CLINICAL

Scaling Care Coordination Through Digital Engagement: Stepped-Wedge Trial Assessing Readmissions

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ABSTRACT

OBJECTIVES: Transitions of care are pivotal, vulnerable times as patients are discharged from the hospital. Telephonic care coordination is standard care, but labor intensive. We implemented a patient postdischarge digital engagement (PDDE) program to scale coordination. We hypothesized that PDDE could reduce readmissions for low-risk patients and supplement care coordination for medium- and high-risk patients.

STUDY DESIGN: Pragmatic, stepped-wedge cluster randomization trial with 5 implementation waves based upon primary care clinic region.

METHODS: All inpatient hospital discharges between March 2020 and November 2020 were stratified by readmission risk. Low-risk patients were offered access to PDDE, and moderate-risk and high-risk patients were offered access to PDDE and care coordination. Readmission was defined as an unplanned inpatient admission within 30 days from discharge. An intention-to-treat primary analysis was conducted using mixed-effects logistic regression clustering for wave; a treatment-on-the-treated analysis was also conducted to assess the impact among program users.

RESULTS: A total of 5490 patient discharges were examined (2735 control; 2755 intervention); 1949 patients were high risk, 2032 were medium risk, and 1509 were low risk. PDDE intervention did not significantly affect readmission among low-risk (95% CI, –0.23 to 0.90; =.23), medium-risk (95% CI, –0.14 to 0.60; =.21), and high-risk (95% CI, –0.32 to 0.64; =.48) groups after adjustment for time and patient factors. In a treatment-on-the-treated analysis, among patients who activated the PDDE program, readmission was also similar among the low-, medium-, and high-risk cohorts.

CONCLUSIONS: Our study expanded resource-limited care coordination by offering low-risk patients a service they were unable to receive previously while having no impact on readmission. PDDE efficiently provided additional touch points between patients and providers.

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Transitions of care represent a pivotal time period for patients as they are discharged from the hospital to a home setting. Hospitals are incentivized to decrease readmissions for efficiency, monetary, and census reasons. Avoidable 30-day readmissions represent financial burdens to patients, providers, and health systems and contribute to a clinical strain on resource-limited health systems and patients' general health.[1] Care coordination represents an opportunity to support patients during this vulnerable time but often requires extensive human resources, making it impractical to scale to every patient every time. Although care coordination has been found to be cost-effective due to reduction in readmissions and emergency department visits, the cost of care coordination was found to be $1643 per Medicaid beneficiary and $174 per Medicare beneficiary.[2] In addition, labor costs are rising, which further incentivizes hospitals to look for avenues to decrease costs.[3] To combat the financial and resource limitations of offering care coordination to all patients, which has been found to be very beneficial for improving transitional care, the use of technology has been proposed.[2] Technology allows for consistent and efficient outreach to discharged patients. With goals of improving care coordination scalability and reducing hospital readmission, technological applications provide avenues to increase patient engagement, support patients experiencing symptoms, and deliver quicker responses to patients.

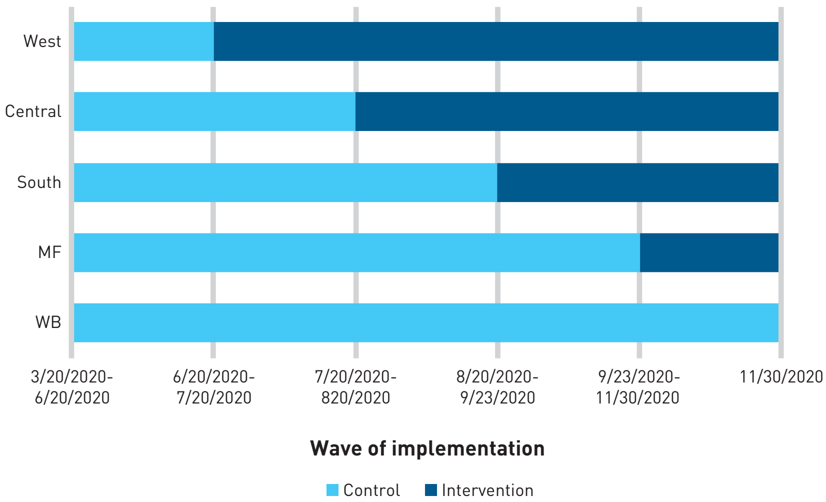
The introduction of digital health platforms and therapeutics has allowed for rapid innovation and improvement within the health care system, including more personalized treatments and care plans.[4-6] A remote patient monitoring system called GetWell Loop (GWL) provides general patient education and direct connection with nurse care coordination teams.[6] Patients receive automated messages through a web or mobile application to complete next steps, assess progress, and receive education. Deviations or exceptions are flagged for nurse follow-up. Patients also have the ability to message nurses. GWL was studied among patients with COVID-19 and was able to address patients' concerns, successfully engaged patients in their symptom monitoring, and was associated with lower odds of hospital admission.[6] GWL was also found to decrease revisits to the emergency department among the general adult population, reducing resource utilization.[7]

Given the success seen in past studies of GWL to target care coordination, we sought to apply remote patient monitoring via GWL to discharged patients to reduce hospital readmission. We implemented the postdischarge digital engagement (PDDE) application of GWL for general, non–disease-specific discharged patients to determine whether it could affect readmissions beyond the currently deployed care coordination model by providing more patient engagement and touch points, education, and efficient communication with nurse care coordinators.

TAKEAWAY POINTS

- Transitions of care represent a pivotal time period for patients as they are discharged from the hospital to a home setting. Our study examined the usage of postdischarge digital engagement (PDDE) to engage patients during this traditionally risky time period.
- Our study was able to expand resource-limited care coordination by offering low-risk patients a service they were unable to receive in the past. PDDE was able to provide more touch points between patients and providers in an efficient manner.

FIGURE 1. Stepped-Wedge Implementation of the GWL Application, Based on Date of Implementation



GWL, GetWell Loop; MF, Menomonee Falls; WB, West Bend.

METHODS

Setting, Design, and Participants

The project was conducted within the academic community health system Froedtert and Medical College of Wisconsin Health Network (F&MCW) in southeastern Wisconsin. A stepped-wedge design was used for PDDE implementation. Clinics were grouped based on 5 primary care practice regions and attributed populations (**Figure 1**).

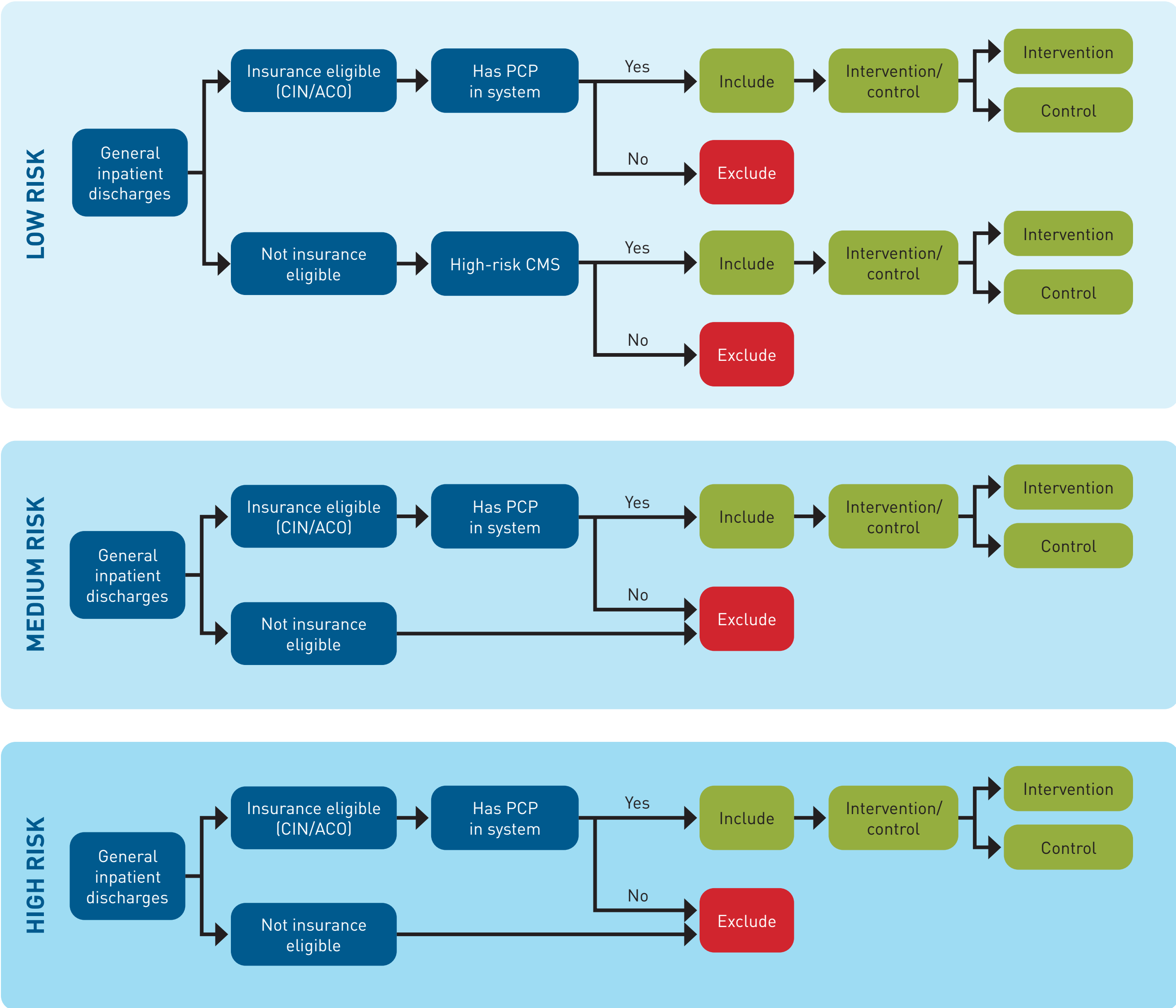
Patients with primary care providers (PCPs) within the F&MCW system who were eligible for care coordination programs were invited. Eligibility of patients was determined by risk and insurance provider (**Figure 2**). The 2 PDDE plans utilized were a 12-day low-risk loop and a 30-day moderate- to high-risk loop. Patients were stratified into low-, moderate-, and high-risk cohorts based on their unplanned readmission risk score, which was determined using an Epic-based algorithm. Patients with an unplanned readmission risk score of 1 to 10 were labeled low risk, scores of 11 to 21 were medium risk, and scores of 22 and higher were high risk. Upon discharge, patients were then automatically enrolled in the appropriate risk-based loop. Patients were not recruited but were sent a link to the GWL program if they qualified based on the study's inclusion and exclusion criteria. In the intervention group, low-risk patients were offered access solely to the PDDE program, and medium- and high-risk patients were offered access to PDDE and traditional care coordination. In the control group, only medium- and high-risk patients were given access to care coordination; low-risk patients did not receive transitional care. Traditional transitional care coordination involves proactive telephonic outreach by nurses focused on assessing for barriers to further care once home, assessing patient understanding of the next steps in their care plan, facilitating appropriate follow-up as needed, assessing for social determinants of health needs, and escalating any needs to the appropriate team. This telephonic support can vary in frequency (number of calls) and length (length of time support is provided) based on a variety of factors, including patient engagement, nursing assessment, and patient risk level. Typically, the support involves frequent calls (1-3 times per week)—with less frequency the further from discharge—within the immediate 30-day period of transitioning home.

This study was reviewed and approved as exempt quality improvement by the Medical College of Wisconsin Institutional Review Board.

Inclusion/Exclusion Criteria

Data were collected from March 2020 through November 2020. Patients who met the criteria for care coordination (based on payer and risk level) were included in the analysis. This included patients with a moderate or high unplanned readmission risk score. Additionally, patients with a low unplanned readmission risk score were included if their payer was part of a risk-based payment program contracted with the system (ie, part of the

FIGURE 2. Patient Inclusion Criteria Based on PCP in System, Risk Level, and Insurance



ACO, accountable care organization; CIN, clinically integrated network; PCP, primary care provider.

clinically integrated network, accountable care organization, or other risk-based relationship). Outpatient and observation patients were removed from the analysis (Figure 2).

Patients whose primary diagnosis was COVID-19 were enrolled in COVID-19–specific PDDE loops and were excluded. Patients who were discharged with a congestive heart failure diagnosis were enrolled in heart failure–specific PDDE loops and were also excluded.

Intervention

The PDDE program is an automated digital engagement solution, supported by registered nurses, designed to improve the patient experience and provide education and follow-up, allowing for coordinated care. Patients can interact using a responsive web or mobile application. After enrollment, patients receive bidirectional questions specific to their stage in the transition of care. The program provides either 12 days (for low-risk patients) or 30 days (for medium- to high-risk patients) of check-ins related to progress and symptoms in the form of questions and structured responses, with an option for free-text comments. The program also provides educational guidance related to the patient's discharge diagnosis.

A centralized care coordination team monitored patient check-ins and free-text comments during normal business hours. If a patient had concerns or questions, the appropriate care coordination team member connected with the patient via text in the application or telephonic outreach. After-hours support was provided by a centralized virtual care team of RNs who reviewed abnormal survey responses (eg, "red" concerning symptoms) and free-text comments.

Data Collection

Clinical and operational metrics were collected from the electronic health records. Clinical metrics included readmission and patients' outcomes. Operational metrics included race, age, zip code, language, inpatient readmission risk score, payer, and PCP location. We used patient addresses geocoded to the Census block level to determine the local Area Deprivation Index, derived from the US Census and American Community Survey[8] as a measure of socioeconomic status and grouped by quartile.[9-11]

Participation in the PDDE program was provided through usage data from the GWL application, including data on system enrollment, activation, check-ins, alerts, comments, and engagement. Data for all patients were collected for up to 30 days following discharge.

Main Outcomes and Measures

Our primary outcome was readmission. Readmission was defined as an unplanned hospital admission within 30 days from a prior inpatient hospital admission and used methodology from Vizient, Inc. The likelihood of missing outside hospitalizations was low, as only patients with an internal PCP were included because patients with external PCPs may be more likely to seek hospital care outside our health system.

Activated patients were defined as patients who signed up for the application and had an activation loop encounter in the GWL data set. The number of specific events (enrollment, check-in, alert, resolution, closure) that occurred while using the PDDE program was counted.

Statistical Analysis

To examine the impact of PDDE on readmission, patients' demographics were compared using ^{2} tests between the control and intervention groups to examine differences. To examine factors associated with readmission, analysis was divided by risk group. Univariate analysis was run on each risk group to understand the intervention's impact on readmission. A mixed-model approach to stepped-wedge design was used to control for clustering and time period to assess the intervention's impact on readmission.[12] To examine activation, patients in the intervention group were divided as activated or not in each risk group. Demographics of patients who activated the PDDE program vs those who did not were also recorded. Univariate analysis was then run to see the impact of activation on readmission.

RESULTS

Cohort Characteristics

Included in the study were 5490 patients who were discharged from F&MCW between March 2020 and November 2020. If patients had multiple admissions, only the first in the analysis counted as the index admission. Overall, 58.4% were female. Mean age at admission was 62.5 years (range, 14-101). For race and ethnicity, 1.6% identified as Asian, 20.7% as Black, 75.4% as White, 2.3% listed another race, and 2.4% identified as Hispanic. For marital status, 48.9% were married, 23.1% were single, 15.0% were widowed, and 10.5% were divorced. Most patients resided in Wisconsin (99.3%) and listed English as their primary language (99.0%). For primary insurance, 21.7% of patients had private insurance, 9.1% of patients had Medicaid, 34.2% of patients had Medicare, and 35.0% of patients had Medicare Advantage plans.

Cohort characteristics of demographics were compared between the control and intervention groups. Differences were seen by age, race, marital status, and insurance category, whereas no differences were seen by sex, ethnicity, state of residence, and primary language spoken (**Table 1**). For quartiles of Area Deprivation Index, 27.5% in the intervention cohort were in the fourth (most deprived) quartile, and 19.5% of control patients were in this quartile (< .001) (Table 1).

Readmission With PDDE by Risk Level

Readmission analysis was categorized by risk level. A total of 1509 patients were low risk, 2032 were medium risk, and 1949 were high risk. In unadjusted analyses, we found no differences in readmission between the control and intervention groups among low-risk (control: 33 of 813 [4.1%]; intervention: 29 of 696 [4.2%]; = .92) (**Table 2** [A]) and medium-risk (control: 118 of 1051 [11.2%]; intervention: 119 of 981 [12.1%]; = .53) (Table 2 [B]) patients, but we did observe a difference among high-risk patients (control: 221 of 871 [24.2%]; intervention: 334 of 1078 [31.0%]; = .001) (Table 2 [C]).

The mixed-model analysis, taking advantage of the stepped-wedge design, revealed nonsignificant differences between control and intervention groups for readmission among low-risk patients (95% CI, −0.23 to 0.90; = .23) (**Table 3** [A]), medium-risk patients (95% CI, −0.14 to 0.60; = .21) (Table 3 [B]), and high-risk patients (95% CI, −0.32 to 0.64; = .48) (Table 3 [C]).

Activation of PDDE

Activation of the PDDE application was analyzed among the intervention group. A total of 696 low-risk, 981 medium-risk, and 1078 high-risk patients were in the intervention group and offered access to the PDDE program. A total of 350 patients activated the system, and 2405 patients did not. Of the intervention group, 25.6% of low-risk, 12.6% of medium-risk, and 10.0% of high-risk patients activated the PDDE program. There were no significant differences in sex, ethnicity, patient state, and patient language between the 2 groups. Patients who activated PDDE were generally younger than those who did not activate it; for example, 19.4% of patients who activated PDDE were 75 years or older compared with 28.0% of patients who did not. Other differences were seen, such as that 85.4% of patients who activated PDDE were White, whereas 68.9% of patients who did not activate PDDE were White (< .001), and 65.7% of patients who activated PDDE were married, whereas 43.7%

TABLE 1. Demographics of Control and Intervention Patient Population[a]

Characteristic	Control	Intervention	*P*
n	2735 (100.0%)	2755 (100.0%)	
Age in years, n (%)			**.004**
< 18	4 (0.1%)	1 (0.0%)	
18-34	354 (12.9%)	326 (11.8%)	
35-49	296 (10.8%)	364 (13.2%)	
50-64	461 (16.9%)	528 (19.2%)	
65-74	790 (28.9%)	792 (28.7%)	
75-89	741 (27.1%)	664 (24.1%)	
90	89 (3.3%)	80 (2.9%)	
Sex, n (%)			.31
Male	1156 (42.3%)	1126 (40.9%)	
Female	1579 (57.7%)	1629 (59.1%)	
Ethnicity, n (%)			.17
Hispanic	60 (2.2%)	72 (2.6%)	
Missing	0 (0.0%)	1 (0.0%)	
Non-Hispanic	2666 (97.5%)	2679 (97.2%)	
Unknown	9 (0.3%)	3 (0.1%)	
Race, n (%)			**< .001**
Asian	45 (1.6%)	44 (1.6%)	
Black	451 (16.5%)	686 (24.9%)	
Other	58 (2.1%)	69 (2.5%)	
White	2181 (79.7%)	1956 (71.0%)	
Marital status, n (%)			**< .001**
Divorced	291 (10.6%)	285 (10.3%)	
Legally separated	26 (1.0%)	27 (1.0%)	
Married	1403 (51.3%)	1282 (46.5%)	
Single	557 (20.4%)	713 (25.9%)	
Unknown	38 (1.4%)	46 (1.7%)	
Widowed	420 (15.4%)	402 (14.6%)	
Patient state, n (%)			.524
Wisconsin	2719 (99.4%)	2734 (99.2%)	
Other	16 (0.6%)	21 (0.8%)	
Primary language, n (%)			.803
English	2710 (99.1%)	2727 (99.0%)	
Other	25 (0.9%)	28 (1.0%)	
Insurance, n (%)			**.025**
Managed care	604 (22.1%)	585 (21.2%)	
Medicaid	217 (7.9%)	283 (10.3%)	
Medicare	944 (34.5%)	934 (33.9%)	
Medicare Advantage	970 (35.5%)	951 (34.5%)	
Other	0 (0.0%)	2 (0.1%)	
Risk level, n (%)			**< .001**
Low	813 (29.7%)	696 (25.3%)	
Medium	1051 (38.4%)	981 (35.6%)	
High	871 (31.8%)	1078 (39.1%)	
Quantiles of Area Deprivation Index, n (%)			**< .001**
1	569 (25.6%)	532 (23.2%)	
2	641 (28.8%)	562 (24.5%)	
3	582 (26.1%)	571 (24.9%)	
4	435 (19.5%)	632 (27.5%)	

[a]Bold values indicate < .05.

TABLE 2. Readmission by Intervention[a]

A. Univariate analysis of readmission among low-risk patients in the control and intervention groups			
	Control	Intervention	*P*
n	813 (100.0%)	696 (100.0%)	
Readmission			.92
No	780 (95.9%)	667 (95.8%)	
Yes	33 (4.1%)	29 (4.2%)	
B. Univariate analysis of readmission among medium-risk patients in the control and intervention groups			
	Control	Intervention	*P*
n	1051 (100.0%)	981 (100.0%)	
Readmission			.53
No	933 (88.8%)	862 (87.9%)	
Yes	118 (11.2%)	119 (12.1%)	
C. Univariate analysis of readmission among high-risk patients in the control and intervention groups			
	Control	Intervention	*P*
n	871 (100.0%)	1078 (100.0%)	
Readmission			**.001**
No	660 (75.8%)	744 (69.0%)	
Yes	221 (24.2%)	334 (31.0%)	

[a]Bold values indicate < .05.

TABLE 3. Mixed-Models Analysis for Risk Cohorts

A. Low-risk mixed-models analysis						
Effect	Time	Estimate	SE	*df*	*t*	*P*
Time	1	−0.40	0.30	0	−1.32	
Time	2	−0.33	0.32	0	−1.05	
Time	3	0.40	0.34	0	−1.18	
Time	4	−0.55	0.37	0	−1.5	
Time	5,6	−0.55	0.38	0	−1.47	
Intervention		0.33	0.27	15	1.25	.23
B. Medium-risk mixed-models analysis						
Effect	Time	Estimate	SE	*df*	*t*	*P*
Time	1	0.09	0.18	0	0.50	
Time	2	0.16	0.19	0	0.84	
Time	3	−0.22	0.21	0	−1.08	
Time	4	−0.09	0.23	0	−0.38	
Time	5,6	−0.21	0.22	0	−0.92	
Intervention		0.23	0.17	15	1.32	.21
C. High-risk mixed-models analysis						
Effect	Time	Estimate	SE	*df*	*t*	*P*
Time	1	0.23	0.23	0	1.01	
Time	2	−0.24	0.24	0	−0.98	
Time	3	0.40	0.26	0	1.51	
Time	4	−0.08	0.28	0	−0.28	
Time	5,6	0.01	0.28	0	0.03	
Intervention		0.16	0.22	14	0.73	.48

of patients who did not activate PDDE were married (< .001). For insurance payers, 40.9% of patients who activated PDDE had private insurance, whereas only 18.4% of patients who did not activate PDDE had private insurance (< .001). A greater percentage of patients who did not activate PDDE had Medicare (36.1%) compared with those who did not activate PDDE (18.6%) (< .001) (**eAppendix Table 1** [eAppendix available at **ajmc.com**]).

Of patients who were offered the PDDE program, we found no differences in low-risk readmission (not activated: 26 of 554 [4.7%]; activated: 3 of 142 [2.1%]; = .19) (**eAppendix Table 2** [A]), medium-risk readmission (not activated: 110 of 871 [12.6%]; activated: 9 of 110 [8.2%]; = .18) (eAppendix Table 2 [B]), and high-risk readmission (not activated: 306 of 980 [31.2%]; activated: 28 of 98 [28.6%]; = .24) (eAppendix Table 2 [C]) between patients who activated and did not activate PDDE.

DISCUSSION

In this retrospective study of 5490 patients, PDDE was able to successfully expand resource-limited care coordination by offering low-risk patients a service they were unable to receive in the past. PDDE was able to provide more touch points between patients and providers in an efficient manner. However, through multivariate analysis, PDDE was found to have no significant impact on readmission among low-, medium-, and high-risk patients.

The results of our study show some differences in findings across the various patient risk levels and demographics in the univariate analysis. This highlights a need for digital care tailored to a patient's risk level and background. Providing a more patient-specific application experience could target intervention on the impact of patient and clinical factors to reduce readmission risk. Features to lower readmission (eg, improved patient education, symptom monitoring, clinical feedback) could be implemented through PDDE. Future research could examine what specific feature of PDDE was most used and most associated with lower readmission rates.

Although a strict control group was unavailable, exploring the driving factors behind the significant increase in readmission among the intervention group compared with the control group in the univariate analysis is necessary. Due to the nature of the stepped-wedge implementation, the control group was mainly discharged between March 2020 and July 2020, and the intervention group was concentrated in August 2020 through November 2020. Given how this time period coincides with the COVID-19 pandemic, the pandemic's effects should be noted. In the early days of the pandemic, many Americans sheltered at home and limited their interactions with each other to minimize the spread of the virus.[13] These effects included reduced emergency department visits for non–COVID-19–related conditions and reduced daily activity that could exacerbate health conditions.[13] Given the activation findings and the timing of the stepped-wedge implementations, we cannot conclude that the increase in readmission among high-risk patient populations is due to the implementation and usage of PDDE. Also, further exploration into why additional provider and patient virtual interactions did not significantly decrease readmission is necessary. Although providers may encourage patients to return to the hospital following their remote engagement if PDDE flags a patient as deviating from plan, further investigation into this impact is necessary to fully understand the usage of PDDE. The PDDE program should be explored for specific features and abilities that could distinctly target and limit future readmission. Readmission is complex and multifactorial and important to target in the current health care state.

Examining patients who truly activated and utilized the PDDE application can provide insight into future improvements. Previous studies using GWL showed various activation rates, with a COVID-19 study having an activation rate of 60.93% and another study that examined emergency department revisits among patients presenting to the emergency department having an activation rate of 27.0%.[6,14] Because specific demographics of age, race, marital status, and insurance were associated with increased activation, specific groups of patients can be targeted to increase their activation and engagement within the PDDE system. Further investigation into user experience can provide insight into why certain demographic groups were more likely to use the application. As such, the application can be modified to best suit the needs of specific patients to improve their transition of care and overall health outcomes.

Although readmission was increased in the intervention PDDE group and it was also found that those who activated the application had a nonsignificant decrease in readmission, it can be concluded that the PDDE system did not cause harm to patients, as supported by previous studies.[7,15] As such, this allows for improvement of resource utilization as technology can be leveraged to advance resource-limited areas of health care. This technology provides avenues of automation and increased health access to patients who were traditionally restricted by resource-limited health care.

Expansion of PDDE should consider access and equity. In previous studies, it has been found that access to digital technology is disproportionately lacking among individuals in racial minority groups and those of low socioeconomic status.[16] Although this technology is accessible to patients with a smartphone or a web browser, technological literacy can limit the successful usage and understanding of this application. As such, it is important to target these user difficulties in the improvement of PDDE.

Limitations

Although this study provides insight into the use of digital technology, limitations exist. This study was completed at a single institution with a specific patient cohort, so the conclusions of our study may not be generalized. The number of patients who activated and used the application was limited, further decreasing the generalizability of our results. In addition, the study was conducted throughout the pandemic, which affected readmissions. Although this is difficult to control for, the limitations of this time period should be noted.

CONCLUSIONS

When comparing readmission rates among intervention and control groups, PDDE was found to have a significant impact among the high-risk population with increased readmission; however, when controlling for time period and patient factors, no difference in readmission was seen. Using technology to target areas of health care that are traditionally risky and resource limited for patients is necessary to advance health care. Remote patient monitoring is an important innovation, especially within the context of the pandemic, to increase access to care. However, barriers remain to engagement via virtual platforms, including limited digital health literacy, unequal access to technology, design barriers, and integration of digital technology with other services needed for effective care. As such, it is essential to develop applications and digital health technologies that will be able to significantly improve transitions of care as patients are discharged from inpatient hospitals to their homes. ■

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eAppendix Table 1. Demographics of non-activated vs activated patients in the intervention group

	Not Activated	**Activated**	**p**
n	2405 (100.0%)	350 (100.0%)	
Age (%)			**0.03**
<18	1 (0.0%)	0 (0.0%)	
18-34	275 (11.4%)	51 (14.6%)	
35-49	318 (13.2%)	46 (13.1%)	
50-64	457 (19.0%)	71 (20.3%)	
65-74	678 (28.2%)	114 (32.6%)	
75-89	602 (25.0%)	62 (17.7%)	
90+	74 (3.1%)	6 (1.7%)	
Sex (%)			0.45
Male	990 (41.2%)	136 (38.9%)	
Female	1415 (58.8%)	214 (61.1%)	
Ethnicity (%)			0.32
Hispanic	67 (2.8%)	5 (1.4%)	
Missing	1 (0.0%)	0 (0.0%)	
Non_Hispanic	2335 (97.1%)	344 (98.3%)	
Unknown	2 (0.1%)	1 (0.3%)	
Race (%)			**<0.001**
Asian	38 (1.6%)	6 (1.7%)	
Black	651 (27.1%)	35 (10.0%)	
Other	59 (2.5%)	10 (2.9%)	
White	1657 (68.9)	299 (85.4%)	
Marital Status (%)			**<0.001**
Divorced	261 (10.9%)	24 (6.9%)	
Legally Separated	26 (1.1%)	1 (0.3%)	
Married	1052 (43.7%)	230 (65.7%)	
Single	660 (27.4%)	53 (15.1%)	
Unknown	38 (1.6%)	8 (2.3%)	
Widowed	368 (15.3%)	34 (9.7%)	
Patient State (%)			0.23
Wisconsin	2389 (99.3)	345 (98.6)	

Other	16 (0.7%)	5 (1.4%)	
Patient Language (%)			0.24
English	2378 (98.9%)	249 (99.7%)	
Other	27 (1.1%)	1 (0.3%)	
Insurance (%)			**<0.001**
Managed_Care	442 (18.4%)	143 (40.9%)	
Medicaid	275 (11.4%)	8 (2.3%)	
Medicare	869 (36.1%)	65 (18.6%)	
Medicare_Advantage	818 (34.0%)	133 (38.0%)	
Other	1 (0.0%)	1 (0.3%)	
Risk Level (%)			**<0.001**
High	980 (40.7%)	98 (28.0%)	
Low	554 (23.0%)	142 (40.6%)	
Medium	871 (36.2%)	110 (31.4%)	

eAppendix Table 2. Readmission by patients who did not and did activate the PDDE, broken out by risk level.
Table 2a Univariate analysis of readmission among low risk patients by those who did not activate and those who did activate the PDDE. Table 2b Univariate analysis of readmission among medium risk patients by those who did not activate and those who did activate the PDDE. Table 2c Univariate analysis of readmission among high risk patients by those who did not activate and those who did activate the PDDE.

	Low Risk		
	Not Activated	Activated	p
n	554 (100.0%)	142 (100.0%)	
Readmission			0.18
No	528 (95.3%)	139 (97.9%)	
Yes	26 (4.7%)	3 (2.1%)	

	Medium Risk		
	Not Activated	Activated	p
n	871 (100.0%)	110 (100.0%)	
Readmission			0.18
No	761 (87.4%)	101 (91.8%)	
Yes	110 (12.6%)	9 (8.2%)	

	High Risk		
	Not Activated	Activated	p
n	980 (100.0%)	98 (100.0%)	
Readmission			0.24
No	674 (68.8%)	70 (71.4%)	
Yes	306 (31.2%)	28 (28.6%)	