Exploring the Complex Interactions of Baseline Patient Factors to Improve Nursing Triage of Acute Coronary Syndrome

BY

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Abstract

Emergency department nurses need to identify patients with potential acute coronary syndrome rapidly because treatment delay could impact patient outcomes. Aims of this secondary analysis were to identify key patient factors that could be available at initial emergency department nurse triage that predict acute coronary syndrome. Consecutive patients with chest pain who called 9-1-1, received a 12-lead electrocardiogram in the prehospital setting and were transported via emergency medical service were included in the study. A total of 750 patients were recruited. The sample had an average age of 59 years old, was 57% male and 40% black. One hundred and fifteen patients were diagnosed with acute coronary syndrome. Older age, non-Caucasian race, and faster respiratory rate were independent predictors of acute coronary syndrome. There was an interaction between heart rate by type II diabetes receiving insulin in the context of acute coronary syndrome. Type II diabetics requiring insulin for better glycemic control manifested a faster heart rate. By identifying patient factors at emergency department nurse triage that could be predictive of acute coronary syndrome, accuracy rates of triage may improve, thus impacting patient outcomes.

KEYWORDS: chest pain, emergency department, emergency nursing, triage, acute coronary syndrome

1. Introduction

Nurses triage over 145 million patients at United States emergency departments (ED) each year (Center for Disease Control and Prevention, 2019). When a patient arrives at the ED, a nurse is often the first provider to assess the patient and identify clinical conditions that may need emergent attention. The nurse must prioritize patients who may have significant risk of morbidity and mortality. This triage decision can often determine if the patient is placed in the waiting room or brought back to an ED room for immediate and further evaluation.

Most EDs in the United States use the Emergency Severity Index (ESI) score to assist in triage (McHugh et al., 2012). The ESI score is an ordinal five level triage scale that helps nurses to separate patients into high acuity (levels 1 and 2), middle acuity (level 3) and low acuity (levels 4 and 5) categories. Although it is widely used, the ESI score has been shown to have limitations. The ESI tool has large inter-rater variability (i.e., scoring is very subjective; Gilboy et al., 2012). ESI scoring is influenced by nurse gender (Vigil et al., 2017). Assigned ESI scores correlate poorly with patient-centered outcomes (Frisch et al., 2019) and fail to properly differentiate patients' acuity (i.e., poor specificity; Dugas et al., 2016). The ESI scores lack the ability to differentiate middle acuity patients with more than 50% of patients being classified as ESI score 3 (Dugas et al., 2016; Levin et al., 2018). As such, the ESI tool does not account for patient-specific factors present at the time of triage that can accurately predict clinical conditions requiring life-saving interventions.

Acute coronary syndrome (ACS) is an umbrella term that includes myocardial infarction, myocardial injury/ischemia and unstable angina (Thygesen et al., 2018). ACS is a common condition with complex symptomology, time-sensitive treatment windows, and variable outcomes. Chest pain is a sign of potential ACS. Although chest pain is the second leading reason to seek emergency care, only 15% to 30% of the seven million annual chest pain visits in the United States are due to ACS (Hollander & Chase, 2018). This vulnerable population of undifferentiated patients with chest pain are difficult to assess because of numerous pathologies that can mimic ACS (Amsterdam et al., 2014; Canto et al., 2012). Further, it is well known that vulnerable populations, especially women (DeVon et al., 2008), racial minorities (DeVon, Burke, et al., 2014; McSweeney et al., 2010), older patients and individuals with diabetes mellites (DeVon, Penckofer, & Larimer, 2008), may not present with chest pain and often experience less frequent symptoms and may have treatment delays, misdiagnoses, and higher in-hospital mortality rates (Canto et al., 2012; Schrader & Lewis, 2013). This complex presentation of possible ACS that can be difficult to assess should be explored by checking all interaction terms of patient factors (Jaccard, 2001). Rapid identification at triage of patients with potential ACS will prevent delays in treatment.

Nurses often do not recognize or prioritize ACS. Of the roughly 800,000 annual ACS cases, nurses do not identify approximately 45% of them during ED triage (Canto et al., 2012; Hitchcock et al., 2014; McSweeney et al., 2010; Sanders & DeVon, 2016; Weeks et al., 2017). Furthermore, we found that only 38% of ED patients with chest pain who had a final diagnosis of ACS during hospitalization were assigned high-acuity ESI scores at initial nurse triage (Frisch et al., 2019). Nurses rely on personal perceptions and experience to inform cardiac triage decisions (Arslanian-Engoren, 2009). Unfortunately, ED nurses have shown cultural biases and hold stereotypes that interfere with clinical decisions at triage; given the same age and sex of a patient, nurses are less likely to consider ACS in women as compared to men (Arslanian-Engoren, 2000, 2005, 2009). These concerning discrepancies during triage have given rise to a few studies.

A number of researchers have explored strategies to rapidly identify patients with potential ACS at triage. Arslanian-Engoren et al. (2010) tested the feasibility of a cardiac decision aid to emphasize gender disparities. This intervention was accepted by nurses and a majority stated post-intervention and at 3-month follow up that the intervention had changed their cardiac triage decisions. Similarly, to improve cardiac triage, Arslanian-Engoren and Hagerty (2013) developed and tested an instrument to understand nurses' cardiac triage decisions. They used factor analysis to determine which factors out of a 30-item instrument had good internal consistency. Patient presentation, unbiased nurse reasoning and nurse action were discovered as contributions to the nurses' cardiac triage decision making process (Arslanian-Engoren & Hagerty, 2013). This tool could be utilized in combination with an objective cardiac triage tool to provide the highest quality of care to patients with a suspected cardiac event.

Many researchers have examined different techniques to improve ED cardiac triage. Zègre-Hemsey and colleagues found that symptoms of sweating and shoulder pain when combined with potential signs of ischemic heart disease on the electrocardiogram (ECG) may improve recognition of ACS at the ED. Investigators showed that using the Front Door Score was a better tool compared to the standard triage tool to improve accuracy of chest pain triage (Ho & Suen, 2013). Sittichanbuncha et al. (2015) developed an online tool that nurses could use to predict ACS given the information available at ED nurse triage. Additionally, Lopez et al. (2011) successfully validated a five-step triage flowchart for patients with suspected ACS at triage. All of these researchers sought to improve ED nurse triage of patients with potential ACS because current universal triage tools demonstrate poor specificity to this vulnerable population of patients (Atzema et al., 2009; DeLaney et al., 2017; Frisch et al., 2019; Leite et al., 2015). The researchers in the above studies did not mention exploring two-way interactions as part of their methodology. This gap indicates an opportunity to identify patient factors in the first five minutes of an ED visit that are most predictive of ACS. The purpose of this study was to identify key patient factors that could be available at initial ED nurse triage assessment that can predict ACS.

2.0 Methods

2.1 Study Design

We conducted a secondary analysis of data from the first cohort of the EMPIRE (Electrocardiogram Methods for the Prompt Identification of Coronary Events) study (Al-Zaiti et al., 2015). This study was a large observational study enrolling consecutive patients with chest pain or symptoms suggestive of ACS (e.g., shortness of breath, syncope) who requested an ambulance for emergent care. For all patients enrolled in the parent study, emergency medical services obtained a 12-lead ECG and transported the patient to one of three participating affiliated tertiary care centers with 24-hour on-site cardiac catheterization centers. Our Institutional Review Board granted a waiver of informed consent to enroll consecutive chest pain patients. We extracted clinical data from the electronic health record (EHR) from an *a priori* patient factor list created by the authors. We collected data from the pre-hospital and in-hospital phases of care, and from 30-day follow-up.

2.2 Participant Inclusion and Exclusion

The EMPIRE study included consecutive patients who met the following criteria: 1) 18 years of age or older; 2) presented to ED with a chief compliant of chest pain or other less frequent symptoms suspicious of ACS (e.g., shortness of breath, palpitations); and 3) arrived at the ED by emergency medical service transport with 12-lead ECG already obtained. There were no restrictions to sex or race. We excluded patients with traumatic chest pain.

2.3 Data Collection of Variables

Independent reviewers manually extracted pertinent clinical data from the in-hospital EHR from an author-developed *a priori* list of patient factors that could be available at ED nurse triage. An expert user of the EHR trained each reviewer to use a standardized data collection tool with well-defined variables. We also collected basic demographic and clinical characteristics for each patient.

2.3.1 Defining Patient Factors (Possible Predictive Independent Variables)

Standard patient charting in the EHR is by exception only (i.e., the nurse only documents abnormal findings; if it is not charted, it is presumed to be normal). We recorded the following variables recommended by the American College of Cardiology/ American Heart Association (Amsterdam et al., 2014; Cannon et al., 2013; Levine et al., 2016; Rodriguez & Mahaffey, 2016) for initial assessment requirements and included them in the multivariable regression model: 1) demographic characteristics (e.g., age, sex, race); 2) chief complaint (e.g., chest pain, shortness of breath, palpitations); 3) initial ED vital signs (e.g., heart rate, systolic blood pressure, respiratory rate, pulse oximetry); and 4) stated past medical history and the past medical history as documented in the EHR (e.g., patient known history of hypertension, patient known history of heart failure, etc.).

2.3.2 Defining Patient Outcome Variable (Dependent Variable): Acute Coronary Syndrome

Our primary outcome was the presence of ACS (myocardial infarction or unstable angina) during the index hospitalization, defined as the presence of symptoms of ischemia (e.g., diffuse discomfort in the chest, upper extremity, jaw or epigastric area for > 20 minutes) and at least one of the following criteria: 1) elevation of cardiac troponin ($\geq 99_{th}$ percentile of normal reference); 2) new or presumed new significant ECG changes indicative of ischemic changes (i.e., ST-segment elevation in two contiguous leads, with or without reciprocal ST-segment depression, and/or new left bundle branch block); 3) echocardiographic or nuclear imaging showing evidence of new loss of viable myocardium or new regional wall motion abnormalities, or 4) coronary angiographic images with greater than 70% stenosis of a major coronary artery with or without treatment (O'Gara et al., 2013; Thygesen et al., 2012). Two independent emergency medicine physician reviewers examined all available medical and diagnostic records to adjudicate the presence of ACS. Disagreement of an outcome of ACS was resolved by a third emergency medicine physician.

2.4 Statistical Analysis

We conducted all statistical analyses using SPSS® version 25 (IBM Corp., Armonk, NY). Prior to any inferential analysis, we performed a detailed descriptive analysis of each variable. We described continuous variables using means with standard deviation or median with interquartile range if not normally distributed. We compared continuous variables between ACS and non-ACS groups using either Student t-tests or Mann-Whitney U-tests if not normally distributed. We summarized categorical variables using percentages and compared groups using Chi-Square test of independence. We used graphical techniques to identify outliers. When data deviated from normality, we made statistical adjustments to patient factor variables such as data transformation and winsorization of outlying values (i.e., score alteration of an outlier to the next highest non-outlying value to lessen the possible impact on descriptive and inferential statistics). We examined the associations of key patient factors for the outcome of ACS with extraneous covariates to determine the need for covariate adjustment. To limit type two error due to misspecification of the scale of continuous type predictor variables and non-additivity, we included predictors of ACS with univariable associations with ACS $p \leq 0.3$ in a multivariable binary logistic regression model. We then used backward elimination approach to remove predictors with $p \geq 0.1$ in multivariable models (Hosmer et al., 2013). We assessed whether the relationship of continuous predictor variables with the logit for the outcome of ACS met the assumption of linearity.

To explore the complexity of patient presentation for possible ACS we included all two-way interactions among patient factor variables (i.e., two independent variables multiplied together) during model development. We kept all interactions with a $p < 0.05$ in the model. For the final identification of predictors, we considered predictor variables in the multivariable binary logistic regression model with $p < 0.05$. We compared competing models based on Pseudo R-squared values (Hosmer et al., 2013). We assumed model goodness of fit using the Hosmer-Lemeshow test. We reported predictor variable relationships with ACS as unadjusted and adjusted odd ratios and 95 percent confidence intervals. The area under the receiver operating characteristic curve described the discrimination power of the final model.

3. Results

Our total sample included 750 patients (mean [standard deviation] age on average 59 [17] years, 57% male, and 60% Caucasian). Overall, we observed one hundred and fifteen (15.4%) participants who had the outcome of ACS. Table 1 reports the descriptive and comparative statistics for the demographic and clinical characteristics between those with or without ACS. Race categories included Caucasian, Black and other. Race analysis compared Caucasian (reference group) and non-Caucasian (i.e., Black and other). For those who developed ACS, the mean age was greater than the non-ACS group ($p = 0.03$). Within the ACS group, 80% were Caucasian and 62% were male. Those who experienced ACS were more likely to be older, non-Caucasians, and have a slightly higher first ED respiratory rate.

We had three participants with a large amount of missing data from the initial ED nurse triage encounter, which would preclude the use of imputation, so they were omitted from subsequent analysis (n = 747). The following patient factors had a $p \leq 0.3$ in univariate analysis and were included as candidate predictor variables in multivariable regression (see Table 2): 1) age, 2) sex, 3) race, 4) chief complaint of angina-like chest pain, 5) chief complaint of syncope, 6) past medical history of type II diabetes mellitus, 7) past medical history of diabetes receiving insulin for glycemic control, 8) past medical history of coronary revascularization, 9) past medical history of myocardial infarction, 10) first ED heart rate, 11) first ED systolic blood pressure, and 12) first ED respiratory rate. The first ED heart rate variable was winsorized, transformed using the log-based function and then was centered to minimize the interaction with the type II diabetes receiving insulin for glycemic control variable. Age, first ED systolic blood pressure, first ED respiratory rate and first ED oxygen saturation were also winsorized. All two-way patient factor interactions (i.e., two independent variables multiplied together) were explored.

3.1 Multivariable Analysis

All multivariate patient factors had a variance inflation factor less than 2.0, indicating a lack of multicollinearity among the candidate predictors. Over 200 possible independent variable interactions (patient factor variables multiplied together) were evaluated yielding six interactions that were statistically significant (see Table 2). Multivariable binary logistic regression models with and without interactions were evaluated. After adding the six interactions that were statistically significant to the model, the pseudo R-Squared increased from 0.157 to 0.185. Upon further model evaluation, we added each statistically significant interaction term (see Table 2) one by one and simultaneously to determine statistical significance within the multivariable model. Only one interaction, first ED heart rate by type II diabetes receiving insulin for glycemic control, remained significant ($p < 0.05$) in the final model including all statistically significant independent variables (see Figure 1). For the outcome of ACS, there was a different relationship between first ED heart rate for those patients who were type II diabetics receiving insulin for glycemic control compared to patients who did not take insulin as part of their regimen to control their type II diabetes. For patients who were type II diabetics receiving insulin for better glycemic control, as heart rate increased, there was an increased predictive probability of ACS.

When compared to the first model without interactions, the addition of one statistically significant interaction (i.e., first ED heart rate by insulin status in type II diabetics) increased the pseudo R-squared from 0.157 to 0.172. The final parsimonious model with all univariately significant variables plus one statistically significant interaction had a Hosmer and Lemeshow test equal to 0.664. The area under the receiver operating characteristic curve was 0.745 (95% confidence interval, [0.695 to 0.790]). In summary, age, race, and first ED respiratory rate with the interaction of first ED heart rate by type II diabetes receiving insulin for glycemic control remaining significant was our final parsimonious model (see Table 3).

4. Discussion

In this study, we sought to identify key patient factors that could be available at initial ED nurse triage using binary logistic regression to predict ACS. The final parsimonious model demonstrated that the following baseline predictors have good discriminate value (area under the receiver operating characteristic curve = 0.75) for ACS detection during initial nursing triage: older age, non-Caucasian race, elevated respiratory rate, and the interaction of first ED heart rate by type II diabetes requiring insulin for glycemic control. By knowing what patient factors are important when a patient walks into the ED seeking emergent care, ED nurses can prioritize and expedite the care of those of utmost need to appropriate ED resources, which can greatly impact outcomes in ACS populations.

It is important to identify patient factors in the first minutes of an ED visit that are most predictive of ACS because timely treatment could affect patient outcomes. Approximately one in five patients with ACS will die very early in the event (Benjamin et al., 2018). Early diagnosis of ACS can reduce mortality by 10%-20% (Benjamin et al., 2018; Wu et al., 2018). Several clinical decision tools (e.g., GRACE, Thrombolysis in Myocardial Infarction [TIMI] and HEART scores) exist to help ED physicians differentiate suspected ACS patients' disposition status (Al-Zaiti et al., 2019; Poldervaart et al., 2017). These tools have a point system to reflect patient likelihood of developing ACS or a major adverse cardiac event, which takes into account patient age, patient presenting symptomology, past medical history, initial ECG findings and initial laboratory values (e.g., troponin or creatine; Antman et al., 2000; Backus et al., 2013; Fox et al., 2006). There are few nursing clinical decision tools to improve cardiac triage. To our knowledge, there are no cardiac specific clinical tools being used in current ED triage practice.

In our study, we have determined similar independent predictors of ACS that could be present at ED nurse triage compared to other studies. Patients with the outcome of ACS were older, which was consistent across multiple studies (Haasenritter et al., 2012). López and colleagues used the cut off age of 40 years old in addition to known past medical history of coronary artery disease (CAD), past medical history of diabetes, and oppressive or retrosternal chest pain as criteria at triage to be admitted to a chest pain unit (López et al., 2011). Another tool called the Front Door Score was developed in China, but also used age as a cut off (i.e., ≥ 65 years old) to help develop a clinically relevant decision aid tool (Ho & Suen, 2013). This tool was modeled after the TIMI Risk score and had the following variables included: previous coronary stenosis with a history of revascularization, at least three risk factors for CAD, use of aspirin in the previous seven days, at least two anginal events in the last 24 hours, and ST-segment depression or elevation $\geq$ 0.5 millimeters. Other patient factors were consistent across other studies that sought to improve triage of patients suspicious of ACS.

Our current research and Tsai et al. (2018) both utilized systematic statistical methods to determine predictive factors that could improve cardiac triage. Their triage model had better performance than the chest pain model (i.e., all patients with chest pain are assumed to have ACS), the Zarich model (Zarich et al., 2004), the flowchart model (López et al., 2011), and the heart broken index model (Hsu et al., 2011). Similar to our research, age was used as a continuous variable in addition to the following variables, in order of importance: chest pain, age, male, proximal radiation pain, shock and acute heart failure. We additionally found that race and initial ED respiratory rate were predictors of ACS.

To the best of our knowledge, no previous researchers have explored two-way interactions among independent variables (i.e., patient factors). The interaction of first ED heart rate by type II diabetes receiving insulin for glycemic control alludes to the complex presentation that may need to be considered by the nurse when triaging patients suspicious of ACS. If a patient is a type II diabetic who requires taking insulin for better glycemic control, the nurse should consider that a slightly higher first ED heart rate may increase suspicion for ACS. It is well known that the diabetic population has higher baseline heart rates when compared to non-diabetics because of impaired parasympathetic control (Zola et al., 1986). Additionally, due to the progression of type II diabetes mellitus, most patients will eventually need a basal insulin regimen to maintain adequate glycemic control (Davies et al., 2018). In our research, we suspect that type II diabetics requiring insulin for glycemic control are potentially at higher risk for ACS because of their progressive disease process (Haffner et al., 1998; Alexander & Gobin, 2010). Taking insulin may be a surrogate for the severity of their diabetic disease process. Furthermore, CAD is more common in diabetics than in non-diabetics. In our study, 50% of patients with CAD were also type II diabetics receiving insulin for glycemic control. The use of beta blocker medication is common in this population but was not available for analysis. The use of beta blocker medication could be contributing to this two-way interaction. Future studies should explore the three-way interaction between past medical history of CAD, type II diabetics receiving insulin for glycemic control and the use of beta blocker medication.

Cardiac triage could benefit from future research focusing on developing a universal tool to improve triage accuracy rates based on patient factors that are predictive of ACS and patient symptoms that are suggestive of ACS. This study begins to shed light on patient factor interactions that may need to be considered at triage to properly identify patients suspicious of ACS. Triage nurses in the ED need to be aware of the complexity of ACS clinical presentation, which will allow for early recognition to potentially improve patient outcomes.

Clinical Implications

Our study’s final parsimonious model had a gain of 30% accuracy for predicting ACS when compared to current triage accuracy rates of ACS (Sanders & DeVon, 2016).

Nurses should be aware of all baseline patient factors that are independently predictive of ACS. Being older and of non-Caucasian race are warning signs to be aware of in all patients for whom ACS is suspected. Additionally, type II diabetics who may or may not be on insulin for glycemic control should be triaged carefully. Nurses also should to be very sensitive to presenting ED respiratory rate. Being slightly tachypneic may be an indication in combination with other patient factors that might suggest ACS. All of these key patient factors should be kept in mind when triaging patients with potential for ACS.

4.1 Limitations

This study has a few limitations. This analysis was limited to patients with chest pain who arrived to the ED via ambulance and who also had an ECG prior to arrival. Patients arriving by other means of transportation may be different than patients arriving via ambulance. These findings may not be generalizable to patients who arrive to the ED via other than by ambulance and who did not receive an ECG prior to arrival. This study is limited to one healthcare system and should be expanded to include multiple systems in future studies. Future studies should examine a larger sample of patients. Due to the retrospective extraction of patient factors from the EHR, some patient factors for ACS could have been missing (e.g., home medications). A future study that utilized a more open-ended style of obtaining the patient's history and perspective on the ACS event may lead to new insight into less recognized patient risk factors and symptoms.

5. Conclusion

We have identified a subset of baseline patient factors available at initial ED nursing triage that have good discriminate value to identify patients with potential ACS. These key patient factors should be considered in future development of triage tools that could help nurses better differentiate patients with presentation suggestive of ACS, which could expedite care to those who require prompt treatment.

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Table 1

Participant Characteristics with Chest Pain and the Outcome of Acute Coronary Syndrome

Patient Factor Variables	**All Patients (n=747)**	**Acute Coronary Syndrome**	
		ACS (n=115, 15%)	**No ACS (n=632, 85%)**
Demographics			
Age (years, mean (standard deviation))	59 ± 17	64 ± 15	58 ± 17
Sex (Male)	431 (58%)	71 (62%)	360 (57%)
Race			
Caucasian	432 (58%)	91 (79%)	341 (54%)
Black	300 (40%)	23 (20%)	277 (44%)
Other	15 (2%)	1 (1%)	14 (2%)
Acute Coronary Syndrome Risk Factors			
Obesity (Body mass index >30)	285 (38%)	43 (37%)	242 (38%)
Ever Smoked	438 (59%)	66 (58%)	372 (60%)
Hypertension	521 (70%)	77 (67%)	444 (70%)
Diabetes Mellitus	198 (27%)	40 (35%)	158 (25%)
Type II Diabetes receiving insulin for glycemic control	97 (13%)	26 (23%)	71 (11%)
Hyperlipidemia	260 (35%)	43 (37%)	217 (34%)
Coronary Artery Disease	249 (33%)	42 (37%)	207 (33%)
History of Myocardial Infarction	206 (28%)	41 (36%)	165 (26%)
Past Medical History of Angina	142 (18%)	22 (19%)	120 (19%)
Known Heart Failure	133 (18%)	19 (17%)	114 (18%)
Past medical history of coronary revascularization	209 (28%)	45 (39%)	164 (26%)
Chief Complaint			
Angina-Like Chest Pain	665 (89%)	108 (94%)	557 (88%)
Shortness of Breathing	215 (29%)	32 (28%)	183 (29%)
Heart Rhythm Abnormality /palpitations	95 (13%)	15 (13%)	80 (13%)
Atypical Symptoms	100 (13%)	13 (11%)	87 (14%)
Emergency Department First Vital Signs			

Heart Rate (beats per minute)	85 ± 24	80 ± 21	85 ± 25
Systolic Blood Pressure (mmHg)	137 ± 25	141 ± 32	137 ± 24
Respiratory rate (respirations per minute)	18 ± 5	20 ± 4	18 ± 5
Oxygen Saturation (%)	97 ± 4	98 ± 6	97 ± 8

Note. ACS = acute coronary syndrome.

Table 2

Patient Factors Associated with Univariate Model for Acute Coronary Syndrome and Patient Factor Variable Interactions

Main Effects	**Univariate Model**	
	Crude Unadjusted Odd Ratio (95% Confidence Interval for Odds Ratio)	p
Age (years)	1.024 (1.011, 1.037)	< 0.001
Sex (male as reference group)	1.219 (0.811, 1.833)	0.341
Race (Caucasian as reference group)	3.121 (1.9251, 5.060)	< 0.001
Chief complaint of angina-like chest pain	2.141 (0.961, 4.767)	0.062
Chief complaint of syncope	1.875 (0.658, 5.345)	0.240
Past medical history of type II diabetes mellitus	0.625 (0.409, 0.955)	0.030
Past medical history of type II diabetes receiving insulin for glycemic control	0.433 (0.262, 0.716)	0.001
Past history of coronary revascularization	1.834 (1.212, 2.777)	0.004
Past medical history of myocardial infarction	1.568 (1.029, 2.389)	0.036
First ED heart rate (beats per minute)	1.005 (0.996, 1.014)	0.296
First ED systolic blood pressure (mmHg)	0.128 (0.02, 0.818)	0.033
First ED respiratory rate (respirations per minute)	1.083 (1.034, 1.135)	0.001
Interaction Terms		
Past history of type II diabetes mellitus by past history of coronary revascularization	2.123 (1.050- 4.211)	0.031
Past history of type II diabetes mellitus by past history of myocardial infarction	1.960 (0.986- 3.893)	0.05
Past medical history of type II diabetes receiving insulin for glycemic control by past medical history of coronary revascularization	4.705 (1.391- 15.908)	0.013
First ED heart rate by past medical history of type II diabetes receiving insulin for glycemic control	1569.754 (7.231- 340758.1)	0.007

First ED respiratory rate by past medical history of type II diabetes receiving insulin for glycemic control	1.186 (1.008- 1.395)	0.040
Past medical history of coronary revascularization by first ED heart rate	167.623 (2.662- 10554.04)	0.015

Note. ED = Emergency Department

Table 3

Multivariable Model

Patient Factors	**Multivariable Model**	
	Odd Ratio (95% Confidence Interval for Odds Ratio)	*p*
Age (years)	1.016 (1.002, 1.030)	0.028
Sex (male as reference group)	- -	
Race (Caucasian as reference group)	3.638 (2.174, 6.089)	< 0.001
Chief complaint of angina-like chest pain	--	
Chief complaint of syncope	- -	
Past history of diabetes mellitus	- -	
Past medical history of type II diabetes receiving insulin for glycemic control	0.370 (0.210, 0.651)	0.001
Past history of coronary revascularization	- -	
Past history of myocardial infarction	- -	
ED first heart rate	17.152 (0.124, 2373.168)	0.259
ED first systolic blood pressure	- -	
ED first respiratory rate	1.114 (1.057, 1.175)	< 0.001
First ED heart rate by past medical history of type II diabetes receiving insulin for glycemic control	0.001 (0.001- 0.138)	0.007

Note. ED = Emergency Department.

Figure 1

Interaction of Mean Centered First Emergency Department Heart Rate by Type II Diabetics Receiving Insulin for Glycemic Control