HHS Public Access

Author manuscript

J Card Fail. Author manuscript; available in PMC 2019 June 01.

Published in final edited form as:

J Card Fail. 2018 June ; 24(6): 357–362. doi:10.1016/j.cardfail.2017.08.458.

Early Identification of Patients with Acute Decompensated Heart Failure

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Abstract

Background—Interventions to reduce readmissions following 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) using data derived from the electronic health record.

Methods and Results—We included 37,229 hospitalizations of adult patients at a single hospital in 2013–2015. We developed four algorithms to identify hospitalization with a principal discharge diagnosis of ADHF: 1) presence of one of three clinical characteristics; 2) logistic regression of 31 structured data elements; 3) machine learning with unstructured data; 4) machine learning with 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, while both machine learning algorithms had AUCs of 0.99. Based on a brief survey of three providers who perform chart review for ADHF, we estimated providers spent 8.6 minutes per chart review; using this this parameter, we estimated 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 was done with algorithms 1, 2, 3, and 4, respectively.

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

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Keywords

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 prior to discharge.[4–6] Many of these intervention target patients early during hospitalization.

In order 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,[78] these codes are only 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 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 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 presence of chronic heart failure during hospitalization.[11] We found that algorithms derived from analysis of free text from clinical notes had 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 acute decompensated heart failure. 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 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 to confirm the hospitalization was for ADHF following initial screening with each algorithm.

Methods

We performed a retrospective study of hospitalizations at Tisch Hospital, the primary acute care hospital at NYU Langone Medical Center, using data obtained from the electronic health record (EHR, Epic, Epic Systems, Verona, WI). We included all hospitalizations for patients ≥18 years admitted on or after January 1, 2013 and discharged by February 28, 2015. We excluded hospitalizations that were less than 24 hours. The cohort was similar to the one 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 current study and these patients were included in the prior study. Additionally, in the current study we developed new algorithms to identify patients with ADHF while algorithms in the prior 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 using standard International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) 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 lists 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 on the EHR problem list at the second 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 a prior 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 echocardiogram reports, chest imaging reports, and admission, physician progress, and consult notes. We included variables up to the second midnight of hospitalization; this time frame was chosen as we wanted to identify cases early during hospitalization and a stay of two midnights is generally considered the minimum time necessary to warrant a hospitalization.[13]

We developed four algorithms for identification of a principal discharge diagnosis of heart failure at the second midnight of hospitalization. The first algorithm was the presence of one or more of the three following characteristics: heart failure on the problem list; inpatient loop diuretic use, or BNP≥500 pg/ml. This algorithm was based on a screening tool currently used by the heart failure transitions team at our hospital. The second algorithm used logistic regression using structured variables thought to be clinically relevant by two clinicians with expertise in heart failure (SB and SDK). The third algorithm used a machine learning approach with the unstructured data. The fourth 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 of ADHF. We then estimated average time needed to perform secondary screening of positive charts (i.e. both true positives and false positives) identified by each algorithm for each true positive case.

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 three providers from heart failure transitions team who were known to have performed EHR chart review for ADHF. All three providers agreed to be surveyed and verbal consent was obtained. 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. As we found a discrepancy between reported average review time per chart (first question) and the average review time per day (second question), we reconciled these by deriving review time per chart based on the second question. We then estimated the parameter for time of chart review as the mean of this value and reported average review time per chart.

Statistical Analysis

We calculated the mean number of new hospitalizations per day for ADHF during the study period by dividing the total number of hospitalizations by the total number of days in the study period.

Classification algorithms were developed in the development set using a principal heart failure discharge diagnosis as the dependent variable. We used a logistic regression model with structured data elements as the independent variables for algorithm 2. For algorithm 3, we developed a machine learning algorithm using L1-regularization logistic regression using free text. In this approach, we identified all individual words that occurred ten times or more in notes or reports. Of the 36,463 word that satisfied this criterion, each individual word was considered a potential variable for the model. L1-regularization, which includes a penalty term to reduce overfitting, used variable selection to select individual words for the final model.[14] Algorithm 4 was developed using L1-regularization logistic regression in consideration of both free text used in algorithm 3 (i.e. 36,463 words) and all data elements (i.e. 31 structured variables) used in algorithm 2.

We calculated sensitivity and PPV for each algorithm in the development set and then validation set using the principal discharge diagnosis of heart failure as the gold standard. As our goal was to minimize false negatives, we set our thresholds above which a hospitalization was classified as for heart failure based on a sensitivity of 0.98 in the development set and again in the validation set. These thresholds only applied to algorithms 2–4, which provide a continuous-valued prediction; we also calculated area under the receiver operative characteristic (AUC) curve for these three algorithms as well as specificity and negative predictive value (NPV) for all algorithms.

We determined the number of hospitalizations that would be identified as positive by each algorithm–thus necessitating secondary chart review–for each true positive case of heart failure. We calculated this as the sum of the true positives (TP) and false positives (FP) for each algorithm in the validation set. As PPV=TP/(TP+FP) and we were interested in total positive charts per TP, we calculated the sum of TP and FP for each algorithm to be 1/PPV.

We estimated time needed for secondary chart review for each true positive (TP) of ADHF with initial screening with each algorithm. First, we surveyed NP and PA providers about review time per chart and review time per day; for providers who responded with a range of times, we used the mean of the range. Second, we calculated a mean reported review time per chart and a mean reported review time per day. Third, we estimated the “derived review time per chart based on review time per day” by dividing mean reported review time per day by the average number of charts needing review per day. To estimate the number of charts per day, i.e. the denominator of the “derived review time per chart based on review time per day,” we multiplied the total positives per TP for algorithm 1 by the average daily number of ADHF cases during the study period; algorithm 1 was used for initial heart failure screening at our hospital. Fourth, we averaged the “derived review time per chart based on review time per day” and the mean reported review time per chart to obtain the parameter of review time per chart. Fifth, we multiplied this parameter by the number of hospitalizations identified as positive for each TP with each algorithm to estimate the time needed for secondary chart review for each TP with each algorithm.

Results

Of 37,229 hospitalizations included in the study, 1,294 (3.5%) carried a principal discharge diagnosis of heart failure (Table 1). Patients hospitalized for heart failure were of older age (76.2 vs. 60.8 years), were more likely to be black/African-American race (14.3% vs. 7.7%), and were more likely to be Medicaid beneficiaries than patients hospitalized with another principal discharge diagnosis. Among patients hospitalized for heart failure, 69.9% had heart failure on the problem list, 91.3% had a prior echocardiography, 79.8% had an inpatient diuretic, and 91.9% had a BNP checked by two midnights of hospitalization (Table 1). There were a total of 2,346,779 notes or imaging reports included in the study, with a mean of 123.9 for patients with a principal discharge diagnosis of heart failure and 60.8 for other patients. We calculated a mean of 1.6 new hospitalizations for acute heart failure per day during the study period.

The first algorithm for identification of hospitalizations for ADHF, defined as the presence of one of three clinical characteristics (heart failure on the problem list, an inpatient diuretic, or BNP≥500), was associated with a sensitivity of 0.98 and PPVs of 0.13 and 0.14 in the development and validation sets, respectively (Table 2).

The second algorithm, which used logistic regression and structured data elements to identify patients hospitalized for ADHF, included 31 data elements in the final model. Variables with the strongest association with a principal discharge diagnosis of heart failure included heart failure in the problem list, inpatient diuretic use, and an elevated BNP (Appendix Table 1). While a prior principal discharge diagnosis of heart failure was associated with a current principal discharge diagnosis of heart failure, prior diagnosis of a secondary heart failure was inversely associated with a current principal discharge diagnosis

(Appendix Table 1). The logistic regression model was associated with an AUC of 0.96 and PPV of 0.15 when the sensitivity was fixed at 0.98 (Table 2).

The third algorithm, in which we used machine learning on unstructured notes, included 427 variables of individual single words in the final model. As shown in Appendix Table 2, the top predictors were related to hospitalizations for heart failure and included “bnp,” “diuresis,” “chf,” and “exacerbation;” the strongest negative predictive term was “ivf.” This model had an AUC of 0.99 in validation and a PPV of 0.30 when setting the sensitivity at 0.98. Algorithm 4, in which we used machine learning on both structured and unstructured data, included 432 elements in the final model. The top predictors in this model were the free text terms of “diuresis,” “bnp,” and “chf;” the top structured data elements–representing the ninth, twelfth, and thirteenth most influential predictors overall–were presence of a bnp laboratory result, heart failure on the problem list, and inpatient diuretic administration (Appendix Table 3). This algorithm had an AUC of 0.99 and a PPV of 0.34 when the sensitivity was 0.98 in the validation set. In the validation set, the specificities of the four algorithms were 77.2%, 79.1%, 91.5%, 93.0%, respectively, while the NPV was 99.9% for all algorithms.

Based on the PPV of the algorithms in the validation set, we calculated that algorithms 1-4 would identify a total of 7.1, 6.7, 3.3, and 2.9 hospitalizations as being positive for each true positive case of heart failure; these values represent the total number of hospital charts needed for secondary chart review for each true positive case. Given the high sensitivity of these algorithms, 98% of all heart failure cases would be identified and confirmed by the gold standard of secondary provider review.

The heart failure NP and PA providers reported a mean of 11.7 (range 10–15) minutes spent on reviewing each charts for heart failure. Providers also reported a mean of 65 (range 53–90) minutes spent on reviewing charts for heart failure per day; based on this rate, we derived a review time per chart of 5.5 minutes, assuming an average of 11.7 charts reviewed per day during the study period. Averaging the reported time per chart (11.7 minutes) and the derived review time per chart based on reported review time per day (5.5 minutes), we estimated that providers spent 8.6 minutes per chart. Using this parameter for review time per chart, the time providers would spend performing chart review for each true positive case of ADHF would be 61.4, 57.3, 28.7, and 25.3 minutes if initial screening was done with algorithms 1, 2, 3, and 4, respectively (Figure).

Discussion

Reducing readmissions is a priority for hospital systems and, as a result, hospitals have put substantial efforts in improving outcomes for patients hospitalized for heart failure. Such efforts have broadly been categorized into three domains: inpatient care, discharge processes and transitional care, and general quality improvement efforts such as performance feedback. Inpatient care initiatives include dedicated heart failure teams, electronic order sets, inpatient education, and provider reminders for evidence based therapies.[5] Transitional care interventions include early discharge planning, providing medications at time of discharge, scheduling follow up with outpatient provider, pharmacist counseling, and post-discharge phone calls.[5,6] The majority of these interventions require early identification of appropriate patients during hospitalizations.[10]

In order to accomplish any inpatient care intervention and many of discharge and transitional care interventions, patients with acute decompensated heart failure need to be easily identified well before discharge. We developed multiple computable phenotypes[15,16] for ADHF early during hospitalization. A simple algorithm based on three clinical characteristics that has been utilized by the heart failure team at our institution demonstrated high sensitivity as intended. However, this algorithm also had a very low PPV, necessitating the team to perform a significant amount of secondary chart review for validation. A second algorithm that relied on a linear combination of 31 structured data elements was similarly limited by high number of false positives. Conversely, two machine learning algorithms that utilized unstructured text from provider notes and imaging reports significantly increased PPV as compared to the algorithms using only structured data.

Nonetheless, even these top performing machine learning algorithms would require a secondary chart review to confirm a diagnosis of AHDF in clinical practice. Given the potential high costs associated with not intervening on patients hospitalized for ADHF, our goal was to capture nearly all of these patients with these algorithms. While the machine learning algorithms had a near perfect AUC, this measure may not reflect classification ability at the extremes. As a result, only one-third of those hospitalizations identified as ADHF by our best algorithm were actual cases when we set the sensitivity at 98%. Nonetheless, with the machine learning algorithm on structured and unstructured data, practitioners would need to review three charts for each correctly identified patient with ADHF; this compares favorably to the seven charts needed to review for each true positive case with algorithms using structured data. As we estimated that our practitioners spend 8.6 minutes per chart, this improved performance of algorithm 4 as compared to algorithm 1 would reduce the amount of time spent on chart review by 36.1 minutes per case of ADHF. The overall time savings with algorithm 4 is dependent on the volume of heart failure patients–in the hospital. At our hospital, we observed 1.6 hospitalizations for ADHF per day during the study period. As a result, the implementation of the more advanced algorithm could save nearly an hour of provider time every day or the equivalent of 0.17 of a full time (40 hour) equivalent. Given this benefit, we will be implementing this algorithm to run at our hospital; the algorithm will be used to build a daily EHR-based screening list for our heart failure team.

The machine learning algorithms performed as well, if not better, in terms of AUC when compared to similarly developed algorithms to identify patients with any heart failure–acute or chronic in the hospital.[11] However, the algorithms for acute decompensated heart failure appeared to have lower PPV than those from the prior study. These differences in performance may be related to differences in prevalence, as there are about four times as many patients are hospitalized with any heart failure as with acute decompensated heart failure.[12] Given the volume of patients with any heart failure coupled with the intensity of resources used to prevent readmissions following hospitalizations for ADHF, hospitals likely prefer targeting interventions to patients hospitalized with a principal discharge diagnosis of heart failure. Thus the algorithms developed for our study will be useful for hospitals focused on preventing readmissions in response to policy and payer efforts such as the Hospital Readmissions Reduction Program.[3]

Our study has limitations that deserve mention. The study used data from a single hospital so results may not be applicable to other institutions. First, while our approaches could be easily replicated, the algorithms that use unstructured data may need to be calibrated for individual institutions as language and documentation can vary from site to site. Given potential differences in data across institutions, machine learning algorithms may not see similar performance improvement at other sites. Second, our gold standard for ADHF was not based on provider chart adjudication but rather discharge diagnosis, an imperfect measure. It is possible that limitations of the algorithms may be partly related to limitations of this gold standard; for instance, some of the false positives could be related to true cases of ADHF that have another discharge diagnosis. Nonetheless, the discharge diagnosis is currently used for quality measurement[3,8] so is of primary interests to hospitals, despite its limitations. Third, ICD-10 codes have replaced ICD-9 codes in most countries which may limit generalizability; however, the algorithms can be easily validated using these newer codes. Fourth, we surveyed only three providers to assess time spent on chart review. These were the total number of providers performing such chart review at our institution at the time, but their approach to chart review was not standardized and their workflow may not be generalizable to other institutions. Fifth, provider responses were based on recall and thus subject to recall bias, and which may partly explain the potential inconsistency between reported time spent on individual chart review and reported time spent reviewing charts per day.

Given current incentive structure to reduce readmissions following hospitalizations for ADHF,[3] early identification of patients with ADHF is needed to initiate interventions for readmission reduction. We found that using traditional approaches with structured data can accurately identify nearly all patients with ADHF but are limited by a large number of false positives. Machine learning algorithms with unstructured notes and radiology reports can significantly reduce false positives, thereby improving provider efficiency for delivery of quality improvement interventions. Nonetheless, our results suggest that some amount of secondary chart review is necessary for interventions designed to target all patients hospitalized with ADHF.

Acknowledgments

This work was supported by the Agency for Healthcare Research and Quality (AHRQ) grant K08HS23683.

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Highlights

- Machine learning improves identification of heart failure patients over automated approaches that rely on a few structured variables
- Improvement in identification may be related to use of free text from clinical notes
- Initial screening with a machine learning algorithm can reduce time needed for providers to perform chart review, thus improving efficiency for care

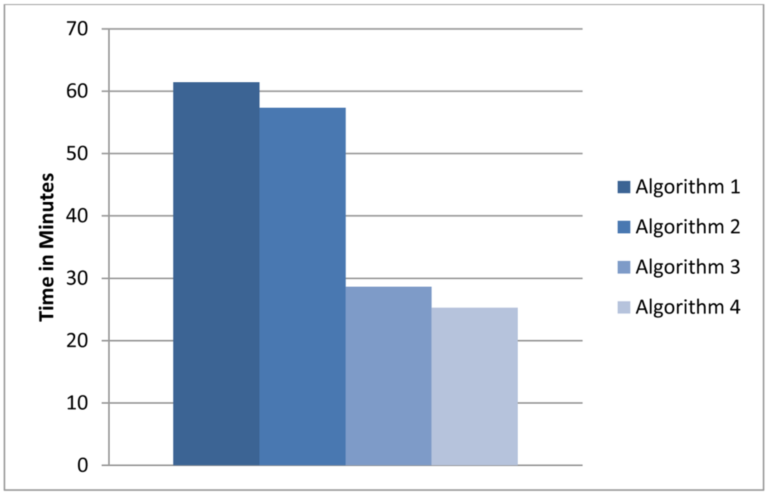

Figure.

Average time needed for secondary screening by providers to confirm each true positive case of acute decompensated heart failure diagnosis following initial screening with one of four automated algorithms: presence of 1 of 3 clinical characteristics (algorithm 1), logistic regression of structured data (algorithm 2), machine learning of unstructured data (algorithm 3), and machine learning of a combination of structured and unstructured data (algorithm 4). Average time was calculated: as estimated time per chart based on provider survey multiplied by the sum of true and false positives when the true positive equals one.

Table 1

Characteristics of 37,229 hospitalizations, by principal discharge diagnosis

Characteristic	Principal Diagnosis of Heart Failure (n=1,294)	All other Hospitalizations (n=35,935)
Age, Mean (SE)	76.2 (13.0)	60.8 (19.3)
Female	44.4	49.3
Black/African American Race	14.3	10.2
Hispanic/Latino Ethnicity	7.7	7.5
Medicaid	26.8	20.5
Heart failure in problem list	69.9	8.0
Prior diagnosis of any heart failure	40.3	7.3
Prior diagnosis of principal heart failure	23.7	2.0
Prior echocardiography	91.3	39.3
Inpatient diuretics	79.8	13.4
Outpatient diuretics	74.5	16.5
Inpatient ACE inhibitors or ARB	35.1	22.8
Outpatient ACE inhibitors or ARB	48.2	31.3
Inpatient beta blockers	58.9	38.2
Outpatient beta blockers	73.4	35.1
Inpatient heart failure beta blockers	41.3	11.5
Outpatient heart failure beta blockers	54.9	18.0
Inpatient aldosterone antagonist	17.2	2.3
Outpatient aldosterone antagonist	22.0	4.5
Systolic blood pressure, Mean (SE)	123.0 (21.1)	123.5 (18.7)
Diastolic blood pressure, Mean (SE)	65.3 (13.8)	68.3 (13.2)
Creatinine, Mean (SE)	1.8 (1.5)	1.1 (1.2)
Sodium, Mean (SE)	138.2 (4.4)	138.2 (3.9)
BNP		
<500	3.4	24.3
500–999	5.9	12.7
1000–4999	34.2	33.9
5000–9999	20.4	12.2
10000–19999	18.4	7.8
≥20000	17.7	9.1
Any Systolic blood pressure	99.7	99.7
Any diastolic blood pressure	99.7	99.7
Any creatinine	99.9	98.8
Any sodium	99.9	98.8
Any BNP	91.9	17.6
Acute MI in problem list	6.8	2.5
Atherosclerosis in problem list	35.2	14.1
Discharge diagnosis of heart failure (primary or secondary)	100.0	15.1
Principal discharge diagnosis of heart failure	100.0	0.0

Values are percent unless otherwise noted. ACE=angiotensin converting enzyme, ARB= angiotensin receptor blocker, BNP=B-type natiuretic peptide , MI=myocardial infarction

Table 2

Performance characteristics of four algorithms for classification of acute decompensated heart failure

Algorithm	Description	Development Set			Validation Set		
		AUC	Sensitivity	PPV	AUC	Sensitivity	PPV
1	Presence of ≥1 clinical characteristic*		0.98 (0.97–0.99)	0.13 (0.13–0.14)		0.98 (0.96–0.99)	0.14 (0.12–0.15)
2	Logistic regression with structured data	0.96 (0.96–0.96)	0.98 (0.97–0.99)	0.14 (0.14–0.15)	0.96 (0.95–0.97)	0.98 (0.97–0.99)	0.15 (0.13–0.16)
3	Machine learning using notes and imaging reports	0.99 (0.99–0.99)	0.98 (0.96–0.98)	0.42 (0.40–0.44)	0.99 (0.98–0.99)	0.98 (0.95–0.99)	0.30 (0.27–0.33)
4	Combination of structured and unstructured data	0.99 (0.99–0.99)	0.98 (0.96–0.98)	0.43 (0.41–0.45)	0.99 (0.98–0.99)	0.98 (0.95–0.99)	0.34 (0.31–0.37)

Appendix Table 1

Classifiers of acute decompensated heart failure, using logistic regression of structured data (algorithm 2)

Characteristic	Beta coefficient
Age	0.01
Female	−0.17
Black/African American Race	0.24
Hispanic/Latino Ethnicity	0.09
Medicaid	0.26
Heart failure in problem list	1.36
Prior diagnosis of any heart failure	−1.02
Prior diagnosis of principal heart failure	0.65
Prior echocardiography	0.64
Inpatient diuretics	1.66
Outpatient diuretics	0.22
Inpatient ACE inhibitors or ARB	0.03
Outpatient ACE inhibitors or ARB	0.14
Inpatient beta blockers	−0.64
Outpatient beta blockers	0.27
Inpatient heart failure beta blockers	0.24
Outpatient heart failure beta blockers	0.28
Inpatient aldosterone antagonist	0.34
Outpatient aldosterone antagonist	0.30
Systolic blood pressure	0.00
Diastolic blood pressure	0.01
Creatinine	0.04
Sodium	0.02
BNP (reference group: no BNP)	
<500	0.93
500–999	1.97
1000–4999	2.35
5000–9999	2.64
10000–19999	2.92
≥20000	3.05
AcuteMI in problem list	−0.08
Atherosclerosis in problem list	−0.20

Appendix Table 2

All 427individual free text words used in classification of acute decompensated heart failure, using a machine learning algorithm on unstructured data (algorithm 3).

Free text feature	Beta coefficient
bnp	0.9996
diuresis	0.8901
chf	0.8785
ivf	−0.6475
hf	0.6437
exacerbation	0.6375
failure	0.5401
lasix	0.4925
vent	−0.3913
pleural	0.3899
injury	−0.3731
wts	0.3598
bumex	0.3508
icd	0.3372
ppi	−0.3319
described	−0.3289
severely	0.3031
fluids	−0.2976
shortness	0.2886
decompensated	0.2859
found	−0.2815
admit	−0.2779
diuresed	0.2703
ef	0.2693
allergies	−0.2635
bladder	−0.2506
risk	−0.2506
salt	0.2466
class	0.2434
ns	−0.2422
steroids	−0.2325
ef	0.2278
obtain	0.2278
impression	−0.2269
maintain	−0.2217
npo	−0.2211
dilated	0.2174
bases	0.2103

Free text feature	Beta coefficient
sepsis	−0.2057
500	0.2056
scds	−0.2023
dyspnea	0.2016
throughout	−0.1999
afebrile	−0.1962
possible	−0.1949
pa	0.1941
breakfast	0.1936
breathing	0.1921
phos	0.186
crackles	0.1835
bb	0.1813
gram	−0.1792
planned	−0.178
guarding	−0.1771
urgent	−0.1745
home	−0.1733
dry	0.1727
digoxin	0.1705
friend	−0.1697
160	−0.1687
q4h	−0.1679
initial	0.164
prilosec	−0.1633
affect	0.1626
control	−0.1624
during	−0.16
pneumonia	0.158
sore	−0.1567
po	−0.156
amendments	−0.1552
ivc	0.1546
hpi	−0.1517
sounds	0.1517
orthopnea	0.1508
cardiomegaly	0.1505
pelvic	−0.1489
diurese	0.1488
dictated	0.1485
troponin	0.1481
resident	−0.148

Free text feature	Beta coefficient
nontender	0.1453
reyentovich	0.1451
1300	0.1424
allergies	−0.1403
asthma	−0.1388
mi	−0.1384
dm	0.1379
prednisone	−0.1378
done	0.1377
glimepiride	0.1357
tolerance	0.1347
assistance	0.1344
tele	0.1327
40mg	0.1317
age	−0.1306
light	−0.1306
worsening	0.1304
back	−0.1302
gait	−0.1301
general	−0.1295
rapid	−0.1273
intervention	−0.1255
region	−0.1236
compliance	0.1219
id	−0.1205
having	−0.1196
49	−0.1191
103	0.1178
assess	0.1175
jvp	0.1172
probnp	0.1159
sulfate	−0.1151
pitting	0.115
pressure	0.1136
atherosclerotic	0.1136
setting	−0.1135
paroxysmal	−0.1099
sitting	0.1085
subjective	−0.1076
702	0.1075
free	−0.1068
filed	0.1056

Free text feature	Beta coefficient
biv	0.1045
1l	0.1038
culture	−0.1034
units	−0.1031
ctab	−0.1029
127	−0.1025
lesion	−0.1022
hr	−0.1013
rashes	0.1006
iii	0.0999
tachypneic	0.0999
milrinone	0.0993
mellitus	0.0984
dyspneic	0.0983
within	−0.0981
auscultation	−0.0976
123	−0.0973
5	0.0954
stage	0.0954
subsequent	−0.0951
rt	−0.0949
likely	−0.094
fatigue	0.094
peripheral	−0.0937
ending	−0.092
function	0.0919
proceed	−0.0912
operative	−0.0911
nd	−0.0908
worsened	0.0902
pleasant	−0.0901
recurrent	−0.0887
furosemide	0.0878
lead	0.087
continues	0.0868
101	−0.0855
neurological	−0.0855
et	−0.0854
aox3	−0.0851
114	−0.084
several	0.0826
wean	0.0822

Free text feature	Beta coefficient
increased	0.0821
episodes	−0.0819
contrast	−0.0804
imaging	−0.0803
administration	0.0802
doing	−0.0788
doe	0.0788
consultation	−0.0784
annular	0.0771
bilitot	−0.077
notable	−0.0763
also	−0.0763
uc	−0.0758
potential	−0.0757
mildly	−0.0757
212	−0.0752
treat	−0.0741
gout	−0.074
asymmetric	0.074
cough	0.0733
strict	0.0731
gain	0.0719
yo	−0.0695
bibasilar	0.0694
please	−0.0688
weights	0.068
flat	0.0677
greater	0.0676
aggressive	0.0663
tab	−0.0659
85	0.0659
attack	0.0649
pelvis	−0.0647
sternal	0.0644
end	0.0642
wd	−0.0635
cardiologist	0.0634
o2	0.0623
78	0.0622
nebs	−0.0612
severity	−0.0609
enlarged	0.0608

Free text feature	Beta coefficient
comfortable	0.0604
goal	0.0603
mod	0.0588
trace	−0.0585
sq	−0.058
ct	−0.0576
presents	0.0574
trop	0.0573
appropriate	−0.0555
cream	0.0554
os	0.0554
prominence	0.0551
stretcher	−0.0545
q8h	−0.0544
carvedilol	0.0541
little	−0.0538
dx	−0.0538
labs	−0.0537
apex	0.0536
increasing	0.0531
started	−0.0529
ppm	−0.0525
compared	0.0524
anti	−0.0523
infarct	0.0522
congestive	0.0521
systems	−0.0517
ultrasound	−0.0515
via	−0.0514
unit	−0.0514
drainage	−0.0513
150	−0.0511
ray	0.0505
close	−0.0503
day	−0.0499
improved	0.0497
examined	−0.0493
ongoing	−0.0492
sxs	0.0492
position	−0.0488
rhonchi	−0.0484
bedside	−0.0482

Free text feature	Beta coefficient
100	−0.048
aiss	0.048
xray	0.0478
138	−0.0475
2	−0.0473
screening	−0.0467
frank	−0.0467
51	0.0464
nc	0.0455
mediastinal	−0.0452
ace	0.0452
vanco	−0.045
icu	−0.045
trauma	−0.045
change	−0.0446
38	−0.0445
424	−0.0436
ventricle	0.0431
eyes	−0.0426
rule	0.0426
144	0.0425
aorta	−0.0419
when	−0.0418
350	0.0416
mouth	−0.0414
returned	−0.0412
could	−0.0409
22	−0.0407
appearing	−0.0405
lv	0.0402
penicillins	0.0401
my	−0.0396
elderly	−0.0392
cell	−0.0391
safety	0.039
dated	0.0389
marital	0.0387
mass	−0.0383
movement	−0.0371
dysfunction	0.0371
arterial	−0.0369
hold	−0.0367

Free text feature	Beta coefficient
cholesterol	0.0367
transferred	−0.0365
prn	−0.0364
lle	−0.0359
meds	−0.0354
tte	0.0354
plt	−0.035
99	−0.035
leads	0.0349
cor	−0.0348
weeks	0.0341
inferior	−0.034
caliber	−0.0339
maintained	0.0334
stenosis	−0.0327
obstruction	−0.0327
small	0.0323
mcv	0.032
questionable	−0.0318
tortuous	−0.0317
plavix	−0.0316
pacing	−0.0315
asa	−0.0314
overload	0.0313
wnl	−0.031
ws	−0.0303
were	−0.0295
established	−0.0293
night	−0.0293
swelling	0.0292
temporal	−0.029
73	−0.0288
cardiovascular	−0.0285
regular	−0.0279
80	−0.0278
phlegm	0.0277
induced	−0.0276
stomach	−0.0271
gastrointestinal	−0.0269
94	0.0268
pvd	−0.0267
legs	0.0262

Free text feature	Beta coefficient
2006	−0.0257
cardiomyopathy	0.0255
chloride	−0.0254
0	−0.0254
ac	−0.0249
removal	−0.0249
teeth	0.0242
pulm	0.0237
fistula	0.0233
spironolactone	0.0232
arrived	−0.0229
15	−0.0228
study	0.0228
necessary	−0.0227
afternoon	0.0227
much	0.0215
going	−0.0204
healthy	0.0204
hrs	−0.0202
addendum	−0.02
inhaler	−0.0192
beta	0.0191
strength	−0.0186
md	−0.0179
sem	0.0178
75	−0.0172
more	0.017
rom	−0.0169
pmd	−0.0165
fair	−0.0164
through	−0.0163
sexually	−0.0161
notified	0.0152
ckd	0.015
staff	−0.0149
daughter	0.0144
medicine	−0.0143
stopped	0.0143
restriction	0.0139
somewhat	−0.0138
dizziness	−0.0135
awake	−0.0134

Free text feature	Beta coefficient
breast	−0.0133
needs	0.0133
stool	−0.012
psychiatric	0.012
check	0.0119
grossly	−0.0113
urine	−0.0113
overall	−0.0107
hepatitis	0.0104
atrovent	−0.0103
intolerance	0.0103
which	−0.0101
133	−0.0099
nt	0.0099
nebulization	−0.0098
fib	−0.0097
ii	0.0097
prophylaxis	−0.0091
probably	0.0091
murmurs	0.009
echocardiography	0.0089
trig	0.0085
spouse	0.0082
sclerae	−0.0081
angioplasty	−0.0078
organomegaly	0.0078
chol	0.0066
170	−0.0065
exertion	0.0062
keep	0.0061
groin	−0.0059
cannot	0.0055
90	−0.0053
septal	0.0053
lbs	0.0052
ersd	0.005
consolidation	−0.0049
146	0.0047
limited	−0.0045
ua	−0.0039
basename	0.0037
post	−0.0036

Free text feature	Beta coefficient
arrhythmia	−0.0031
decrease	−0.0031
evidence	−0.0026
load	−0.0024
routine	−0.0022
twice	−0.0021
3d	−0.002
dysuria	0.0018
meals	0.0014
cooperative	−0.0004
63	−0.0004

Appendix Table 3

All 432 features for classification of acute decompensated heart failure, using a machine learning algorithm on both structured and unstructured data (algorithm 4). Features with a * are structured data elements; all others are individual free text words from unstructured data.

Characteristic or free text feature	Beta coefficient
diuresis	0.8772
bnp	0.8576
chf	0.7207
hf	0.6239
ivf	−0.6103
exacerbation	0.596
injury	−0.4181
failure	0.4087
Any BNP*	0.405
wts	0.3886
vent	−0.3735
Heart failure in problem list*	0.37
Inpatient diuretic*	0.3673
pleural	0.3567
lasix	0.3456
ppi	−0.3353
severely	0.3289
icd	0.3221
fluids	−0.3209
BNP≥20000*	0.3037
described	−0.2972
bumex	0.2889
decompensated	0.2801
found	−0.2765
wbc	−0.2758
diuresed	0.2718
deformities	−0.2582
admit	−0.2578
shortness	0.2522
risk	−0.2506
bladder	−0.2506
salt	0.2466
class	0.2434
ns	−0.2422
steroids	−0.2325
obtain	0.2278
ef	0.2278

Characteristic or free text feature	Beta coefficient
impression	−0.2269
maintain	−0.2216
npo	−0.2211
dilated	0.2174
bases	0.2103
sepsis	−0.2057
500	0.2056
scds	−0.2023
dyspnea	0.2016
throughout	−0.1999
afebrile	−0.1962
possible	−0.1949
pa	0.1941
breakfast	0.1935
breathing	0.1921
phos	0.186
crackles	0.1836
bb	0.1813
gram	−0.1793
planned	−0.178
guarding	−0.177
urgent	−0.1744
home	−0.1732
dry	0.1727
digoxin	0.1705
friend	−0.1696
160	−0.1687
q4h	−0.1679
initial	0.164
prilosec	−0.1633
affect	0.1626
control	−0.1624
during	−0.16
pneumonia	0.1579
sore	−0.1567
po	−0.156
amendments	−0.1552
ivc	0.1546
hpi	−0.1517
sounds	0.1517
orthopnea	0.1508
cardiomegaly	0.1505

Characteristic or free text feature	Beta coefficient
pelvic	−0.1488
diurese	0.1488
dictated	0.1485
troponin	0.1481
resident	−0.148
nontender	0.1453
reyentovich	0.1452
1300	0.1424
allergies	−0.1404
asthma	−0.1388
mi	−0.1384
dm	0.1379
prednisone	−0.1378
done	0.1377
glimepiride	0.1357
tolerance	0.1347
assistance	0.1344
tele	0.1327
40mg	0.1317
light	−0.1306
age	−0.1305
worsening	0.1304
back	−0.1302
gait	−0.1301
general	−0.1294
rapid	−0.1272
intervention	−0.1255
region	−0.1236
compliance	0.122
id	−0.1205
having	−0.1196
49	−0.1191
103	0.1178
assess	0.1175
jvp	0.1172
probnp	0.1158
sulfate	−0.1151
pitting	0.1149
pressure	0.1137
setting	−0.1135
atherosclerotic	0.1135
paroxysmal	−0.1099

Characteristic or free text feature	Beta coefficient
sitting	0.1085
subjective	−0.1076
702	0.1075
free	−0.1068
filed	0.1056
biv	0.1044
1l	0.1038
culture	−0.1034
units	−0.1032
ctab	−0.1029
127	−0.1026
lesion	−0.1022
hr	−0.1014
rashes	0.1006
iii	0.0999
tachypneic	0.0999
milrinone	0.0993
mellitus	0.0984
dyspneic	0.0983
within	−0.0981
auscultation	−0.0976
123	−0.0972
5	0.0955
stage	0.0954
subsequent	−0.0951
rt	−0.0949
likely	−0.0941
fatigue	0.094
peripheral	−0.0937
ending	−0.092
function	0.0919
proceed	−0.0912
operative	−0.0911
nd	−0.0909
pleasant	−0.0901
worsened	0.0901
recurrent	−0.0887
furosemide	0.0878
Creatinine*	0.0875
lead	0.0869
continues	0.0868
neurological	−0.0856

Characteristic or free text feature	Beta coefficient
101	−0.0855
et	−0.0854
aox3	−0.0852
114	−0.084
several	0.0826
wean	0.0821
increased	0.0821
episodes	−0.0819
contrast	−0.0803
imaging	−0.0802
administration	0.0802
doing	−0.0788
doe	0.0788
consultation	−0.0784
annular	0.0771
bilitot	−0.077
notable	−0.0763
also	−0.0761
uc	−0.0758
potential	−0.0757
mildly	−0.0756
212	−0.0752
treat	−0.0741
gout	−0.074
asymmetric	0.074
cough	0.0733
Inpatient bblocker*	−0.0731
strict	0.0731
gain	0.0719
yo	−0.0695
bibasilar	0.0694
please	−0.0687
weights	0.068
flat	0.0677
greater	0.0676
aggressive	0.0664
tab	−0.0659
85	0.0659
attack	0.0649
pelvis	−0.0648
sternal	0.0644
end	0.0642

Characteristic or free text feature	Beta coefficient
wd	−0.0636
cardiologist	0.0634
o2	0.0623
78	0.0622
nebs	−0.0613
severity	−0.0609
enlarged	0.0608
comfortable	0.0604
goal	0.0603
Prior hospitalization with principal diagnosis of heart failure*	0.0593
mod	0.0588
trace	−0.0585
sq	−0.058
ct	−0.0576
presents	0.0574
trop	0.0573
appropriate	−0.0555
cream	0.0554
os	0.0554
prominence	0.0551
stretcher	−0.0545
q8h	−0.0543
carvedilol	0.0542
little	−0.0538
dx	−0.0538
labs	−0.0536
apex	0.0536
increasing	0.0531
started	−0.0529
ppm	−0.0525
compared	0.0524
anti	−0.0523
infarct	0.0522
congestive	0.052
systems	−0.0517
ultrasound	−0.0515
drainage	−0.0514
via	−0.0514
unit	−0.0514
150	−0.0511
ray	0.0505

Characteristic or free text feature	Beta coefficient
close	−0.0503
day	−0.0499
improved	0.0497
ongoing	−0.0492
examined	−0.0492
sxs	0.0492
position	−0.0488
rhonchi	−0.0484
bedside	−0.0482
100	−0.048
aiss	0.048
xray	0.0478
138	−0.0475
2	−0.0473
screening	−0.0468
frank	−0.0467
51	0.0462
nc	0.0455
mediastinal	−0.0452
ace	0.0452
vanco	−0.0451
trauma	−0.045
icu	−0.045
change	−0.0446
38	−0.0446
Echo*	0.044
424	−0.0436
ventricle	0.0431
rule	0.0427
eyes	−0.0426
144	0.0425
when	−0.0419
aorta	−0.0419
350	0.0416
mouth	−0.0414
returned	−0.0412
could	−0.0409
22	−0.0407
appearing	−0.0405
lv	0.0402
penicillins	0.0401
my	−0.0396

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Characteristic or free text feature	Beta coefficient
elderly	−0.0394
cell	−0.0391
safety	0.039
dated	0.0389
marital	0.0387
mass	−0.0383
movement	−0.0371
dysfunction	0.0371
arterial	−0.0368
hold	−0.0367
cholesterol	0.0366
transferred	−0.0365
prn	−0.0365
lle	−0.0359
Sodium*	−0.0355
meds	−0.0354
tte	0.0354
plt	−0.035
99	−0.035
leads	0.035
cor	−0.0348
weeks	0.0341
inferior	−0.034
caliber	−0.0339
Outpatient evidence based bblocker*	0.0337
maintained	0.0334
stenosis	−0.0328
obstruction	−0.0327
small	0.0322
mcv	0.032
tortuous	−0.0318
questionable	−0.0318
plavix	−0.0316
pacing	−0.0315
asa	−0.0313
overload	0.0313
wnl	−0.031
ws	−0.0303
were	−0.0295
established	−0.0293
night	−0.0293

Characteristic or free text feature	Beta coefficient
temporal	−0.029
73	−0.0288
cardiovascular	−0.0285
regular	−0.0278
80	−0.0278
phlegm	0.0277
induced	−0.0276
Inpatient ACE/ARB*	−0.0276
stomach	−0.0271
gastrointestinal	−0.0269
94	0.0268
pvd	−0.0267
legs	0.0262
2006	−0.0257
cardiomyopathy	0.0255
chloride	−0.0254
0	−0.0253
ac	−0.0249
removal	−0.0249
pulm	0.0237
arrived	−0.0229
15	−0.0229
study	0.0228
necessary	−0.0227
afternoon	0.0227
much	0.0215
going	−0.0204
healthy	0.0204
hrs	−0.0202
addendum	−0.0201
inhaler	−0.0192
beta	0.0191
strength	−0.0186
sem	0.0179
md	−0.0177
75	−0.0173
more	0.0171
rom	−0.0168
pmd	−0.0165
fair	−0.0164
through	−0.0163
sexually	−0.0162

Characteristic or free text feature	Beta coefficient
notified	0.0153
staff	−0.0149
medicine	−0.0144
daughter	0.0144
stopped	0.0143
somewhat	−0.0139
restriction	0.0138
dizziness	−0.0136
awake	−0.0134
breast	−0.0133
needs	0.0132
stool	−0.012
check	0.0119
grossly	−0.0113
urine	−0.0113
overall	−0.0107
hepatitis	0.0104
atrovent	−0.0103
intolerance	0.0103
which	−0.0101
nt	0.01
133	−0.0099
nebulization	−0.0098
fib	−0.0097
ii	0.0097
prophylaxis	−0.0091
probably	0.0091
echocardiography	0.009
murmurs	0.0089
spouse	0.0082
sclerae	−−0.0081
organomegaly	0.0079
angioplasty	−0.0078
chol	0.0066
170	−0.0065
age*	0.0064
exertion	0.0062
keep	0.0061
groin	−0.0059
Outpatient Aldosterone antagonist*	0.0058
cannot	0.0055
90	−0.0053

Characteristic or free text feature	Beta coefficient
lbs	0.0052
consolidation	−0.0049
146	0.0047
limited	−0.0046
ua	−0.0039
post	−0.0036
basename	0.0036
decrease	−0.0031
arrhythmia	−0.0031
evidence	−0.0026
Diastolic Blood Pressure*	−0.0024
load	−0.0024
routine	−0.0022
twice	−0.0021
3d	−0.002
Systolic Blood Pressure*	0.0019
meals	0.0014
cooperative	−0.0006
63	−0.0004