of Ealing). This may be able to reflect the change in trend in these outcomes over time, with similarities indicating the likelihood of the pandemic's effect on outcome changes rather than the model itself.

Our study also included several limitations that were mainly confined to the nature of the dataset provided. First, in segmented regression ITS studies, more time points indicate more power.[27] Instead, with 24 monthly measures, seasonality could be evaluated more adequately.[29] The number of time points analysed in this study (n=22) might not have been enough, given the complexity of the evaluated model. Moreover, such limitations might bias short-term evaluations of ICMs when adopting ITS methods.[30]

Furthermore, we lacked access to hospital data such as 30-day hospital readmissions, which could have provided more insight into the effectiveness of the model compartments involved in postacute care, such as DM, on hospital readmission. Such outcomes, rather than just NEL admissions, may provide more explicit indications of the efficacy of such models. Furthermore, due to limitations in the dataset we obtained, other hospital outcomes such as A&E visits could not be differentiated as preventable and non-preventable, potentially biasing the estimates of effects on A&E visits. The findings of this study should be interpreted with caution because they do indicate a decrease in hospital utilisation outcomes, but these changes could be considered general rather than specific. Finally, because our dataset lacked a scale to reflect the severity of illnesses, we could not risk adjust the model for severity, which could have biased our estimates.

Second, given that the dataset included a few missing values, the subgroup analysis of patients of LTCs might have been subjected to some biases. Patients with a particular LTC were assigned to a particular group. However, it was clear from the data that some patients had additional LTCs in different durations. For example, a patient might be assigned to the hypertension group from October 2018 to September 2019 and then develop diabetes in September 2019. However, analysing the data on the individual level might have accounted somehow for the potential bias that might have occurred concerning this point, but to a certain extent. Besides, although MI was used to replace missing data in the LTC group, we are still expecting some biases in the subgroup analysis, given the known limitations of such methods.[31] Nevertheless, our sensitivity analysis did still provide a valid indication of the negligible effect of missing values on the analysis.

Future research should evaluate the model's effectiveness in reducing the three outcomes with more data (from the same or a different source) and time points concerning the limitations highlighted above. Increasing power would give more indication of the model's effectiveness and evaluate seasonal measures more adequately.

Also, the inclusion of a control group might increase the relevance of estimation by considering time-varying confounders, such as other interventions. Assessing more outcomes that might indicate the model's effectiveness, such as patient condition-related knowledge and patient satisfaction, is recommended. In addition, it is also recommended to assess outcomes that relate to the different interactions of various parts of the model. For example, communication between MDTs and GPs and CCTs could be assessed using mixed methods. This evaluation can be alongside an implementation analysis to provide more expansive knowledge on the facilitators and barriers to the model's effectiveness and what could be done by policy-makers to improve the model and the outcomes.

CONCLUSION

This study assessed the effectiveness of an ICM implemented in the London borough of Hillingdon, UK. The model showed effectiveness in reducing NEL admissions, A&E visits and LoS throughout the study. We also found a reduction in the three outcomes across diverse populations with various LTCs. However, given the limitations of this study, the results need to be interpreted with caution. Further research should include more data with more data points and consider long-term effect evaluation. The inclusion of a control group is also recommended and could increase the power of this analysis. The model's effect on other outcomes, such as condition-related knowledge, should also be evaluated. Finally, an implementation evaluation with an assessment of facilitators and barriers to effectiveness and implementation could add more to this study.

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