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Reducing Heart Failure Readmissions at a Community Hospital by Channeling Resources toward High-Risk Patients

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Abstract

Objective: The objective is to evaluate an intervention that utilized a real-time predictive model to identify patients at high risk of readmission among heart failure (HF) patients and to offer targeted intervention to these patients.

Participants: HF patients in a 227-bed hospital in Texas, USA.

Methods: We employed a quasi-experimental, nonrandomized, pre-/post-intervention concurrent-controlled retrospective cohort design. Unadjusted readmission rates among HF patients at non-study hospitals in the network and among acute myocardial infarction (AMI) patients at the study hospital over the same time frame served as controls. We derived a predictive, mixed-effects, multivariable logistic regression model accounting for temporal as well as within-person and across-person variation in readmission risk.

Results: Among HF patients at the study hospital, there were 449 pre-intervention and 196 post-intervention discharges (unadjusted readmission rates: 19.4% and 9.4%, respectively [p=0.02]). Readmission rates among HF patients significantly decreased, independent of patient-level and temporal effects (adjusted odds ratio=0.49; 95% confidence interval: 0.25-0.93). The healthcare costs per index discharge fell from $15,583 pre-intervention to $14,186 post-intervention (p=0.37), resulting in an estimated $750,000 in annual savings.

Conclusions: Real-time, proactive and accurate matching of post-discharge resources with the risk of readmission significantly reduces the rate of 30-day all-cause readmissions among HF patients.

Keywords: Heart failure; 30-day readmissions; Predictive modeling; Risk stratification; Machine learning

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Introduction

Between 2011 and 2014, an estimated 6.5 million Americans ≥ 20 years of age suffered from congestive heart failure (HF) [1]. HF prevalence is projected to increase by 46% from 2012 to 2030 when> 8 million adults aged ≥ 18 years will have heart failure [2]. Total national costs for HFare projected to rise 127% from $30.7 billion in 2012 (68% attributable to direct medical expenses) to $69.7 billion in 2030 [2]. Roughly11.6 hospitalizations for HFoccur annuallyamong every 1000 people aged ≥ 55 years; with 6.6 readmissions per 1000 population per year [3]. Hospitalizations [4] and deaths [5] are more frequent among those previously hospitalized for HF, with almost one in four patients being readmitted within 30 days of discharge [6]. Reduction of HF readmissions is thus a national priority [6,7].

Efforts to reduce HF admissions have yielded significant progress in recent years. Among Medicare beneficiaries, the HF admission rate, adjusted for age, sex, and race, declined by 29.5% from 1998-2008, due to improved care and risk factor management [8]. Yet readmission rates, after an index HF hospitalization, remain high [9]. The Centers for Medicare and Medicaid Services (CMS) pioneered reimbursement reforms to incentivize hospitals to reduce unplanned, all-cause readmissions of HF patients [10,11]. The reforms have often had a lower-than-expected impact

[12]. The impact of readmission-reduction interventions by hospitals isalsoinadequate [13]. Varied methods like discharge planning [14], pharmacist consultation [15,16], early outpatient follow up [17], interdisciplinary coordination[18], intensive patient education [19,20] or self-management [21], likely need to be combinedfor greatereffectiveness at reducing subsequent re-hospitalizations [10]. Applying such high-intensity interventions indiscriminately to all HF patients can be financially prohibitive. One study showed that among U.S. hospitals that developed successful readmission programs, the majority subsequently abandoned them due to financial constraints [22]. Programs to reduce readmissions are more sustainable when focused on highest-risk patients, who are likely to derive the greatest benefit, and targeted prospectively and in real-time, right from admission [23]. Hence the need for risk scores that accurately discriminate the HF patients at high risk of short-term readmission [24]. Besides risk-specific targeting of resources, pro-active risk stratification strengthens shared decision-making by helping clinicians to engage affected families à priori.

Published predictive models for stratifying 30-day re-hospitalization risk among HF patients tend to have modest discrimination, with c-statistic values ranging from 0.59 – 0.65[24-30]. Amarasingham and colleagues published a real-time readmission risk prediction e-Model, based on clinical, social, behavioral, and utilization data, extracted from the EMR within 24 hours of admission, that had better discrimination (c-statistic=0.72) than hither to published models [31]. This model was subsequently shown to reduce HF readmission rate by 26% ata safety net hospital [32]. Unlike models based onretrospective claims data, whose variables are coded post-discharge, real-time predictive algorithms, like the Amarasingham et al. model,utilize variables available in the EMR to model readmission risk in real time, which facilitatespoint-of-care interventions [33]. Most readmission risk models inadequately account for health-related social determinants [34,35]. The Amarasingham et al. model, by contrast,includes wide-ranging clinical, behavioral, social, and utilization variablesderived within the context of a safety-net county hospital [31-33]. Questions remain about whether the model is replicable among non-safety net hospital settings.

The purpose of the present study was to replicateand evaluate the Amarasingham et al.predictive modelwithin a new hospital setting whose catchment population is not drawn from the safety net. We aimed to investigate the extent to which the model was generalizable to contexts different from where it was first developed, as an initial step towards establishing the scope of its applicability and utility. In addition to reporting readmission rates before versus after the intervention, we also report total costs of care within 30 days of index discharges before versus after the intervention.

Methods

Study setting

The study setting was the Texas Health Resources (THR) Harris Methodist Hospital at Hurst-Euless-Bedford (HEB). THR is one of the largest faith-based, not-for-profit health care systems in the United States (U.S.), the largest in North Texas in terms of volume of patients served. THR hasa primary service areaconsisting of 16 counties in north central Texas, home to >6.2 million people. TH-HEB, one of 26 THR network hospitals, is a 227-bed facilitythat receives ≈12,000 healthcare visits annually, and typifies many U.S. hospitals. Its baseline readmission and in-hospital mortality rates for HF patients, per Medicare's Hospital Compare™ ratings [36], approximated national averages.

TH-HEB installed the Parkland Intelligent e-Coordination and Evaluation System (Pieces™), cloud-based software that uses Natural Language Processing (NLP) to identify patients with specific illnesses, appliesrisk stratification algorithms, enables secure messaging to clinical/case managers to assign evidence-based interventions to high-risk patients, then provides a dashboard for tracking interventions, and monitoring patient outcomes. Pioneered by Parkland Center for Clinical Innovation (PCCI), Pieces™has been in use at Parkland Health and Hospital System (PHHS) since December 2009. Pieces™ interfaces with a hospital's electronic medical record (EMR) system via the cloud. In April 2013, it was installed, and began extracting patient-level data from TH-HEB's EPIC® (EPIC Systems Incorporated, Verona, Wisconsin) EMR.

Study design and participants

We employed a quasi-experimental non-randomized pre-/post-intervention concurrent-controlledretrospective cohortdesign. We targeted, for inclusion in the study sample, patients admitted to TH-HEB Hospital with a principal diagnosis of HF, indicated by International Classification of Diseases, Ninth Revision – Clinical Modification (ICD-9-CM) codes 402.00-402.91 or 404.00-404.93 or 428.0-428.9, in the pre- and post-intervention phases of the study. Patients admitted to TH-HEB with acute myocardial infarction (AMI), indicated by ICD-9-CM codes 422.00-422.99, and those admitted for HF at non-HEB hospitals within the THR system, served asconcurrent controls. Adult patients (age ≥ 18 years) admitted to the general medicine services at TH-HEB Hospital with a primary 'final discharge' diagnosis of HF pre- and post-intervention were eligible for inclusion in the intervention arm of the study, regardless of age, gender, race, ethnicity, income, or secondary diagnoses. Patients admitted to the intensive care unit (ICU) with a primary diagnosis of HF andcognitively challenged general medicine inpatients with HF were eligible.

Children or pregnant women were ineligible. Patients admitted for surgical or obstetric problems, and thosereadmitted solely for the purpose of rehabilitation (DRG462), were excluded. Due to periodic limitations inavailability of key hospital staff, we excluded from further analysis patients who were admitted between Friday afternoon and Sunday morning then discharged by Sunday afternoon or admitted then discharged during a federal holiday without receiving the interventions. Patients whose principal diagnosis ended up not being HF at the time of discharge were also excluded from analysis. We tracked readmissions to any THR facility within 30 days afterdischarge from the index HF admissions. Index admission and 30-day readmissions were calculated using the CMS methodology developed by Horwitz et al. [37].

Patient recruitment occurred via an automated electronic process that used Pieces™ to identify eligible participants from the hospital EMR on admission. HF patients were assigned a risk score within 24 hours of admission. The intervention was initiated for moderate or high-risk HF patients after confirmation of the HF diagnosis and approval by their attending physician.

Human subjects' protection

The study was approved by the Institutional Review Board at THR, who determined that the projectpresented onlyminimal risk to participants, which did not exceed the risk typically involved in

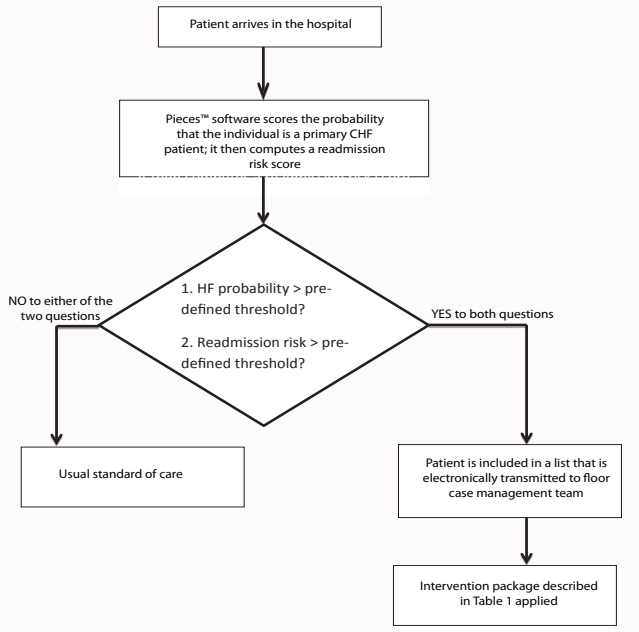

Figure 1: THR Workflow Implementation of the Pieces™-based Intervention Package.

standard clinical care, and thus waived the requirement for written informed consent.

Intervention package

HF patients received a package of inpatient and outpatient interventions tailored to their level of risk. Interventions were structured along three dimensions: 1) identifying HF patients on admission to TH-HEB Hospital in real time; 2) risk-stratifying patients and providing point-of-care clinical decision support to clinicians to facilitate risk-based targeting of interventions; and 3) electronic coordination, monitoring, and tracking of evidence-based interventions provided to high-risk HF patients. All-cause readmission risk scores were based on the Amarasingham et al. e-Model [31,32].

Table 1 (below) details the package of intensive inpatient/outpatient counseling and monitoring activities, drawn from evidence-based readmission reduction strategies that were implemented for high-risk HF patients. In summary, the interventions comprised (1) additional inpatient education by a multidisciplinary team, (2) enhanced inpatient clinical and pharmacy consultation, (3) facilitated discharge planning, plus (4) outpatient clinical and pharmacy follow-up. Some components (e.g., inpatient interventions and chronic illness program consult) predated the study and were part of the baseline standard of care. However, the intensity or involvement of outpatient case managers was increased, during the post-intervention period, among patients in the intervention arm. Intervention-group patients were encouraged to complete all components but were free to decline any of them. Intervention tasks were documented in the hospital EMR as clinical orders. The intervention was enabled by mining of data in real time from THR-HEB's EMR, via the Pieces™ platform. Through ongoing EMR surveillance, Pieces™ software tracked whether patients were receiving recommended interventions then triggered automatic alerts to case managers if any of the ordered interventions was/were not implemented. We conducted monthly evaluations of the adherence of interventions to the study protocol. Figure 1 is a flow diagram of the procedures that we utilized to identify/target recipients of the interventions.

Similar to what prevails at many hospitals [38,39], a specialized but finite level of transition-of-care ordisease management resources is available for all HF patients during daytime hours from Monday to Friday. This includes a hospital-wide case management department and a dedicated proportion of pharmacy clinic resources who maintain other clinical responsibilities beyond the post-discharge follow-up of HF patients. No case management staffers were added for the study. The intervention package was thus designed to allocate the finite pool of resources that are available from Monday to Friday in the most efficient way possible, to maximally reduce 30-day all-cause readmissions among HF patients.

Study variables and measures

Outcomes: The primary outcome is all-cause re-hospitalization within 30 days of discharge from any THR network hospital. Readmission was coded as a binary yes/no variable indicating whether it happened or not. A secondary outcome was total costs of care within 30 days of index discharges, defined as costs of all inpatient stays (including the index admission), plus outpatient, and emergency department (ED) visits within 30 days of discharge from index admission. AMI readmission rates at THR-HEB and CHF readmission rates for the entire THR system were similarly calculated.

Contextual variables: We collected data on demographics, clinical severity and comorbid illness burden (according to the Charlson comorbidity index [40]) plus patient [31] and neighborhood-level [41] measures of social disadvantage. We also extracted key socio-behavioral readmission risk factors such as marital status [31], payer status [42], number of home address changes in the precedingyear[31] (indicative of housing instability [43]), history of positive urine cocaine test in the precedingyear [31], missed clinic visits in the preceding six months [44], and number of hospital admissions prior to index admissions [45]. We extracted EMR data on clinical prognostic factors, e.g. brain natriuretic peptide, troponin-I, creatine kinase, blood urea nitrogen, and albumin [31].

Cost estimates: We estimated costs from the payer's perspective, based on average healthcare costs and accounting for missing charge classes. We restricted cost estimates to expenses within the THR system. We did not include costs forhealthcare visits or admissions outside the THR system and home care charges. Also, five patient accounts were not available for cost estimation because charges had beenwaived (flagged within the EMR as "Do Not Bill") for reasons that were difficult toascertain after the fact. Cost estimates did not include installation costs for the Pieces™ platform. Indirect costs, such as travel costs by the family, were also not included.

Statistical analyses

The hospitalization was the unit of analysis. Clinical, demographic, administrative, and risk score characteristics of the pre-intervention and intervention discharge cohorts werefirst compared using the Chi-square (χ^2) test of associationfor categorical variables and unpaired Studentt-test or Wilcoxon's rank-sum test for continuous variables.

Based on the Clopper-Pearson method [46], a conservative approach to power and sample size estimation [47], we required a minimum sample of 150 primary discharges among HF patients to achieve 80% power (β=0.20) in detecting a 5% absolute reduction in readmission rate at 95% confidence level (α=0.05). We derived pre-intervention read mission rates over a 12-month period for the HF

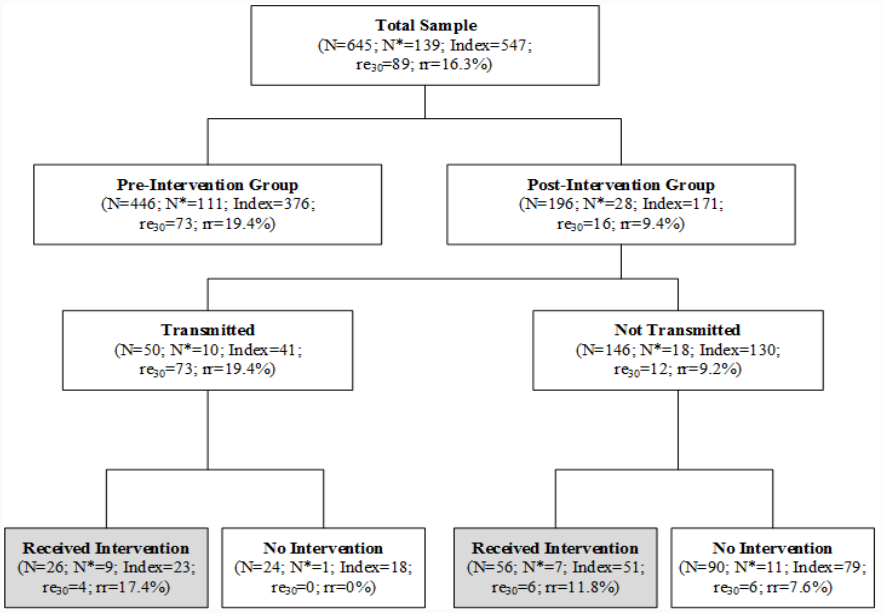

Figure 2: Variation in Risk of Readmission for Different Segments of the Study Sample.
Key: N* = number of inpatient admissions followed by readmission within 30 days of discharge; re_{30} = number of readmissions within 30 days; rr = relative risk of readmission within 30 days.

Table 1: Inpatient and Outpatient Interventions for HF Patients at High Risk.

THR-HEB Inpatient Interventions	THR-HEB Outpatient Interventions
Case Manager validates and submits the following care transition coach order in EPIC®:	At the time of discharge, the Case Manager makes outpatient appointment as follows:
a) Case Management consult	a) Pharmacist clinic visit within 7 days after discharge (Optional)
b) HF disease-specific education consult	b) Follow up by primary care provider within 30 days (Recommended)
c) Dietician consult	c) Chronic illness program consult as needed (Optional)
d) Financial counseling consult	Care transition coach/Case Manager provides post-discharge phone interventions as follows:
e) Pharmacy consult	d) Appointment reminder and scheduling
f) Pharmacist (PharmD) clinic order	e) Confirmation of medication refill, necessary changes, and medication reconciliation
g) Social worker (LICSW) consult	f) Reinforce low-sodium diet, other nutrition advice
	g) Disease management consulting
	h) Resolve appointment barriers
	i) Resolve other social barriers to care

cohort discharged from THR-HEB between January 1 and December 31, 2012; and post-intervention readmission rates over a 7-month period for the HF cohort discharged from THR-HEB between April 1 and October 31, 2013. We excluded the period between January 1 and March 31, 2013 from analysis becauseit was a time of transitioning to and rolling out of interventions. The controls were concurrent discharges of HF patients from non-HEB THR hospitals and of AMI patients from THR-HEB hospital. Unadjusted HF readmission rates at THR-HEB and non-HEB THR hospitals, plus unadjusted AMI readmission rates at HEB, during the pre- and post- intervention periods, were compared using the Chi-square test of association. Differences in total costs of care within 30 days of index discharges were compared using unpaired t-tests and the Mann–Whitney U test.

Finally, to account for potential autoregressive correlation over time, seasonal variations or secular trends, within-subject correlation for patients with more than one index admission during the study period, and potential changes in patient attributes, we synthesized a predictive multivariable generalized mixed effects logistic regression model of the risk-standardized outcomes. As a sensitivity analysis, we compared its findings with those froma nonparametric regression model. We utilized R statistical software version 3.2.3 (R Development Core Team, Vienna, Austria) for all analyses.

Results

Study population demographics and utilization profile

There were 449 primary HF discharges among 381 unique patients (48% male; 69.7% white), during the pre-intervention period, with an unadjusted readmission rate of 19.4%; and 196 primary HF discharges, among 170 uniquepatients (47% male; 69.5% white), with an unadjusted readmission rate of 9.4% (p=0.02), during the post intervention period. The unadjusted HF readmission rate across non-HEB hospitals in the THR system fell from 16.2% pre-intervention to 14.0% post-intervention (p=0.11). Unadjusted AMI readmission rate at THR-HEB fell from 9.4% pre-intervention

Table 2: Patient Characteristics and Clinical Outcomes in Pre- versus Post-intervention Periods.

Variable	Pre-intervention (N=449)	Post-intervention (N=196)	Significance level of difference (*p* value)
Age in years [mean (±SD)]	73.90 (±14.49)	74.20 (±14.11)	0.81
Race [N (%)]			0.25
• Black	19 (4.23)	7 (3.57)	
• White	313 (69.71)	123 (62.76)	
• Asian/Pacific Islander	5 (1.11)	2 (1.02)	
• Other/Unknown	112 (24.94)	64 (32.65)	
Payer [N (%)]			0.11
• Medicare	225 (50.11)	105 (53.57)	
• Medicaid	1 (0.22)	1 (0.51)	
• Private health insurance	194 (43.21)	69 (35.20)	
• Other	29 (6.46)	21 (10.71)	
Number of readmissions within 30 days [N (%)]			**<0.01**
0	338 (75.28)	167 (85.20)	
1	93 (20.71)	28 (14.29)	
≥2	18 (4.01)	1 (0.51)	
Number of outpatient visits within 30 days [N (%)]			**<0.01**
0	428 (95.32)	167 (85.20)	
	Readmit rate: 19.89%	Readmit rate: 9.66%	
1	12 (2.67)	13 (6.63)	
	Readmit rate: 10%	Readmit rate: 9.09%	
>1	9 (2.00)	16 (8.16)	
	Readmit rate: 11.11%	Readmit rate: 6.67%	
Number of emergency room visits within 30 days [N (%)]			0.36
0	387 (86.19)	168 (85.71)	
	Readmit rate: 19.33%	Readmit rate: 8.9%	
1	42 (9.35)	23 (11.73)	
	Readmit rate: 16.22%	Readmit rate: 15%	
>1	20 (4.45)	5 (2.55)	
	Readmit rate: 30.77%	Readmit rate: 0%	
Average total cost of care within 30 days [N (%)]	$15,583	$14,186	0.37
Had a pharmacist consult within 30 days [N (%)]	0	82	

to8.0% post-intervention (p=0.83). Table 2 outlines, in greater detail, the demographic representation and utilization patterns of the two cohorts of patients during the pre- and post- intervention periods. There were no significant differencesbetween themin the distribution of demographics (age, race/ethnicity, health insurance), or pattern of emergency department (ED) utilization. The patient cohort in the post-intervention period was significantly less likely (than that in the pre-intervention period) to have inpatient admissions but also more likely to have outpatient visits within 30 days of the primary discharge. Total costs of care within 30 days of discharge from the index admission (including costs of the index admission itself) showed a statistically non-significant decrease (p=0.37) from $15,583 pre-intervention to $14,186 post intervention (Table 2). Although this cost reduction did not meet our significance threshold, due to sample size limitations, giventhe 449 index discharges over the post-intervention (12-month) period, itcould potentially translate into total annual savings of approximately $750,000. The reduction in costs resulted from marked decrease in number of inpatient admissions within 30 days of discharge, partially offset by an increase in outpatient visits. Outpatient visits are less costly than inpatient admissions;hence the estimated overall cost reduction.

Intervention frequency

Table 3 (below) shows the frequency of interventions during the post-intervention period. We present information on the interventions along three dimensions: 1) transmission via the Pieces™platform to the case management team; 2) post-discharge pharmacy clinic visit; and 3) case management related order sets. Patients who were "transmitted" were more likely to have subsequently completed pharmacy clinic visits and to have at least one case management related order set, although those who were not transmitted may also have either or both the other intervention components.

Post-intervention outcomes

In Figure 2 we present the counts/frequencies of admissions that were followed by at least one inpatient readmission within 30 days after discharge, plusindex counts and readmission rates per the

Table 3: Frequency of Interventions by Pharmacy Clinic in the Post-intervention Period (N=196).

Pieces™ Intervention Package	Transmitted to Case Management Team?	Not Transmitted	Transmitted
	N (%)§	146 (74.5)	50 (25.5)
Had a pharmacy visit within the first 30 days after discharge?	YES, n (%)ł	56 (38.4)	26 (52.0)
	NO, n (%)ł	90 (61.6)	24 (48.0)
Frequency of Orders, n (%)ł	No orders	132 (90.4)	11 (22.0)
	1 – 2 orders	3 (2.1)	6 (12.0)
	≥ 3 orders	11 (7.5)	33 (66.0)

§ = Percent of total N (=196); ł = Percent of column subtotal (transmitted N=50, not transmitted N=146)

CMS definition. Since patients with higher risk were more likely to receive the intervention, those who received the intervention had higher readmission rates in both "transmitted" and "not transmitted" groups.

The unadjusted AMI readmission rate at HEB was 9.4% pre-intervention and 8.0% post-intervention (p=0.83). We observed a statistically significant reduction in HF readmission rate after adjusting for patient characteristics (adjusted odds ratio=0.49; 95% confidence interval: 0.25-0.93).

Discussion

We aimed to stratify the risk of unplanned all-cause readmission(s) within 30 days post-discharge among HF patients, and to evaluate effectiveness, in reducing all-cause readmissions, of a pilotset of interventions that channeled transitional care resources to HF patients at highest risk. The multi-component intervention package successfully reduced HF readmissions rate at TH-HEB by about 50%, whereas neither HF readmission rates at comparison hospitals in the same ecosystem, nor AMI readmission ratesat TH-HEB itself, manifested similar reductions. This large reduction in readmission rates was achieved at a lower total cost for the healthcare delivered within 30 days of index discharges, although the difference in costs did not reach statistical significance.

In this study, we report apost-intervention (50%) reduction in readmissions rate that exceeds that typically reported by other quality improvement studies among HF patients. In one study of the efficacy of targeted HF patient education/support program, Krumholz et al. found that intervention was associated with a 39% reduction in readmissions [19]. In an observational study of early physician follow-up for Medicare-beneficiary HF patients, Hernandez *et al.* found post-intervention readmission rates ranging from 23.3% among patients in the lowest quartile of early follow up to 20.9% among those in the fourth quartile [17]. In a non-randomized concurrent-controlled study of transitional care for HF patients, Stauffer et al. report a 48% post-intervention reduction in adjusted 30-day readmission rates [48]. One randomized study of intensive education targeted at HF patients upon discharge found a similar (51%) post-intervention reduction in readmissions to ours, but this was for 180-day HF-specific readmissions, and 30-day all-cause readmission rates were not reported [49]. Within the limits of our study setting, where the baseline variation in readmissions was relatively low, we contend that the superior reduction in all-cause readmissions found among HF patients in our study, when compared to most published studies, is due to the quality improvement being based on the more accurate Amarasingham et al. model. As stated before, this parent model includes a wide range of clinical and non-clinical predictor variables. The intervention package tested was thus more multi-faceted, transdisciplinary, and inter-sectoral than quality improvement programs reported in the studies cited above.

While the empirical data showed that our intervention program was effective, the specific mechanisms by which various intervention components reducedreadmissions are complicated by the fact that some patients who were not "transmitted" by the Pieces™-based e-model to the case management team are likely to have received one or more of the interventions. Implementation of the project likely led to increased efficiency by the clinical team at the study facility in early identification of patients with HF at high risk for readmission within 30 days of discharge.Hawthorne effects [50] could have partially influenced our findings given the high visibility of the project, although the continuedreduction in readmissions beyond the study timeline (data not shown) suggests otherwise.

Implications of the study

Potential benefits to patients in the intervention group are numerous. They received enhanced inpatient and outpatient education about their disease process and appropriate management, tailored one-on-one counseling about the practicalities of compliance, early and more specialized outpatient follow-up, pharmacy counseling, and follow-up telephone calls as needed. Societal benefits are also potentially large. The findings from this study have important implications for reducing costly readmissions not only for HF but for other chronic illnesses. The Pieces™ e-model represents a novel technology-driven approach that integrates automated real-time risk stratification or predictive analytics, protocol adherence monitoring, and point-of-careelectronic notifications plus clinical decision support provided to the healthcare team. The electronic nature of the system would allow hospitals to tailor programs to a specific patient's risk profile, enabling effective, pragmatic delivery ofpersonalized healthcare.Furthermore, a technological platform like this e-model has the potential to improve patient-centered inter-disciplinary, cross-sectoral and even cross-organization coordinationin the delivery of healthcare and social services, overcoming the inefficient/wasteful fragmentation that prevails in current delivery systems. On a larger scale, the findings of this study have important implications for improving HF outcomes and mitigating thesignificant financial burden that HF readmissionsimpose upon hospitals. Technology-driven approaches to quality improvement are likely to apply to additional chronic illnesses in this era of EMR-enabled big data and could thus be widely disseminated as more healthcare delivery institutions automate and digitize their health information systems.

Limitations and Strengths

There are notable limitations of this study. First, this is a single-institution study, so it is unclear how well results of this study can be generalized to different types ofhealthcare delivery organizations. Second, we only had information on outpatient utilizations (or post-discharge deaths) documented within the EMR; data on outpatient

visits (or post-discharge deaths that occurred) outside the THR system were unavailable. There is no reason to believe that the percentages of outpatient visits/post-discharge deaths that were within the THR system were systematically different in the pre- versus post-intervention periods, so our results could still hold if we assume that the percentages remained stable. This assumption however cannot be definitively ascertained. Thirdly, the study did not provide sufficient information to ascertain the effectiveness of individual intervention component, nor did it provide information on any interaction among the intervention components. Fourthly, the program might have influenced healthcare teams in ways that potentially benefitted all HF patients. Further research is required to clarify mechanisms by which components of the intervention influence the risk of readmission. Fifthly, because costs for implementation of software and those incurred outside the THR system were not available for inclusion in the analysis, this study is not a comprehensive cost effectiveness or cost benefit analysis. Finally, owing to limitations in the non-randomized design of our study, we do not claim to establish causality. Not with standing the limitations in the study's design, one would be hard pressed to find alternative credible explanations for the statistically significant post-intervention reduction in the all-cause readmissions rate.

A strength of this study is that its findings replicate those froma similar quality improvement program previously implemented in a safety net hospital setting , where the Amarasingham et al model, the first one to show high discrimination/accuracy in stratifying HF readmission risk, was pioneered. This suggests that the intervention's effectiveness might generalize to a broad range of institutions. The e-model could, thus, be replicated in other hospital settings and potentially manifest similar effectiveness, thereby increasing the prospects for wide spread adoption of the Pieces™ platform. Given this platform's seamless compatibility with EPIC® EMRs, and the latter's dominant market share compared to other EMR configurations, the e-model has potential utility in most U.S.-based healthcare markets. Future studies should demonstrate effectiveness of this technology-driven quality improvement program in yet more real-world hospital settings, further validating its wide applicability.

Conclusion

Overall, the present study achieved the primary purpose of validating, within a new hospital setting,the findings from a previous study conducted at a safety net hospital. While the difference in total costs of care within 30 days of index discharge was not statistically significant, we did observe a large and statistically significant post-intervention reduction in 30-day all-cause readmission rates among HF patients, implying that the intervention package has the potential to lead to health-related cost savings.

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Disclosures

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