Identifying predictive factors of rapid response/code blue: A retrospective study using logistic regression analysis

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Abstract

Background: Rapid response calls and cardiac arrests are often preceded by observable signs of clinical deterioration often hours prior to the adverse event.

Objectives: The purpose of this retrospective study was to identify risk factors that provide predictive value in determining the likelihood of a Rapid Response Call on adult telemetry patients at a single-centre community hospital.

Design: This was a retrospective study based on secondary data analysis. After approval by the Institutional Review Board was obtained (CANV DHIRB-2018-362), we utilized the electronic medical record system to extract de-identified quantitative data from patient medical records.

Setting: This study utilized medical records from patients on the Telemetry unit at a single-centre, 230-bed community hospital.

Participants: The sample consisted of 250 randomized de-identified medical records from both patients who did and did not require a rapid response between January and December, 2018. Patients who were less than 18 years of age and those who were transferred to another facility or to another hospital were excluded from the analyses.

Methods: The variables that were collected included age, gender, race, primary admitting medical diagnosis, hemoglobin, potassium, magnesium, creatinine, lactic acid, and urine output. Additional variables collected in four-hour increments included the vital signs: temperature, heart rate, oxygen saturation, respirations, systolic and diastolic blood pressure, and level of consciousness which was scored using the adult Glasgow Coma Scale. Logistic regression analysis was used to identify which of these variables were statistically significant in predicting patient deterioration.

Results: The following predictors were statistically significant ($a = 0.05$ with 95% Confidence Intervals [CI]): For every one beat increase in heart rate 4 hours prior to a RRT, the odds of a RRT increased by 4.9% (p=0.003) (CI=95% 1.016, 1.084). For every one increase in respirations, the odds of a RRT increased by 42.8% (p=0.004) (95% CI 1.11, 1.82), 8 hours before the RRT, and by 47% (p=0.002) (95% CI 1.15, 1.87), 12 hours before a RRT. African Americans had 20.6 times the odds of experiencing an RRT compared to Caucasians (p<0.001) (95% CI 3.4, 124.6), Hispanics had 56.6 times the odds of experiencing a RRT compared to Caucasians (p<0.001) (95% CI 11.4, 280.4), and other races had 6.3 times the odds of a RRT compared to Caucasians (p=0.044) (95% CI 1.05, 38.5).

Conclusions: Such predictors can be used to identify early signs of deterioration that can alert health care providers to early intervention.

Introduction

Hospitalized patients may deteriorate to the point wherein an unexpected rapid response is called. Rapid response systems have been implemented in acute care settings in order to reduce the risk of cardiopulmonary arrest and improve the outcomes of patients who are progressively deteriorating or exhibiting clinical instability. Clinical deterioration is defined as abnormal vital signs that deviate from a defined standard range. The rapid response team (RRT) is a multidisciplinary team that consists of trained staff (e.g., critical care nurse, respiratory therapist, supervising nurse) that provide a rapid evaluation of unstable patients in order to expedite implementation of physician-ordered interventions with the goal of improving patient outcomes. The purpose of the RRT is to respond to urgent inpatient situations throughout the hospital and facilitate a rapid multidisciplinary assessment and intervention when a rapid response is called. The RRT may be summoned by anyone at any time; reasons may include, but are not limited to: an acute change in vital signs from previously recorded baseline, respiratory distress, threatened airway, acute decrease in oxygen saturation, acute significant bleeding, acute mental status changes or decreased level of consciousness, suspected stroke or seizure, sudden onset or acute increase in pain, a positive screen for sepsis, or signs of organ dysfunction.

Although rapid response teams have been associated with improved patient outcomes[1], they are a *reactive* measure in response to patient deterioration as opposed to a *preventative* measure. According to Duncan, McMullan, and Mills (2012)[2], hospitalized patients usually experience observable signs of decline six to eight hours before going into cardiac arrest. Additionally, Mathukia, Fan, Vadyak, Biege, and Krishnamurthy (2015)[3], found that 84% of patients who underwent cardiopulmonary arrest expressed new complaints or had signs of clinical deterioration within eight hours before the event. A study done by Rosenberg and Watts (2000)[4] found that physiologic abnormalities such as abnormal heart rate and respiratory rate have been shown to be highly associated with the risk of patient deterioration; specifically, an increased respiratory rate was found to be the most frequent predictor in patients prior to arrest, ICU admission, or death[5]. Predictors of patient deterioration included bradycardia, tachypnea, pyrexia, hypotension, low mean arterial pressure, and hyperkalemia[4,5]. Recognition of early deterioration has the potential to enhance patient safety, decrease mortality rates, identify patients that need to be closely assessed by a critical care nurse or medical doctor, and potentially save lives[6].

The purpose of this study is to identify risk factors that provide predictive value in determining the likelihood of a rapid response called on adult patients on the telemetry unit. Such predictors can be used to identify early signs of deterioration in patients that can alert health care providers to early intervention, and findings may be used and referenced in the future in order to develop an early-alert algorithm that could be integrated into the electronic medical record system, better enabling clinicians to identify and provide essential care to patients before they further decompensate to potentially life-threatening status.

Methods

Design

This was a retrospective study based on secondary data analysis. After approval by the Institutional Review Board (IRB) was obtained (CANV DHIRB-2018-362), we utilized the electronic medical record system to extract de-identified quantitative data from medical records pertaining to telemetry patients at a 230-bed community hospital.

Sample

The logistic regression sample size algorithm was used to determine the appropriate number of records to gather based on the characteristics of the continuous and categorical predictor variables. The sample consisted of 250 randomized de-identified medical records from patients who did and did not require a rapid response between January, 2018 and December, 2018. Patients who were less than 18 years of age and those who were transferred to another facility or to another hospital were excluded from the analyses.

Data Collection

The variables that were collected included age, gender, race, primary admitting medical diagnosis, laboratory values to include white blood cells, hemoglobin, potassium, magnesium, creatinine, lactic acid, and urine output measured in milliliters for 12-hour increments. Race was categorized into African American, Asian, Caucasian, Hispanic, and Other races. Primary medical diagnoses that were collected were Myocardial Infarction (MI), Congestive Heart Failure (CHF), Stroke, Acute Respiratory Failure (ARF), Sepsis, and Other diagnoses. Additional variables that were collected included the vital signs: temperature, heart rate, oxygen saturation, respirations, systolic and diastolic blood pressure, and level of consciousness (LOC) which was scored using the adult Glasgow Coma Scale (GCS).

Each of the vital signs and GCS were collected 4, 8, and 12 hours prior to the exact time an RRT was called; these time increments were chosen in order to remain consistent with the existing literature that has been published regarding early warning score systems. Time 4 (T4) was defined as 4 hours before the time of the RRT, Time 8 (T8) was defined as 8 hours before the time of the RRT, and Time 12 (T12) was defined as 12 hours before the time of the RRT. There was limited existing research in the literature on determining the time frame for a control group for a study designed similar to ours, therefore, in order to determine T4, T8, and T12 for the control group (non-RRT) records, a mean time from admission to RRT was calculated and was found to be 2.38 (SD=5.36) days. T4 data for the control group was therefore collected 4 hours before the 2-day mark, T8 data was collected 8 hours before the 2-day mark, and T12 data was collected 12 hours prior to the 2-day mark.

Deterioration criteria were defined as abnormal laboratory values and vital signs according to hospital policy. Abnormal adult laboratory values are defined as a white blood cell count less than 3.8 or greater than 11.0, hemoglobin below 11.5 or above 15.1, potassium below 3.4 or above 4.5, magnesium less than 1.6 or greater than 2.6, creatinine less than 0.72 or greater than 1.25, lactic acid greater than 2.0, and urine output less than 0.5 ml/kg/hr. Abnormal adult vital signs are defined as temperature less than 36 degrees Celsius and above 37.5 degrees Celsius, heart rate less than 50 or greater than 119, oxygen

saturation of less than 93%, respiratory rate less than 13 or greater than 20, systolic blood pressure less than 91 or above 139, and diastolic blood pressure less than 51 or greater than 89.

Data Analysis

Statistical analyses were performed using IBM Statistical Package for the Social Sciences (SPSS) software version 25. Logistic regression was used to identify which variables were statistically significant in predicting acute patient deterioration, requiring a rapid response. Additionally, we computed descriptive statistics to better comprehend these predictors.

Approval was granted by the Institutional Review Board (CANV DHIRB-2018-362).

Results

Data

The original data pull produced a total of 1,239 records; 61 records contained data from patients who experienced a rapid response (RRT), and 1178 did not experience an RRT. We randomly selected 250 records from the 1,239; 32 records contained data from patients who experienced an RRT, and 218 did not experience an RRT. Patient demographics and clinical data are summarized in Table 1.

Table 1. Patient Demographics and Clinical Data

Patient Characteristics	All Patients n=250	RRT n=32	Non-RRT n=218
Mean age in years, (SD)	69.72 (16.19)	70.97 (15.75)	69.54 (16.29)
Gender *n* (%)			
Female	130 (52%)	14 (43.8%)	116 (53.2%)
Male	120 (48%)	18 (56.3%)	102 (46.8%)
Race *n* (%)			
Caucasian	172 (68.8%)	11 (34.4%)	161 (73.9%)
Hispanic	22 (8.8%)	11 (34.4%)	11 (5.0%)
Other	21 (8.4%)	3 (9.4%)	18 (8.3%)
Asian	18 (7.2%)	3 (9.4%)	15 (6.9%)
African American	17 (6.8%)	4 (12.5%)	13 (6%)
Diagnosis *n* (%)			
Other	163 (65.2%)	21(65.6%)	142 (65.1%)
CHF	48 (19.2%)	4 (12.5%%)	44 (20.2%)
Sepsis	31 (12.4%)	6 (18.8%)	25 (11.5%)
MI	8 (3.2%)	1 (3.1%)	7 (3.2%)
Stroke	0 (0)	0 (0)	0 (0)
ARF	0 (0)	0(0)	0 (0)

Significant Findings

Logistic regression analysis showed that African Americans had 20.6 times the odds of experiencing an RRT compared to Caucasians ($p<0.001$) (95% CI 3.4, 124.6), Hispanics had 56.6 times the odds of experiencing an RRT compared to Caucasians ($p<0.001$) (95% CI 11.4, 280.4), and other races had 6.3 times the odds of experiencing an RRT compared to Caucasians ($p=.044$) (95% CI 1.05, 38.5). During T4 (4 hours prior to an RRT), for every one-beat increase in heart rate, the odds of an RRT increased by 4.9% ($p=0.003$) (95% CI 1.016, 1.084). Eight hours before an RRT, T8 findings showed that for every one increase in respirations, the odds of an RRT increased by 42.8% ($p=0.004$) (95% CI 1.11, 1.82); similarly, at T12 (12 hours before an RRT), the odds of an RRT increased by 47% ($p=0.002$) (95% CI 1.15, 1.87).

In addition to the above logistic regression analysis, we also ran a separate logistic regression analysis model that examined the differences between the vital signs temperature, heart rate, respiratory rate, oxygen saturation, systolic blood pressure, and diastolic blood pressure between T4 and T12. In order to

do so, we created a Δ% variable that would capture the change between these variables between T4 and T12, and these values were used in the logistic regression run. Although this logistic regression model did not produce any statistically significant results, we observed a 6.94% increase in heart rate 12 hours prior to an RRT.

Discussion And Limitations

The usage of this logistic regression analysis as a predictive model for patient deterioration appears to be a viable method for identifying patients that are at risk for having an RRT, which is consistent with previous studies. Our analysis indicated that race is a statistically significant predictor of an RRT being called. An increased heart rate was a statistically significant predictor 4 hours prior to an RRT, and an increased respiratory rate was a significant predictor of an RRT both 8 hours and 12 hours before an RRT was called.

The data for this study represents a single-centre encounter solely with patients on a telemetry unit; to facilitate generalizability, additional further research should be conducted across multiple units as well as additional hospitals.

As expected in a data set of this size, some of the clinical data such as vital signs and adult GCS that were manually charted by unit nurses, was missing. Of the 32 RRT records, 15 records were missing a temperature value. Records that had 2 or more missing temperatures were ruled-out; in cases wherein 2 of the 3 temperatures were recorded, we used linear interpellation to derive the (1) missing temperature value based on the 2 present temperatures. Of the 218 non-RRT records, 7 records were missing one temperature value, 3 were missing one oxygen saturation value, and 1 record was missing a respiratory rate. Additionally, 37 records were missing 1 GCS score, 16 were missing 2 GCS scores, and 2 records were missing 3 GCS scores. We used the same linear interpellation process to reasonably estimate the missing values for temperature, oxygen saturation, respiratory rate, and GCS; these variables were relatively stable among the complete records spanning the three timepoints, hence we were more confident in our management of missing data.

The data also revealed considerable missing values in the laboratory records. Our overall data set contained 73 records that were missing magnesium levels, and 232 records were missing lactic acid level, as such, we eliminated two these predictors from our analysis, however, these variables should still be considered in future studies.

Conclusion

This study demonstrated that there are indeed distinguishable risk factors that can identify patients who are at risk for having an RRT called. This predictive model revealed that race, an increased heart rate, and an increased respiratory rate are all statistically significant predictors that contribute to acute patient deterioration up to 12 hours before an RRT or code blue occurs. Recognition of early deterioration has the

potential to enhance patient safety, decrease mortality rates, and identify patients that need to be closely assessed by a critical care nurse or medical doctor. These findings could potentially be referenced and utilized in implementing an early alert algorithm, which may be integrated into EMS systems, or for appropriate clinical intervention by an internist or intensivist.

Declarations

Sources of Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of Interest: None

Acknowledgements: We would like to thank Alan Borchardt for extracting the data.

Ethics approval and consent to participate

Approval by the Institutional Review Board (IRB) was obtained (CANV DHIRB-2018-362), and no consent form was necessary per IRB.

Consent for publication

Not applicable

Availability of data and material

The datasets generated during and/or analysed during the current study are not publicly available due to IRB limitations, but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests

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Authors' contributions

BT: Conceptualization, Formal Analysis, Investigation, Data Curation, Writing- Original draft preparation, Visualization. HK: Methodology, Software, Validation, Resources, Writing-Review and Editing, Supervision, Project administration. FP: Validation, Writing-Review and Editing, Supervision. All authors read and approved the final manuscript

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