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Linking electronic health record-extracted psychosocial data in real-time to risk of readmission for heart failure

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Abstract

Background—Knowledge of psychosocial characteristics that helps to identify patients at increased risk for readmission for heart failure (HF) may facilitate timely and targeted care.

Objective—We hypothesized that certain psychosocial characteristics extracted from the electronic health record (EHR) would be associated with an increased risk for hospital readmission within the next 30 days.

Methods—We identified 15 psychosocial predictors of readmission. Eleven of these were extracted from the EHR (six from structured data sources and five from unstructured clinical notes). We then analyzed their association with the likelihood of hospital readmission within the next 30 days among 729 patients admitted for HF. Finally, we developed a multivariable predictive model to recognize individuals at high risk for readmission.

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Results—We found five characteristics—dementia, depression, adherence, declining/refusal of services, and missed clinical appointments—that were associated with an increased risk for hospital readmission: the first four features were captured from unstructured clinical notes, while the last item was captured from a structured data source.

Conclusions—Unstructured clinical notes contain important knowledge on the relationship between psychosocial risk factors and an increased risk of readmission for HF that would otherwise have been missed if only structured data were considered. Gathering this EHR-based knowledge can be automated, thus enabling timely and targeted care.

Keywords

Heart failure; 30-day readmission risk; risk factors; predictive models; behavior

INTRODUCTION

The rate of hospital readmission following a recent hospitalization for heart failure (HF) has come under increased public scrutiny. Such events are relatively common; about 25% of patients are readmitted within 30 days[1-3] and as many as 45% are readmitted within 3 to 6 months of hospital discharge. Unfortunately, patients with HF experience high rates of morbidity and mortality,[4] and their hospital readmissions contribute significantly to rising healthcare costs.[1] Total costs associated with care for HF have been estimated at $39.2 billion, with $20.9 billion directly attributable to hospital stays.[5] A large proportion of these costs are due to unplanned readmissions, with HF being the most common cause for 30-day readmission among Medicare recipients.[1]

Several interventions can reduce hospital readmissions. In general, these strategies ensure safe transitions from the hospital to another care facility or to a patient's home. For example, several controlled studies have demonstrated that patient education and care coordination at the time of discharge reduces readmission rates.[6-8] Other successful supplemental services (such as remote monitoring,[9-11] home health,[12] and palliative care[13]) have reduced readmission rates.

To capitalize on the benefits of these interventions, patients with HF at high risk for readmission should be provided with appropriate support services before, or shortly after, discharge from the hospital.[14] Given that the number of patients with HF is large, the cost of services is high, and staffing constraints are ubiquitous, some services may only be available to a small subset of patients. Therefore, to best match patients and their problems to appropriate services, we need to identify why a patient is labeled as high risk. Unfortunately, knowledge about patients has proven challenging to capture electronically, thereby making it difficult to use it as a readmission risk predictor. Our work intended to capture that information with a predictive algorithm, and to develop a decision support tool that can sort patients along a psychosocial dimension rather than just a biomedical one. By so doing, we believe that patients identified by such an algorithm will be better matched for high intensity interventions that involve provider-patient interactions.

Previous predictive models have identified the risk status of patients with HF.[15] However, most of them use demographic (e.g., age, race/ethnicity), clinical factors (e.g., medical history, levels of blood urea nitrogen, hemoglobin concentration, systolic blood pressure[16-18]) and billing data as predictors. Such models typically have two main limitations: they eschew psychosocial factors despite their association with readmission risk[15], and they fail to focus on the root cause (the psychosocial characteristics that caused cardiac decompensation) of a patient's increased risk status. In fact, 25% to 50% of HF admissions are preventable.[19, 20] Not surprisingly, the impact of psychosocial factors and health behaviors on clinical outcomes among patients with chronic disease has become the focus of increased attention.[21] Certain psychosocial factors (e.g., depression, dementia, and anxiety[22-24]), have been linked to an increased risk of readmission. Even though these factors are found commonly among HF patients, they often go undetected.[25] As a result, psychosocial factors often receive inadequate attention during routine care.

Psychosocial factors may not have been considered because that information is often not easily extractable electronically from electronic health record (EHR) systems. Using billing data for clinical purposes has its' limitations; it lacks sensitivity (e.g., up to 40% of patients with depression go unrecognized[26]), and timeliness (i.e., it lags behind clinical care by several months). However, electronic notes contain data entered by multiple providers (including nurses, primary care physicians, specialists, and administrators) that contribute (and document) a more complete picture of a patient's psychosocial characteristics and may predict a HF patient's risk of readmission. Currently, a provider encountering a patient for the first time cannot synthesize all of that collective knowledge before selecting an intervention.

We sought to identify key psychosocial characteristics that contribute to a patient's high-risk of early readmission. Linking a HF patient's psychosocial factors to his or her risk of readmission can lead to efficient, appropriate, and timely interventions. Furthermore, we sought to develop an approach that can extract knowledge of a patient's psychosocial characteristics from all EHR data, and make that knowledge easily interpretable to any clinical provider.

We opted to examine only psychosocial predictors to demonstrate the feasibility and value of extracting this type of data for predictive purposes. We do not assume that psychosocial variables are preferable to clinical ones. On the contrary, we believe that using clinical variables to predict early readmission may likely be more accurate than using psychosocial ones, mainly because clinical variables are more readily available in the EHR. There are 2 main reasons why we decided to only focus on psychosocial variables at this particular stage. First, we wanted to find out whether psychosocial variables are significant predictors of early readmission in and of themselves. Second, we suspect that poor psychosocial behaviors may be precursors of poor clinical performance for heart failure patients. Therefore, understanding a HF patient's psychosocial profile independently of the clinical one may be useful in preventing poor clinical outcomes. It is our hope to eventually investigate the potential impact of novel interventions by targeting HF patients based on their psychosocial profiles, prior to the worsening of their clinical outcomes.

METHODS

To evaluate whether psychosocial characteristics are associated with a 30-day hospital readmission risk, we first conducted semi-structured interviews with 24 clinical providers (experienced in the care of HF patients) to identify potential predictors of 30-day readmission. We then narrowed down the list of potential predictors by extracting only psychosocial-related predictors available in the EHR. Working with two HF nurses we developed open-ended questions to capture clinical and psychosocial characteristics believed to be predictive of 30-day hospital readmissions for HF patients. Finally, we developed univariate and multivariable logistic regression models to evaluate the strength of association between potential predictors and 30-day readmission risk. This study was approved by the Massachusetts General Hospital (MGH) Institutional Review Board.

(See appendix.)

Extracting Potential Predictors from the EHR

Two MGH physicians and an informatician further narrowed down that list of predictors by identifying those predictors captured by the MGH EHR System.[27] Since structured data are of higher quality than unstructured data, we first extracted such items (e.g., language, gender) from the EHR's structured fields.

If the potential predictor was not represented in a structured format, we looked for structured proxies that best represented the meaning of the predictor of interest. For instance, our interviewees identified "living alone" as a potential predictor. But since this information was not stored in a structured manner in our EHR, our interviewees selected "marital status" as the closest structured proxy.

If no structured proxy was available, we used regular expressions,[28, 29] a computerized method, to locate specific word patterns from unstructured electronic text. First, a set of word patterns was created for each potential predictor by manually reviewing the notes for 20 patients and extracting those phrases relevant to the psychosocial predictor of interest. For instance, we detected several word patterns for the adherence predictor including "non-compliance", "poor compliance", "non-adherence". Then, we developed a computer program using the Java programming language (JDK 1.6, Sun Microsystems) to extract these word patterns. To reflect the most recent psychosocial characteristics of the patient, the computer program sought to find the match to the pre-defined word patterns in the most recent patient note. If a match was detected, the value of the predictors was set to "Yes". Otherwise, the program continued to search notes in descending chronological order until a match was found or all notes within the past five years of the visit were searched. We limited our search to five years because most HF patients in our study cohort have been within our system for that time period. Beyond 5 years, we cannot guarantee the same consistency in clinical notes available for our free text search.

Our goal was to reach a sensitivity and specificity of at least 80% for the extraction algorithms, as calculated by reading through and evaluating patient characteristics in the EHR notes of 26 randomly selected patients. This evaluation was treated as a "gold standard" and was compared to the programmatically extracted values for each of the 26 patients. Word patterns that did not meet our sensitivity and specificity criteria were removed from future analysis.

Developing a 30-Day Readmission Risk Model

Patient inclusion criteria—Patients discharged from the MGH with a principal diagnosis of HF between 10/1/2007 and 9/30/2008 were included in the study. The International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) criteria were used to classify the hospitalization for HF, based on use of the following codes: 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, and 428.x. This process identified 812 patients. We excluded 58 patients who died during the study period, 17 cardiac transplant patients (identified through a payer code) due to their unusually high rate of readmission, and 8 patients with missing key demographic data. Therefore, the final dataset (which was constructed using both inpatient and outpatient information) included 729 patients, 93 of whom were readmitted within 30 days of the index hospitalization.

Outcome Measures for Model Development—To evaluate whether psychosocial characteristics extracted from the EHR were associated with readmission, we developed logistic regression models. In these models, the main outcome was the all-cause hospital readmission within 30 days of all HF hospitalizations. For patients with more than one HF admission, we selected the last hospitalization as their index admission, so that each patient only contributed one index hospitalization.

Statistical Analysis—We modeled the probability of readmission within 30 days of an index admission using both univariate and multivariable logistic regressions. These models included five potential predictors—declining/refusing of services, adherence, dementia, anxiety, and depression—extracted from clinical notes, and six potential predictors—missed appointments, gender, age at admission, marital status, payer type, and language—extracted from the structured fields of the EHR. Multivariable logistic regression model included all predictors and a p-value < 0.05 was considered statistically significant. Statistical analyses were performed using SAS version 9.2 (SAS Institute Inc., Cary, NC).

RESULTS

Predictors Identified by Clinical Provider Interviews

During interviews with clinical providers we identified 15 potential psychosocial predictors (Table 1): six predictors—gender, age at admission, payer type, missed appointments, language, and marital status—were captured from structured data sources; five predictors—adherence, dementia, depression, declining/refusal of services, anxiety—were extracted from unstructured clinical notes; four predictors—limited social support, lower social economic status, higher stress, inability to perform daily activities—could not be extracted from the EHR.

Potential HF Readmission Predictors

Extraction of Potential Predictors from Clinical Notes—To extract potential predictors from the EHR, we constructed several word patterns designed to capture and match phrases frequently used in the clinical notes. For instance, "refuse", "refuses", "refusing" were used in notes predominantly to describe the "decline/refusal of service" predictor. However, for other predictors (such as non-adherence and depression), capturing their concepts was more challenging. For example, we had to examine the words "non-compliant", "adherent", and "compliant" closely to ensure that phrases (such as "reports good compliance", "non-compliant left ventricle" or "non-compliant right atrium") were excluded from the search.

Evaluation of the Extraction Algorithm—Manual extraction of the predictors from the notes showed a high degree of agreement with the automated extraction process. All of the predictors extracted had greater than 80% sensitivity and specificity. Certain phrases were excluded from the pattern-matching algorithm (as "decline" and "reject" was used for a decline/refusal of services or recommendations, or as a worsening of symptoms (e.g., "significant decline in EF over the past year"). Similarly, the word "reject" was commonly used to describe organ rejections and not rejection of services (e.g., "liver transplant complicated by rejection").

30-Day HF Readmission Risk Model

We identified 729 patients who were discharged from the MGH with a principle diagnosis of HF between 10/1/2007 and 9/30/2008. Out of 729 patients, 93 were readmitted within 30 days of the index admission. Characteristics of the study patients are shown in Table 2.

Results of univariate regression analysis are shown in Table 3. Univariate logistic regression detected four variables that predicted hospital readmission. Service decline/refusal was the strongest predictor of readmission, with an odds ratio (OR) of 2.21 for 30-day readmission. Patients identified with non-adherence or missed scheduled appointments in their EHR record were 1.99 times more likely to be readmitted. Presence of dementia or depression in the record significantly increased the risk of readmission (see Table 3).

In the final multivariable model with c-statistics=0.67, only 3 predictors—decline/refusal of services, adherence, and missed appointments—remained significantly associated with the risk of hospital readmission.

Discussion

We have developed a multivariable model with "declining/refusal of services", "adherence," and "missed appointments" as significant predictors of readmission. The resulting model was comparable to the existing published models (with a c-statistic of 0.67).[16-18] We believe that targeting HF patients with the highest risk of readmission based only on traditional clinical parameters may not be the most effective approach for improving HF care; instead, targeting patients with certain psychosocial variables may be more meaningful and manageable.

We chose to do semi-structured interviews because: (1) the current literature was limited in identifying potential psychosocial risk factors for predicting the risk of early readmission for HF patients, (2) we wanted to obtain buy-in from the clinical staff prior to implementing the algorithm into the EHR, and (3) predictive algorithms work best when they are developed locally as the strength of predictors may vary from one institution to the next.

Our study demonstrated a link between psychosocial factors in HF patients and early all-cause readmission. Our goal was to only use psychosocial data that is available in the EHR. With this approach, we developed a real-time electronic inpatient HF registry that automatically identified key psychosocial characteristics that were linked to a patient's high risk for readmission. Such a registry could be invaluable in connecting HF inpatients to services that address specific behaviors in a timely and cost-effective manner.

Prior studies have confirmed that adherence to diet and medical treatment is a critical precipitating factor for HF decompensation in up to 40% of patients with HF.[19, 30] Therefore, we were not surprised to find that "adherence" was a significant predictor for early readmission for HF patients. However, we were surprised to learn that "declining/ refusal of services" and "missed appointments"—two concepts we initially thought were related to "adherence"—were independent predictors of early readmission. Several explanations may account for this finding: (1) Regardless of whether a patient is adherent to care, missing appointments right after hospital discharge[31] independently results in inadequate care during the most vulnerable period; (2) "Declining/refusal of services" could be an indicator of a certain personal trait that affects the risk of readmission; (3) Our definition of "adherence" was not inclusive enough to capture patients who were likely to decline/refuse care or miss appointments. Patients with these risk factors would benefit from interventions that target improved adherence as this has been effective for the prevention of unplanned hospital admissions.[32, 33]

Mild cognitive impairment affects as many as 30%-80% of patients with HF.[34] Despite its clinical importance and high rate in patients with HF, dementia was mentioned in the notes of only 12% of our patients. However, depression was mentioned in the clinical notes of 37% of our patients. This finding corresponds with the reported rate of 14%-38% of patients with HF who exhibit signs of depression.[35] We purposefully avoided identifying "depression" or "dementia" from problem lists or structured diagnoses fields because these conditions are typically underreported in the EHR. Both dementia and depression were significant predictors of readmission in univariate analysis, but these features lost their significance when the predictive model was adjusted for other risk factors. We attributed this lack of significance to: (1) the difficulty of identifying mild cognitive impairment and depression based on unstructured clinical notes; (2) the lack of power due to our small sample size; (3) poor electronic documentation of both characteristics among patients with HF; and, (4) the association between these two characteristics to adherence-related predictors. Our data suggests that dementia and depression are intermediate variables that may be associated to the risk of readmission by affecting a patient's ability to adhere to recommended medical care. Therefore, in addition to evaluating a patient for adherence, the underlying reasons for non-adherence should be assessed.

Our findings underscore the importance of considering patient behaviors as features that influence clinical outcomes. Providers already factor in patients' behaviors when making key treatment decisions. For example, when deciding to start a patient with diabetes on insulin, providers rely more heavily on certain subjective factors (such as adherence and motivation), over clinical factors (such as age or weight).[36] However, our approach aggregated the combined subjective knowledge of many providers familiar with high-risk HF patients, and formalized it by creating an objective link to risk of readmission that can be shared with a provider in a timely manner. This work highlights the impact of an informatics approach when extracting relevant information and presenting it to providers.

Conclusion

In summary, our work illustrated the potential benefits of linking behavioral predictors to high-risk readmission rates and clinical outcomes. Although care providers agreed on the majority of behavioral predictors associated with the risk of readmission, most of the information on declining or refusing services or tests deemed important was not readily available in the EHR. It was not feasible to design a regular expression model to capture this concept with high sensitivity or specificity due to the multitude of contexts in which the word "decline" was used in the medical record.

Since understanding psychosocial factors should be part of the assessment of a patient readmission risk status, we recommend that these factors be recorded in a structured and standardized format in the EHR; this may enable them to be searched and used in a meaningful manner.

Limitations

Our universe of assumptions was created through a series of provider interviews and therefore may be biased at the outset. Our efforts represent a first step in elucidating (using only the EHR data) the association of behavioral predictors and hospital readmissions. We failed to directly measure certain behavioral factors. The proxies to the psychosocial concepts we sought to capture may provide an incomplete or inaccurate view of how our patients think, feel, and behave with regard to their health. Further work is clearly needed to refine and expand our findings to gain a more complete picture of how these factors are related to health outcomes.

Our methodology for identifying psychosocial variables may not be easily reproducible due to the numerous local considerations (e.g., the local culture of how clinical notes are written) we needed to account for. But since our purpose was to recognize that some psychosocial characteristics are important predictors to early readmission, we felt our approach was justified.

Although our health care institution is large, our findings may not be generalizable to other institutions. It is likely that there are specific phrases (used to capture our psychosocial concepts) that are specific to our culture and/or situation. By applying our method at other healthcare systems, the regular expression models would need to be revalidated (to ensure that they retain high sensitivity and specificity). As a result, we strongly recommend collection of useful psychosocial data (electronic data that describe a patient's psychological development in and interaction with a social environment) in a structured and standardized format.

Our outpatient information was limited to information available in clinical notes for patients who had a primary care provider located at the MGH. As a result, patients who did not have outpatient care at MGH had missing outpatient information.

Next steps

Pursuing logical extensions of this work will allow us to evaluate the usefulness of this approach (e.g., lead to better outcomes because supportive services can be better tailored to meet a patient's needs) in a clinical setting.

We hope to survey providers to show how it might influence their clinical decision-making, implement this behavioral algorithm into our HF registry (to facilitate early identification of HF patients at high risk of readmission) and measure changes in post-discharge service selection in a randomized control trial.

Finally, we believe that the approach used in our study on psychosocial characteristics among HF patients, may be used for evaluating the risk for readmission for patients with dementia, psychosis, or suicidal ideation.

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APPENDIX: A. Questionnaire

What are the clinical factors that predict a 30-day hospital readmission for HF patients?

What are important behavioral characteristics of HF patients that result in an increased risk for a hospital readmission?

What demographic predictors are important in assessing the patients' risk of being readmitted?

What psychosocial predictors are important in assessing the patients' risk of being readmitted?

What patient functioning predictors are important in assessing the patients' risk of being readmitted?

What resource utilization predictors are important in assessing the patients' risk of being readmitted?

What operational processes of a patients care at the hospital are important in assessing the patients' risk of being readmitted?

Please describe the role of various programs in the successful reduction of readmissions

Please describe the profiles of patients who are at high risk of readmission

What are the modifiable factors among those mentioned? How would it affect readmission rates?

Finally, where would we find this data would in the medical record, and what would be good proxies for some of these parameters in existing records?

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Table 1

Proxies to behavior that may result in early readmission captured from qualitative interviews

Patient Behavioral Characteristics	Frequency*	Predictor
Male sex‡	15	gender
Older patients‡	15	age over 65
Non-compliance§	13	adherence
Uninsured/under-insured‡	13	payer type
Low motivation - higher missed appointments, lower compliance‡	12	any missed appointments
Mild undiagnosed dementia§	12	dementia
Non-English speaking ethnic minorities‡	12	language
Limited social support†	11	
Living alone, unable to cook‡	9	marital status
Lower socioeconomic status (SES)†	9	
Mild to moderate undiagnosed/untreated depression§	9	depression
Higher refusal rate of services§	9	service decline
Higher stress (disease, age) †	8	
Unable to perform daily activities†	6	
Moderate anxiety§	4	anxiety

*Numbers indicate the number of interviews in which this factor was mentioned (15 interviews).

†These potential predictors were eliminated from further consideration due to lack of electronic data available.

‡These potential predictors were extracted from the structured fields in the EHR

§These potential predictors were extracted from the clinical notes.

Table 2

Characteristics of the Study Patients (N=729)

Patient Characteristic	**Percentage (count)**
Gender (Female)	40.4 (295)
Age at admission†	71.4 (14.4)
Marital Status	
Married	48.8 (355)
Widowed	21.3 (155)
Single	19.7 (143)
Divorced or separated	9.5 (69)
Missing	0.8 (6)
Payer	
Public	76.5 (558)
Private	23.5 (171)
Ethnic group	
White	85.1 (620)
Black	5.5 (40)
Hispanic	4.9 (36)
Other	4.5 (33)
Language	
English	90.8 (662)
Spanish	2.9 (21)
Italian	1.4 (10)
Other	4.9 (36)
Decline/refusal of service (Yes)	39.0 (284)
Adherence (No)	33.2 (242)
Dementia (Yes)	12.2 (89)
Anxiety (Yes)	35.8 (261)
Depression (Yes)	37.0 (270)
Any missed appointments (Yes)	33.2 (242)
Number of notes in EHR†	46.1 (65.1)

†Data presented as mean (Standard Deviation)

Table 3

Univariate and Multivariable Behavioral Predictors of 30-Day Hospital Readmission Risk (N=729)

	Univariate			Multivariable Regression		
Predictor	**OR**	**95% CI**	**P**	**OR**	**95% CI**	**P**
Service decline (Yes) *	**2.21**	**1.42-3.43**	**0.0004**	**1.75**	**1.07-2.87**	**0.03**
Adherence (No) *	**1.99**	**1.28-3.10**	**0.002**	**1.72**	**1.07-2.76**	**0.03**
Dementia (Yes)*	**1.91**	**1.08-3.40**	**0.03**	1.51	0.81-2.81	0.19
Depression (Yes)*	**1.55**	**1.00-2.40**	**0.05**	1.14	0.68-1.91	0.62
Anxiety (Yes)*	1.35	0.87-2.10	0.19	0.97	0.58-1.62	0.87
Missed app (Yes).	**1.99**	**1.28-3.09**	**0.002**	**1.73**	**1.06-2.80**	**0.03**
Gender (Male)†	1.03	0.66-1.61	0.89	1.07	0.66-1.74	0.78
Age at admission (over 65)	1.18	0.72-1.92	0.52	1.45	0.83-2.55	0.20
Marital status (not married)	0.83	0.54-1.29	0.41	0.72	0.45-1.15	0.17
Payer ‡	0.86	0.52-1.42	0.57	0.61	0.34-1.07	0.08
Language §						0.95
Italian	1.74	0.36-8.35	0.58	1.64	0.31-8.60	
Spanish	1.16	0.34-4.03	0.92	0.97	0.27-3.56	
Other	1.13	0.43-2.98	0.84	1.07	0.39-2.95	

Bold font indicates statistical significance P<0.05.

*Yes versus Unknown;

†Male versus Female;

‡Public payer vs. Private payer;

§Italian vs. English, Spanish vs. English, Other vs. English