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Use of electronic critical care flow sheet data to predict unplanned extubation in ICUs

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ABSTRACT

This study utilized critical care flow sheet data to develop prediction models for unplanned extubation. A total of 5180 patients with 5412 cases of endotracheal tube extubation treated in a tertiary care teaching hospital were evaluated. A total of 60 extubation cases were classified as unplanned, and 5352 as planned. Features documented in the critical care flow sheet for the 24 h prior to extubation were grouped into those with recording frequencies ≤ 3 and > 3. The nearest values to the extubation were identified for all features. For features recorded > 3 times, the maximum, minimum, mean, and recording frequencies were calculated. Univariate analyses were performed to select features for inclusion in multivariate analyses. Three multivariate logistic regression models were compared. Model 1 contained only the nearest value, Model 2 added a recording frequency, and Model 3 replaced the nearest value with the maximum, minimum, or mean that had the highest effect size for each feature recorded > 3 times.

Univariate analyses showed that 18 features differed significantly between the unplanned extubation and control groups. These included vital signs (e.g., pulse and respiration rates, body temperature), ventilator parameters (e.g., minute volume, peak pressure), and consciousness indicators (e.g., Glasgow coma scale score, Richmond agitation sedation scale score, motor power). On all three multivariate analyses, the Glasgow coma scale score, pulse rate, and peak pressure were statistically significant. The frequency of patient positioning (Model 2) and the minimum respiration rate (Model 3) were also significant. Area under the curve, sensitivity, and positive and negative predictive values improved slightly from Model 1 to Model 2 and from Model 2 to Model 3.

This study found that minute volume, peak pressure, and motor power are significant risk factors for unplanned extubation that have not been previously reported. Recording frequency, which reflects how often nursing activities were provided, was also a useful predictor. The indicators identified in this study may help to predict and prevent unplanned extubation in clinical settings.

1. Introduction

Patient safety in intensive care units (ICUs) is a priority concern, and ICU patients are more likely to be exposed to frequent use of invasive procedures, medical devices, and polypharmacy [1]. Many studies have reported a high rate of patient safety incidents in ICUs [2], with airway-related incidents being the most common [3]. Thomas and McGrath [4] analyzed patient safety incidents associated with ICU airway devices and found that unplanned endotracheal tube extubation was the most frequent post-airway device displacement incident.

Unplanned extubation (UE) includes self-extubation and accidental extubation [5]. Self-extubation is caused by the patient's intentional action, whereas accidental extubation is attributed either to a patient's non-intentional action or to inappropriate movement during patient care, including changing the patient's position or moving the patient for X-rays [4,5]. Several studies have associated UE in ICUs with increased hemodynamic complications, hospital-acquired pneumonia, longer mechanical ventilation duration, and longer ICU stay [5–7].

Abbreviations: ADT, admission–discharge–transfer; APACHE, acute physiology and chronic health evaluation; AUC, area under the curve; BP, blood pressure; BT, body temperature; EMR, electronic medical record; EHR, electronic health record; e-tube, endotracheal tube; FiO_2, fraction of inspired oxygen; GCS, glasgow coma scale; ICU, intensive care unit; LOS, length of stay; MBP, mean blood pressure; PEEP, positive end-expiratory pressure; PR, pulse rate; RASS, Richmond Agitation Sedation Scale; ROC, receiver operating characteristic; RR, respiration rate; SBP, systolic blood pressure; UE, unplanned extubation

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Previous studies have examined the known features considered significant risk factors for UE [8–11]. Data for these studies were collected with a pre-defined data collection tool by retrospectively reviewing medical records. With this method, only one type of value is collected, and it is measured at a specific time point, usually the nearest time point before extubation.

The rapid growth of electronic health record (EHR) systems has led to a significant increase in the amount of clinical data available. In turn, this has led to the concept of a 'learning healthcare system,' a data-driven knowledge system based on the vast amounts of clinical data accumulated in EHRs [12]. EHR systems allow the use of accumulated data without the need for a data collection form, and thus allow the extraction of new knowledge about unanticipated significant features.

The ICU is a pertinent setting to apply a learning healthcare system with time series data. ICU patients require more frequent observation and documentation of measures such as consciousness level and urine volume compared to those in general wards. Physiological data, including vital signs and ventilator-related parameters, are continuously monitored and may be recorded hourly. Fialho, Cismondi [13] reported a pulse rate (PR) recording frequency of 27.25 per day. The use of time series data to extract data-driven knowledge is challenging. Chandra, Agarwal [14] extracted the nearest value to ICU discharge for each feature to predict ICU readmission, and Fialho, Cismondi [13] used mean, standard deviation, maximum, and minimum values during the last 24 h of ICU stay for each physiological feature to predict ICU readmission.

To increase the predictive power of a model, it is essential to find the best representative value among the time series data describing patient status. Time series data collected in the 24 h prior to extubation can be used in several ways. Data documented just before the event can be used as a simple model, and advanced models may use minimum, maximum, or mean values as well as recording frequency. Minimum or maximum values may reflect the best or worst status of the patient, whereas mean value reflects the status over 24 h. The number of recordings indirectly reflects how often nursing activities were provided, and can be interpreted as patient need for nursing care.

In this study, critical care flow sheet data were used to develop and test three models using various combinations of data aiming to predict UE.

2. Methods

2.1. Setting

Electronic medical records (EMR) data were obtained from a tertiary care teaching hospital. The hospital had five types of adult ICUs: medical ICU (MICU), surgical ICU (SICU), neurological care unit (NCU), and emergency ICU (EICU). There were a total of 61 ICU beds.

2.2. Study subjects

Adult ICU patients with data on the time of endotracheal tube intubation and the time of endotracheal tube extubation between July 1, 2013, and June 30, 2016, were included in the study. For patients intubated multiple times, each occurrence was considered an independent extubation case. A total of 5180 patients representing 5412 extubation cases were included. The study was approved by the Institutional Review Board of the study hospital.

2.3. Data sources

Data sources included nurses' progress notes, admission–discharge–transfer (ADT) records, critical care flow sheets, and Acute Physiology and Chronic Health Evaluation (APACHE). Unplanned and planned extubation cases were identified by reviewing nurses' progress notes made at the time of endotracheal tube extubation. Nurses documented extubation using coded text of "extubation performed" with the reason for extubation added to the text as a value of the attribute, such as "doctor's order" or "unplanned." If the progress note contained the coded text of "extubation performed" with "unplanned" as the reason, the case was categorized as UE. Other extubation cases served as controls. Extubation cases without the coded text of "extubation performed" were classified as planned based on expert nurses' advice in our study hospital. A total of 60 extubation cases were classified as unplanned, and 5352 as planned.

Patient characteristics such as age, gender, type of ICU, length of stay in ICU and hospital were extracted from ADT records. Patient data entered by nurses (e.g., motor power, urine amount) or collected by devices (e.g., systolic blood pressure [SBP], PR) during the 24 h prior to extubation were extracted from the critical care flow sheet. APACHE II score, representing a patient's status for 24 h prior to extubation, was extracted from the APACHE scoring system. All patient data were de-identified.

2.4. Data preparation

Data extracted from ADT records, APACHE scoring system, and critical care flow sheets were prepared for analysis. Of 487 features documented in the critical care flow sheets, those with coded string, coded ordinal, and real number data types were used for completeness evaluation to minimize the rate of missing data. A total of 23 features with recording rates $> 90\%$ (recorded in 4871 of 5412 cases) were used for analysis. The mean recording frequencies of 23 features over the 24 h prior to extubation were calculated. The features were then grouped into two categories: those recorded > 3 times (thus more than once per shift) and ≤ 3 times. We assumed that nurses would assess and document patient status more than once during their shifts if the patient is unstable.

Three different datasets were prepared (Fig. 1).

For all features, the value recorded closest to the time of extubation was identified and saved in the "nearest" dataset prior to multivariate analysis.

For features recorded > 3 times, the maximum, minimum, and mean values over the 24 h prior to extubation were identified and saved in a "maximum, minimum, and mean" dataset. Also, the recording frequencies of all features were saved in a "recording frequency" dataset prior to multivariate analysis. For features with categorical values, such as patient position, the use of a restraint, and ventilator mode, we noted only the recording frequencies.

2.5. Data analysis

Prior to multivariate analysis, significant features were selected via univariate and correlation analyses.

For each feature in the "nearest" and "recording frequency" datasets, univariate analyses were performed to identify significant differences between the UE and control groups using the *t*-test or chi-squared test. Only features with p-values < 0.05 were used for model development. For features in the "maximum, minimum, and mean" datasets, the values that had the greatest effects of the maximum, minimum, mean, or the nearest values of the features, using a p-value < 0.05 as the cut-off, were selected for model development.

If similar features were associated with Pearson correlation coefficients > 0.5, the feature with the higher effect size (only) was included in the model, to minimize collinearity among features.

We then developed three risk prediction models (Fig. 2) for multivariate analysis. Model 1 used only the nearest values. Model 2 added recording frequencies of features with > 3 records to Model 1. In Model 3, the nearest values of features with > 3 records were substituted with the values exhibiting the highest effect size among the maximum, minimum, mean, or nearest value.

Logistic regression was used for the multivariate analyses. The

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