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Research and Applications

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Predicting emergency department visits and hospitalizations for patients with heart failure in home healthcare using a time series risk model

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ABSTRACT

Objectives: Little is known about proactive risk assessment concerning emergency department (ED) visits and hospitalizations in patients with heart failure (HF) who receive home healthcare (HHC) services. This study developed a time series risk model for predicting ED visits and hospitalizations in patients with HF using longitudinal electronic health record data. We also explored which data sources yield the best-performing models over various time windows.

Materials and Methods: We used data collected from 9362 patients from a large HHC agency. We iteratively developed risk models using both structured (eg, standard assessment tools, vital signs, visit characteristics) and unstructured data (eg, clinical notes). Seven specific sets of variables included: (1) the Outcome and Assessment Information Set, (2) vital signs, (3) visit characteristics, (4) rule-based natural language processing-derived variables, (5) term frequency-inverse document frequency variables, (6) Bio-Clinical Bidirectional Encoder Representations from Transformers variables, and (7) topic modeling. Risk models were developed for 18 time windows (1–15, 30, 45, and 60 days) before an ED visit or hospitalization. Risk prediction performances were compared using recall, precision, accuracy, *F*1, and area under the receiver operating curve (AUC).

Results: The best-performing model was built using a combination of all 7 sets of variables and the time window of 4 days before an ED visit or hospitalization (AUC = 0.89 and *F*1 = 0.69).

Discussion and Conclusion: This prediction model suggests that HHC clinicians can identify patients with HF at risk for visiting the ED or hospitalization within 4 days before the event, allowing for earlier targeted interventions.

Key words: heart failure, home care services, natural language processing, electronic health records, nursing informatics, machine learning

INTRODUCTION

Every year, more than 11 000 home healthcare (HHC) agencies across the United States (US) provide care to more than 3.4 million older adults.[1] One in 3 HHC patients is diagnosed with heart failure[2] (HF)—a chronic condition that causes high levels of symptom burden, which results in low quality of life.[3,4] Despite efforts to improve care for patients with HF, negative outcomes remain prevalent.[5] Specifically, hospitalization rates for patients with HF remain relatively high (∼17%).[5] Treatment of HF has a direct cost of over $34 billion per year, with hospitalizations accounting for the majority of the costs.[5] Furthermore, more than 1 million emergency department (ED) visits for HF per year highlights the severity of the condition and the need for early detection and proper management of HF.[6]

Patients with HF in HHC are frequently hospitalized for reasons related to symptom aggravation (eg, dyspnea, fluid overload) and comorbidity burden.[7–9] Symptom presentation may occur days before negative outcomes, such as ED visits or hospitalizations; 1 study reported dyspnea presented on average 3 days before hospitalization.[8] Hence, close monitoring of symptoms and timely intervention based on risk prediction may allow HHC clinicians (registered nurses, social workers, physical, and occupational therapists) to prevent ED visits or hospitalizations.[10,11] HHC clinicians can also help

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at-risk patients to improve their self-management skills, leading to better outcomes.[12] The most appropriate time to have early intervention with patients with HF in the HHC setting would depend on the specific architecture and experiment of the predictive model and the patients being monitored. Therefore, it would be ideal to design a predictive model using time-variant temporal variables to identify patients who are at risk and intervene as soon as possible to prevent negative outcomes. The exact timing would need to be determined by further testing and implementing the clinical decision support tools in the HHC setting.

However, no previous studies have demonstrated the feasibility of using time series risk prediction models based on routinely collected electronic health record (EHR) data to identify at-risk patients in HHC.[13] A significant amount of information on potential risk factors, which is not always present in structured data (eg, standardized assessments, vital signs), is often recorded in clinical notes.[14] Our group has previously developed and validated natural language processing (NLP) approaches to identify and extract "concerning" notes,[15] as well as potential risk factors,[15,16] symptoms,[17] and poor self-management in patients with HF[18] from HHC clinical notes.

However, these NLP algorithms have not yet been integrated into predictive modeling in a manner that allows us to take into consideration the dynamic visit-to-visit changes in patients' health status. Several models predicting ED visits and hospitalizations have been developed; however, these models focus on the hospital setting and primarily use limited data (mostly administrative)[16–20] for risk profiling. In addition, patients' assessments are documented irregularly and are asynchronously extracted from HHC EHRs. Furthermore, patients may experience dynamic and nonlinear symptom severity or condition changes across treatment trajectories. Data issues, such as varying time gaps between record points, and fluctuating and nonlinear longitudinal symptom dynamics across the HF treatment continuum, make the analysis of EHR data challenging. While traditional statistical analysis using EHRs has not been successful in dealing with these challenges,[19] this study explores the feasibility of comprehensive and time series risk modeling using longitudinal EHR data in the HHC setting for patients with HF.

This study is the first to integrate comprehensive patient information across the HHC EHR into a time series risk prediction models for ED visit and hospitalization risk. The specific aims of this study are: (1) to develop a time series risk model for predicting risk for ED visits and hospitalizations in patients with HF using longitudinal EHR data, (2) to determine what combined datasets of variables result in creating the best-performing risk models over various outcome time windows, and (3) to identify the highly correlated variables associated with increased risk for ED visits and hospitalizations.

MATERIALS AND METHODS

Study design and study population

We extracted data for all patients with HF (ICD-10 codes 50.x, I11.0, I13.0, I13.1, I13.2)[20] admitted between January 1, 2015 and December 31, 2017 to one of the largest nonprofit HHC organizations in the Northeastern US. The unit of analysis was 1 HHC visit, defined as any visit provided by HHC health care providers (eg, registered nurses, physical therapists, and social workers). A HHC episode was defined as all services provided during the time between HHC admission and HHC discharge.

We used structured data (Outcome and Assessment Information Set [OASIS], vital signs, visit characteristics) and unstructured data (HHC clinical notes) with 7 different sets of variables explained in the "Variable Selection" section below in our analysis. We extracted all clinical notes ($n = 125\,979$) including visit notes and care coordination notes generated by mostly nurses, as well as some physical and occupational therapists and social workers during or between HHC visits. Visit notes describe the care provided and the patient's status during an HHC visit. Care coordination notes document communication between HHC health care providers (eg, calling a physician) and other care-related activities (eg, ordering wound care supplies).

Study outcome

Our primary outcome of interest was hospitalization anytime within a 60-day HHC episode or ED visits. This was determined in accordance to Medicare reimbursement for HHC for up to 60 days.[21]

Variable selection and the final dataset preparation

We created 7 sets of variables starting with: (1) the OASIS, and then adding (2) vital signs, (3) visit characteristics, (4) rule-based NLP algorithm, (5) term frequency-inverse document frequency (TF-IDF), (6) Bio-Clinical Bidirectional Encoder Representations from Transformers (BERT), and (7) topic modeling for the analysis. Each set of variables is described below.

Set of variables 1: OASIS data

In order to select variables to be incorporated into a risk prediction model, we used univariate analysis (ie, t tests for continuous variables and chi-square tests for categorical variables) at the statistically significant level with $P < .01$. From the start of care OASIS, sociodemographic characteristics were examined at the patient level, while clinical characteristics were examined at the episodic level to be compared with those with ED visits or hospitalizations, HF or other related reasons, without ED visits or hospitalizations. To select clinically meaningful variables, we consulted with 5 HHC and informatics experts (J.S., K.B., M.M., Y.B., and M.T.) who have extensive experience in HHC nursing, research, and cardiology. Based on this discussion, the selected variables were deemed conceptually associated with risk for ED visits and hospitalizations in patients with HF in HHC settings; therefore, they are included in the final data set for building a risk model. All OASIS variables selected are listed in Supplementary Table S1.

Set of variables 2: vital signs

Similar to other studies,[22,23] we used 2 cardiovascular-related vital signs, blood pressure and pulse rate, since both are routinely monitored by HHC healthcare providers and are associated with hospitalization or ED visits for patients with HF. Blood pressure was scored as 0 = missing, 1 = normal (less than 120/80 mm Hg), 2 = elevated (systolic between 120 and 129 mm Hg and diastolic less than 80 mm Hg), 3 = stage 1 hypertension (systolic between 130 and 139 mm Hg or diastolic between 80 and 89 mm Hg), 4 = stage 2 hypertension (systolic at least 140 mm Hg or diastolic at least 90 mm Hg), or 5 = hypertensive crisis (systolic over 180 mm Hg and/or diastolic over 120 mm Hg), as per the 2017 American College of Cardiology/American Heart Association (ACC/AHA) guidelines.[24] Blood pressure could be measured up to 3 times as needed during a visit. The total number of blood pressure measurements (a sum of first, second, and third blood pressure measurement scores, where 0 means no blood pressure measurement recorded at the visit, 1 means that 1 blood pressure reading was recorded, and 2 means 3 blood pressure readings) were recorded. Pulse rate was used as a continuous variable. The analysis used 3 variables—the ACC/AHA blood pressure classification, the number of blood pressure measurements taken, and the heart rate—to develop a set of variables.

Set of variables 3: visit characteristics

We extracted the following variables from administrative data, including time-series visits information and visit purpose to create visit characteristics: the number of days after admission (visit date—admission date); and the purpose of the visit (eg, rehabilitation-related, nursing training, and education). The term discharge includes: (1) discharge from HHC when HHC services are no longer required for patients without hospitalization or ED visits and (2) discharge from HHC due to acute care utilization for patients with hospitalization or ED visits (Supplementary Table S1).

Set of variables 4: NLP technique 1—rule-based NLP-derived variables

We applied 4 different NLP techniques using the same clinical notes because different NLP techniques provide different performance and interpretability.[25] For creating the set of Variables 4, we used previously developed and validated NLP approaches to extract symptoms, "concerning" notes, and risk factors for hospitalization and ED visits from HHC clinical notes. The methods briefly summarized below are fully described in previous publications.[15–18] We merged the following 2 episode-level data sets from preliminary work into a single visit-level data set: (1) HF data set: HF patient characteristics and symptoms documented in HHC clinical notes associated with ED visits and hospitalizations ($n = 9362$ HF patients who received 12 223 episodes); and (2) risk factor data set: potential risk factors and "concerning" notes for ED visits and hospitalizations extracted from clinical notes ($n = 66\,317$ patients who received 86 866 HHC episodes). We used a total of 46 rule-based NLP-derived variables: 12 HF symptoms (eg, dyspnea, fatigue etc.), the total number of symptoms, and poor self-management,[17,18] "concerning" notes and "having a problem," and 30 general risk factors (Supplementary Table S1).

NLP approach no. 1: HF symptoms and poor self-management indicators

Based on relevant literature, a standardized health terminology (the Omaha System), and expert consensus, we identified 12 symptom domains relevant to HF in HHC (anorexia, chest pain, confusion, cough, dizziness, dyspnea, fatigue, nausea, palpitation, peripheral edema, weight loss, and weight gain).[17,26] Next, we used an open-source NLP tool called *NimbleMiner*[27] to expand and refine synonymous terms for each symptom domain. If a patient had at least 1 instance of a documented symptom, they were classified as having a symptom.

In addition, our team identified HHC patients with HF who have poor self-management by applying rule-based NLP to clinical notes.[18] Six domains of HF self-management were identified: poor diet adherence, poor medication adherence, poor exercise/physical activity tolerance, issues with other self-care activities/self-monitoring, missed healthcare encounters, and unspecified nonadherence. If a patient had at least 1 instance of documented poor self-management, they were classified as having poor self-management. Our risk prediction model incorporated statistically significant ($P < .01$) and clinically meaningful variables from these previous analyses.[14,18]

NLP approach no. 2: "concerning" clinical notes

Previously, our team developed machine learning based NLP methods to classify HHC clinical notes as either "concerning" or "not concerning."[15] A "concerning" note was defined as a note including 1 or more risk factors associated with deterioration, thus resulting in ED visits or hospitalizations. We applied Convolutional Neural Networks (CNN), which demonstrated better performance for the binary classification task to classify each clinical note as either "concerning" or "not concerning."[16]

NLP approach no. 3: general hospitalization and ED visit risk factors

General risk factors for ED visits and hospitalization during HHC visits were extracted from HHC clinical notes using a valid, rule-based NLP algorithm based on the Omaha System, a standardized nursing terminology.[15,16] Omaha System problems such as "Circulation," "Bowel function," and "Abuse" were identified as high risk factors associated with ED visits or hospitalization during HHC. The methods for our dataset preparation are fully described in Supplementary Table S2.

Set of variables 5: NLP technique 2-term frequency-inverse document frequency (TF-IDF) and lexical features

We generated TF-IDF vectors for each clinical note to count the word weight by considering the term frequency (TF) and inverse document frequency (IDF). TF reflects the frequency of a term within a note, while IDF assigns higher weight to less frequent words.[28] TF-IDF quantifies word relevance in a document, and this information can be used to build predictive models that can classify or analyze text data.[29]

Set of variables 6: NLP technique 3—pre-trained language model (Bio-Clinical BERT)

We used Bio-Clinical BERT, a pretrained NLP model that uses a large amount of health-related text on the web.[30–32] A state-of-the-art neural language model, Bio-Clinical BERT, which is trained on large amounts of biomedical data, such as medical records and scientific articles, achieved the best performance in comparison with conventional machine learning models.[33] Its ability to accurately process and extract information from large amounts of biomedical text data makes it a valuable tool for building a predictive model that can be trained to identify the presence of negative outcomes based on patient symptoms and medical history. In this study, we generated the Bio-Clinical BERT vectors for all the available clinical notes at each HHC visit.

Set of variables 7: NLP technique 4—topic modeling

We applied Latent Dirichlet Allocation (LDA) topic modeling to extract another variable set of the inherent latent topics of HHC clinical notes. LDA is a technique for content analysis designed to automatically organize large sets of documents based on latent topics, measured as patterns of word (co-)occurrence.[34] The resulting topics can then be used as variables in a predictive model, providing additional information about the content of the documents that can be used to make predictions.[35] We ran the model for 10, 20, and 30 topics, calculated the *F*1 score for each model, and selected the 10 topic models that demonstrated the highest *F*1 score. We generated the topic models for all the available clinical notes at each HHC visit.

Building risk prediction models

Machine learning model development and evaluation

To address Aim 1, we developed a risk prediction model using a machine learning approach with an open-source AutoGluon-Tabular classifier (version v 0.6.0).

Different risk models, such as the Cox Proportional Hazards model (CPH), have their own strengths and limitations. The AutoGluon-Tabular classifier prioritizes predictive performance, while the CPH model offers interpretability through hazard ratio estimation.[36] However, the CPH model assumes the proportional hazards assumption, which may not hold true in our study due to the changing risk levels for ED visits or hospitalization over time. In this study, our goal is to identify the best-performing risk models for different outcome time windows. Given this objective, and the limitations of applying the CPH to this study, the AutoGluon-Tabular classifier aligns better with our research goals.

AutoGluon-Tabular automatically selects best-performing algorithms and hyperparameters tuning for effective application of machine learning.[37] AutoGluon streamlines the machine learning pipeline by incorporating automated hyperparameter tuning, making it easier for users to achieve high-performing models without manual adjustments.[38] This approach allows users to obtain optimized results without specifying hyperparameters or comprehending the optimization process in-depth. We developed 7 risk prediction models with additive datasets that build off of each other: (ie, 1. OASIS only, 2. OASIS + vital signs, … 7. OASIS + vital signs + visit characteristics + rule-based NLP-derived variables + TF-IDF+Bio-Clinical BERT + topic modeling etc.). The rationale for our data processing order is based on the accessibility of each data source: We initiated our analysis with OASIS, a universally available and federally required standardized assessment for all HHC agency patients. Following this, we integrated increasingly complex data sources, necessitating more extraction effort from raw HHC data. This process began with vital signs and HHC visit characteristics, and we proceeded to include NLP-extracted variables such as rule-based, BERT, TF-IDF, and topic models.

For Aim 2, we experimented with several risk prediction time windows as an outcome of the risk prediction model based on the time frame from previous research for predicting adverse events in patients with HF.[39] Specifically, we developed 15 models to predict hospitalization or ED visit over each day within 2 weeks (1–15 days). Existing literature suggests that HHC patients are at heightened risk for hospitalizations and ED visits in the first 2 weeks of HHC services.[40,41] Therefore, we wanted to examine the performance of risk prediction models at every day within those first 2 weeks of HHC services (1–15 days). Further, we also wanted to explore the longer-term performance of risk prediction models with intervals of 2 weeks, specifically at 30, 45, and 60 days. Our time period is limited to 60 days because HHC episodes are mostly limited to 60 days by the payer (Center for Medicare and Medicaid Services). For each time window, we collected the most recent values from model variables generated at least that many days before the next ED visit or hospitalization. For example, when the time window was 7 days, the duration of the time we are predicting the events (ED or hospitalization) is, at the most, 7 days (1–7 days).

The dataset included 25 OASIS variables, 3 vital signs, 2 visit characteristics, 46 rule-based NLP-derived variables, TF-IDF-driven variables, 768 variables from Bio-Clinical BERT, and the 10 most relevant topic modeling variables in our final model.

Data were stratified into the training (80%) and test (20%) sets. Next, the final model was evaluated on the test set. We evaluated the predictive ability of models on the test set using the following criteria: recall, precision, accuracy, *F*1, and area under the receiver operating characteristic curve (AUC). Figure 1 provides a general overview of the study methods.

In terms of missing data, our study utilized 3 types of variables: (1) OASIS variables, which are federally mandated and have a high completion rate of 99%+; (2) vital signs, of which unmeasured values were categorized as "not available"; and (3) NLP-derived variables, including rule-based, TF-IDF, Bio-Clinical BERT, and LDA, of which the absence of documentation resulted in categorization as "not available."

Identifying the most highly correlated variables associated with risk for ED visits and hospitalizations

To identify both positively and negatively highly correlated variables with risk for ED visits and hospitalizations considering coefficients, we used an approach based on the least absolute shrinkage and selection operator (LASSO).[42] One of the core strengths of the LASSO approach is the ability to identify the set of predictors associated with the outcome variable, subject to a constraint on the total size of the coefficients. The idea behind LASSO is to shrink the coefficients of less important predictors toward zero, eliminating them from the model and only including the strongest relationship to the outcome variable.[42] We implemented LASSO using Python's scikit-learn and presented the top 20 variables either positively or negatively associated with the risk of ED visits or hospitalizations using the optimal value of alpha.

RESULTS

Patient characteristics

In total, we identified 9362 patients diagnosed with HF who received 176 209 visits during 12 223 episodes of HHC. The characteristics of patients are listed in Table 1. A majority of the patients were female (61%) and on average 81.7 years old (standard deviation [SD] 11 years) at the start of care. The average length of stay in HHC was 48 days (SD 56 days). About 1 in 4 patients (2379/9362 = 25%) experienced hospitalization or ED visits within the 60-day period. The rule-based NLP algorithm identified documented symptoms in 41.5% ($n = 3886$) of patients. Frequently documented

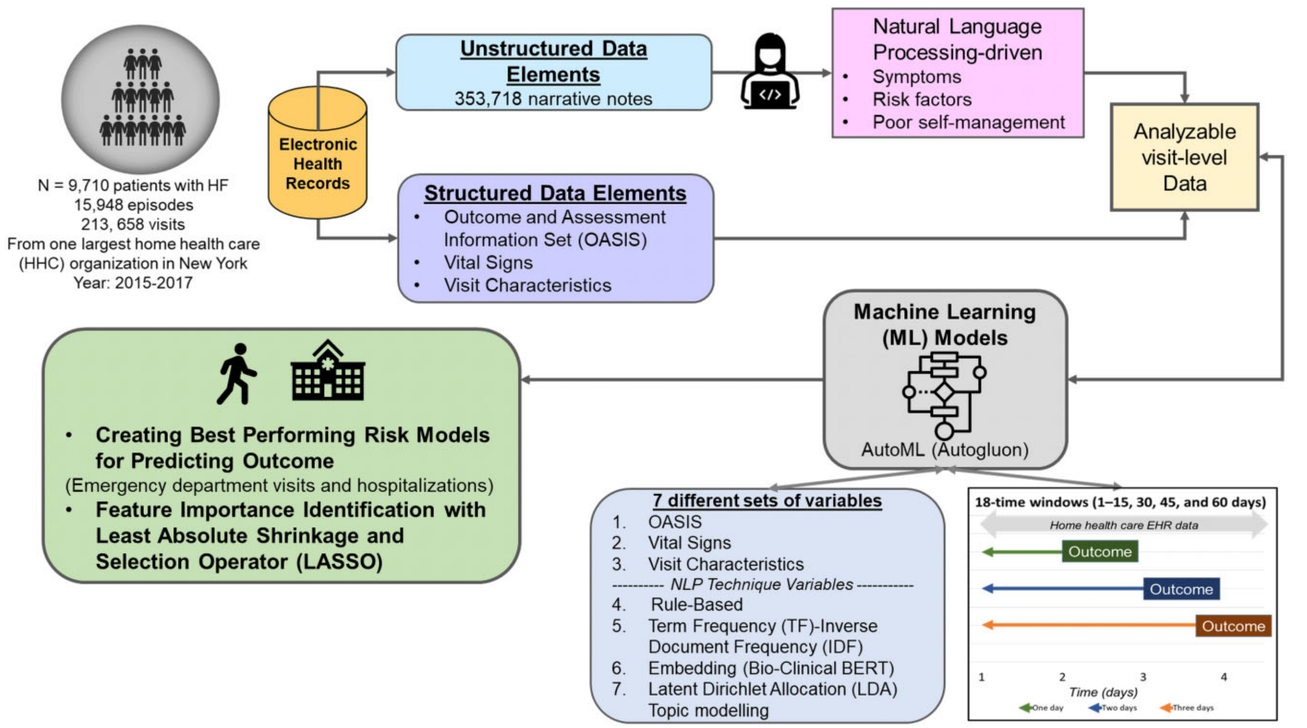

Figure 1. Overview of study methods.

symptoms were dyspnea (17.5%), peripheral edema (13.7%), and fatigue (11.4%).

Performance of risk prediction models

Risk prediction results using different sets of variables

With the addition of increasingly complex sets of variables, the risk prediction ability of the model improved. When we only used OASIS variables, the model had the lowest *F*1 score of 0.57 (95% confidence interval [CI]: 0.54, 0.6) (Figure 2). When we added rule-based NLP-derived variables, the *F*1 score of the model improved from 0.57 to 0.67 (10% improvement compared to baseline). Additional detailed metrics are reported in Table 2. Our findings show that our model can predict ED visits and hospitalizations using a 4-day time window with all 7 sets of variables with an *F*1 score of 0.69.

Risk prediction results using different time windows

Using the best predictive model with all 7 sets of variables, we tested its predictive ability in different time windows (1–15, 30, 45, and 60 days before the date of ED visit or hospitalization). Overall, we achieved relatively high and stable performance for predictions of ED visits or hospitalizations starting on day 4 (*F*1 score = 0.69; further details are provided in Supplementary Table S3), shown in Figure 3. Even though we observed the best performance using 7 days of data, there was only 0.8% improvement on the F1 score using 7 days compared to predictions using 4 days. Clinically, predictions within shorter time windows are more valuable; hence we decided to use the 4-day time window moving forward (Table 2). Additional details of prediction performance on the different days are in Supplementary Table S3.

To further describe the performance of our model, we also applied the receiver-operating characteristic (ROC) curves and the precision-recall (PR) curves, shown in Figure 4. Our risk model had a relatively high AUC (0.89), and area under the PR curve (0.72), indicating good predictive performance.

Highly correlated variables associated with risk for ED visits and hospitalizations

Figure 5 displays the top 20 variables either positively or negatively correlated with the outcome within the 4-day time window as identified by LASSO. Three variables related to HHC visit characteristics were identified. First, the "number of days since admission for the current visit" was the highest-ranked variable, signifying those patients with shorter HHC stays between their HHC admission and the current visit had a higher risk for negative outcomes. Similarly, the sixth-ranked variable, "the number of days between last visit and previous visit," showed that patients with less time between visits faced increased risk. Moreover, the fifth-ranked variable, "visit purpose (for the current visit)," was linked to negative outcomes. A sub-analysis of categorical documented visit purposes revealed that patients with missed visits (eg, when not at home or not answering the door) had a higher likelihood of ED visits and hospitalizations.

Next, 14 NLP-extracted variables were identified. Three of these variables were indicators of the "total number of HF symptoms" at previous visit, 12, and 25 visits previously (second, seventh, and 13th ranked variables, respectively). Interestingly, this directionality of association for this variable changed over time. Specifically, having more HF symptoms at a previous HHC visit indicated higher risk, whereas having more HF symptoms at visits that happened a while ago (ie, 12 and 25 visits previously) indicated lower risk. Other important NLP-extracted variables included 2 Bio-Clinical BERT-derived variables (not explainable) and 4 tokens extracted from the TF-IDF vector, specifically "ER [emergency room]"

Table 1. Characteristics of patients

Clinical and demographic profile (OASIS item)	Total ($n = 9362$, 12 223 HHC episodes)
	Patient *n* (%)[a]
Age at start of care (mean, years, SD)	81.7 (11)
Race	
Asian/Others/Unknown/Native Hawaiian or Pacific Islander	3498 (37)
Non-Hispanic Black	1279 (14)
Non-Hispanic White	3494 (37)
Hispanic	1091 (12)
Gender	
Male	3644 (39)
	Episode *n* (%)[b]
Length of stay in HHC (mean, days, SD)	47.6 (56)
Comorbidities (mark all that apply)	
AIDS	95 (1)
Arthritis	1553 (13)
Diabetes	4746 (39)
Dementia	1338 (11)
Hypertension	8851 (72)
Peripheral vascular disease	444 (4)
Pulmonary diseases	3151 (26)
Renal diseases	726 (6)
Skin ulcer	1631 (13)
Prior conditions within past 14 days	
Indwelling/suprapubic catheter	152 (1)
Impaired decision-making	1285 (11)
No inpatient facility discharge and no change in medical or treatment regimen	1105 (9)
Urinary incontinence	3743 (31)
Risk factors	
Drug	71 (1)
Obesity	2279 (19)
Shortness of breath	
Never	4039 (33)
With exertion	7909 (65)
At rest	183 (2)

[a] The descriptions of demographic characteristics were analyzed at the patient level.
[b] The descriptions of clinical characteristics were analyzed at the episode level.

and "has pain" were associated with higher risk, whereas "no further" and "generic" were associated with lower risk. The third-ranked feature was the rule-based NLP-derived variable, "community resources at previous visit," showing that the fewer total number of risk factors related to "community resources" documented in clinical notes during the previous visit is also associated with a higher risk. Two lexical variables were associated with risk: "ratio of nonalphanumeric symbols to text length" and "ratio of numeric digits to text length" (fourth, and 17th ranked variables, respectively). Two variables describing topics identified by topic modeling were identified as associated with higher risk, including the presence of "Referral related language at current visit" and "Comorbidity management at previous visit" (18th and 19th ranked variables, respectively).

Finally, 3 OASIS variables were identified as associated with increased risk, namely "[lower level of] Prior functioning," "Skin ulcer," and "Diabetes." Of note, no vital signs were selected among the top variables associated with risk.

DISCUSSION

This study generated a time series risk model to predict ED visit and hospitalization risk in patients with HF. The novelty of a time series risk model to predict ED visit and hospitalization in patients with HF is in its ability to analyze data over time and account for the dynamic nature of the disease, assisting HHC providers to identify these changes and be alerted to intervene early, potentially preventing an ED visit or hospitalization. This is the first study in HHC to use all available data over the episode of care to generate risk models. Specifically, we extended the rigor of previous research in HHC that primarily relied on standardized assessments, such as an OASIS, for risk prediction tasks.[43,44] We added information extracted from structured data (including vital signs and visit characteristics) and NLP-derived variables to our risk models. We found that gradually adding different variable sets improves risk prediction performance. In line with previous

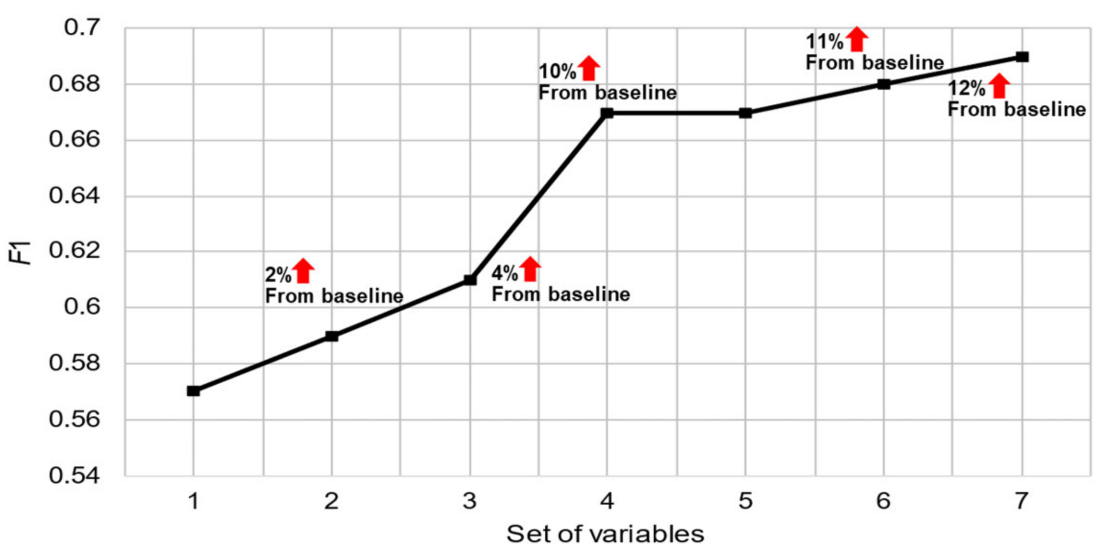

Figure 2. F1 score of risk prediction models when adding the different sets of variables. Set 1: OASIS only. Set 2: OASIS+vital signs. Set 3: OASIS+vital signs+visit characteristics. Set 4: OASIS+vital signs+visit characteristics+NLP variables. Set 5: OASIS+vital signs+visit characteristics+NLP variables+TF-IDF variables. Set 6: OASIS+vital signs+visit characteristics+NLP variables+TF-IDF variables+Bio-Clinical BERT variables. Set 7: OASIS+vital signs+visit characteristics+NLP variables+TF-IDF variables+Bio-Clinical BERT variables+topic modeling variables.

Table 2. Four-day ED visit and hospitalization risk prediction performance

Sets of variables	Recall	Precision	Accuracy	*F*1	AUC
OASIS data	0.69 [0.61, 0.77]	0.49 [0.44, 0.54]	0.79 [0.76, 0.82]	0.57 [0.54, 0.60]	0.82 [0.80, 0.84]
Vital signs	0.66 [0.60. 0.78]	0.54 [0.47, 0.61]	0.82 [0.78, 0.84]	0.59 [0.57, 0.63]	0.84 [0.82, 0.86]
Visit characteristics	0.66 [0.57, 0.79]	0.57 [0.48, 0.64]	0.83 [0.79, 0.87]	0.61 [0.58, 0.64]	0.85 [0.83, 0.87]
NLP technique-derived variables					
Rule-based NLP	0.73 [0.69, 0.77]	0.62 [0.58, 0.66]	0.86 [0.84, 0.86]	0.67 [0.64, 0.70]	0.88 [0.86, 0.90]
TF-IDF	0.71 [0.67, 0.77]	0.63 [0.58, 0.68]	0.86 [0.84, 0.88]	0.67 [0.64, 0.70]	0.89 [0.87, 0.91]
Bio-clinical BERT	**0.76** [0.65, 0.81]	0.61 [0.56, 0.72]	0.85 [0.84, 0.88]	0.68 [0.65, 0.71]	0.90 [0.87, 0.91]
LDA topic modeling (the number of topics: 10)	0.73 [0.66, 0.80]	**0.65** [0.59, 0.73]	**0.87** [0.85, 0.89]	**0.69** [0.66, 0.72]	**0.89** [0.87, 0.91]

Note: The best result on each metric is shown in bold.
Abbreviation: AUC: area under the receiver operating characteristic curve.

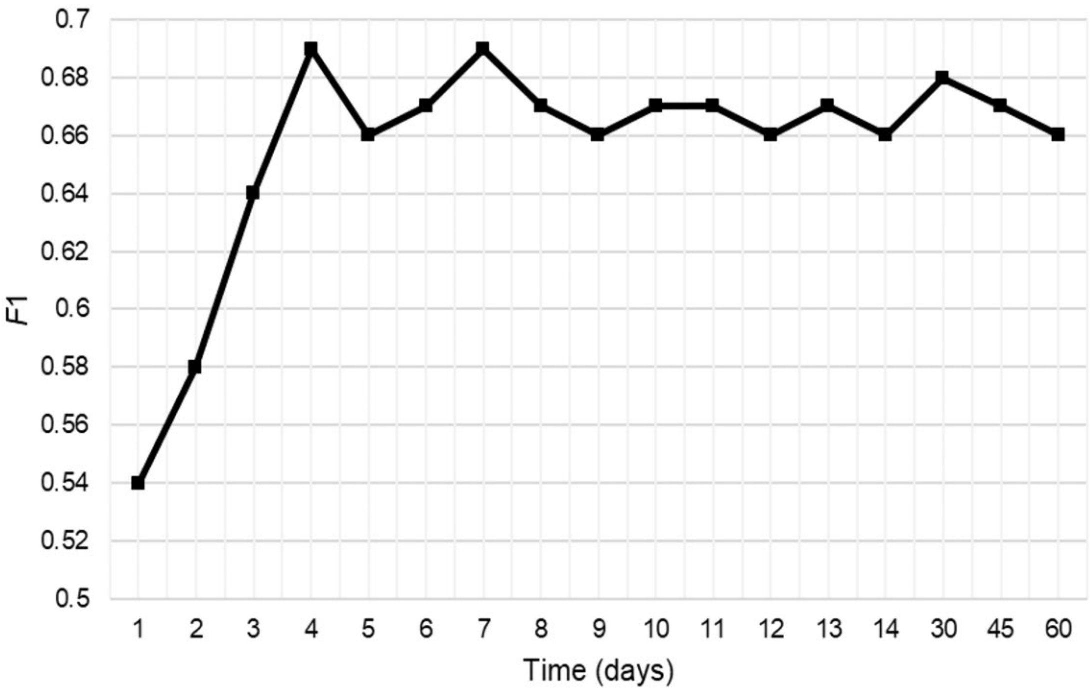

Figure 3. F1 score of ED visit and hospitalization risk prediction for different time windows.

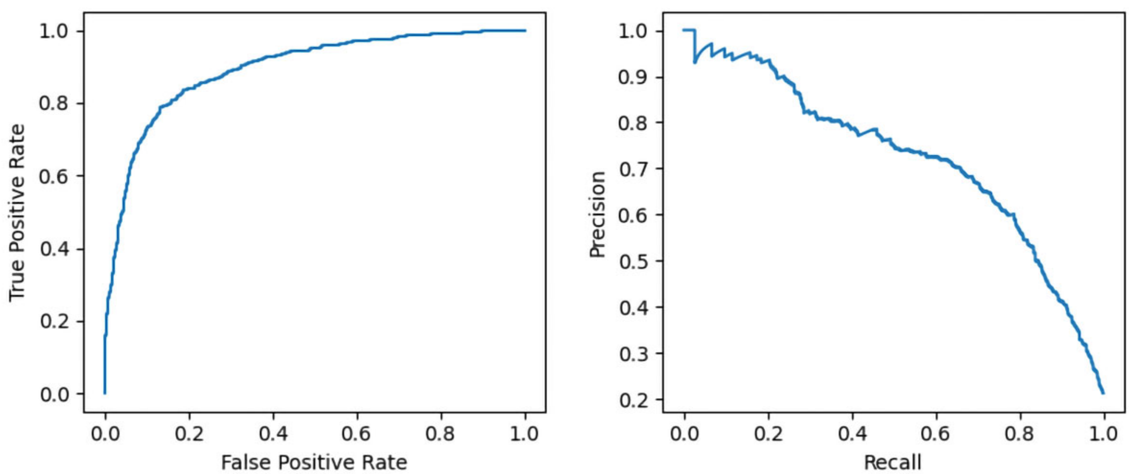

Figure 4. Performance of prediction model to predict emergency department visits and hospitalizations within 4 days. (Left) Receiver-operating characteristic curves. (Right) precision-recall curves.

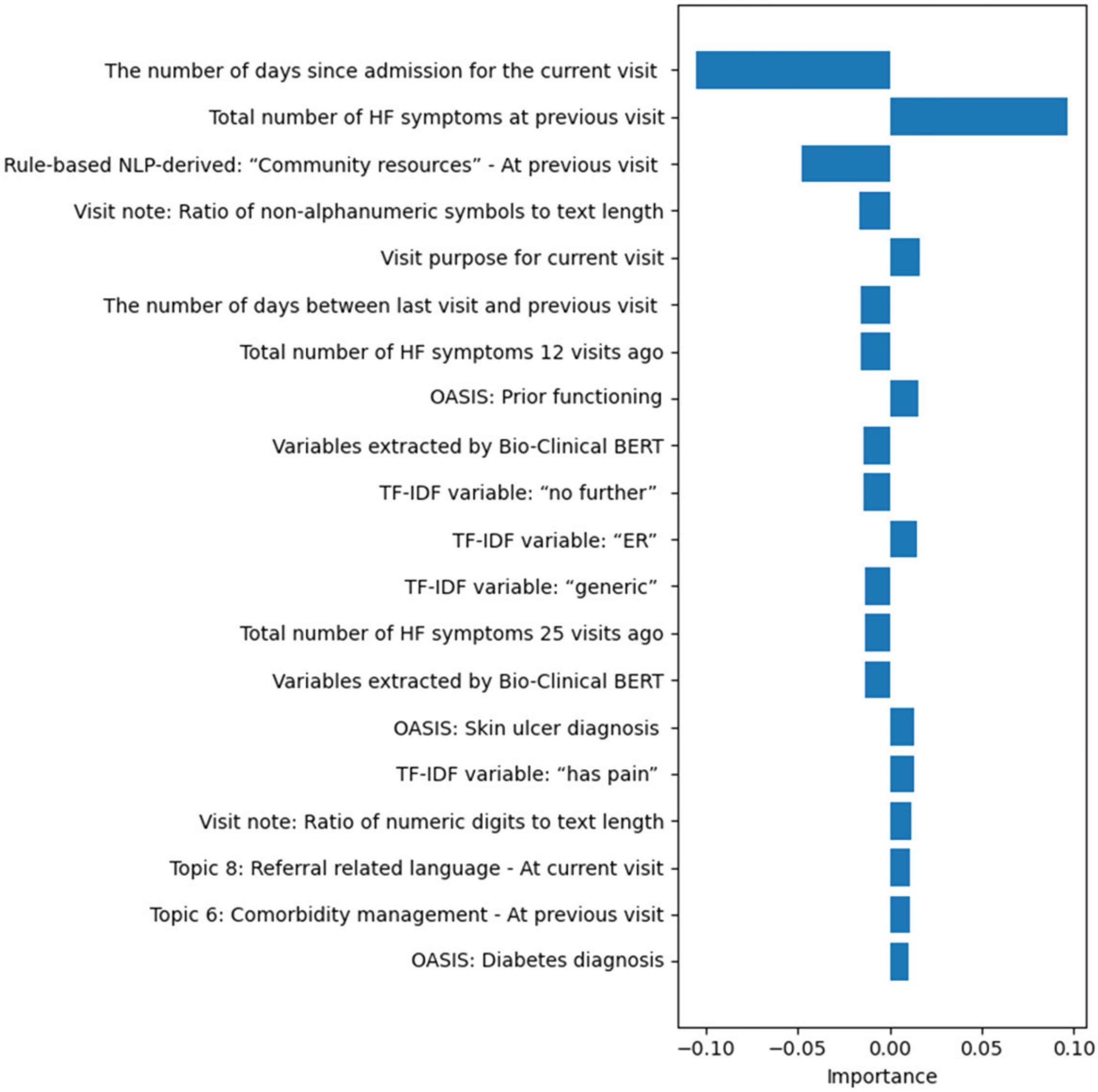

Figure 5. Twenty variables associated with risk for ED visits and hospitalizations using LASSO. The *x* axis represents the log of the L1 penalty parameter (alpha), and the *y* axis represents the coefficient values of the predictors in the model. The L1 penalty parameter shows the strength of the regularization, and as the value of alpha increases, the coefficients shrink toward zero. Each line in the plot represents a different predictor in the model, and the slope of the line represents the change in the magnitude of the coefficient as alpha increases. Predictors with nonzero coefficients at high values of alpha are considered more important, while predictors with zero coefficients are less important. We generated several variables of TF-IDF, describing lexical features of the text, including the "ratio of nonalphanumeric symbols to text length" and "ratio of numeric digits to text length."

research,[16,45] we found that the *F*1 score improved the most when we included rule-based NLP-derived variables (an improvement of 10% compared to using only OASIS-based risk prediction). This result demonstrates that more information is captured in the clinical notes. This finding indicates that HHC risk prediction models can be improved by including a wide array of risk factors, including data extracted from administrative sources and clinical notes.

To minimize the risk of negative outcomes, it is essential for HHC providers to quickly identify deteriorating patients to provide early interventions before they need to be hospitalized or visit the ED.[14] In the hospital setting, early risk identification models accurately identify patients at risk for negative outcomes as early as 24 hours before the event.[46] In HHC, our study achieved relatively high and stable risk prediction performance 4 days before the outcome. This gap in risk prediction windows between HHC and hospitals might be partially explained by the frequency of data collection. In hospitals, patient data is collected very frequently—sometimes every second (eg, continuous patient monitoring).[46,47] However, in the HHC setting, observations and new data points are generated much less frequently, as HHC visits typically occur every 2–4 days on an average.[41] Additionally, the mean length of stay for patients was shorter by one-third (3.2 vs 4.9 days) in HHC compared to hospital settings.[48] Hence, less frequently collected data in HHC allowed us to build risk prediction with a longer time window of 4 days or longer compared to hospital settings.

Previous studies have used various time windows to predict ED visits or hospitalizations in HHC, ranging from 30 days[44,49] to 60 days.[50,51] In this study, we discovered that using a 4-day time window for risk prediction produces adequate risk models. On one hand, identifying risk at this time window could help HHC providers intervene and prevent negative outcomes. On the other hand, a shorter risk time window may help identify patients who need immediate attention due to rapid deterioration. For example, HHC providers could use the identified features to guide their decision-making around when to visit or call the physician, and to conduct more thorough assessments within a 4-day time window after the patient's HHC admission. Additionally, healthcare providers could use the identified features to guide patient education around HF self-management, including symptom recognition, dietary guidelines, medication management, and weight monitoring. This education could be based on randomized controlled trials of home nursing visits for HF to ensure that patients receive the best possible care.[52] More research is needed to determine the best risk time window for HHC settings.

Another significant and innovative contribution of this study is identifying risk factors associated with time series risk for ED visits and hospitalizations in the HHC setting. Applying the LASSO variable selection technique, we found that visit characteristics collected over the previous HHC visits correlate highly with the patient's risk. Specifically, we found that shorter HHC episodes and shorter times between the current and previous HHC visits were highly correlated with the risk of ED visits and hospitalizations. This is not surprising; more frequent clinician visits often correlate with patients' clinical complexity or deterioration in patient health status.[53] These findings are similar to those from the hospital setting, where having a shorter interval between assessments by clinicians was found to be early deterioration signals.[54,55] Previous research also shows that patients with episodes less than 21 days were more likely to be readmitted.[41] This finding highlights the importance of providing timely interventions, including comprehensive assessments, education, and management of HF symptoms within a specific time frame during the HHC episode to prevent future ED visits or hospitalizations. We also found that missed HHC visits are associated with higher risk, consistent with previous studies that show that missing or refusing HHC services increases patient risk.[56] Further risk prediction modeling in HHC should strongly consider using care patterns and visit characteristics.

We also found that multiple rule-based NLP-derived variables correlate highly with patient risk. The first set of NLP variables is a total number of specific HF-related symptoms extracted from clinical notes at previous HHC visits. Our previous work shows that this is an important factor in HHC episode-level risk prediction,[15,16,18] and this study confirms its importance in time series risk modeling. Interestingly, our current results extend the previous research by identifying that the total number of HF symptoms at the previous visit indicated increased risk. In contrast, the same variable indicated lower risk when observed during visits that occurred some time ago. This might further imply that recent symptom documentation indicates risk, whereas earlier documentation might pertain to symptoms that have since been addressed and managed, thus correlating with a lower risk.

In addition, we found that topic models indicating comorbidity management or referral language are associated with higher risk. These findings further advance our HHC episode-level insights showing that the presence of health service use is a significant risk indicator.[57] We also found several Bio-Clinical BERT variables were associated with risk; these variables are not easily explainable to HHC clinicians. Further, several words were identified based on their TF-IDF values, including high-risk words like "ER" (which often indicates previous ED visits) and "has pain" and low-risk words like "no further" (which often indicates that no further HHC is needed) and "generic" as variables associated with risk for ED visit and hospitalization. Creating a clinician-interpretable risk prediction model is essential for clinical adoption and implementation of models because it builds trust in decision-makers, enables error identification and correction in the model, and facilitates integration into clinical workflows.[58] Further research is needed to understand how to best present these risk factors to HHC providers.

In hospitals, trends in vital signs often offer strong signals for risk prediction, and some hospital-based risk models mainly rely on these routinely collected measurements.[46] Surprisingly, vital signs were not selected as the top variables highly correlated with HHC patient risk in this study. This might indicate that vital signs collected every few days in HHC offer less signal for risk prediction than in hospitals, where vital signs are collected frequently (eg, hourly). The patient with HF might have abnormal vital signs at baseline or HHC admission, so it might be more important if the vital signs changed or worsened and how much they changed than whether they were normal or abnormal. Additionally, sudden or gradual changes in vital signs are often one of the last signals to show up before deterioration in patients with HF[59] and therefore, the visit-level time window might be too wide to pick them up. Further research is needed to understand why vital signs in HHC offer little risk prediction value for patients with HF and to further utilize patterns of vital sign changes over time with a shorter time window.

This prediction model suggests that HHC clinicians can identify patients with HF at risk for visiting the ED or being hospitalized 4 days before the event, allowing clinicians to deliver earlier, more targeted interventions. For example, HHC nurses could use the identified risk factors to guide their decision-making about when to call the patient's physician or conduct more thorough clinical assessments. Further risk prediction modeling in HHC should consider using care patterns, visit characteristics, and clinical notes, as these were among the most important features associated with a high risk of ED visits or hospitalizations. Early interventions can be triggered to prevent these negative outcomes through clinical decision support modules integrated into EHR systems. Further studies are needed to explore possible clinical decision support applications in HHC that can improve patient outcomes, optimize resource allocation, and enhance the quality of care delivered for patients with HF.

Study limitations

This study has several important limitations. The study sample was drawn from a single, albeit large, HHC organization in New York City, which may limit the generalizability of the findings to other locations. The study focused on patients with HF, and the findings may not apply to other patient populations. When running risk prediction models with different combinations of data sets, we did not consider the order in which specific data sets were added. Specifically, the improvement of 2 percentage points in the *F*1 from sets of variables 4 (0.67) to 7 (0.69) is limited to justify all the extra work of obtaining and using sets of variables 5, 6, and 7. We recognize that our study's data, collected from 2015 to 2017, may be considered outdated. Although this is a limitation, the data was collected rigorously, and the methods remain pertinent and valuable for the HHC setting. To address this limitation, future research should use more recent data. Further, more advanced machine learning models might achieve better risk prediction results.

Clinical implications and further research

The risk prediction model developed in this study can help provide more targeted treatment for patients with HF in HHC, helping to better manage symptoms and risk factors.[60] Further research is needed to inform the clinical implementation of such models in HHC, tailoring these models to the needs of HHC providers and patients with HF. Some central questions remain about presenting the risk score to HHC providers, explaining certain risk factors (eg, Bio-Clinical BERT variables), applying different advanced machine learning models, and developing sets of interventions to prevent ED visits and hospitalizations.

CONCLUSIONS

In conclusion, this study demonstrated the feasibility of using routinely collected HHC data to develop a time series ED visit and hospitalization risk prediction model for patients with HF. The risk model was built on a combination of structured and unstructured datasets and visit characteristics and rule-based NLP-derived variables were highly correlated with patients' risk. The ability to predict negative outcomes would allow for more targeted treatment and better management of symptoms and risk factors in this patient population. Further research is needed to understand how to apply this risk model in HHC practice.

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AUTHOR CONTRIBUTIONS

SC conducted variable identification, data extraction, statistical analysis, and drafting of the work. AD conducted model development, statistical analysis, and drafting of the work. SC, JS, and MH conducted rule-based NLP variable selection. AD, JS, LE, MH, KHB, MVM, YB, KC, SC, SS, and MT helped to design experiments and revise the drafted manuscript. All authors approved the submitted version. SC and AD are equally contributed, first authors.

ETHICS APPROVAL

This study was approved by the VNS Health Institutional Review Board (IRB No. I20-003).

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY

The data underlying this article cannot be shared publicly due to the privacy protection requirements of patient healthcare data.

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