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Research Article

Prediction of Mortality in Intubated Patients Following Admission to the Intensive Care Unit After an Emergency Room Visit: A Retrospective Cohort Study of Machine Learning Techniques Using Electronic Medical Records

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Abstract: Objectives: The purpose of this study is to develop a mortality prediction model for Intensive Care Unit (ICU) patients following endotracheal intubation using machine learning and identify key predictors of outcomes. Methods: A retrospective cohort study analysis was conducted using electronic medical records of 1,229 adult patients who were admitted to the ICU through the Emergency Department (ED) from January 2018 to December 2022. The collected data included general characteristics, blood test results at the time of ED and ICU admission, vital signs, the Braden scale, the Acute Physiology and Chronic Health Evaluation (APACHE) II score, and the duration of stay in both the ED and ICU. A comparison of five machine learning models (Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, and Xtreme Gradient Boosting (XGBoost)) was performed. Model performance was evaluated using stratified *k*-fold cross-validation, and key metrics were reported as mean ± standard deviation. The best-performing model was further analyzed using SHapley Additive exPlanations (SHAP) to ensure interpretability. Results: The Logistic regression analysis revealed that intubation time, time to transfer to the ICU after intubation, duration of stay in the ICU, total length of hospital stay, lactic acid levels in both the ED and ICU, APACHE II scores, and oxygen saturation significantly influenced mortality. Among the five machine learning models compared, the XGBoost model showed the highest predictive performance based on stratified *k*-fold cross-validation. SHAP analysis of the XGBoost model identified Total Length of Stay (T_LOS), ICU Length of Stay (I_LOS), and the APACHE II score as the most influential variables for predicting outcomes. Conclusions: The XGBoost model demonstrated high accuracy in predicting mortality. The combination of this high-performing model with SHAP analysis provides a powerful tool for clinical decision-making, offering both predictive accuracy and transparent, patient-specific interpretations. Implications for Clinical Practice: In managing patients in the ED and ICU, total length of stay ICU length of stay and APACHE II score can be considered to predict patient prognosis and develop tailored treatment plans.

Keywords: emergency department, intensive care units, intubation, mortality, machine learning

1. Introduction

Patients presenting to the emergency department with conditions such as cardiac arrest, acute pulmonary edema,

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and major trauma are classified as Korea Triage and Acuity Scale (KTAS) levels 1 and 2. These critically ill patients often require advanced airway management in the emergency department [1]. Intubation is indicated in cases of respiratory failure, airway protection, and cardiac arrest [2]. Repeated intubation attempts are associated with a higher incidence of adverse events [3]. In contrast, factors such as age and final diagnosis are significantly associated with mortality rates [4].

The admission rate for pneumonia patients in the emergency room is high [5]. Hospital-acquired pneumonia is a common and serious complication in critically ill patients, necessitating accurate diagnosis and timely management [6]. Additionally, there is an elevated risk of death for patients experiencing acute respiratory failure and septic shock [7]. Furthermore, mechanical ventilation in the emergency room is associated with a higher likelihood of resuscitation procedures and increased mortality rates compared to those in the Intensive Care Unit (ICU). It also contributes to the occurrence of acute respiratory distress syndrome. The high severity of a patient's condition [8], such as respiratory failure, is associated with increased morbidity and mortality [9].

Interventions prior to ICU admission have been demonstrated to reduce the incidence of pneumonia, emergency room mortality, and the number of ICU admissions. While admission factors such as illness severity are associated with prolonged ICU stays [10], rapid transfer to the ICU after acute treatment in the emergency room has been shown to reduce both ICU and in-hospital mortality [11, 12]. An increase in the length of stay in the ICU is associated with higher mortality rates [13].

In this context, the patient population central to our study, those admitted to the ICU via the emergency department following endotracheal intubation, represent a critical, high-risk subgroup. This cohort not only exhibits markedly elevated mortality rates compared to the general ICU population [14], but existing general-purpose prediction models have also been shown to inadequately capture their clinical trajectory [15]. This effectively creates a 'predictive blind spot' for these acutely ill patients.

Focusing on this high-risk cohort is clinically relevant, as early mortality prediction may guide timely interventions and ICU transfer decisions. The study also aims to examine how early ED respiratory interventions are linked to ICU admission and outcomes, thereby enhancing the applicability of predictive models.

There is a notable lack of integrated research that connects the initial point of respiratory intervention in the emergency room to ICU admission and discharge outcomes [16]. In this study, we analyzed emergency department and ICU factors based on electronic medical records and applied machine learning, which are widely used in recent medical data analyses to maximize predictive accuracy and robustness [17, 18]. The study aims to identify factors influencing mortality through multivariate regression analysis and to evaluate whether machine learning–based predictive models, utilizing key clinical variables, can effectively predict patient mortality.

2. Methods

2.1 *Research design*

This study is a retrospective secondary data analysis that identifies predictive factors for mortality among patients admitted to the intensive care unit from adult emergency departments in tertiary hospitals in Seoul. The analysis utilizes statistical analysis using Statistical Package for the Social Sciences (SPSS) Statistics (Version 29.0) and evaluates the model through machine learning techniques.

2.2 *Research subjects*

This study is a retrospective secondary data analysis focusing on adult patients aged 18 and older who visited the emergency room and were admitted to the intensive care unit following intubation from January 1, 2018, to December 31, 2022. The sample size was not determined. Patients who transferred after intubation from other hospitals (32 patients) were excluded from the study.

2.3 *Ethical aspects of the study*

Before conducting this study, we obtained approval from the Institutional Review Board (IRB) of Seoul National

University Hospital. Since this was a retrospective study, we were unable to obtain prior consent. No identifiable information about the subjects was included, and the data was stored in an encrypted format.

2.4 *Data collection procedure*

During the research period, patients who visited the adult emergency room were targeted, with a focus on the standard nursing statement "endotracheal intubation" and those admitted to the ICU. Data were extracted from the subjects after excluding cases of intubation from unstructured free-text records.

General characteristics, including gender and age, were collected alongside initial blood test results (pH, pCO_2, HCO_3^-, pO_2, Oxygen Saturation (O_2SAT), Lactic acid, creatinine, and C-reactive protein) recorded at the time of admission to the emergency room and intensive care unit. The initial vital sign values (Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Heart Rate (HR), Respiratory Rate (RR), Body temperature (BT), SPO_2), Braden score and Acute Physiology and Chronic Health Evaluation (APACHE) II score, included automatically calculated values at the time of ICU admission.

Environmental factors such as the length of stay in the emergency room, the number of days spent in the ICU, the total length of stay (including the emergency room), the time taken for intubation, the time from intubation to ICU admission, and whether a blood transfusion was performed were also extracted. The dependent variable was defined as mortality status at the time of discharge from the ICU.

Our final analytic dataset was defined by a complete set of 33 features. To fully utilize all available clinical data and prioritize model interpretability, we explicitly avoided the implementation of independent feature selection or dimensionality reduction techniques. Consequently, all predictive models were developed and trained using this complete, non-transformed set of 33 input variables.

2.5 *Data analysis method*

This study aimed to develop machine learning models and identify key predictors within a specific cohort of patients who were admitted to the ICU from the emergency department following endotracheal intubation. To this end, both the APACHE II score and its individual components (i.e., vital signs including temperature, systolic and diastolic blood pressure, heart rate, and respiratory rate) were included as separate predictors. This approach allowed us to explore the predictive potential of individual variables that might otherwise be obscured within the composite score, while enabling the machine learning models to capture nonlinear relationships and interactions among variables. Rather than directly comparing with other clinical scoring systems, the model was developed focusing on variables reflecting the clinical characteristics and treatment course specific to this cohort.

Traditional statistical analyses, including descriptive statistics and univariate logistic regression, were conducted using IBM SPSS Statistics (Version 29.0). The implementation and evaluation of all advanced machine learning models were performed in Google Colaboratory using Python (Version 3.11.12). Key Python libraries utilized were scikit-learn (Version 1.6.1) for general machine learning tasks and Xtreme Gradient Boosting (XGBoost) (Version 3.1.1) for tree-based ensemble methods. A total of five machine learning models (Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, and XGBoost) were developed and evaluated. Model performance was assessed using stratified *k*-fold cross-validation, and key performance metrics were reported as mean ± standard deviation to ensure robust and generalizable results. Model explainability was achieved using the SHapley Additive exPlanations (SHAP) framework, specifically the SHAP library (Version 0.50.0), to calculate global feature contributions across all non-linear models.

During data extraction and analysis, duplicate records and incomplete records were excluded, and variables with missing values exceeding 10% were removed. Missing values below 10% were replaced with the mean of each group. For the SpO_2 variable, which had a missing rate of 19.6%, Multiple Imputation by Chained Equations (MICE) was applied due to its clinical importance. The missing data pattern of SPO_2 was identified as non-monotone, and 5 imputed datasets were generated over 10 iterations using the Fully Conditional Specification (FCS) method. Both predictor and outcome variables were included in the imputation model. Analyses were conducted separately on each imputed dataset, and the final estimates and standard errors were pooled using Rubin's rules. The missing data patterns for other variables are presented in Supplementary Appendix 1.

General characteristics were calculated using descriptive statistics, including frequency, percentage, median (minimum, maximum), and were analyzed using univariate analysis methods such as *t*-tests and chi-squared tests. Subsequently, the logistic regression statistical method was employed to calculate *p*-values and odds ratios. To build the predictive model, normalization was applied to adjust the values of continuous variables between 0 and 1. Categorical variables were dummy-coded using one-hot encoding.

The entire dataset (N = 1,229) consisted of 754 survivors and 475 non-survivors, corresponding to a mortality rate of 38.6% (survival-to-death ratio 6 : 4). Although this does not represent a severe class imbalance commonly observed in medical datasets, class weights (class_weight = 'balanced') were applied during model training to mitigate potential bias. Model performance was evaluated using stratified k-fold cross-validation, and the class distribution was preserved across all folds.

The predictive models used were Logistic Regression, Decision Tree, Linear Support Vector Machine, Random Forest, and XGBoost. These models were selected based on interpretability and clinical applicability. Logistic Regression provides intuitive interpretation of results, Linear Support Vector Machine efficiently classifies complex data, Decision Tree offers clear visual representation of the prediction process, and XGBoost delivers high predictive performance along with feature importance. The performance of these predictive models was evaluated using Area Under the Curve (AUC), accuracy, precision, recall, and F1 score.

To move beyond performance metrics and enhance model interpretability, we applied SHAP analysis to the best-performing model, XGBoost. This method quantifies the contribution of each feature to a prediction for an individual patient, providing transparent, patient-specific explanations.

3. Results

3.1 *General characteristics*

The general characteristics of the subjects are presented in Table 1.

Table 1. Demographics and clinical characteristics of all patients (N = 1,229)

Characteristics	Non-survived (N = 475)	Survived (N = 754)	x^2/t	p
	n (%) or median (min-max)	n (%) or median (min-max)		
	Sex			
Male	311 (65.5)	504 (66.8)	0.245	0.621
Female	164 (34.5)	250 (33.2)		
Age	75 (21-101)	72.5 (20-102)	2.721	0.007
	Mental			
Alert	166 (34.9)	266 (35.3)	17.762	< 0.001
Verbal respose	51 (10.7)	84 (11.1)		
Pain response	98 (20.6)	221 (29.3)		
Unresponse	160 (33.7)	183 (24.3)		
Time to intubation (minute)	41 (0-6,722)	41 (0-4,298)	2.519	0.012
Time from intubation to ICU admission (minute)	249 (8-6,762)	239 (1-4,051)	1.583	0.114
ED length of stay (minute)	390 (72-7,445)	326.5 (47-48,901)	0.475	0.635
Total length of stay (day)	9 (1-234)	24 (1-237)	-9.645	< 0.001
ICU length of stay (day)	8 (1-122)	11 (1-112)	-3.574	< 0.001

Table 1. (cont.)

Characteristics	Non-survived (N = 475)	Survived (N = 754)	x^2/t	p
	n (%) or median (min-max)	n (%) or median (min-max)		
	ED lab result			
ED-pH	7.29 (6.8-7.63)	7.33 (6.8-7.72)	-4.201	< 0.001
ED-pCO_2 (mmHg)	38 (7-134)	41.5 (9-129)	-1.118	0.264
ED-HCO_3 (mmol/L)	19 (4-58)	22 (3-53)	-6.279	< 0.001
ED-pO_2 (mmHg)	75 (3-656)	79.5 (2-573)	-0.258	0.796
ED-O_2SAT (%)	93 (2-100)	94.45 (1-100)	-3.451	< 0.001
ED-Lacticacid (mmol/L)	5 (0-20)	3 (0-15)	8.915	< 0.001
ED-Creatinine (mg/dL)	1.46 (0.34-11.24)	1.11 (0.33-17.56)	0.257	0.797
ED-CRP (mg/dL)	3.93 (0.01-36.89)	1.195 (0.01-46.86)	3.558	< 0.001
	ICU lab result			
ICU-pH	7.3 (6.8-7.79)	7.4 (6.89-7.79)	-11.550	< 0.001
ICU-pCO_2 (mmHg)	36 (10-150)	36.5 (11-101)	1.527	0.127
ICU-HCO_3 (mmol/L)	18 (3-55)	22 (4-73)	-9.700	< 0.001
ICU-pO_2 (mmHg)	92 (7-591)	104 (26-523)	-0.505	0.614
ICU-O_2SAT (%)	96 (4-100)	98 (39-100)	-5.875	< 0.001
ICU-Lacticacid (mmol/L)	4 (1-20)	2 (0-20)	12.091	< 0.001
ICU-Creatinine (mg/dL)	1.56 (0.34-10.24)	0.97 (0.2-17.97)	0.304	0.761
ICU-CRP (mg/dL)	8.74 (0.02-46.18)	6.45 (0.01-42.27)	1.966	0.050
Braden scale	11 (6-16)	12 (6-18)	-5.784	< 0.001
APACHE II score	35 (15-53)	28 (0-51)	16.886	< 0.001
Body temperature (℃)	36 (0-40)	36 (32-40)	-4.411	< 0.001
SBP (mmHg)	116 (0-217)	129.5 (46-272)	-8.476	< 0.001
DBP (mmHg)	71 (0-188)	77 (31-191)	-6.252	< 0.001
Pulse rate (bpm)	102 (0-208)	99 (13-174)	2.875	0.004
Respiratory rate (min)	23 (0-97)	21.5 (10-92)	2.544	0.011
SpO_2 (%)	95 (0-100)	98 (47-100)	-6.803	< 0.001
	Transfusion			
Yes	379 (79.8)	281 (37.3)	39.871	< 0.001
No	96 (20.2)	473 (62.7)		

*ED: Emergency Department; ICU: Intensive Care Unit; CRP: C-Reactive Protein; APACHE: Acute Physiology and Chronic Health Evaluation II; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure

This study involved a total of 1,229 patients, with the survival group comprising 754 individuals (61.4%) and the mortality group consisting of 475 individuals (38.6%). Although no significant difference was observed between the two groups, the median age of the mortality group was higher ($p = 0.01$). Significant differences were found in levels of consciousness, total length of stay, and length of stay in the ICU ($p < 0.001$). Emergency room blood test results indicated that the mortality group had lower pH (7.29 vs. 7.33), HCO_3^- (19 vs. 22 mmol/L), and O_2SAT (93% vs. 94.45%), while C-Reactive Protein (CRP) (3.93 vs. 1.195 mg/dL) and lactic acid (5 vs. 3 mmol/L) were higher in the mortality group (all $p < 0.001$). In the ICU test results, significant differences were observed between the two groups in pH, HCO_3, O_2SAT, and lactic acid values, excluding CRP ($p < 0.001$). The APACHE II score was higher in the mortality group at 35 points compared to the survival group ($p < 0.001$). Among the vital signs in the ICU, blood pressure and oxygen saturation showed significant differences, and blood transfusion rates were 79.8% in the mortality group and 37.32% in the survival group, indicating a significant difference between the groups ($p < 0.001$).

3.2 *Mortality prediction through logistic regression analysis*

The Mortality Prediction using Logistic Regression Analysis is presented in Table 2.

The results of the logistic regression analysis revealed significant findings regarding the time until intubation ($p = 0.017$), the duration of transfer to the intensive care unit following intubation ($p = 0.011$), the length of stay in the intensive care unit ($p = 0.001$), and the total length of hospital stay ($p < 0.001$). In the blood test results, the Odds Ratio (OR) for lactic acid levels in the emergency room was 0.940 (95% Confidence Interval (CI): 0.889-0.994, $p = 0.030$). For lactic acid levels in the intensive care unit, the OR was 0.918 (95% CI: 0.868-0.971, $p = 0.003$), indicating predictors of mortality. Additionally, pCO_2 levels in the intensive care unit emerged as a significant variable with $p = 0.041$. The severity indicator, the APACHE II score, had an OR of 0.910 (95% CI: 0.886-0.934, $p < 0.001$). Among the vital signs in the intensive care unit, oxygen saturation had an OR of 1.029 (95% CI: 1.011-1.046, $p = 0.001$), both of which were significant variables.

Table 2. Logistic regression analysis results: Predictors of survival and mortality

Characteristics	*n* (%) or median (min-max)	OR (95% CI)	*p*
	Sex		
Female	414 (33.7)		
Male	815 (66.3)	1.353 (0.985-1.856)	0.062
Age	74 (20-102)	0.999 (0.989-1.009)	0.851
	Mental		0.135
Alert	432 (35.2)		
Verbal respose	135 (11.0)	1.076 (0.659-1.757)	0.770
Pain response	319 (26.0)	1.007 (0.676-1.501)	0.973
Unresponse	343 (27.9)	0.649 (0.420-1.003)	0.052
Time to intubation (minute)	41 (0-6,722)	1.000 (0.999-1.000)	0.017
Time from intubation to ICU admission (minute)	243 (1-6,762)	1.000 (0.999-1.000)	0.011
ED length of stay (minute)	350 (47-48,901)	1.000 (1.000-1.000)	0.510
Total length of stay (day)	17 (1-237)	1.040 (1.027-1.052)	< 0.001
ICU length of stay (day)	10 (1-122)	0.975 (0.960-0.990)	0.001

Table 2. (cont.)

Characteristics	*n* (%) or median (min-max)	OR (95% CI)	*p*
	ED lab results		
ED-pH	7.31 (6.8-7.72)	0.599 (0.116-3.104)	0.542
ED-pCO_2 (mmHg)	41 (7-134)	1.000 (0.985-1.015)	0.992
ED-HCO_3 (mmol/L)	21 (3-58)	0.981 (0.941-1.024)	0.382
ED-pO_2 (mmHg)	78 (2-656)	0.999 (0.998-1.001)	0.490
ED-O_2SAT (%)	94 (1-100)	1.002 (0.993-1.010)	0.708
ED-Lacticacid (mmol/L)	4 (0-20)	0.940 (0.889-0.994)	0.030
ED-Creatinine (mg/dL)	1.24 (0.33-17.56)	0.989 (0.839-1.167)	0.899
ED-CRP (mg/dL)	2.15 (0.01-46.86)	0.990 (0.968-1.013)	0.404
	ICU lab results		
ICU-pH	7.36 (6.80-7.79)	0.348 (0.019-6.368)	0.477
ICU-pCO_2 (mmHg)	36 (10-150)	0.967 (0.936-0.999)	0.041
ICU-HCO_3 (mmol/L)	21 (3-73)	1.047 (0.979-1.119)	0.181
ICU-pO_2 (mmHg)	100 (7-591)	1.000 (0.998-1.002)	0.871
ICU-O_2SAT (%)	97.1 (4-100)	1.003 (0.978-1.029)	0.789
ICU-Lacticacid (mmol/L)	3 (0-20)	0.918 (0.868-0.971)	0.003
ICU-Creatinine (mg/dL)	1.17 (0.2-17.97)	1.120 (0.955-1.314)	0.162
ICU-CRP (mg/dL)	7.17 (0.01-46.18)	0.990 (0.967-1.012)	0.365
Braden scale	12 (6-18)	1.065 (0.982-1.155)	0.127
APACHE II score	30 (0-53)	0.910 (0.886-0.934)	< 0.001
	ICU vital signs		
Body temperature (℃)	36 (0-40)	1.015 (0.900-1.145)	0.804
SBP (mmHg)	125 (0-272)	1.006 (1.000-1.012)	0.069
DBP (mmHg)	76 (0-191)	1.002 (0.992-1.013)	0.710
Pulse rate (bpm)	100 (0-208)	1.006 (1.000-1.012)	0.059
Respiratory rate (min)	22 (0-97)	1.004 (0.987-1.022)	0.644
SpO_2 (%)	97 (0-100)	1.029 (1.011-1.046)	0.001
	Transfusion		
No	377 (30.7)		
Yes	852 (69.3)	0.599 (0.417-0.859)	0.005

*ED: Emergency Department; ICU: Intensive Care Unit; CRP: C-Reactive Protein; APACHE: Acute Physiology and Chronic Health Evaluation II; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure

3.3 *Feature importance and interpretation using SHAP analysis*

In the predictions generated by the XGBoost, the total length of stay, ICU length of stay, and the APACHE II score were identified as the most significant factors. The feature importance ranking of the XGBoost model, as determined by SHAP analysis, is presented in Figure 1.

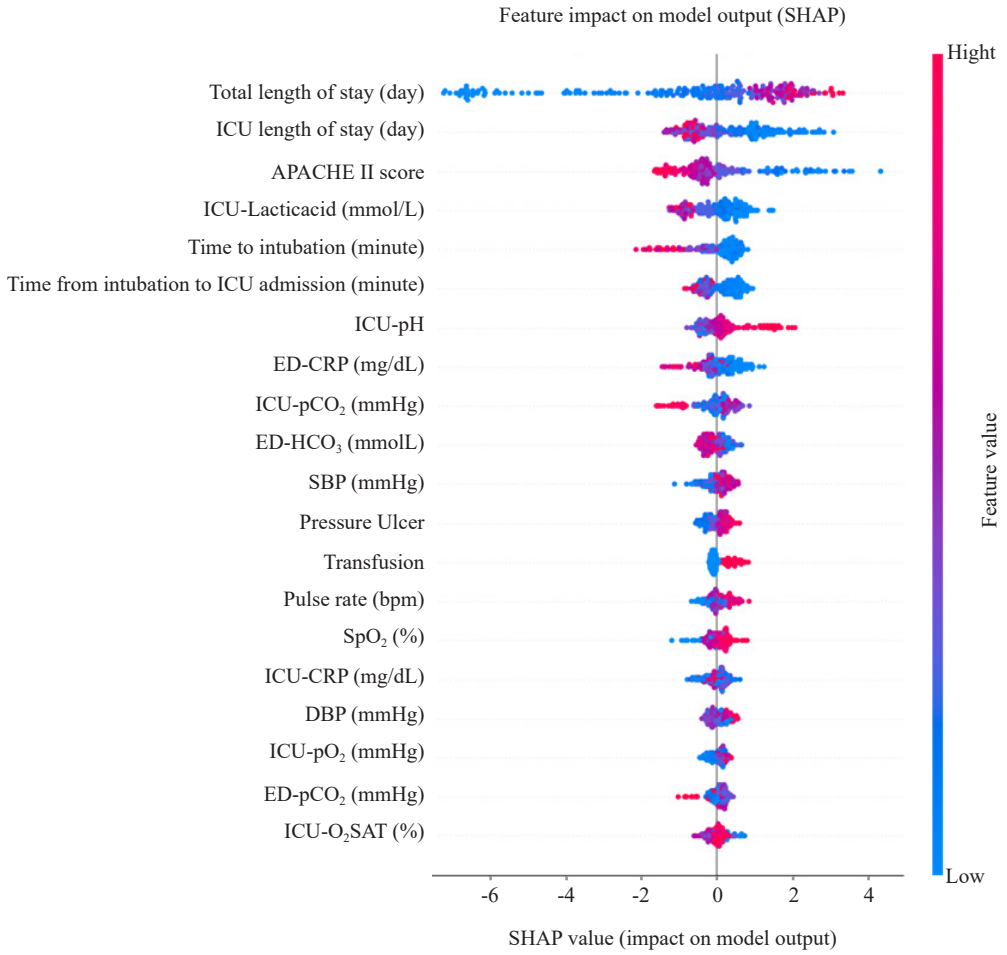

Figure 1. SHAP summary plot of feature importance for the XGBoost model

3.4 *Comparison of machine learning model performance*

For descriptive comparison, the performance metrics from the original 80/20 train-test split are presented in Table 3. In this study, we applied five models: Logistic Regression, Decision Tree, Linear Support Vector Machine, Random Forest, and XGBoost to compare their performance. The XGBoost model demonstrated the highest performance, achieving AUC 0.861 ± 0.017 and F1 score 0.844 ± 0.017 based on stratified 5-fold cross-validation. Consequently, the XGBoost model appears to be the most suitable predictive model for assessing mortality in patients who undergo intubation after visiting the emergency room and are subsequently admitted to the intensive care unit. The Receiver Operating Characteristic (ROC) curves for the models are illustrated in Figure 2.

Table 3. Comparison of machine learning model performance

Model	Accuracy	Precision	Recall	F1 score	AUC	95% CI
Logistic regression	0.699	0.774	0.701	0.736	0.766	0.704-0.826
Decision tree	0.695	0.777	0.687	0.729	0.697	0.642-0.753
Support vector nachine	0.728	0.744	0.830	0.785	0.774	0.711-0.833
Random forest	0.772	0.746	0.939	0.831	0.813	0.753-0.867
XGBoost	0.789	0.803	0.857	0.829	0.841	0.788-0.894

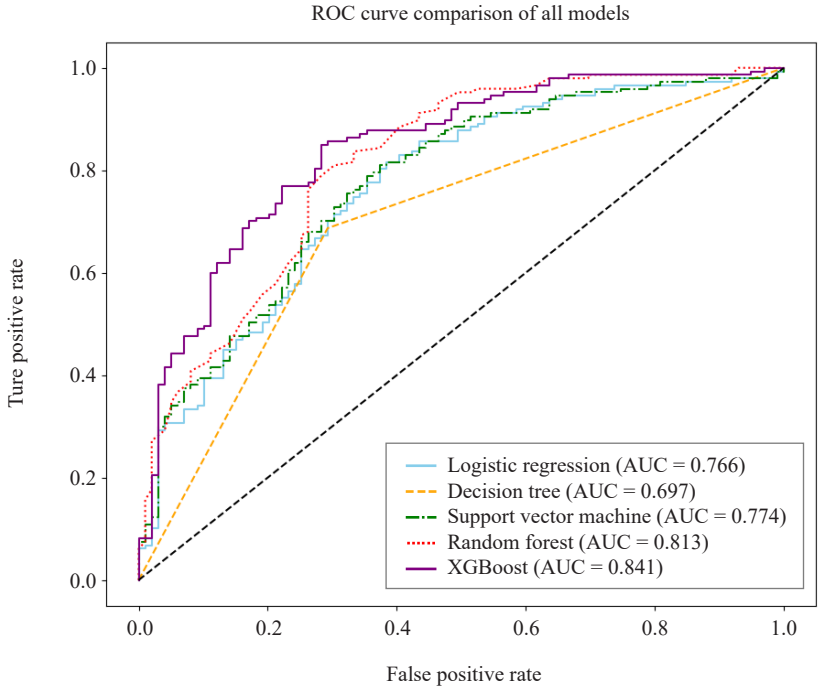

Figure 2. ROC curve of four algorithms

4. Discussion

This study analyzed the factors influencing mortality in the ICU using logistic regression. The evaluation of model performance was based on significant variables and their contributions, as identified through XGBoost, and SHAP analysis.

The severity of the disease and the use of mechanical ventilation are significant factors that influence the duration of stay in the ICU, with an extended ICU stay correlating with increased mortality rates [16]. This observation aligns with the findings of the present study, which identified both the total length of stay and the ICU length of stay as critical variables for mortality prediction. However, total length of stay is inherently determined after the patient's outcome, which restricts its utility for early prediction. Nevertheless, given that this study also sought to explore factors associated with mortality, its observed importance should be regarded as an exploratory finding rather than a causal predictor.

Although Length of Stay (LOS) is not an early intervention variable, its high feature importance serves as a robust proxy for the patient's cumulative clinical complexity. A prolonged LOS, even if largely spent outside the ICU, signals a greater total burden of comorbidities, refractory treatments, and sustained critical illness or secondary complications.

Also, the significance of Total LOS extending beyond the ICU stay implies that the risk of mortality is not eliminated upon discharge from the critical care unit, but remains associated with the entire hospitalization course. This finding strongly highlights the need for enhanced transition-of-care protocols and rigorous, data-driven post-ICU monitoring to mitigate the risk of adverse outcomes and prevent failure-to-rescue events on general wards.

Prompt transfer to the ICU following acute treatment in the emergency department has been shown to reduce both ICU and hospital mortality rates [19]. In this study, the duration of intubation and the time taken to transfer patients to the ICU post-intubation were identified as significant variables. Time from intubation to ICU admission was not statistically significant in the univariate analysis, but it emerged as an important variable in both the multivariate logistic regression and XGBoost, indicating that univariate analysis alone may not fully capture the variable's importance.

Previous research has indicated that longer pre-admission stay times are associated with an increased length of stay in the ICU [12, 16]. Furthermore, the application of mechanical ventilation is a known factor affecting mortality; implementing lung-protective strategies in the emergency department facilitates earlier extubation, thereby reducing both ICU and hospital length of stay and resulting in cost savings [20]. Consequently, timely stabilization and airway management prior to ICU admission, along with appropriate nursing care for patients requiring mechanical ventilation in both the emergency department and the ICU, may be pivotal in minimizing hospital stays and enhancing patient outcomes.

In patients presenting with a high KTAS level upon admission to the emergency room, prompt blood tests are conducted, with additional periodic assessments performed upon admission to the ICU to evaluate the patient's condition and inform subsequent treatment plans. Among the various blood tests, arterial blood gas analysis and lactate levels serve as critical indicators for assessing patient status. Previous studies have demonstrated that the longitudinal monitoring of lactate levels can predict mortality [21]. The importance of lactate levels was consistently identified across our analyses. The traditional logistic regression revealed that lactate levels in both the ER and ICU were significant variables, and this finding was further substantiated by our best-performing model. The SHAP analysis for the XGBoost model confirmed that lactate levels at ICU admission had a substantial contribution to its predictions. By incorporating SHAP analysis, our study adds a layer of interpretability to the high-performing model, allowing clinicians to understand why the model predicts varying levels of risk for individual patients—a capability that cannot be achieved by APACHE II alone. This approach enhances the clinical applicability of the model beyond traditional benchmarks. This finding is consistent with previous studies reporting lactate as a key mortality predictor, regardless of variations in machine learning methodologies [22]. Given that the subjects of this study faced challenges with continuous monitoring over time, it is essential to extract and analyze test results specifically at the points of emergency room and ICU admission, necessitating careful interpretation. Nonetheless, lactate levels are recognized as a vital factor in predicting patient mortality.

Additionally, the Partial pressure of carbon dioxide, Lactate, and Acidity (PLA) score, which considers lactate, carbon dioxide partial pressure, and acidity, has been identified as a factor increasing ICU admission rates and mortality rates [23]. Although the PLA score was not calculated in this study, logistic regression analysis indicated that ICU pCO_2 and lactic acid were significant variables. Furthermore, XGBoost analysis demonstrated a high contribution of lactic acid and pH, indicating that pH, pCO_2, and lactic acid are critical factors for predicting mortality.

A previous investigation comparing the predictive capabilities of the APACHE II score and the patient classification tool (Korean Patient Classification System for Critical Care (KPCSC)) revealed that the mortality prediction power of the APACHE II score surpassed that of the patient classification tool [24]. In the current study, the APACHE II score exhibited a significant contribution in the XGBoost analysis, and significant results were also obtained from the logistic regression analysis, corroborating the findings of prior research [16].

Among the vital signs monitored in the intensive care unit, oxygen saturation yielded significant results. Existing studies indicate that respiratory rate and heart rate are critical factors influencing mortality in patients with Acute Respiratory Distress Syndrome (ARDS) [25]. Furthermore, research involving elderly patients exhibiting respiratory symptoms has demonstrated that body temperature also affects mortality rates [26]. The influence of vital sign variables on mortality depends on the patient's condition, necessitating careful interpretation of results tailored to each individual.

The APACHE II score has been identified as a significant predictor of mortality. Since the components of the APACHE II score are recognized as important variables for mortality, and since these components include vital signs at the time of ICU admission, the score is considered an important indicator for predicting outcomes in critically ill

patients, as well as a crucial factor in assessing patient status and guiding interventions. Given its strong predictive performance, the APACHE II score may support early clinical decision-making and risk stratification. We propose an automated Electronic Health Record (EHR) alert for high-risk patients, mandating intensified monitoring and expedited consultation within the critical first six hours. Concurrently, the score should act as a decision support trigger for clinicians to initiate more aggressive initial management (e.g., proactive fluid and vasopressor use) than standard guidelines for this cohort.

Our findings suggest that clinical interventions aimed at improving vital signs after ICU admission may reduce mortality, highlighting the importance of careful monitoring and timely management of these parameters.

5. Limitations

This study developed and evaluated a model to predict mortality in mechanically ventilated patients admitted to the intensive care unit. However, there are several limitations.

(1) This study was based on data from a tertiary institution with high patient severity, which may limit the generalizability of the findings to community hospitals or settings with less severe patients.

(2) Only key physiological variables were analyzed, and dynamic intervention variables, such as mechanical ventilation settings and medication administration, were not included.

(3) Total length of stay was included in the analysis; however, given its limitations as a variable for early prediction, it should be interpreted as an exploratory finding. Future studies should re-evaluate early prediction models using only variables available at the time of admission. This omission may influence model performance and should be addressed in future studies to improve clinical interpretability.

(4) The APACHE II score was used as a predictor of mortality; however, a comparative analysis with other, more current severity scores, such as Acute Physiology and Chronic Health Evaluation IV (APACHE IV), Sequential Organ Failure Assessment (SOFA), and Simplified Acute Physiology Score II (SAPS II), was not performed. Future studies should include these scores to further validate and enhance the predictive performance of the model.

6. Conclusion

This study employed logistic regression analysis to identify the factors influencing mortality among ICU patients who were intubated following their admission to the emergency room. The analysis indicated that a reduction in the total length of stay in both the ICU and the hospital, the duration required for initial intubation, and prompt transfer to the ICU were significant variables. The APACHE II score also emerged as a significant factor, with certain vital sign parameters included in the APACHE II assessment proving to be influential. Furthermore, Lactic acid measured in both the Emergency Department (ED) and ICU was found to be significant, with ICU measurements having a greater impact on mortality than those obtained in the ED. Although cardiac enzymes were not central predictors in this study, their timing and dynamic changes may influence outcomes and warrant further investigation.

Future studies should assess how serial laboratory measurements contribute to early and accurate mortality prediction. Additionally, the evaluation of the performance of the mortality prediction model confirmed the appropriateness of the XGBoost model for this purpose.

Based on these findings, several implications can be considered. Periodic monitoring of blood tests may provide valuable information for assessing mortality risk. Therefore, it is essential to conduct repeated studies that analyze the results based on the timing of blood tests and continuously verify whether the test values influence mortality outcomes. Developing predictive models facilitates rapid decision-making in clinical practice and supports efficient treatment strategies. Consequently, it is vital to continuously evaluate the performance of these predictive models by incorporating a diverse range of variables.

Clinical trial registration

This study was a retrospective cohort study and was not registered as a clinical trial.

Conflict of interest

The authors declare no competing financial interest.

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Appendix

Variable name	Number of missing values
Total length of stay	3
ICU length of stay	37
ED_pH	24
ED_pCO_2	27
ED_HCO_3	63
ED_O_2SAT	63
ED_Lacticacid	83
ED_Cr	62
ED_CRP	52
ICU_pH	35
ICU_pCO_2	35
ICU_HCO_3	41
ICU_pO_2	34
ICU_O_2SAT	40
ICU_Lacticacid	73
ICU_Cr	41
ICU_CRP	83
APACHE II score	14
Body Temerature	55
DBP	55
Pulse rate	41
Respiratory rate	64
SBP	55
SpO_2	241