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Novel Method of Atrial Fibrillation Case Identification and Burden Estimation Using the MIMIC III Electronic Health Dataset

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Abstract

Background: Atrial fibrillation (AF) portends poor prognoses in septic ICU patients. However, AF research is challenging: previous studies demonstrate that International Classification of Disease (ICD) codes may underestimate incidence of AF, but chart review is expensive and often not feasible. We aim to examine the accuracy of nurse charted AF and its temporal precision in critical care patients with sepsis.

Methods: Sepsis patients with continuous ECG waveforms were identified from the Medical Information Mart for Intensive Care (MIMIC III) database, a de-identified, single center intensive care unit EHR source. We selected a random sample of ECGs of 6 to 50 hours duration for manual review. Nurse charted AF occurrence and onset time and ICD-9 coded AF were compared to gold-standard ECG adjudication by a board-certified cardiac electrophysiologist blinded to AF status. Descriptive statistics were calculated for all variables in patients diagnosed with AF by nurse charting, ICD-9 code, or both.

Results: From 142 ECG waveforms (58 AF and 84 sinus rhythm), nurse charting of AF identified AF events with 93% sensitivity (95% CI: 87% - 100%) and 87% specificity (95% CI: 80% - 94%) compared to the gold-standard manual ECG review. Furthermore, nurse-charted AF

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Supplemental Materials:
The MIMIC-III dataset is completely open-source and all waveform files used in this study can be accessed upon request to the database administrators.

Declaration of Conflicting Interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

onset time was within 1-hour of expert reader onset time for 85% of the reviewed tracings. ICD-9 codes were 97% sensitive (95% CI: 88% - 100%) and 82% specific (95% CI: 74% - 90%) for incident AF during admission but unable to identify AF time of onset.

Conclusion: Nurse documentation of AF in EHR is accurate and has high precision for determining AF onset to within 1 hour. Our study suggests that nurse-charted AF in the EHR represents a potentially novel method for AF case identification, timing, and burden estimation.

Keywords

atrial fibrillation; nurse documentation; sepsis; accuracy; case identification

Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia among critically ill patients[1], with an especially high incidence among patients with sepsis[2]. New-onset AF during sepsis is associated with higher in-hospital mortality and important post-discharge outcomes[3–6], including incident heart failure, stroke and death[7]. Furthermore, AF that occurs in the context of a suspected infection may be an indicator of acute cardiac dysfunction consistent with sepsis[8]. It is therefore important to accurately identify cases of AF in health records to facilitate research regarding triggers, treatments and associated outcomes.

Case identification of AF often relies on administrative databases[9,10] that use International Classification of Disease (ICD-9 or 10) systems primarily used for billing purposes. Although administrative data are widely available, previous studies have shown that the accuracy of using the ICD-9 and 10 codes of AF varies widely across populations and suffers from poor sensitivity[9,11–13]. Another key limitation of ICD-codes is the inability to determine AF onset time, an important factor in studies of time-varying AF triggers and treatment outcomes. Current AF guidelines recommend clinician interpretation[14] of a 12-lead ECG[15] for determination of AF onset, but large scale ECG-clinical databases are rare, and large scale manual review of ECG data is costly, time consuming and generally infeasibile[16]. The widespread integration of electronic health records (EHR) into hospital systems provides the opportunity to develop more efficient and accurate tools that facilitate the detection of AF.

Clinical information technologies in intensive care units (ICUs) have increased the speed of nurse charting[17] and enabled the timely documentation of a number of clinical parameters by nursing staff, including cardiac rhythm status[18]. However, AF events adjudicated by routine nurse charting have not previously been validated against gold-standard, manual ECG interpretation. We sought to determine the accuracy of nurse-charted AF compared with gold-standard manual ECG interpretation by an electrophysiologist and ICD-9, and evaluate codes in an electronic health database of critically ill patients with sepsis.

Methods

Study population

The study cohort was derived from the Medical Information Mart for Intensive Care (MIMIC-III) database[18]. MIMIC-III is a large, single center database of critical care admissions to a tertiary care hospital in Boston, MA. The database consists of patients admitted to surgical and medical ICUs from 2001 to 2012, and contains hourly data on vital signs, charted events, laboratory values, clinical notes, as well as waveform data from continuous ECG telemetry recordings. The use of open source, deidentified MIMIC-III data for the current study has been deemed not human subjects research by the Institutional Review Boards at both UMMS and BU with data use approved by MIMIC-III database administration staff.

We included adult patients over 18 years of age with available continuous ECG waveforms who were diagnosed with sepsis according to the Angus definition combining acute infection and organ dysfunction International Classification of Disease (ICD-9) codes or ICD-9 codes specifically used for severe sepsis (995.92) or septic shock (785.52)[19,20]. Patients were excluded from study analysis if they had less than 6 hours of telemetry data (to ensure sufficient data for analysis) or more than 50 hours of telemetry data (to enhance feasibility of manual ECG analysis), or if the rhythm status was not clearly discernable (poor data quality). Patients with ECG waveforms showing atrial flutter, electronic ventricular pacemaker, or significant artifact obscuring ECG interpretation were also excluded. Finally, ECG waveforms were excluded from accuracy analysis if the nurse-charted AF onset time did not occur within 1 hour of available telemetry data. The duration of available telemetry data does not necessarily reflect the length of the patient's ICU stay or the duration of their sepsis. All exclusionary criteria were implemented to facilitate and ensure accuracy of review. If a patient had multiple admissions with sepsis, only the first admission was analyzed.

Clinical variables

We abstracted vital signs, laboratory data, inpatient medication, diagnosis and procedure information from MIMIC III. We used ICD-9 codes to identify comorbid medical conditions, including hypertension (401.X), diabetes (250.X), congestive heart failure (CHF) (428.X), and ischemic stroke (433–434, 436) and procedures including electrical cardioversion (99.61), cardiac catheterization (37.2X), intubation (96.01–96.06), pulmonary artery (PA) catheterization (89.64) and coronary artery bypass graft (CABG) procedures (36.1X) were also determined through their ICD-9 procedure codes. Vital signs were collected from the first 24 hours of ICU stay, including mean arterial pressure, systolic and diastolic blood pressure, and heart rate. Laboratory values included creatinine, troponin, brain natriuretic peptide (BNP), and hemoglobin on admission. We collected medication dosing information for oral anticoagulants (including vitamin K antagonists and direct oral anticoagulants), digoxin, beta blockers, calcium channel blockers, antiarrhythmics, and vasopressors.

Atrial fibrillation status based on electronic hospital and administrative records

AF status was determined through two methods, based on data from the nursing records in the EHR. Nurse-charted rhythm status is encoded in the MIMIC III dataset and is recorded hourly, consistent with standard nursing practice and EHR documentation. We defined "nurse-charted AF" as any documentation by the nurse of "AF," "atrial fibrillation," "AFib," or "atrial fib." Only the first instance of AF was identified for each patient. ICD codes in MIMIC, as with many EHR datasets, were coded at the time of hospital discharge and thus included all cases present on admission or occurring during hospitalization. As has previously been conducted, the ICD-9 code of 427.31 was used to define AF based on claims data.

Telemetry data analysis and gold-standard AF ascertainment

Approximately thirty percent of all telemetry ECG waveforms were randomly selected for manual screening by 3 trained study personnel (DA, SB, ED). Rhythm status was ascertained by trained study staff at baseline and every 60 minutes thereafter for the entirety of the telemetric ECG recording. If over 30 seconds of uninterrupted AF was detected at any time in this interval scanning, the exact onset and offset times of the AF episode were then ascertained. Similar to identification of nurse charted AF, only the first instance of AF was reviewed. A board-certified cardiac electrophysiologist (DM) who was blinded to AF status was then presented with approximately equal numbers of AF and non-AF ECGs as determined by research staff. An unequal distribution was chosen to maintain integrity of the expert reviewer's blinding to rhythm status throughout all adjudications. The physician then manually adjudicated all potential ECG waveforms to confirm the rhythm status and AF onset times.

Statistical analysis

Descriptive statistics were calculated for all abstracted clinical, physiologic, and laboratory parameters. These data were categorized according AF status. We evaluated differences in characteristics using ANOVA and Chi Square across 4 categories of AF status: 1) patients without AF, 2) those with AF identified by both ICD-9 codes and nurse-charted AF, 3) those with only ICD-9 identified AF, and 4) those with only nurse-identified AF. To directly compare two samples, the Tukey test and Chi-squared were used.

Sensitivity and specificity were calculated for "nurse-charted AF" and ICD coded AF were calculated via comparison with gold standard rhythm assessment by a blinded board-certified cardiac electrophysiologist (gold standard). Exact Clopper-Pearson confidence intervals were calculated based on the binomial distribution. The proportion of "charted AF" onset times that were within 60 minutes of manual adjudication of AF onset was also calculated in order to evaluate the accuracy of timing in nurse charted AF.

Results:

The characteristics of the 2,974 patients with sepsis and available ECG telemetry data included in our analyses are shown in Table 1. The average age of the study population was 65.2 ± 15.4 years, 54.6% were male, and a majority were Caucasian. The cohort had a median length of hospital stay of 12 (IQR: 7 – 20) and more than 40% of patients required intubation and mechanical ventilation. Patients had a high burden of cardiovascular comorbidity, 45% had hypertension, 34% diabetes, and 43% CHF. The clinical profiles of patients with AF compared to those without AF are presented in Table 1.

Patient characteristics differed according to the presence of AF and the manner in which AF was identified. Patients with ICD-9 coded AF as well as nurse charting had higher rates of electrical cardioversion, longer length of stay, lower rates of discharge home, and higher rates of medication use than patients with only nurse-charted AF. (Table 2).

Among all ECG waveforms reviewed, 142 (58 AF and 84 sinus rhythm) met inclusion and exclusion criteria (see supplemental figure for flow diagram detailing waveform selection). Nurse-charted AF had 93% sensitivity (95% CI: 87% - 100%) and 87% specificity (95% CI: 80% - 94%) for detection of AF (Table 3). Forty-six (85%) of nurse-documented AF episodes had onset times within 60 minutes of manually-adjudicated AF based on primary analysis of continuous ECG data. ICD-9 showed 97% sensitivity (95% CI: 88% - 100%) and 82% specificity (95% CI: 74% - 90%) (Table 4).

Discussion:

Methods of identifying the presence of AF from administrative claims data may be limited by low sensitivity and lack of information regarding timing of AF. We explored the performance of novel methods of AF identification using hourly nurse charting of events in electronic health record data. We evaluated the accuracy of nurse charted AF, which were 93% sensitive and 87% specific, as well as ICD-9 identified AF, which were 97% sensitive and 82% specific. In addition, timing associated with nurse documentation allows for estimation of AF onset, which matched manual review in 85% of cases. Our findings suggest that nurse-charted AF was accurate for identifying AF cases, performing as well as administrative claims date data, but with the additional benefit of reasonable temporal precision unavailable with administrative data. Our study also suggest that nurse chart reporting of AF may be a useful tool in research seeking to evaluate triggers for AF and near-term outcomes associated with new-onset AF during critical illness[3,21].

Although accuracy of AF detected by nurse events and ICD-9 codes was similar, characteristics of patients differed based upon the methods used to identify AF. In addition, patients with AF identified via both nurse charting as well as ICD-9 codes had generally worse health outcomes as compared to patients identified through only nurse charting (Table 2). Because the method of AF detection yielded cohorts of patients with different characteristics and outcomes, understanding the methods of AF identification in epidemiological research is critical. Mechanisms driving differences in outcomes associated with these methods of detection would require further study.

Previous work detailing the duration and frequency of AF episodes required manual ECG waveform interpretation[23,24], a labor intensive process that is not conducive to research involving large electronic datasets. Nurse-charted AF performs adequately for the accurate determination of AF onset timing during a patient’s stay in the ICU, thus circumventing this limitation. Future research is needed to establish if nurse-abstracted offset times can accurately enable estimation of the length of AF episodes. In addition, developments in machine learning algorithms and deep neural networks in recent years also provide an additional avenue for more granular estimation of AF burden. Further investigations comparing these technologies with nurse documentation may provide valuable insight on novel and effective strategies for AF identification in the EHR.

Our study has numerous strengths. To the best of our knowledge, only one large study (n = 1,782) has used hourly ICU nurse charting for AF case identification[5], and no study to date has manually validated its accuracy in a EHR database. Additionally, unlike many other validation studies that use chart review as a comparison group, our study's gold standard is manual ECG adjudication by a board-certified cardiac electrophysiologist, which strengthens validity of our results. We also examined AF onset times, which offers a more complete picture of the accuracy of nurse charting than just AF status alone. The temporal precision of AF episodes is critical for studies aiming to assess acute AF triggers and determine length of the latency period between trigger and AF onset. This timing is also crucial in comparative effectiveness studies for treatment of acute AF, as precise timing of AF episodes is necessary to accurately determine the efficacy and time course of its treatments.

The study also has several limitations. The available ECG waveform data only reflects the patients' ICU stay, and thus any AF that may have occurred outside of the ICU, and subsequently prompting ICD-9 designation, would be unable to be captured. Our study has potentially limited generalizability to other electronic health record databases. The dataset we used originates from a large tertiary care center with significant resources invested into its ICU clinical information systems. However, with rapid advancements in EHRs and better integration into hospital systems, we expect similar quality data to be more widely available across different health systems in the future. In addition, the collected data has undergone extensive cleaning and processing, which enables its usability. Curation of the ECG waveforms to focus on interpretable tracings limits the scope of our conclusion to patients whose ECG waveform is of high quality, and thus may not be fully representative of real-world settings. By restricting our dataset to patients with AF and excluding those with other atrial arrhythmias, we may have over-estimated the accuracy of nurse-charted AF. Lastly, some patients in the database with nurse-charted AF without ICD diagnoses could also potentially be misclassification of similar electrocardiographic waveforms such as atrial flutter or atrial tachycardia because not all waveforms in the database were formally adjudicated.

We have identified and validated a novel and accurate method for AF case identification, timing, and burden estimation from administrative databases. When available, nurse-charted AF may be a useful tool to augment ICD-9 codes for identifying, classifying, and timing AF episodes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1.

Patient Characteristics of ICU Patients with Sepsis

	No AF (n = 1704)	Any AF (n = 1270)	p-value
Demographics			
Age, mean (SD)	60.7 (16.0)	71.4 (12.0)	<0.001
Male sex, (%)	53.1%	56.7%	0.052
Race			<0.001
White	65.6%	73.9%	
Black	11.3%	7.9%	
Latino	3.8%	2.0%	
Asian	2.9%	2.8%	
Other	16.4%	13.5%	
Discharge location			<0.001
Home	32.9%	22.9%	
SNF	17.7%	18.3%	
Transfer	3.5%	3.1%	
Long term,	12.3%	12.0%	
Hospice	1.3%	1.3%	
Expired	16.6%	24.3%	
Other	15.8%	18.3%	
In-hospital factors, diagnoses, and procedures			
Length of stay, days, mean (SD)	15.1 (15.1)	16.2 (14.1)	0.053
Hypertension	43.1%	47.9%	0.010
CHF	29.3%	60.7%	<0.001
Diabetes	31.6%	38.6%	<0.001
Ischemic stroke	4.9%	6.8%	0.032
Electrical cardioversion	0.1%	3.5%	<0.001
CABG	3.8%	10.6%	<0.001
Intubation	39.5%	45.2%	0.002
Echocardiogram	8.7%	16.5%	<0.001
Pulmonary artery catheterization	4.0%	7.2%	<0.001
Cardiac catheterization	11.7%	20.7%	<0.001
Medications			
Warfarin	12.9%	43.7%	<0.001
Other anticoagulants	89.3%	90.3%	0.38
Digoxin	2.2%	24.4%	<0.001
Beta blocker	63.6%	85.7%	<0.001
Calcium channel blocker	15.6%	40.3%	<0.001
Antiarrhythmic	4.0%	43.7%	<0.001

	No AF (n = 1704)	Any AF (n = 1270)	p-value
Vasopressor	49.9%	69.2%	<0.001
Physiologic and laboratory values on admission			
Mean arterial pressure, mmHg, mean (SD)	81.4 (43.6)	79.1 (43.0)	0.33
Systolic blood pressure, mmHg, mean (SD)	124.6 (29.8)	120.1 (27.5)	0.002
Diastolic blood pressure, mmHg, mean (SD)	60.9 (18.5)	57.2 (16.8)	<0.001
Heart rate, bpm, mean (SD)	92.2 (20.4)	89.3 (20.7)	<0.001
Creatinine, ng/dl, mean (SD)	1.8 (1.9)	1.9 (1.7)	0.044
Troponin, ng/ml, mean (SD)	0.4 (1.7)	0.4 (1.6)	0.84
NT-proBNP, pg/ml, mean (SD)	6,588 (9,796)	10715.0 (11302.0)	<0.001
Hemoglobin, g/dl, mean (SD)	11.5 (2.3)	11.3 (2.2)	0.019

Table 2:

Characteristics of MIMIC III Patients by Atrial Fibrillation Status

	Nurse charted AF plus ICD coded AF (n = 835)	**Only Nurse charted AF (n = 227)**
Age, mean (SD)	72.6 (11.3)	69.1 (13.0)
Male sex, n (%)	55.8%	58.1%
Race		
White	73.8%	73.1%
Black	7.9%	7.9%
Latino	1.8%	3.1%
Asian	3.0%	3.1%
Other	13.5%	12.8%
Discharge location		
Home	21.6%	34.4%
SNF	20.6%	17.2%
Transfer	2.8%	2.2%
Long term facility	12.7%	7.0%
Hospice	1.3%	1.3%
Expired	22.5%	20.7%
Other	18.6%	17.2%
Length of stay in days, mean (SD)	16.1 (13.4)	13.0 (12.0)
Hypertension	51.0%	46.3%
CHF	63.4%	59.0%
Diabetes	38.3%	45.8%
Ischemic stroke	6.3%	7.5%
Electrical cardioversion	4.9%	0.4%
CABG	11.5%	7.5%
Intubation	42.3%	43.3%
Echocardiogram	16.6%	15.9%
Pulmonary artery catheterization	7.3%	6.2%
Cardiac catheterization	20.1%	22.0%
Warfarin	49.9%	42.7%
Digoxin	30.4%	14.1%
Beta blocker	88.6%	84.6%
Calcium channel blocker	47.8%	22.5%
Antiarrhythmic	49.5%	32.2%
Other anticoagulants	92.6%	86.3%
Vasopressors	71.6%	56.4%
Heart rate, bpm, mean (SD)	91.0 (20.8)	82.0 (17.7)
Mean arterial pressure, mmHg, mean (SD)	80.2 (47.5)	80.9 (30.7)

	Nurse charted AF plus ICD coded AF (n = 835)	**Only Nurse charted AF (n = 227)**
Systolic blood pressure, mmHg, mean (SD)	118.7 (25.6)	127.1 (29.3)
Diastolic blood pressure, mmHg, mean (SD)	57.4 (16.2)	57.6 (16.3)
Creatinine, ng/dl, mean (SD)	1.9 (1.7)	2.0 (1.7)
Troponin, ng/ml, mean (SD)	0.4 (1.8)	0.4 (1.1)
Hemoglobin, g/dl, mean (SD)	11.3 (2.3)	11.4 (2.1)
NT-proBNP, pg/ml, mean (SD)	11153.2 (11270.1)	9351.7 (11592.8)

Table 3.

Accuracy of Nurse Documented AF Compared to Manual Adjudication

		Manual Adjudication		
		AF	**No AF**	**Total**
Nurse documentation	AF	54	11	65
	No AF	4	73	77
	Total	58	84	142

Abbreviations: AF, atrial fibrillation; CI, confidence interval; PPV, Positive predictive value. Sensitivity = 93% (95% CI: 87% – 100%), specificity = 87% (95% CI: 80% – 94%), PPV = 83%.

Table 4.

Accuracy of ICD-9 AF Compared to Manual Adjudication

		Manual Adjudication		
		AF	**No AF**	**Total**
ICD-9 defined	AF	56	15	71
	No AF	2	69	71
	Total	58	84	142

Abbreviations: AF, atrial fibrillation; CI, confidence interval; PPV, Positive predictive value. Sensitivity = 97% (95% CI: 88% – 100%), specificity = 82% (95% CI: 74% – 90%), PPV = 79%.