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Clinical Investigation

Early Identification of Patients With Acute Decompensated Heart Failure

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ABSTRACT

Background: Interventions to reduce readmissions after acute heart failure hospitalization require early identification of patients. The purpose of this study was to develop and test accuracies of various approaches to identify patients with acute decompensated heart failure (ADHF) with the use of data derived from the electronic health record.

Methods and Results: We included 37,229 hospitalizations of adult patients at a single hospital during 2013–2015. We developed 4 algorithms to identify hospitalization with a principal discharge diagnosis of ADHF: 1) presence of 1 of 3 clinical characteristics, 2) logistic regression of 31 structured data elements, 3) machine learning with unstructured data, and 4) machine learning with the use of both structured and unstructured data. In data validation, algorithm 1 had a sensitivity of 0.98 and positive predictive value (PPV) of 0.14 for ADHF. Algorithm 2 had an area under the receiver operating characteristic curve (AUC) of 0.96, and both machine learning algorithms had AUCs of 0.99. Based on a brief survey of 3 providers who perform chart review for ADHF, we estimated that providers spent 8.6 minutes per chart review; using this this parameter, we estimated that providers would spend 61.4, 57.3, 28.7, and 25.3 minutes on secondary chart review for each case of ADHF if initial screening were done with algorithms 1, 2, 3, and 4, respectively.

Conclusions: Machine learning algorithms with unstructured notes had the best performance for identification of ADHF and can improve provider efficiency for delivery of quality improvement interventions.

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Key Words: Phenotype, electronic health record, heart failure, hospitalization.

Acute decompensated heart failure (ADHF) is among the most common reason for hospitalizations among older adults in the United States.[1] Hospitalizations for heart failure are associated with high rates of readmission, many of which may be preventable.[2] As a result, initiatives such as Medicare's Hospital Readmissions Reduction Program have focused on decreasing the number of readmissions following a hospitalization with a principal discharge diagnosis of heart failure.[3] Hospitals have responded to these policies by targeting patients hospitalized for ADHF with inpatient interventions including medicine reconciliation, patient and family education, heart failure order sets or protocols, involvement of multidisciplinary teams, and scheduling outpatient follow-up before discharge.[4–6] Many of these interventions target patients early during hospitalization.

To target patients hospitalized for ADHF, a rapid method is needed identify them during hospitalization. Although most assessments of quality of care or readmission rates related to heart failure have relied on identification using discharge diagnosis codes,[7,8] these codes are documented after the patient is discharged. A multidisciplinary approach to prevention of readmission requires early identification of patients with ADHF. Indeed, one recent study suggested that a care plan intervention coupled with the use of natural language processing (NLP) to identify hospitalized heart failure patients may lead to improvement in post-discharge outcomes.[9] However, there have been limited evaluations of the

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comparative advantage of advanced approaches to identify patients hospitalized for ADHF with more conventional methods based on important clinical factors that have also been shown to improve provider efficiency.[10]

We recently developed a series of algorithms to identify the presence of chronic heart failure during hospitalization.[11] We found that algorithms derived from analysis of free text in clinical notes had the best performance and could be used for quality improvement efforts such as problem list enhancement. However, more targeted algorithms are needed to guide expensive, resource-intensive interventions to identify patients hospitalized for ADHF. Our goal was to develop and compare algorithms of increasing complexity to identify hospitalizations with a principal discharge diagnosis of heart failure. Given the emphasis that hospitals currently place on patients with ADHF, we focused on developing models with high sensitivity to avoid missed opportunities for care improvement; this approach assumed that secondary chart review by providers may be necessary to confirm a diagnosis in clinical practice. To determine the potential benefit of each algorithm in hospital delivery, we estimated the time needed for secondary review by providers after initial screening to confirm that the hospitalization was for ADHF with each algorithm.

Methods

We performed a retrospective study of hospitalizations at Tisch Hospital, the primary acute care hospital at New York University Langone Medical Center, with the use of data obtained from the electronic health record (EHR; Epic; Epic Systems, Verona, Wisconsin). We included all hospitalizations for patients ≥18 years of age admitted on or after January 1, 2013, and discharged by February 28, 2015. We excluded hospitalizations that were shorter than 24 hours. The cohort was similar to the one previously used in developing algorithms to identify patients with chronic heart failure,[11] although we did not include patients hospitalized at the Hospital for Joint Diseases in the present study. In addition, we developed new algorithms in the present study to identify patients with ADHF, whereas algorithms in the previous study[11] were developed to identify all hospitalized patients with chronic heart failure.

We randomly divided our dataset into 75% model development and 25% validation sets. The primary dependent variable was ADHF defined by a principal discharge diagnosis with the use of standard International Classification of Diseases (ICD), 9th Revision, Clinical Modification discharge diagnosis codes (402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, and 428[8,12]).

Potential structured predictor variables included demographics, laboratory results, vital signs, problem-list diagnoses, and heart failure–related medications. For laboratory results and vital signs, we included an indicator of presence or absence of results and the value. We also included an indicator of the presence of an echocardiogram but did not include specific results, including ejection fraction (EF), which were reported in note form. Problem-list diagnoses were those that were an active problem in the EHR problem list on the 2nd night of hospitalization and included heart failure, acute myocardial infarction, and atherosclerosis; problem-list diagnoses need not be related to the primary reason for hospitalization. We also included variables of an earlier discharge diagnosis of heart failure, both as a principal discharge diagnosis and as a secondary diagnosis. Medications included both inpatient and active outpatient therapies for a loop diuretic, an angiotensin-converting enzyme (ACE) inhibitor or angiotensin receptor blocker (ARB), a beta-blocker, an evidence-based heart failure beta-blocker, and an aldosterone antagonist. We used unstructured data from echocardiography reports, chest-imaging reports, and admission, physician progress, and consultation notes. We included variables up to the second midnight of hospitalization; this time frame was chosen because we wanted to identify cases early during hospitalization, and a stay of 2 midnights is generally considered to be the minimum time necessary to warrant a hospitalization.[13]

We developed 4 algorithms for identification of a principal discharge diagnosis of heart failure at the second midnight of hospitalization. The 1st algorithm was the presence of ≥1 of the 3 following characteristics: heart failure on the problem list, inpatient loop diuretic use, and B-type natriuretic peptide (BNP) ≥500 pg/mL. This algorithm was based on a screening tool currently used by the heart failure transitions team at our hospital. The 2nd algorithm used logistic regression with the use of structured variables thought to be clinically relevant by 2 clinicians with expertise in heart failure (SB and SDK). The 3rd algorithm used a machine learning approach with the unstructured data. The 4th algorithm used a machine learning approach and combined both structured and unstructured data elements for patient classification.

To understand the potential use of the algorithms in clinical practice, we calculated the number of hospitalizations that would be identified as positive by each algorithm for each true positive case (TP) of ADHF. We then estimated the average time needed to perform secondary screening of positive charts (ie, both TPs and false positives [FPs]) identified by each algorithm for each TP.

We performed a brief survey of nurse practitioner (NP) and physician assistant (PA) providers at our hospital to estimate the time needed for chart review. We approached all 3 providers from the heart failure transitions team who were known to have performed EHR chart reviews for ADHF. All 3 providers agreed to be surveyed, and verbal consents were obtained. The providers were asked to respond to the following questions based on recall of usual work in clinical practice: 1) the average time needed to review a new chart to determine whether the patient had ADHF and 2) the average time needed to review all charts for ADHF on days in which they were reviewing charts. Because we found a discrepancy between reported average review time per chart (1st question) and the average review time per day (2nd question), we reconciled these by deriving review time per chart