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Automated identification and predictive tools to help identify high-risk heart failure patients: pilot evaluation

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ABSTRACT

Objective Develop and evaluate an automated identification and predictive risk report for hospitalized heart failure (HF) patients.

Methods Dictated free-text reports from the previous 24 h were analyzed each day with natural language processing (NLP), to help improve the early identification of hospitalized patients with HF. A second application that uses an Intermountain Healthcare-developed predictive score to determine each HF patient's risk for 30-day hospital readmission and 30-day mortality was also developed. That information was included in an identification and predictive risk report, which was evaluated at a 354-bed hospital that treats high-risk HF patients.

Results The addition of NLP-identified HF patients increased the identification score's sensitivity from 82.6% to 95.3% and its specificity from 82.7% to 97.5%, and the model's positive predictive value is 97.45%. Daily multidisciplinary discharge planning meetings are now based on the information provided by the HF identification and predictive report, and clinician's review of potential HF admissions takes less time compared to the previously used manual methodology (10 vs 40 min). An evaluation of the use of the HF predictive report identified a significant reduction in 30-day mortality and a significant increase in patient discharges to home care instead of to a specialized nursing facility.

Conclusions Using clinical decision support to help identify HF patients and automatically calculating their 30-day all-cause readmission and 30-day mortality risks, coupled with a multidisciplinary care process pathway, was found to be an effective process to improve HF patient identification, significantly reduce 30-day mortality, and significantly increase patient discharges to home care.

Keywords: clinical decision support, heart failure, risk stratification

INTRODUCTION

Heart failure (HF) affects 2.4% of US adults, or nearly 6 million people, 11% of whom are over 80 years old. The HF cost burden is expected to reach $44.6 billion in 2015,[1] and hospitalization represents ∼70% of that cost.[2] Although current therapies for HF help improve the quality of and prolong HF patients' lives, they infrequently reverse the condition's progression. Thus, as more HF patients live longer, the overall prevalence of symptomatic HF has increased[3] and is a major cause of hospitalization.[4] Moreover, as the prevalence of HF has increased, so has the incidence of hospital readmission and mortality.[5] An analysis of Medicare claims data from 2003 to 2004 found that HF was the leading cause of recurrent hospitalizations.[6]

The increasing prevalence of HF and a possible need for transplantation and mechanical circulatory support for patients living with advanced HF signal the need for a new approach to decision making and better communication techniques to support those decisions. The goal is to help healthcare providers deliver effective, safe, efficient, timely, equitable, and patient-centered care.[7] To reach this goal, healthcare will need to involve patients in decision making processes and utilize clinical decision support (CDS) to identify high-risk HF patients as soon as possible.[8]

One method that has helped healthcare providers identify high-risk HF and advanced HF patients is the use of predictive models, which can identify potential HF patients along with their risk of 30-day hospital readmission and 30-day mortality.[9–22] Although numerous risk factors and predictors for HF, 30-day hospital readmission, and 30-day mortality have been identified, little is known about how these predictors have been used in the clinical setting or what impact they have had on patient care.[9,23] In 2010, the Intermountain Risk Score (IMRS), which predicts HF hospital readmission and incident HF, was published.[24] The IMRS was also used to calculate mortality risk information from all components of the complete blood count, basic metabolic profile, and patient age,[25] and was found to significantly stratify survival and life expectancy within age-defined subgroups during more than a decade of follow-up. Other studies found that repeated IMRSs using laboratory values measured about 1 year apart were independently prognostic for mortality among initially hospitalized patients and that IMRS can predict cardiovascular disease (CVD)-specific outcomes.[26,27]

As a result of that work, and in an effort to provide that information quickly to providers, a CDS application that uses natural language processing (NLP) to help improve the identification of HF patients was developed, while another application was developed, based on the IMRS, to calculate the 30-day all-cause readmission risk and 30-day mortality risk for all hospitalized patients, including those with HF. A new report that identifies high-risk HF inpatients who need to be closely followed using a multidisciplinary care process pathway (CPP) is currently used by the Cardiovascular Clinical Program at Intermountain Healthcare (IH) on a daily basis. This paper reports the development and use of these applications and the impact their use has had on the readmission rate, mortality, length of stay, hospital cost, and discharge location of patients with HF.

METHODS

Background

The IH system is comprised of 22 hospitals, 197 clinics, urgent care centers, physician offices, and several home health practices in the states of

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Utah and Idaho and has its own health plan, which insures 750 000 individuals. A key feature of IH's current independently developed hospital information system is the integrated electronic medical record (EMR), which contains most forms of clinical information. The coded data in the EMR facilitates the development and use of CDS applications that are used to analyze patient data and constantly monitor patient care. NLP is also used to analyze non-coded (free-text) dictated reports.

It became apparent to the Cardiovascular Clinical Program at IH that the key to improving the care of hospitalized HF patients was based on early patient identification and stratification based on severity of disease. A multidisciplinary team used predictive modeling to create a better way to identify HF patients. The team started by learning from IH's historic data. A simple descriptive statistical analysis was then done, to help identify predictors of the patients who had a primary discharge diagnosis of HF. The team reviewed the risk factors for HF that were identified from the initial analysis and added other potential risk factors based on clinical expertise. To make an automated tool, the final list of potential predictors for the model only included data found in IH's EMR.

Five predictors were included in the final HF identification model: diuretic use, b-type natriuretic peptide level >200 pg/ml, ejection fraction ≤40 in the previous year, ever been eligible for any of the Centers for Medicare and Medicaid Services or Joint Commission HF core measures,[28] and ever been discharged with a primary diagnosis of HF. The predicted probability of a patient being discharged with a primary diagnosis of HF was categorized as low, medium, or high. The report was validated on three subsequent months of hospital admissions data. During the validation process, we learned that the predictive model computed a low predicted probability for some HF patients, due to nonexistent coded International Classification of Diseases 9 (ICD-9) data for a prior primary discharge diagnosis of HF in our EMR.

Application Development

To improve the predictive model's ability to identify HF patients early, an application that runs at 6:30 a.m. each day and looks for any new dictated reports stored in the EMR during the previous 48 h was developed (Figure 1). We programmed the application to look back the extra day in case any dictated reports were amended within the 24 h after they were first input to the EMR or in case there was a storage delay. The application uses NLP to read the different types of dictated reports and uses "key words/terms" to identify any inpatients or outpatients with HF. Information on each identified HF patient is stored in an Oracle table on the network, which is then moved to a long-term data mart of HF patients in IH's enterprise-wide data warehouse. That information is then used to improve the "prior primary discharge diagnosis of HF" predictor used by the HF identification model. We also found that using ICD-9 codes not only often resulted in missed HF patients, but also, these codes are not stored in the EMR until after patients are discharged and sometimes already rehospitalized at the same or a different hospital.

Another application, which also runs at 6:30 a.m. each day, looks at each hospitalized patient in all 22 IH hospitals and calculates their 30-day all-cause hospital readmission score and 30-day mortality risk score using a modified version of the IMRS. The risk scores for 30-day all-cause hospital readmission and 30-day mortality were grouped into low, moderate, and high groups and based on gender (Table 1). That information is also stored in an Oracle table on the network. The information in both Oracle tables is then included in the Cardiovascular Clinical Program's HF patient Identification and Risk Stratification Daily Report, developed using Tableau software (Tableau Software, Seattle, WA), which is e-mailed to 281 clinicians at 9:15 a.m. each morning (Figure 2). In addition to the stratified likelihood of being discharged with a primary diagnosis of HF, 30-day all-cause hospital readmission, and 30-day mortality risks, the report includes other pertinent information, including other predictive variables that can facilitate the clinicians' work-up for each patient, which are derived from the echocardiogram and laboratory data. Other types of information in the HF patient Identification and Risk Stratification Daily Report is also stored in the enterprise-wide data warehouse each day.

Figure 1: Flow chart of patient information needed for the heart failure identification model, predictive tools, and report. EMR, electronic medical record; NLP, natural language processing.

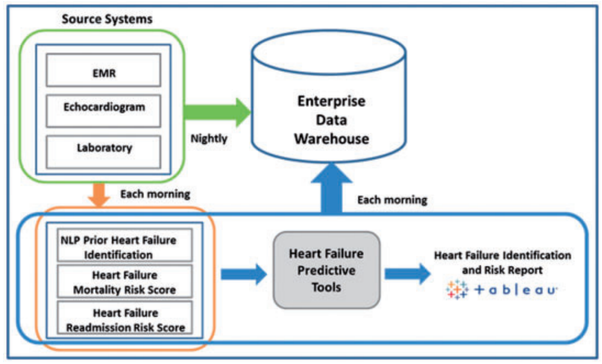


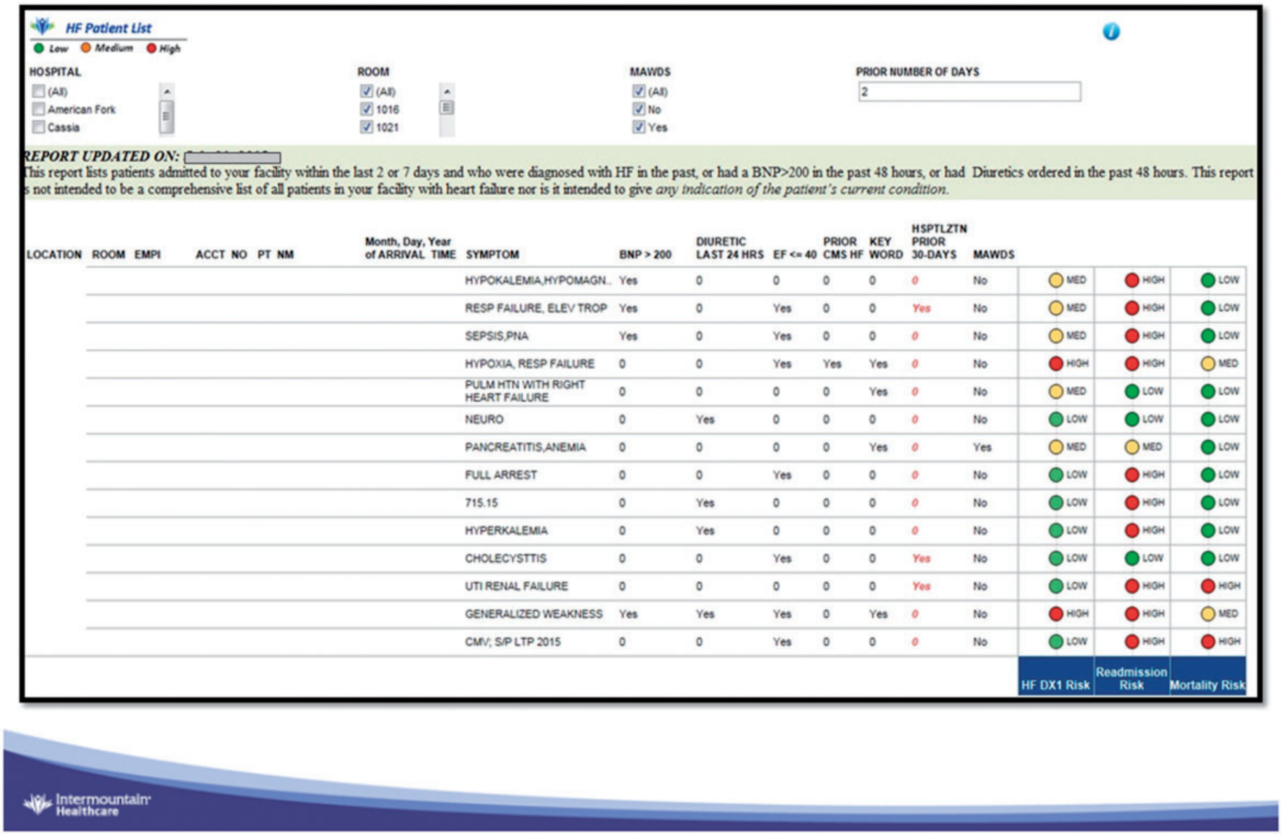
Table 1: 30-day Hospital Readmission and Mortality Risk Score Levels, by Gender, Used in the Heart Failure Predictive Tool

Risk level	30-day readmission score		30-day mortality score	
	Female	Male	Female	Male
Low	1–5	1–3	1–14	1–14
Medium	6–8	4–5	15–19	15–18
High	≥9	≥6	≥20	≥19

Care Process Pathway Development and Evaluation

From February 3, 2014 to June 30, 2014, the IH Cardiovascular Clinical Program initiated a new CPP for HF patients that targeted those patients who were identified in the HF patient Identification and Risk Stratification Daily Report. The CPP used evidence-based practice for HF patients for whom the different interventions involved in patient care were defined, optimized, and sequenced each day. This included an enhanced assessment performed by a multidisciplinary team, coupled with the inclusion of home care and close follow-up for patients specifically identified as having a high risk of a primary discharge diagnosis of HF and a high risk of 30-day hospital readmission or 30-day mortality. A sticker with a red dot was placed on the chart of high-risk HF patients. The initial evaluation was conducted at a 354-bed IH hospital that treats high-risk HF patients. The aim of the study was to improve the transition of HF patients from hospital to home care, decrease admissions to skilled nursing facilities, and reduce 30-day hospital readmissions and 30-day mortality for HF patients.

Figure 2: Example of an Identification and Risk Stratification Daily Report for heart failure patients.



Initial Pathway Evaluation

A before-and-after study design was used to measure the use and impact of the new HF patient Identification and Risk Stratification Daily Report and CPP for HF patients. Patients treated using the new CPP from February 3, 2014 to June 30, 2014 were compared with patients who had received standard care at the same hospital before the CPP was implemented, from October 1, 2013 to February 2, 2014. These patients were manually identified as having a high risk of a primary discharge diagnosis of HF and as having a high risk of 30-day hospital readmission and 30-day mortality.

Statistical Analysis

Model to Identify Heart Failure Patients

Potential predictors of patients with a primary discharge diagnosis of HF included laboratory, pharmacy, clinical, and echocardiogram data. Inpatient data from 16 971 hospitalizations between January 2013 and February 2013 in the IH system were used in a univariate analysis to refine the list of potential predictors. Data associations were assessed using the chi-square test (or the Fisher exact test, when appropriate), for categorical variables, and the two-sample *t*-tests (or the Wilcoxon rank sum test, when appropriate), for continuous variables. Predictors that showed a moderate level of association ($P < .1$) were entered into a multivariate logistic regression model and removed stepwise, using backward elimination procedures. Only variables that showed a level of association ($P < .05$) were retained in the final model. The area under the receiver operator curve (C statistic) was used to test the model's performance. A C statistic of 0.5 indicates that a model predicts an outcome that is no better than random chance, and a C statistic of 1 indicates that a model has perfect discrimination. Sensitivity, specificity, and positive predictive value were calculated to evaluate the performance of the HF identification application.

Pathway Evaluation

Baseline characteristics and outcomes were compared between the groups using Stata 12 statistical software (StataCorp, College Station, TX). Data associations were assessed using the Fisher exact test, for categorical variables, and two-sample *t*-tests, for continuous variables. A multivariate logistic regression model was used to evaluate the impact of the HF patient Identification and Risk Stratification Daily Report and the CCP, and to control for confounding factors. Variable cost was calculated by adding up costs related to volume, such as supplies, direct nursing time, imaging, labs, etc. This study was approved for publication by the IH Office of Research.

RESULTS

New Applications

The NLP-identified HF patients were added to the HF identification model, which increased the model's sensitivity from 82.6% to 95.3% and its specificity from 82.7% to 97.5%. The model's current positive predictive value is 97.45%. The unit manager (N.G.) at the study hospital reports that the hospital staff's daily multidisciplinary discharge planning meeting is based on the information from the HF patient Identification and Risk Stratification Report, which allows for earlier identification of HF patients, and the clinicians' review of potential HF admissions takes less time compared to the previously used manual HF identification methodology (10 vs 40 min).

The HF NLP application used by the HF identification model and the 30-day risk application were installed in the production environment and are now running at all 22 IH hospitals. Progress notes and patients' admission diagnosis were the leading dictated documents used by the NLP application to identify HF patients (Table 2). A few modifications to the NLP logic, based on clinician feedback, were made during the first few months of the NLP application's implementation, to improve the positive and negative prediction value. Updates to the logic are facilitated based on the fact that the "alerting text" in a specific sentence and document type and date and time are stored in the Oracle table for each identified patient.

Impact

From February 2, 2014 to June 30, 2014, 100 patients were treated using the new CPP. These 100 patients were compared with 75 patients who received standard care between January 10, 2013 and February 2, 2014 (before the CPP was implemented). Baseline characteristics of the two groups were compared. Patients who were treated with the CPP were slightly older, but otherwise were similar to patients who had been treated with standard care in terms of gender, race, severity of illness, and risk of mortality (Table 3).

Although there was no difference in the number of HF patients readmitted within 30-days in the CPP group compared to the pre-CPP group, the raw 30-day mortality rate was significantly lower in the CPP group (7% vs 19%; $P = .03$; Table 4). After adjusting for age and sex, participation in the pilot study remained predictive of lower mortality (odds ratio = 0.31; 95% confidence interval, 0.11-0.81; $P = .017$). In the CPP group, the proportion of patients discharged to home care was significantly greater (34% vs 19%, $P = .02$), average length of stay was half a day less, and the average hospital variable costs were lower by $807.60, but these latter values are not statistically significant ($P = .44$ and $P = .56$, respectively).

Table 2: Dictated Reports Accessed by the Natural Language Processing Application and the Number of Times Each Report Was Used to Identify a Patient with Heart Failure (September 21, 2013 to July 28, 2015)

Dictated report type	Number of times HF patient identified
Progress note	27 489
Admission diagnosis	11 745
ED nurse visit	6919
Pharmacy note	2873
History and physical report	2847
Discharge summary	1929
ED physician/LIP report	932
CT angiogram chest	139
CT angio chest	133
Progress note generic	100
Cardiology office clinic note	99
Operative report	77
CT chest with contrast	68
CT chest high resolution	64
Heart failure follow-up progress report	61
CT chest without contrast	56
History and physical	48
Internal medicine progress note	46
ED note physician	41
ED patient summary	36
CT chest without IV contrast	34
Discharge summary	34
Cardiovascular progress note	20
Anticoagulation progress note	12
Nursing discharge summary	11

CT, computed tomography; ED, emergency department; HF, heart failure; IV, intravenous; LIP, licensed independent practitioner.

DISCUSSION

In order to improve the continuum of care for hospitalized HF patients, accurate and early identification of such patients during their hospitalization is crucial. Manual identification of hospitalized HF patients is time-consuming and hampered by inconsistent and poorly sensitive processes. We developed two new CDS applications and the HF patient Identification and Risk Stratification Daily report to aid and facilitate the early identification and care of HF patients. The first application uses NLP to improve our ability to identify HF patients based on outpatient as well as inpatient information, and the other application uses that information, along with additional data from our EMR, to automatically predict the 30-day all-cause hospital readmission score and 30-day mortality score for each patient. This information is automatically provided to clinicians each day and allows them to prioritize their limited time based on the identified HF patients, rather than spending time identifying them manually.

Table 3: Comparison of Heart Failure Patients Treated with the Care Process Pathway and Those Treated Before Its Implementation

Characteristics	Pathway	Non-pathway	*P*-value
Age (years)	72.0 + 1.3	68.0 + 1.5	.053
Sex (male) (%)	91.0	90.6	1.00
Race (non-white) (%)	7.0	2.7	.30
APR-DRG severity of illness ($n = 96$, $n = 74$) (%)			
Minor	2.1	4.0	.84
Moderate	15.7	20.3	–
Major	66.7	55.4	–
Extreme	15.7	20.3	–
APR-DRG risk of mortality ($n = 96$, $n = 74$) (%)			
Minor	2.1	4.0	0.47
Moderate	28.2	29.7	–
Major	42.7	48.6	–
Extreme	27.1	17.6	–

APR-DRG, all patient refined diagnosis related group.

Table 4: Outcome of Care Process Pathway (CPP) Targeting High-Risk Heart Failure Patients

Category	Group		*P*-value
	CPP	Non-CPP	
Number of patients	100	75	–
Number of 30-day all-cause readmissions, *n* (%)	12 (12.0)	9 (12.0)	1.00
Number of patients discharged to home care, *n* (%)	34 (34.0)	14 (18.7)	.02
Number of patients discharged to a special nursing facility, *n* (%)	17 (17.0)	11 (14.7)	.84
30-day all-cause mortality, *n* (%)	7 (7)	14 (18.7)	.03
Average length of stay (days)	4.5 ± 0.4	5 ± 0.6	.44
Average variable cost ($)	8636	9443	.56

Although the overall HF hospitalization rate may have declined substantially in the United States from 1998 to 2008,[29] patients who are discharged after hospitalization for HF remain at high risk of death and hospital readmission.[4,10] One study reported that the decrease in HF hospitalizations may not represent the corresponding increase in outpatient and emergency department care.[30]

We found that clinician use of the HF patient Identification and Risk Stratification Daily Report as part of the CPP significantly reduced 30-day mortality and significantly increased patient discharges to home care rather than to a specialized nursing facility. The results of this study also suggest that using a real-time, structured, and multidisciplinary CPP for HF patients who are at risk for poor outcomes can significantly reduce mortality by improving the use of ideal postacute care. Delineating the roles and responsibilities of care team members was also critical. It appears that using ideal postacute care may have the largest impact on mortality in patients with HF caused by left ventricular systolic dysfunction.[3] However, despite this improvement in mortality with the use of the CPP, the prognosis of patients with HF remains poor, and the development of new strategies to deliver improved care remains a priority for this growing group of patients. Due to the encouraging result of the pilot study and the fact that the 30-day risk application is currently monitoring HF patients at all 22 IH hospitals, the CPP based on the HF patient Identification and Risk Stratification Daily Report has been implemented in three other high-volume HF hospitals in the IH system and an enterprise-wide implementation has been planned.

The HF patient Identification and Risk Stratification Daily Report and associated CPP did not reduce the all-cause 30-day hospital readmission rate for patients at the study hospital, which has the third lowest HF readmission rate in the United States. In addition, enhanced patient care may not always result in a decrease in readmissions,[31] and some all-cause readmissions may not be preventable when a specific care pathway for HF is used only for patients with multiple morbidity.[32] Although others have used a pathway implemented at the primary care level to reduce both all-cause and HF readmissions,[33] our pathway was hospital-based and did not include primary care professionals, and we also did not look at readmissions that were due to only HF. We used the 30-day all-cause hospital readmission score in the HF patient Identification and Risk Stratification Daily Report as an outcome, because that is the quality metric that the Centers for Medicare and Medicaid Services has endorsed for HF.[31,32] Although this study did not reduce readmissions at the study hospital, our results suggest that appropriate allocation of resources can impact other meaningful outcomes.

Lack of data and inadequate identification of individuals with HF prevents efficient patient monitoring and reduces the opportunity to improve care.[33] Patients are often diagnosed with HF as outpatients, and that information is not always reported when those patients are hospitalized due to another health problem.[30] In addition, patients seen in the emergency department were found to have the highest proportion of subsequent HF all-cause readmissions. Thus, a lack of documented discharge ICD-9 codes for HF resulted in a low predicted probability for some HF patients in our initial HF identification model. For that reason the NLP application we developed to improve the identification of HF patients looks at dictated reports for all patients, including any from primary care, emergency room, or clinic visits. A previous evaluation of IMRS found that patient risk can change over time, and reevaluations of patient risk can be of clinical significance.[26] Thus, we run the 30-day all-cause hospital readmission and 30-day mortality risk application on each patient every day. The need to do manual scoring of each patient every day could only be done at the expense of reduced time for patient care. The change in a patient's risk also can be used by clinicians to review the patient's current therapy and identify what medications and therapies could help improve patient care or identify the need for therapeutic changes.[5,15]

Predictive models can target high-risk patient populations and help prevent/delay HF occurrence, improve quality of life, and reduce mortality,[11] but leave large uncertainties around estimates of survival for an individual patient and have been only modestly effective.[9] Assessing patient prognosis is the foundation for selecting therapies for life-threatening diseases, but this is particularly challenging for HF.[34] More than 100 variables in a number of different risk models have been associated with mortality and hospital readmission in HF.[8] Although a number of predictive models have been developed to identify patients with poor outcomes, they are rarely used because of their complexity or because they rely on costly tests.[23] A simple prognostic model that includes variables routinely obtained at clinical visits is required, so that practitioners can quickly identify and refer patients with HF symptoms before they decompensate to the point that their only options are desperation therapies. Once a predictive model can be automated, clinicians do not need to remember to manually run it or remember what specific patient information they need to collect. Others have also found that EMR data are sufficient to categorize coronary heart disease and HF events without the need to manually review patient records.[17] However, electronic predictive models are only as good as the quality and availability of the predictive variables in the EMR. Fortunately, IH has an extensive EMR that contains most clinical patient information and contains all the predictive variables needed for our model, based on the IMRS. We have also been able to use services to pull the needed predictive variables from the new vendor EMR that has been installed at two IH hospitals and continue to run the same applications each day.

HF continues to be a major health burden based on rates of patients' first hospitalization, poor overall survival, and premature life-years lost.[4] HF also continues to be the number one discharge diagnosis in the United States and is associated with significant mortality.[23] With the current HF prevention and treatment methods, medical costs of CVD, including HF, have grown at an average annual rate of 6% and have accounted for 15% of the increase in medical spending,[35] a number that is projected to increase by 10% over the next 15–20 years.[2] Thus, direct costs of CVD will continue to account for a large share of overall medical expenditures, and, by 2030, 40% of adults in the United States, or 116 million people, will have CVD. More recent HF populations have a higher percentage of very old individuals with an increased number of comorbidities, medications, and a high rate of early hospital readmission.[36,37] In an era of an increased push for patient input in and control of their medical care, patients will need to understand and select treatment options that result in longer life or improved quality of life but reduced survival.[38] The long-term pathways of treatment for HF will require not only new medications and therapies, but improved coordination between cardiologists, general practitioners, nurses, and dieticians. This improved coordination will become increasingly dependent on the design, development, and use of new medical informatics methods and tools.

Limitations

Although the two new applications and the daily HF report we developed are currently used at multiple hospitals, the evaluation was conducted as a before-after study design and at only one hospital. We were not able to detect any potential temporal trends, surveillance bias, or Hawthorne effects, which may have contributed to an overestimation of the true association between mortality and the CCP. Further studies at additional hospitals are needed and planned.

In addition, some clinicians may have provided care beyond the standard of care for a few prepilot patients who were identified as high-risk. We did not conduct a thorough chart review to determine whether some prepilot patients received any of the enhanced assessments described in the CPP.

It is known that social factors, such as alcohol and tobacco use and the absence of social support, predict hospital readmission.[13] For the CPP evaluation, we were unable to stratify the HF patients by either of these risk factors, and, thus, we do not know what impact the lack of that information had on our results.

We only calculated and reported the impact of the use of the HF patient Identification and Risk Stratification Daily Report on 30-day mortality, rather than longer-term mortality. However, the risk of HF death is greatest in the early period after hospital discharge for HF and is directly related to the duration and frequency of HF hospitalizations.[39] The long-term monitoring of HF patients is continuing at IH but is outside the scope of this methods paper.

CONCLUSIONS

Using computer decision support to help identify HF patients and automatically calculating their 30-day all-cause hospital readmission and 30-day mortality risks, coupled with a multidisciplinary risk-stratified CPP, was found to be an effective process to improve HF patient identification, significantly reduce 30-day mortality, and significantly increase patient discharges to home care instead of to a specialized nursing facility.

CONTRIBUTORS

R.S.E., J.F.L., J.B., A.B., and B.D.H. had full access to all of the data in the study and take responsibility for the integrity of the data and accuracy of the data analysis. The authors report no conflicts of interest or relevant financial interests pertaining to this study.

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COMPETING INTERESTS

None.

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