BMJ Open Quality

Impact of geographical cohorting, multidisciplinary rounding and incremental case management support on hospital length of stay and readmission rates: a propensity weighted analysis

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To cite: Jolly Graham A, Platt A, Knutsen K, *et al*. Impact of geographical cohorting, multidisciplinary rounding and incremental case management support on hospital length of stay and readmission rates: a propensity weighted analysis. *BMJ Open Quality* 2024;**13**:e002737. doi:10.1136/bmjoq-2023-002737

► Additional supplemental material is published online only. To view, please visit the journal online (https://doi.org/10.1136/bmjoq-2023-002737).

This work was previously presented as an abstract/poster presentation at the Society of Hospital Medicine CONVERGE annual meeting in Austin TX, 29 March 2023.

Received 28 December 2023
Accepted 10 May 2024

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ABSTRACT

Hospital length of stay (LOS) in the USA has been increasing since the start of the COVID-19 pandemic, with numerous negative outcomes, including decreased quality of care, worsened patient satisfaction and negative financial impacts on hospitals. While many proposed factors contributing to prolonged LOS are challenging to modify, poor coordination of care and communication among clinical teams can be improved.

Geographical cohorting of provider teams, patients and other clinical staff is proposed as a solution to prolonged LOS and readmissions. However, many studies on geographical cohorting alone have shown no significant impact on LOS or readmissions. Other potential benefits of geographical cohorting include improved quality of care, learning experience, communication, teamwork and efficiency.

This paper presents a retrospective study at Duke University Hospital (DUH) on the General Medicine service, deploying a bundled intervention of geographical cohorting of patients and their care teams, twice daily multidisciplinary rounds and incremental case management support. The quality improvement study found that patients in the intervention arm had 16%–17% shorter LOS than those in the control arms, and there was a reduction in 30-day hospital readmissions compared with the concurrent control arm. Moreover, there was some evidence of improved accuracy of estimated discharge dates in the intervention arm.

Based on these findings, the health system at DUH recognised the value of geographical cohorting and implemented additional geographically based medicine units with multidisciplinary rounds. Future studies will confirm the sustained impact of these care transformations on hospital throughput and patient outcomes, aiming to reduce LOS and enhance the quality of care provided to patients.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Length of stay in US hospitals has been increasing, with negative outcomes on quality of care, patient satisfaction and hospital financial performance.

⇒ Geographical cohorting of provider teams, patients and clinical staff has been proposed as a quality improvement intervention to help reduce hospital length of stay, with most studies showing no impact.

WHAT THIS STUDY ADDS

⇒ This study used a bundled intervention of geographical cohorting of medicine inpatients and their care teams, increased multidisciplinary rounds and incremental case management support. This bundled intervention was associated with reduced lengths of stay in the intervention versus concurrent and historical controls.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ A bundled approach rather than single interventions may result in reduced lengths of stay and improved quality of patient care in hospital inpatient populations.

INTRODUCTION

Hospital length of stay (LOS) has been increasing in the USA since the COVID-19 pandemic began in 2020,[1] with many associated negative outcomes. Quality of care decreases inversely as LOS increases. Prolonged LOS is associated with negative clinical quality outcomes such as nosocomial infections.[2] Patients with longer LOS have decreased patient satisfaction with their hospital experience.[3] Hospitals are realising significant negative financial impacts related to prolonged LOS and the resultant reduction in hospital throughput. Kaufman-Hall reports that 69% of US Hospitals have reported an increase in LOS in 2022 with much of that increase attributed to challenges

with discharging patients to postacute care facilities.[1] When coupled with labour shortages and their associated increased costs in 2022, prolonged LOS has had a profound impact on finances, with most hospitals now experiencing negative operating margins.[4]

To address prolonged LOS, hospital medicine leaders, researchers and practising clinicians need to understand potential contributing factors such as advanced age and frailty; poor home support; cognitive and functional impairment; clinical complexity; limited English proficiency; postacute care delays; the need for inpatient procedures, tests, consultations; different services on weekends; hospitalist experience and workload.[5–11] Many of these factors are either non-modifiable or difficult to address. However, discoordination of care and poor communication between clinical team members can contribute to prolonged LOS and readmissions, and these factors could be improved.

Due to the pressures of emergency department throughput and bed placement priorities, general medicine patients are often placed in a variety of units throughout a hospital. This results in hospitalists rounding on many diverse units resulting in poor communication and collaboration with nursing and other clinical staff on those units. Therefore, geographical cohorting of provider teams, patients and other clinical team members is a proposed solution for some of the inefficiencies of care which contribute to worsened LOS, readmissions and other quality metrics. Most geographical cohorting studies have shown no beneficial effect on LOS or readmissions[12–17] except for Maniaci *et al*,[18] who combined geographical cohorting with multidisciplinary rounds (MDRs) and showed a reduction in LOS and a reduction in quality 'at-risk events' with no change in readmissions. Most of the remaining studies that showed no effect on LOS or readmissions used geographical cohorting of providers and patients alone without paired MDR. In the studies by Dunn *et al*[13] and Maniaci *et al*,[18] both sets of authors recommended that future studies consider 'comprehensive transformation' (Dunn) which includes geographical cohorting, MDR and other interventions combined to have a greater impact on these measures. Additional benefits of geographical cohorting may include improvements in the quality of care, the learning experience of students and residents, communication between providers and nurses, teamwork, and efficiency.[14] Non-geographical placement of general medicine patients on non-general medicine units may be associated with higher mortality.[19]

At Duke University, there has been a consistent rise in the LOS for patients in the General Medicine service, a trend that predates the COVID-19 pandemic. Drawing from existing literature, we hypothesised that a bundled approach to care transformation including geographical cohorting in addition to MDR would primarily reduce LOS and readmissions, and secondarily improve the accuracy of estimated discharge dates (EDDs) and result in earlier discharge time each day. This study evaluates the impact of a pilot quality improvement intervention of both geographical cohorting, multidisciplinary rounding and incremental case management support to determine whether it reduced hospital LOS or 30-day readmission rates.

METHODS

Prestudy pilot programme

During the initial years of the COVID-19 pandemic, we geographically cohorted all COVID-19 positive patients on specific general medicine COVID-19 isolation units. We observed benefits of geographical cohorting in efficiency and provider satisfaction. We then began MDR on this geographical COVID-19 unit and observed significant improvements in LOS and readmissions.[20] This quality improvement project on our COVID-19 unit involved a bundled approach including geographical cohorting of patients and providers, twice daily MDR on weekdays informed by software from General Electric (GE) Healthcare Command Center that we have called 'Care Hub', and the addition of incremental case management support. The 'Care Hub' software is viewed on a large wall-mounted video monitor at the nursing unit and helped to standardise patient presentation and discussion of discharge barriers. The success of this initial pilot work on a COVID-19 unit allowed us to gain acceptance for a similar pilot on a traditional inpatient general medicine unit. This required significant support from hospital leadership given the hospital flow pressures to place patients in any unit that has open beds rather than wait for a geographical bed to become available.

Study design and setting

This is a retrospective study based on a quality improvement intervention at DUH, beginning in April 2021 and is currently ongoing. For evaluation and analysis, the study intervention period spans April 2021 through September 2021 and uses data extracted from our electronic medical records (EMR). Patients were included in the analysis if they were at least 18 years of age and were admitted to DUH with General Medicine as the discharging service. We excluded patients who were discharged from observation or outpatient status, were discharged by a team with resident physicians, were discharged from inpatient psychiatric service, were discharged from non-General Medicine teams or were discharged from the General Medicine Admitting team.

Intervention

In partnership with hospital patient flow, general medicine patients were assigned to the intervention unit, unit 4300, and were then cared for by one of the two geographically located hospitalist teams. There were not any residents on these two provider teams. One team consisted of an attending physician and an advanced practice provider (APP) corounding, and the second team consisted of a single attending physician provider. The target census for the combined attending MD-APP

team was 18 patients, and of the attending MD-only team was 12 patients. The unit simultaneously began twice daily MDR. The morning rounds consisted of a discussion of every patient on the unit. Attendees typically included the charge nurse, nurse manager or appointed nurse leader designee, the three providers rounding on the unit, the case managers (CM) assigned to the unit, and the physical and occupational therapists working on the unit. Generally, there was a CM for each of the two rounding teams and a supplemental third CM who provided 'incremental' support by fulfilling additional CM duties not typical of the assigned CM. The additional CM focused on referring patients to outpatient resources and programmes after discharge as well as helping the primary CM with various tasks relating to discharge. The nursing leader served as the huddle facilitator, joined the virtual meeting link for off-site access of attendees and managed the Care Hub monitor. The afternoon MDRs were more concise and focused on patients who would be discharged the same day, or the next day, and the barriers or action items required to ensure their timely discharge. The CM updated the EDD at least once each day based on the discussion that occurred during rounds. The workroom where the MDR occurred was equipped with a monitor to display Care Hub, a software application providing a visual cue for standardised team discussion, with icons highlighting potential discharge barriers or patient care orders that needed to be completed prior to discharge, such as a radiology study, physical therapy assessment or dialysis session.

Iterative improvements were made to the MDRs to improve efficiency, under the direction of the unit 'Quad' leadership team, which consisted of the unit medical director, unit nurse manager, CM leader and hospital service unit leader. This team worked together to suggest process improvements, improve discharge processes, escalate common discharge barriers and monitor unit-level data.

Control units

We included two comparison arms, a historical control and a concurrent control. The historical control included patients discharged from the same unit 4300 between October 2020 and March 2021 (before the intervention). The concurrent control included patients discharged from other general medicine units (unit 8100 or 8300) during the intervention period (between April 2021 and September 2021). Units 8100 and 8300 were selected as concurrent controls because they were the only other general medicine units (aside from 4300) that were not dedicated to acute COVID-19 care during the study time period, and these are traditional medicine units without geographical cohorting of provider teams. In order to reduce variation due to provider type, we excluded patients in the control arms if they were discharged from resident teaching teams. These patients on control units were, therefore, cared for by hospitalist teams. Non-geographical hospitalist teams who also rounded on control units had similar daily patient census values as intervention teams. All of the units analysed (4300, 8100, 8300) had no patients with active COVID-19 infection.

Primary outcomes

This study focuses on two primary outcomes, LOS and 30-day hospital readmission rate. 30-day hospital readmission was defined as an unplanned hospital readmission to any of the three Duke University Health System Hospitals within 30 days of previous discharge alive and excluded patients that were discharged to other acute care facilities, left against medical advice or were discharged from medical oncology or psychiatry services. The criteria were used to most closely approximate the Center for Medicare and Medicaid Services definition of hospital-wide unplanned readmissions. LOS was quantified as days from inpatient admission to discharge alive from DUH.

Secondary outcomes

Secondary outcomes included accuracy of EDD measured as a binary indicator that a patient was discharged on their EDD. EDD is the best estimate for the day of eventual discharge estimated by the multidisciplinary team and entered into the electronic record by the CM. For a given patient encounter, the last entered EDD was used to determine EDD accuracy. Discharge time of day was measured in minutes from midnight of the day of discharge, with earlier discharge times preferred over later discharge times.

This study is guided by the Strengthening the Reporting of Observational Studies in Epidemiology[21] guidelines.

Statistical analysis

Patient demographics and clinical characteristics were summarised by arm (intervention, historical control, concurrent control) using means, medians, SD and IQR (25th and 75th percentiles), counts, and percentages.

To account for the non-randomised nature of the study, propensity score weighting was used to balance sociodemographic and clinical characteristics between arms using the overlap weighting method.[22] Logistic regressions modelled the probability of being discharged from the 4300 intervention unit with separate models used for each type of control. Propensity score models included age, gender, race, ethnicity, insurance status, Medicare Severity Diagnosis Related Group weight, hours spent in intensive care unit (ICU) and an indicator for whether or not the patient was a Duke Primary Care patient. Missing race and ethnicity information was included as an additional category in the models while missing insurance information was assumed to be self-pay. Distributions of propensity scores were compared to assess overlap in the probability of being discharged by 4300 during the intervention period. Standardised differences were computed[23] to compare the balance between characteristics of patients in the intervention arm versus the two control arms (each evaluated separately) before and after weighting, with standardised differences smaller than

0.10 in absolute value considered acceptable balance between arms.

Due to known skew in the distribution of LOS and the possibility of censoring due to inpatient death, LOS was analysed using accelerated failure time models (with log-logistic error distribution)[24] with outcomes of days to discharge alive and intervention arm as the sole covariate. Estimates were exponentiated to give the interpretation of an event time ratio (ETR). ETRs can be interpreted as a relative expected time to discharge with ETRs>1 indicating that LOS was longer for the intervention arm and ETR<1 indicating that LOS was shorter for the intervention arm, and an ETR of 1 indicating that LOS was the same for intervention and control arms. Estimates generated from overlap weighted models were considered primary, with unweighted models computed to assess the magnitude of potential bias caused by the non-randomised nature of the study.

Rates of 30-day hospital readmission were analysed using Cox proportional hazard models[25] with days to readmission as the outcome and death as a censoring event. Regression estimates were exponentiated to give the interpretation of HRs. Regressions were performed with and without overlap weighting, with weighted models considered primary.

In the case of LOS and 30-day hospital readmission, death was considered as a potential semicompeting risk if the prevalence of death (inpatient death for LOS or death during the 30-day window postdischarge for 30-day readmission) was substantial overall or differential between intervention and control arms. Death was treated as a censoring event in the main models. Where death was considered a plausible semicompeting risk, companion regression models were included with time to death as the outcome and discharge alive or 30-day readmission events as censoring events in the LOS and 30-day readmission analyses, respectively.

Weighted and unweighted Kaplan-Meier curves were plotted for time to discharge (in days) and time to 30-day readmission (in days) with separate curves for time to death, where death was considered a semicompeting risk.

Accuracy of EDD was analysed as a binary outcome using generalised linear models with binomial distribution and log link function. Coefficients were exponentiated to give the interpretation of a risk ratio. Time of day was analysed as a continuous variable in minutes from midnight of discharge date, using linear regression models.

To account for repeated measures by patient and uncertainty in the estimation of the propensity scores, bootstrapping methods were employed to calculate valid percentile-based 95% CIs using 1000 resamples at the level of the individual patient.

Evaluation of primary outcomes of LOS and 30-day hospital readmission were both considered as individual hypotheses, thus no adjustment for multiple comparisons was applied.[26]

RESULTS

A total of 2608 discharges (2462 unique patients) were extracted from the EMR of which 1591 discharges (1515 unique patients) met the criteria for inclusion in the analytic sample, composed of 723 discharges from 4300 during the intervention period, 502 for the concurrent control and 366 for the historical control. Details of sample reduction and reasons for exclusion can be found in figure 1. Across all arms, discharged patients were a median of 61 years old (IQR=45.0–74.0), relatively balanced by gender (50.8% female vs 49.2% male), predominantly white (49.2%) or black (43.1%), with 3.8% of patients identifying as Hispanic (table 1). A majority of patients (67.9%) were on public insurance and 22.0% of patients spent at least some portion of their hospital stay in the intensive care unit (ICU). Inpatient

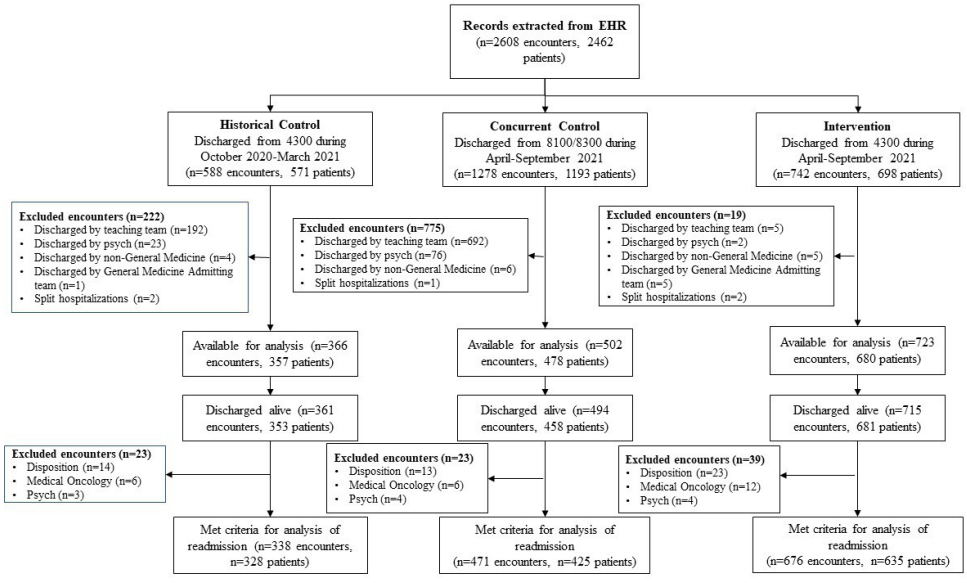

Figure 1 Study cohort composition. EHR, electronic health record.

Table 1 Baseline characteristics of analytical sample by cohort

	Historical control (N=366)	Concurrent control (N=502)	Intervention (N=723)	Total (N=1591)
Age at discharge (years)				
Mean (SD)	59.5 (18.8)	58.7 (19.9)	59.4 (18.2)	59.2 (18.9)
Median (Q1, Q3)	61.0 (45.0, 74.0)	61.0 (43.0, 74.0)	61.0 (46.0, 73.0)	61.0 (45.0, 74.0)
Gender*				
Female	185 (50.5%)	260 (51.8%)	363 (50.3%)	808 (50.8%)
Male	181 (49.5%)	242 (48.2%)	359 (49.7%)	782 (49.2%)
Race†				
Black	159 (43.4%)	239 (47.6%)	288 (39.8%)	686 (43.1%)
White	177 (48.4%)	225 (44.8%)	381 (52.7%)	783 (49.2%)
American Indian/Alaska Native, Asian/Pacific Islander, two or more races or other	19 (5.2%)	30 (6.0%)	45 (6.2%)	94 (5.9%)
Refused/not reported	11 (3.0%)	8 (1.6%)	9 (1.2%)	28 (1.8%)
Ethnicity‡				
Hispanic	17 (4.6%)	18 (3.6%)	25 (3.5%)	60 (3.8%)
Non-Hispanic	337 (92.1%)	472 (94.0%)	679 (93.9%)	1488 (93.5%)
Refused/not reported	12 (3.3%)	12 (2.4%)	19 (2.6%)	43 (2.7%)
Insurance				
Private/other	81 (22.1%)	124 (24.7%)	180 (24.9%)	385 (24.2%)
Public	258 (70.5%)	330 (65.7%)	492 (68.0%)	1080 (67.9%)
Self-pay	27 (7.4%)	48 (9.6%)	51 (7.1%)	126 (7.9%)
MSDRG weight				
Mean (SD)	1.9 (1.9)	1.9 (2.3)	1.7 (1.4)	1.8 (1.8)
Median (Q1, Q3)	1.4 (0.9, 1.9)	1.3 (0.9, 1.9)	1.4 (0.9, 1.9)	1.4 (0.9, 1.9)
Time spent in ICU (hours)				
No ICU	295 (80.6%)	434 (86.5%)	512 (70.8%)	1241 (78.0%)
<24 hours	9 (2.5%)	7 (1.4%)	30 (4.1%)	46 (2.9%)
24–72 hours	28 (7.7%)	21 (4.2%)	95 (13.1%)	144 (9.1%)
>72 hours	34 (9.3%)	40 (8.0%)	86 (11.9%)	160 (10.1%)
Died (inpatient)	5 (1.4%)	8 (1.6%)	8 (1.1%)	21 (1.3%)
Died within 30 days of discharge	4 (1.1%)	6 (1.2%)	7 (1.0%)	17 (1.1%)
Duke primary care active patient	102 (27.9%)	137 (27.3%)	186 (25.7%)	425 (26.7%)
Discharge disposition				
Home	268 (73.2%)	363 (72.3%)	545 (75.4%)	1176 (73.9%)
Skilled nursing facility	62 (16.9%)	88 (17.5%)	117 (16.2%)	267 (16.8%)
Other	36 (9.8%)	51 (10.2%)	61 (8.4%)	148 (9.3%)

*One patient's gender was missing in intervention group.
†Race is a mix of self-report and healthcare worker perceived race recorded in electronic medical records.
‡Ethnicity is predominantly self-reported in electronic medical records.
ICU, Intensive Care Unit; MS DRG, Medicare Severity Diagnosis-Related Group.

death occurred in 1.3% of hospital encounters across all arms and 73.9% of patients were discharged home.

Propensity scores and balance between arms

A comparison of the distribution of propensity scores between intervention and control arms revealed good overlap in the probability of being in the intervention arm, with the historical control having more overlap in the probability of being in the intervention arm (based on included characteristics) than the concurrent control suggesting slightly better balance in characteristics between the intervention and historical control prior to weighting (online supplemental figure 1). Parameter

estimates for final propensity score models can be found in online supplemental table 1. Standardised differences computed with and without weighting (online supplemental figure 2) indicate that characteristics were well balanced between the intervention and both control arms prior to weighting except in the case of race, with white patients more likely to be assigned to the intervention (OR 1.51, 95% CI 1.16 to 1.95) compared with concurrent control and patients spending more time in ICU being more likely to be discharged from the intervention unit, with more than quadruple the odds of spending up to 72 hours in the ICU than concurrent control and more than twice the odds of spending up to 72 hours in the ICU than the historical control (online supplemental table 1).

Primary outcomes

Length of stay

Median LOS was 4.8 days (IQR 2.9–8.6) for patients in the intervention condition, 5.6 days (IQR 3.5–10.4) for patients in the concurrent control, and 5.7 days (IQR 3.5–11.9) for patients in the historical control (table 2 shows results for weighted outcomes and online supplemental table 2 for unweighted outcomes). Kaplan-Meier plots suggest little difference between weighted and unweighted estimates for time to discharge alive (figure 2). Accelerated failure time models estimated that patients in the intervention arm had 16%–17% shorter LOS than patients in the control arms, with CIs excluding one indicating a statistically significant effect (ETR 0.83, 95% CI 0.76 to 0.92 for historical control; ETR 0.84, 95% CI 0.76 to 0.93 for concurrent control) (table 2). Estimates were virtually identical when censoring all patients after 30 days (or >95th percentile) indicating that results were not driven by outliers for LOS.

30-day readmission

Across all conditions, 676 patients (93.5%) in the intervention arm, 471 patients (93.8%) in the concurrent control and 338 patients (92.3%) in the historical control condition met the criteria for being included in the analysis of time to 30-day hospital readmission. Of those, 15.6% in the intervention condition, 20.3% in the concurrent control condition and 15.7% in the historical control condition were readmitted within 30 days of discharge with median days to readmission of 14.4 (IQR 7.9–21.5) for the intervention condition, 12.4 days (IQR 8.2–21.8) for the concurrent control and 13.2 days (IQR 8.8–22.9) for the historical control (table 2). Evaluation of Schoenfeld residuals confirmed that assumptions of proportional hazards were met across all weighted and unweighted analyses. Comparisons of weighted estimated hazard rates provide some evidence that the rate of readmission was reduced by approximately 27% when compared with a concurrent control condition (HR 0.73, 95% CI 0.55 to 0.98) but little evidence of a difference when compared with a historical control (HR 0.99, 95% CI 0.70 to 1.39).

Secondary outcomes

Accuracy of EDD

Of patients discharged alive (n=715 for intervention, 494 for concurrent control, 361 for historical control), EDD was available for 680 patients (95.1%) in the intervention arm, 460 patients (93.1%) in the concurrent control and 339 patients (93.9%) in the historical control. For patients discharged alive, EDD was accurate for 62.1% of patients in the intervention condition, 61.7% of patients in the concurrent control condition and 56.3% of patients in the historical control condition (table 2). There was some evidence of increased accuracy of EDD for patients in the intervention condition compared with those in the historical control (risk ratio (RR) 1.10, 95% CI 0.99 to 1.23) but little evidence of differential accuracy when using a concurrent control (RR 1.01, 95% CI 0.92 to 1.11 for concurrent control). Hours from last update of EDD were comparable between all arms.

Time of day of discharge

There was weak evidence that patients in the intervention condition were discharged earlier in the day than those in the concurrent and historical control conditions (mean estimate −3.6 min, 95% CI −22.2 to 14.5 for concurrent control; mean estimate −11.8 min, 95% CI −32.5 to 10.3 for the historical control) (table 2).

Impact of death

Greater than 98% of the study sample were discharged alive with five inpatient deaths (1.4%) for the historical control, and eight inpatient deaths each for the two other conditions (1.6% and 1.1% for concurrent control and intervention arm, respectively). Because inpatient death was rare and non-differential by the study arm, inpatient death was not deemed a substantial semi-competing risk with discharge for the purposes of evaluation of the intervention.

Lower proportions and hazard rates of death postdischarge but pre-30-day endpoint in the intervention arm indicate that it is unlikely that death presented a substantial competing risk with readmission for patients in the intervention (Kaplan-Meier plots for time to death postdischarge can be found in online supplemental figure 3).

DISCUSSION

In our retrospective study at one academic hospital of a bundled intervention of geographical cohorting of patient and provider teams, in addition to twice daily MDRs and incremental CM support, we observed shorter LOS in the patients on our intervention unit, as compared with both the historical control and the concurrent control. We used propensity score weighting to balance patient and clinical characteristics between treatment arms in order to provide a more accurate estimate of the effect of the bundled intervention. We found that many characteristics were well balanced between arms (with the exception of race and time spent in ICU) and found that the historical control is slightly more comparable to the intervention

Table 2 Weighted* mean outcomes and regression estimates† with 95% CIs, by control type

	Weighted sample summaries by arm			Weighted regression estimates	
Outcome	Historical control	Concurrent control	Intervention	Historical control	Concurrent control
Primary outcomes					
Length of stay (days)‡				Event time ratio (95% CI)	Event time ratio (95% CI)
Mean (SD)	12.2 (22.5)	10.9 (19.7)	7.8 (10.3)	0.83 (0.76 to 0.92)	0.84 (0.76 to 0.93)
Median (IQR)	5.7 (3.5–11.9)	5.6 (3.5–10.4)	4.8 (2.9–8.6)		
Inpatient death (%)	1.4	1.5	0.9		
Length of stay (censored at 95th percentile)				Event time ratio (95% CI)	Event time ratio (95% CI)
Mean (SD)	9.3 (8.7)	8.7 (8.1)	7.2 (6.6)	0.84 (0.76 to 0.93)	0.84 (0.76 to 0.93)
Median (IQR)	5.7 (3.5–12.0)	5.6 (3.5–10.4)	4.8 (2.9–8.6)		
Days to readmission (30-day endpoint)‡				HR (95% CI)	HR (95% CI)
Mean (SD)	15.3 (8.7)	14.5 (8.4)	14.7 (8.0)	0.99 (0.70 to 1.39)§	0.73 (0.55 to 0.98)§
Median (IQR)	13.2 (8.8–22.9)	12.4 (8.2–21.8)	14.4 (7.9–21.5)		
Readmitted within 30 days (%)	15.7	20.3	15.6		
Days to death postdischarge (within 30-days)				HR (95% CI)	HR (95% CI)
Mean (SD)	13.9 (10.6)	10.4 (7.9)	12.6 (9.1)	0.48 (0.26 to 0.90)¶	0.58 (0.31 to 1.09)¶
Median (IQR)	14.8 (4.0–22.0)	8.7 (2.9–13.7)	13.0 (3.0–19.8)		
Death postdischarge (within 30 days) (%)	6.3	5.1	3.0		
Secondary outcomes					
				Risk ratio (95% CI)	Risk ratio (95% CI)
Estimated discharge date accurate (%)‡	56.3	61.7	62.1	1.10 (0.99 to 1.23)	1.01 (0.92 to 1.11)
Hours from last EDD update to discharge					
Mean (SD)	35.8 (19.6)	33.5 (15.3)	33.9 (17.2)		
Median (IQR)	28.7 (25.7–32.7)	28.4 (25.8–31.6)	27.9 (24.6–32.5)		
Time of day of discharge‡				Mean estimate (95% CI)	Mean estimate (95% CI)
Mean (SD**)	14:41 hours (2.7)	14:32 hours (2.5)	14:29 hours (2.9)	−11.8 (−32.5 to 10.3)	−3.6 (−22.2 to 14.5)
Median (IQR)	14:5 (12:43–16:34 hours)	14:29 (14:39–16:20 hours)	14:22 (12:11–16:30 hours)		

*Overlap weights used to weight sample means, proportions and regression estimates.
†Event time ratios are estimated with accelerated failure time models (log-logistic distribution), HRs with Cox proportional hazards models, risk ratios with binomial models (log link) and mean estimates with linear regression. All 95% CIs calculated using percentile intervals generated using cluster bootstrapping.
‡Outcomes prespecified as main outcomes of interest, all others meant to provide additional information and/or context.
§Test of Schoenfeld residuals p=0.548 for analysis with concurrent control, p=0.392 for analysis with historical control.
¶Test of Schoenfeld residuals p =0.284 for analysis with concurrent control, p=0.438 for analysis with historical control.
**SD of sample mean in minutes.
EDD, estimated discharge dates.

arm (based on their overall probability of receiving the intervention). We attribute the 16%–17% shorter LOS in the intervention condition to a combination of efficiencies gained in geographical localisation of both providers and patients and improved communication and care coordination among the multidisciplinary team. Readmissions were not increased in the intervention group, despite the observed shorter LOS and higher proportion of patients who were in the ICU for a portion of their hospital stay. We suggest the incremental CM support may

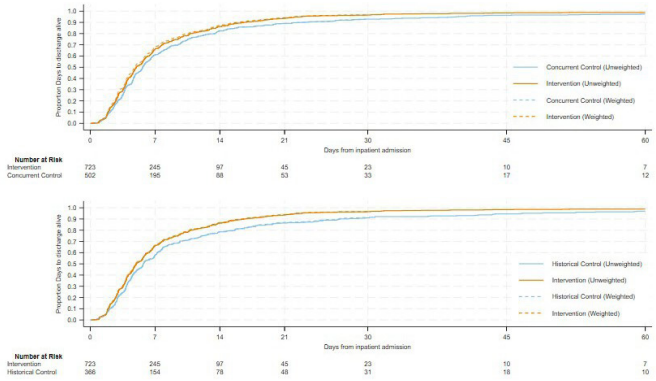

Figure 2 Weighted and unweighted Kaplan-Meier plots illustrating time to discharge alive by treatment arm and control type (plots display time to discharge only up to 60 days due to small numbers).

have helped to 'protect' against further readmissions. There was weak evidence that patients in the intervention group were discharged earlier in the day than patients in either control group.

Our analysis of the accuracy of the last documented EDD showed some evidence for improved accuracy in the intervention group as compared with the historical control, but less difference when compared with the concurrent control. This is likely attributed to other concurrent initiatives focused on improving EDD documentation and accuracy by CM and provider teams across our health system during the intervention time frame.

The initiation of geographical cohorting of both patients and providers on our 4300 unit resulted in some unanticipated consequences regarding patient flow. First, due to the exclusion of resident teaching team patients, and patient assignment practices for overnight admissions, the morning bolus of ICU patients who were ready to transfer out of the ICU to the general medicine floors were often assigned to the intervention unit, more so than the other general medicine units. Similarly, afternoon admissions who were not being admitted by resident teams were assigned to the intervention unit, with a higher portion of these coming from the ICU as opposed to new admissions from the ED or clinic locations. The high number of ICU patients resulted in increased care complexity for our provider and nursing teams. The intervention unit observed favourable patient flow outcomes despite the increased proportion of ICU patients, although balancing the proportion of ICU transfers across our general medicine units would be more favourable for the resiliency of our team members. Our project leaders did experience encouragement to place patients 'non-geographically' during times of high bed demand. We had significant support from hospital leadership to address this. Overcoming throughput pressures in geographical placement projects like this is a significant challenge for all hospitals and leadership buy-in is vital.

Limitations

Limitations of our study are a short time duration (6 months), on a single general medicine unit, at a single academic medical centre. Despite our pilot occurring in an academic medical centre, we chose to exclude resident teaching teams from our geographical unit and comparison groups. We recognised the need to focus this project on non-learner teams only to remove some of the challenges facing learner teams. These challenges include patient volume 'caps' and conflicts with educational conferences during the clinical day. Eliminating resident-learner teams from geographical units is not a feasible long-term strategy for an academic hospital. Following this initial project, we have subsequently expanded our geographical unit model to include both resident-learner teams and hospitalist teams in each designated unit. We will examine the impact of these changes in future studies. Our study was a QI study, and thus, patients were not randomised between units or comparison groups. We did not anticipate the effect on patient selection that occurred in our intervention unit, namely the increased proportion of patients who were in the ICU. Finally, our intervention was a bundled approach that appears to have been effective in improving the efficiency of care, however, it is not possible to discern which elements of the intervention were the most impactful, and any elements that may have been unnecessary.

CONCLUSION

Based on the results of this quality improvement pilot our health system has recognised the value of geographical cohorting of patients, provider teams, nurses, CMs and other supporting clinical team members. We have negotiated support to open three additional geographically based medicine units at our main academic hospital and to integrate our resident teaching teams into this geographical care model and have implemented multidisciplinary rounding on these units. Future studies will confirm the sustained impact of these care transformations on hospital throughput. We hope this will allow us to further reduce LOS for our hospitals and to improve the quality of care we deliver for our patients.

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Acknowledgements The authors would like to thank and acknowledge Sharon Farrow RN, Lanie Dreibelbis, and Elizabeth Anderson RN for their work in this project.

Contributors We followed the ICMJE authorship guidelines in that all authors: contributed substantially to the design of the work (including data acquisition, analysis and interpretation); helped draft the manuscript in all phases; had final approval of the version to be published and have agreed to be accountable for all

aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Specific author's main responsibilities: Concept and design: AJG, DG, EF and KK Acquisition of data: KK and AP. Analysis and interpretation of data: AP, DG and AJG. Drafting of the manuscript: DG, AJG, AP, EF and KK. Critical revision of paper for important intellectual content: DG, AJG, AP, EF and KK. Statistical analysis: AP. Provision of study materials or patients: N/A. Obtaining funding: N/A. Administrative, technical or logistic support: DG, AJG and KK Supervision: AJG, DG, EF and AP. Guarantor: DG.

Funding Funding for Alyssa Platt via Duke Clinical and Translational Award (CTSA) grant # UL1TR002553.

Competing interests None declared.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval This study (protocol ID: Pro00108539) was approved by the Institutional Review Board of Duke University as exempt without the need for informed consent as it is a quality improvement project to apply best practices to reduce length of stay and unplanned readmissions. As this is a retrospective observational study of a quality improvement project, patient and public involvement in its design were not involved.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available on reasonable request. All data sharing requests are subject to approval by relevant Duke University agencies as outlined in the relevant Duke University Institutional Policies and Procedures.

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