Yu Zhang, Hefeng Tang, Liping Ying, Li Zhang, Ling Zhang
Emergency Department of Shaoxing People's Hospital, Shaoxing, China

Cardiac Arrest, Patient Characteristics and Prognosis: a Machine Learning Approach

Background	Cardiac arrest is a severe medical emergency with poor prognosis. This study aimed to analyze the clinical characteristics of cardiac arrest patients and explore the key factors influencing their outcomes. Additionally, we applied machine learning methods to evaluate the performance of different models in predicting return of spontaneous circulation (ROSC), with the goal of optimizing strategies for managing cardiac arrest.
Material and methods	We comprehensively assessed the demographic characteristics, physiological parameters, and laboratory results of 748 cardiac arrest patients, and compared the differences between the ROSC and non-ROSC groups. We applied LASSO regression analysis to identify the key variables predictive of ROSC. Furthermore, we evaluated the performance of various machine learning models, including GBDT and LGBM, in ROSC prediction, including calibration, decision curve analysis, and ROC curves.
Results	Patients in the ROSC group were younger and predominately male. They had more normal blood pressure, temperature, and oxygen saturation, as well as less severe organ dysfunction, LASSO regression analysis identified age, WBC, and lactate as key predictors of ROSC. Among the machine learning models, GBDT and LGBM exhibited the best performance, with superior calibration, decision curve analysis, and ROC curves compared.
Conclusions	This study identified key clinical factors influencing the prognosis of cardiac arrest patients, and it identified machine learning models that were superior for predicting ROSC.
Keywords	Cardiac arrest; spontaneous circulation; machine learning
For citations	Yu Zhang, Hefeng Tang, Liping Ying, Li Zhang, Ling Zhang. Cardiac Arrest, Patient Characteristics and Prognosis: A Machine Learning Approach. Kardiologiia. 2025;65(10):91–100. [Russian: Юй Чжан, Хефэн Тан, Липин Ин, Ли Чжан, Лин Чжан. Остановка сердца, клинические характеристики пациента и прогноз: подход, основанный на машинном обучении. Кардиология. 2025;65(10):91–100].
Corresponding author	Ling Zhang. E-mail: 13867561180@163.com

Introduction

Cardiac arrest is a severe medical emergency. Cardiopulmonary resuscitation (CPR) is the key therapeutic measure for rescuing cardiac arrest patients, with the goal of promptly restoring the patient's independent circulation and respiratory function [1–4]. However, only about 10–20% of cardiac arrest patients achieve return of spontaneous circulation (ROSC) and ultimately survive to discharge. ROSC is the critical objective of emergency treatment, as it is closely associated with the patient's prognosis and quality of life.

In recent years, CPR techniques have continued to advance. The standardized application of measures such as chest compressions, ventilation, and defibrillation have significantly improved ROSC success rates. However, the factors underlying ROSC are highly complex, involving multiple aspects of cardiac and pulmonary function, organ perfusion, and inflammatory responses. Prior studies have largely focused on the analysis of single prognostic factors, making it difficult to comprehensively understand the determinants of ROSC [5–8].

The rapid development of big data and machine learning technologies has led to their increasing application in the medical field. These methods are able to extract key predictive factors from multidimensional data, providing a basis for clinical decision-making [9–12]. Therefore, this study aims to comprehensively analyze the clinical characteristics of cardiac arrest patients from multiple dimensions, and apply least absolute shrinkage and selection operator (LASSO) regression and various machine learning models to identify the key predictive factors influencing ROSC, in order to provide a basis for optimizing treatment strategies.

Compared to previous studies, the innovations of this work are primarily reflected in the following aspects:

1. Utilizing a large retrospective sample to comprehensively evaluate the various clinical factors influencing ROSC;
2. Applying LASSO regression techniques to screen important predictive variables, improving the interpretability of the prediction models;
3. Systematically evaluating the performance of advanced machine learning models such as GBDT and LGBM in ROSC prediction, providing reliable evidence for clinical decision-making. This systematic study is expected to provide new insights and a basis for improving the prognosis of cardiac arrest patients.

Through in-depth analysis of the demographic characteristics, physiological parameters, and laboratory examinations of cardiac arrest patients, we aimed to elucidate the key clinical differences between the ROSC and non-ROSC groups. At the same time, by employing advanced statistical and machine learning techniques, we comprehensively explored the determinants of ROSC, providing a basis for the clinical formulation of more optimized treatment strategies. This research will contribute to improving the success rate of cardiac arrest rescue, reducing the occurrence of adverse outcomes, and enhancing patient prognosis and quality of life.

Material and methods

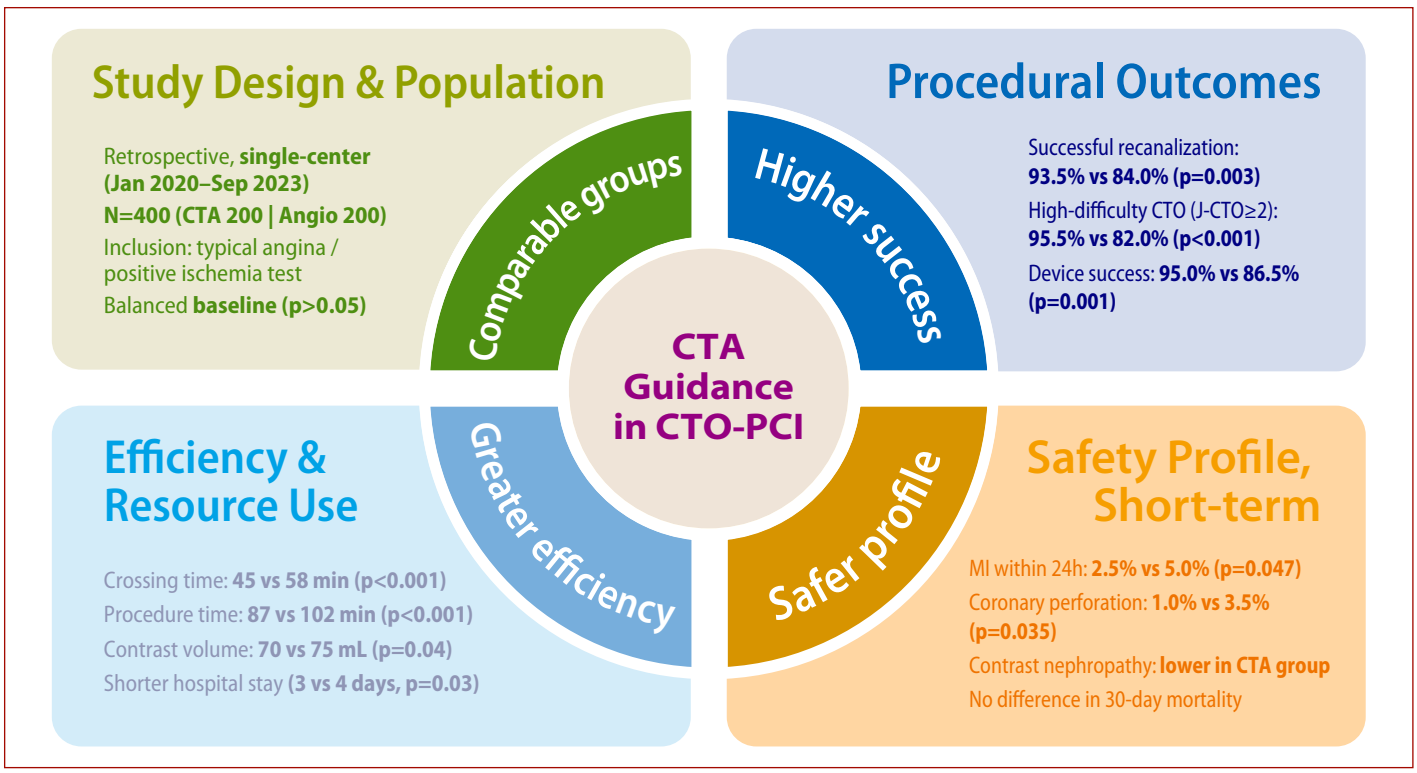
Study design

This study included patients diagnosed with cardiac arrest between January 2022 and June 2024, aged 18–85 years, with complete clinical and laboratory records, and who had received standard cardiopulmonary resuscitation (CPR). Patients were excluded if more than 20% of the key variables required for analysis were missing. The percentage of missing data was calculated relative to the predefined dataset that included demographic characteristics, vital signs, major laboratory indicators (e.g., WBC, lactate, renal and liver function), and outcome variables. For patients with <10% missing values, multiple imputation was applied, while those with >20% missing in these core data elements were excluded. Other exclusion criteria were the presence of severe terminal diseases, expected survival less than 3 months, do-not-resuscitate (DNR) protocols, pregnancy, inability to be followed up, or traumatic cardiac arrest. These criteria helped ensure that the included cohort had relatively complete and comparable records, thereby improving data consistency and reliability for subsequent analysis. Ultimately, 748 cardiac arrest patients were enrolled, including 474 who achieved return of spontaneous circulation (ROSC) and 274 who did not.

Data collection

This was a single-center, retrospective clinical research study. Patient data were collected from institution electronic medical records and registration archives. These data included demographic characteristics (age, gender, body mass index), medical history (cardiovascular diseases, diabetes, hypertension), physiological parameters (systolic blood pressure, heart rate, body temperature, oxygen saturation), laboratory values (white blood cell count, lactate levels, liver and kidney function indicators), cardiac arrest-related clinical characteristics (occurrence location, initial rhythm, CPR duration), and disease severity scores (APSIII, SOFA). The research also focused on patient prognosis-related variables, such as ROSC, hospital stay, discharge status, and detailed recordings of organ function, comorbidities, and neurological function. To ensure data quality, double-entry independent input and cross-verification were used, with random spot checks of 20% of cases. For missing data under 10%, multiple imputation methods were applied. The data collection process strictly adhered to medical research ethical guidelines. Patient privacy was protected by data anonymization, thus providing a solid ethical foundation for the research.

Central illustration. Cardiac arrest, patient characteristics and prognosis: a machine learning approach



ISSN 0022-9040. Кардиология. 2025;65(10). DOI: 10.18087/cardio.2025.10.n2896

Table 1 (Beginning). Clinical characteristics and outcome analysis of the patients

Variable	Total (n=748)	ROSC (n=474)	No-ROSC (n=274)	Statistic	p
Age (years)	65.88±16.44	63.73±16.21	69.59±16.20	t=-4.76	<0.001
WBC ($\times 10^9$/L)	11.32±6.14	9.99±4.96	13.61±7.22	t=-7.36	<0.001
Basophils Abs ($\times 10^9$/L)	0.03±0.02	0.03±0.02	0.03±0.02	t=3.22	0.001
Eosinophils Abs ($\times 10^9$/L)	0.18±0.18	0.21±0.21	0.14±0.10	t=5.89	<0.001
Lymphocytes Abs ($\times 10^9$/L)	1.44±0.59	1.41±0.52	1.50±0.68	t=-1.94	0.053
Monocytes Abs ($\times 10^9$/L)	0.73±0.27	0.76±0.27	0.67±0.25	t=4.25	<0.001
Neutrophils Abs ($\times 10^9$/L)	8.84±4.38	7.95±3.93	10.38±4.69	t=–-7.24	<0.001
Hematocrit (%)	33.45±6.59	33.55±6.24	33.27±7.17	t=0.54	0.586
Hemoglobin (g/dL)	10.83±2.30	10.92±2.21	10.66±2.44	t=1.54	0.124
MCH (pg)	29.71±2.52	29.66±2.39	29.81±2.73	t=-0.80	0.426
MCHC (g/dL)	32.34±1.64	32.47±1.64	32.11±1.61	t=2.92	0.004
MCV (fL)	91.86±6.77	91.31±5.85	92.81±8.03	t=-2.70	0.007
Platelet ($\times 10^9$/L)	203.96±93.10	200.76±83.86	209.48±107.18	t=–1.16	0.248
RBC ($\times 10^{12}$/L)	3.66±0.77	3.69±0.73	3.60±0.82	t=1.55	0.122
RDW (%)	15.28±2.05	15.04±1.96	15.70±2.13	t=-4.28	<0.001
SCr baseline (mg/dL)	1.28±1.23	1.32±1.38	1.20±0.90	t=1.29	0.198
Anion gap (mmol/L)	16.02±4.99	14.93±3.98	17.93±5.91	t=-7.48	<0.001
Bicarbonate (mmol/L)	23.04±4.99	24.45±4.42	20.60±4.99	t=10.60	<0.001
BUN (mg/dL)	32.97±22.70	30.40±20.72	37.43±25.18	t=-4.12	<0.001
Calcium (mg/dL)	8.62±0.95	8.69±0.80	8.51±1.17	t=2.26	0.024
Chloride (mmol/L)	102.90±6.20	102.05±5.74	104.37±6.69	t=-4.81	<0.001
Creatinine (mg/dL)	1.95±1.88	1.93±2.12	2.00±1.39	t=-0.50	0.619
Glucose (mg/dL)	154.03±70.20	141.81±61.73	175.18±78.59	t=-6.03	<0.001
Sodium (mmol/L)	138.94±4.79	138.65±4.57	139.44±5.13	t=-2.18	0.029
Potassium (mmol/L)	4.36±0.73	4.28±0.69	4.50±0.78	t=-3.89	<0.001
CRP (mg/L)	92.98±35.40	91.31±38.16	95.87±29.89	t=-1.81	0.071
ALT (U/L)	213.58±591.15	128.04±399.07	361.57±803.50	t=-4.50	<0.001
ALP (U/L)	113.44±79.69	110.94±80.09	117.78±78.95	t=-1.13	0.258
AST (U/L)	335.95±950.45	170.88±593.68	621.52±1316.05	t=-5.36	<0.001
Amylase (U/L)	115.57±67.45	103.41±48.84	136.61±87.26	t=-5.80	<0.001
Bilirubin Total (mg/dL)	0.90±0.93	0.79±0.64	1.11±1.26	t=-3.93	<0.001
Bilirubin Direct (mg/dL)	1.75±0.98	1.57±0.90	2.06±1.03	t=-6.53	<0.001
Bilirubin Indirect (mg/dL)	0.96±0.41	0.85±0.31	1.16±0.47	t=-9.82	<0.001
CK (U/L)	1353.44±7765.71	1295.07±9568.72	1454.41±2521.91	t=-0.27	0.787
CK-MB (U/L)	30.44±56.01	24.57±50.00	40.60±63.95	t=–3.57	<0.001
LDH (U/L)	679.85±1014.33	461.85±697.17	1056.99±1322.05	t=–6.92	<0.001
Lactate (mmol/L)	3.50±2.94	2.62±1.81	5.02±3.77	t=-9.89	<0.001
APS III (score)	64.05±27.92	54.49±22.11	80.59±29.21	t=-12.82	<0.001
Heart Rate (beats/min)	88.03±14.66	85.78±12.44	91.92±17.21	t=-5.18	<0.001
SBP (mmHg)	121.82±18.60	123.50±17.49	118.93±20.08	t=3.26	0.001
DBP (mmHg)	68.40±14.06	69.43±12.52	66.62±16.24	t=2.46	0.014
MBP (mmHg)	82.43±14.35	83.89±13.05	79.89±16.07	t=3.51	<0.001
Temperature (°C)	36.36±0.79	36.57±0.56	35.99±0.98	t=9.08	<0.001
SpO_2 (%)	95.56±5.17	96.70±3.47	93.58±6.80	t=7.10	<0.001
Urine output 24 h (ml)	236.13±227.58	259.45±251.96	195.79±170.72	t=3.72	<0.001
GCS (score)	14.31±1.69	14.50±1.10	13.98±2.35	t=3.42	<0.001
Hourly Patient Fluid Removal (ml/hr)	146.75±71.61	152.03±66.10	137.62±79.56	t=2.66	0.008
Ventilation Duration (hours)	36.13±40.22	31.11±29.49	44.81±52.92	t=-3.95	<0.001

Data are mean±standard deviation or number (percentage). t, t-test; χ^2, chi-square test; ROSC, return of spontaneous circulation.
Abbreviations: WBC = white blood cell count; RBC = red blood cell count; Abs = absolute count; MCH = mean corpuscular hemoglobin; MCHC = mean corpuscular hemoglobin concentration; MCV = mean corpuscular volume; RDW = red cell distribution width; SCr = serum creatinine; BUN = blood urea nitrogen; CRP = C-reactive protein; ALT = alanine aminotransferase; ALP = alkaline phosphatase; AST = aspartate aminotransferase; CK = creatine kinase; CK-MB = creatine kinase-MB isoenzyme; LDH = lactate dehydrogenase; APS III = Acute Physiology Score III; SBP = systolic blood pressure; DBP = diastolic blood pressure; MBP = mean blood pressure; SpO_2 = peripheral oxygen saturation; GCS = Glasgow Coma Scale.

Table 1 (Continuation). Clinical characteristics and outcome analysis of the patients

Variable	Total (n=748)	ROSC (n=474)	No-ROSC (n=274)	Statistic	p
Gender				χ^2=7.13	0.008
• Female	289 (38.6%)	166 (35.0%)	123 (44.9%)	—	—
• Male	459 (61.4%)	308 (65.0%)	151 (55.1%)	—	—
Insurance				χ^2=1.04	0.594
• Medicaid	42 (5.6%)	24 (5.1%)	18 (6.6%)	—	—
• Medicare	382 (51.1%)	240 (50.6%)	142 (51.8%)	—	—
• Other	324 (43.3%)	210 (44.3%)	114 (41.6%)	—	—
Marital Status				χ^2=15.36	0.002
• Divorced	45 (6.0%)	29 (6.1%)	16 (5.8%)	—	—
• Married	373 (49.9%)	244 (51.5%)	129 (47.1%)	—	—
• Single	246 (32.9%)	164 (34.6%)	82 (29.9%)	—	—
• Widowed	84 (11.2%)	37 (7.8%)	47 (17.1%)	—	—
Myocardial Infarction (Yes)	227 (30.4%)	150 (31.7%)	77 (28.1%)	χ^2=1.03	0.310
Congestive Heart Failure (Yes)	367 (49.1%)	267 (56.3%)	100 (36.5%)	χ^2=27.33	<0.001
Peripheral Vascular Disease (Yes)	112 (15.0%)	72 (15.2%)	40 (14.6%)	χ^2=0.05	0.827
Cerebrovascular Disease (Yes)	106 (14.2%)	60 (12.7%)	46 (16.8%)	χ^2=2.44	0.119
Dementia (Yes)	30 (4.0%)	16 (3.4%)	14 (5.1%)	χ^2=1.36	0.244
Chronic Pulmonary Disease (Yes)	187 (25.0%)	119 (25.1%)	68 (24.8%)	χ^2=0.01	0.930
Rheumatic Disease (Yes)	31 (4.1%)	18 (3.8%)	13 (4.7%)	χ^2=0.39	0.531
Peptic Ulcer Disease (Yes)	20 (2.7%)	12 (2.5%)	8 (2.9%)	χ^2=0.10	0.751
Mild Liver Disease (Yes)	103 (13.8%)	57 (12.0%)	46 (16.8%)	χ^2=3.32	0.069
Paraplegia (Yes)	33 (4.4%)	19 (4.0%)	14 (5.1%)	χ^2=0.50	0.480
Renal Disease (Yes)	255 (34.1%)	170 (35.9%)	85 (31.0%)	χ^2=1.81	0.178
Malignant Cancer (Yes)	57 (7.6%)	31 (6.5%)	26 (9.5%)	χ^2=2.14	0.143
Severe Liver Disease (Yes)	23 (3.1%)	7 (1.5%)	16 (5.8%)	χ^2=11.09	<0.001
Age (years)	65.88±16.44	63.73±16.21	69.59±16.20	t=–4.76	<0.001
WBC ($\times10^9$/L)	11.32±6.14	9.99±4.96	13.61±7.22	t=–7.36	<0.001
Basophils Abs ($\times10^9$/L)	0.03±0.02	0.03±0.02	0.03±0.02	t=3.22	0.001
Eosinophils Abs ($\times10^9$/L)	0.18±0.18	0.21±0.21	0.14±0.10	t=5.89	<0.001
Lymphocytes Abs ($\times10^9$/L)	1.44±0.59	1.41±0.52	1.50±0.68	t=–1.94	0.053
Monocytes Abs ($\times10^9$/L)	0.73±0.27	0.76±0.27	0.67±0.25	t=4.25	<0.001
Neutrophils Abs ($\times10^9$/L)	8.84±4.38	7.95±3.93	10.38±4.69	t=–7.24	<0.001
Hematocrit (%)	33.45±6.59	33.55±6.24	33.27±7.17	t=0.54	0.586
Hemoglobin (g/dL)	10.83±2.30	10.92±2.21	10.66±2.44	t=1.54	0.124
MCH (pg)	29.71±2.52	29.66±2.39	29.81±2.73	t=–0.80	0.426
MCHC (g/dL)	32.34±1.64	32.47±1.64	32.11±1.61	t=2.92	0.004
MCV (fL)	91.86±6.77	91.31±5.85	92.81±8.03	t=–2.70	0.007
Platelet ($\times10^9$/L)	203.96±93.10	200.76±83.86	209.48±107.18	t=–1.16	0.248
RBC ($\times10^{12}$/L)	3.66±0.77	3.69±0.73	3.60±0.82	t=1.55	0.122
RDW (%)	15.28±2.05	15.04±1.96	15.70±2.13	t=–4.28	<0.001
SCr baseline (mg/dL)	1.28±1.23	1.32±1.38	1.20±0.90	t=1.29	0.198
Anion gap (mmol/L)	16.02±4.99	14.93±3.98	17.93±5.91	t=–7.48	<0.001
Bicarbonate (mmol/L)	23.04±4.99	24.45±4.42	20.60±4.99	t=10.60	<0.001
BUN (mg/dL)	32.97±22.70	30.40±20.72	37.43±25.18	t=–4.12	<0.001
Calcium (mg/dL)	8.62±0.95	8.69±0.80	8.51±1.17	t=2.26	0.024
Chloride (mmol/L)	102.90±6.20	102.05±5.74	104.37±6.69	t=–4.81	<0.001
Creatinine (mg/dL)	1.95±1.88	1.93±2.12	2.00±1.39	t=–0.50	0.619
Glucose (mg/dL)	154.03±70.20	141.81±61.73	175.18±78.59	t=–6.03	<0.001
Sodium (mmol/L)	138.94±4.79	138.65±4.57	139.44±5.13	t=–2.18	0.029

Data are mean±standard deviation or number (percentage). t, t-test; χ^2, chi-square test; ROSC, return of spontaneous circulation.
Abbreviations: WBC = white blood cell count; RBC = red blood cell count; Abs = absolute count; MCH = mean corpuscular hemoglobin; MCHC = mean corpuscular hemoglobin concentration; MCV = mean corpuscular volume; RDW = red cell distribution width; SCr = serum creatinine; BUN = blood urea nitrogen; CRP = C-reactive protein; ALT = alanine aminotransferase; ALP = alkaline phosphatase; AST = aspartate aminotransferase; CK = creatine kinase; CK-MB = creatine kinase-MB isoenzyme; LDH = lactate dehydrogenase; APS III = Acute Physiology Score III; SBP = systolic blood pressure; DBP = diastolic blood pressure; MBP = mean blood pressure; SpO_2 = peripheral oxygen saturation; GCS = Glasgow Coma Scale.

ISSN 0022-9040. Кардиология. 2025;65(10). DOI: 10.18087/cardio.2025.10.n2896

Table 1 (Ending). Clinical characteristics and outcome analysis of the patients

Variable	Total (n=748)	ROSC (n=474)	No-ROSC (n=274)	Statistic	p
Potassium (mmol/L)	4.36±0.73	4.28±0.69	4.50±0.78	t=-3.89	<0.001
CRP (mg/L)	92.98±35.40	91.31±38.16	95.87±29.89	t=-1.81	0.071
ALT (U/L)	213.58±591.15	128.04±399.07	361.57±803.50	t=-4.50	<0.001

Data are mean±standard deviation or number (percentage). t, t-test; χ^2, chi-square test; ROSC, return of spontaneous circulation.
Abbreviations: WBC = white blood cell count; RBC = red blood cell count; Abs = absolute count; MCH = mean corpuscular hemoglobin; MCHC = mean corpuscular hemoglobin concentration; MCV = mean corpuscular volume; RDW = red cell distribution width; SCr = serum creatinine; BUN = blood urea nitrogen; CRP = C-reactive protein; ALT = alanine aminotransferase; ALP = alkaline phosphatase; AST = aspartate aminotransferase; CK = creatine kinase; CK-MB = creatine kinase-MB isoenzyme; LDH = lactate dehydrogenase; APS III = Acute Physiology Score III; SBP = systolic blood pressure; DBP = diastolic blood pressure; MBP = mean blood pressure; SpO_2 = peripheral oxygen saturation; GCS = Glasgow Coma Scale.

Machine learning methods

The study utilized LASSO regression for variable selection, employing L1 regularization to screen the most critical predictive variables while balancing model complexity and predictive performance. Multiple machine learning algorithms were introduced, including Gradient Boosting Decision Trees (GBDT) and Light Gradient Boosting Machine (LGBM), supplemented by comparative algorithms such as Random Forest, Support Vector Machine, and Logistic Regression. Model evaluation employed multidimensional methods, including calibration curves, decision curve analysis, and ROC curves, to comprehensively assess the model from perspectives of prediction probability accuracy, clinical utility, and classification performance. Data preprocessing rigorously handled missing value treatment, variable standardization, and encoding, with a 7:3 train-validation set split and hyperparameter optimization through grid and random searches [10, 13–15]. To enhance model interpretability, the research conducted feature importance ranking and SHAP value analysis, focusing not only on model predictive accuracy but also on revealing the mechanism of clinical factors influencing ROSC in cardiac arrest patients, thus providing more precise and interpretable data support for clinical decision-making.

Statistical analysis

SPSS 26.0, R language, and SAS 9.4 software were used. The study employed comprehensive statistical methods to analyze cardiac arrest patient data. Descriptive statistics were first used to characterize the distribution of continuous and categorical variables. Independent sample t-tests, Mann–Whitney U tests, and chi-square tests compared clinical characteristics between the ROSC and non-ROSC groups. To evaluate inter-variable relationships, Pearson correlation coefficients were applied when both variables were continuous and normally distributed, whereas Spearman rank correlation coefficients were used for non-normally distributed or ordinal variables. Multicollinearity testing was performed prior to regression modeling. Multifactor logistic regression and Cox proportional hazards models were then employed to assess independent risk factors affecting spontaneous circulation recovery. Statistical test results with an α=0.05 significance level and p<0.05 were considered statistically significant.

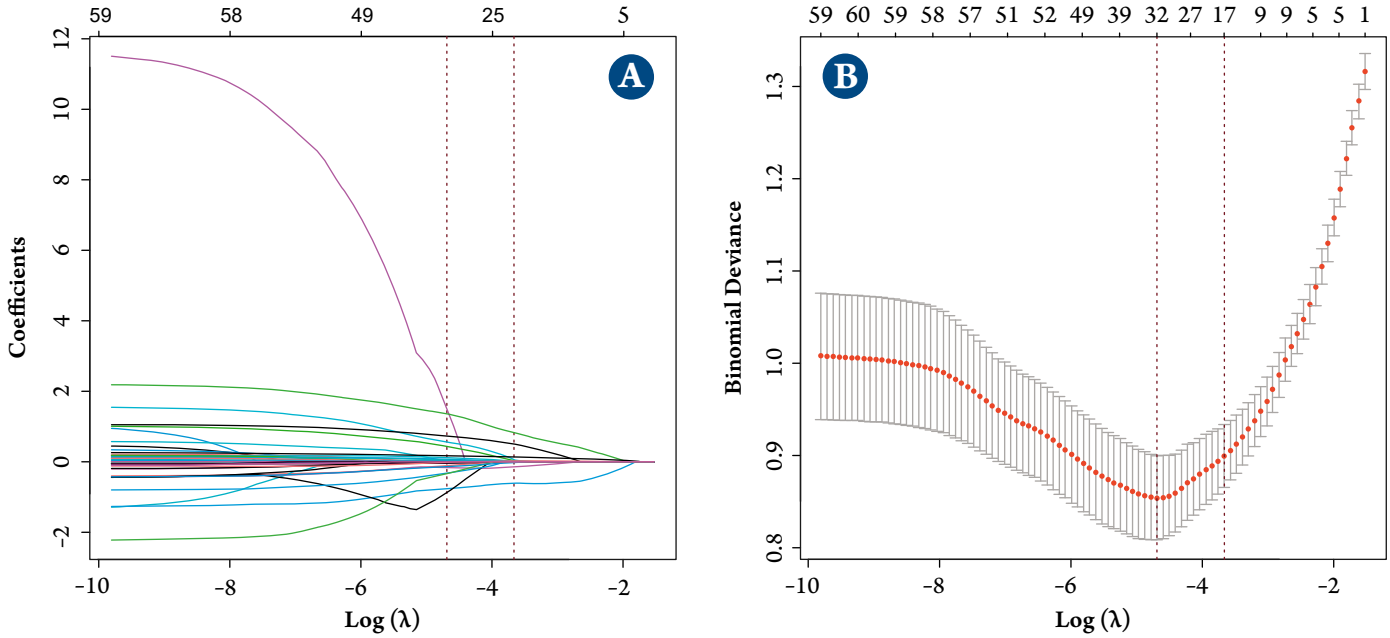
Results

Clinical characteristics and outcome analysis

The analysis of 748 cardiac arrest patients revealed significant differences between those who achieved return of spontaneous circulation (ROSC, n=474) and those who did not (non-ROSC, n=274). Patients in the ROSC group were younger (63.7±16.2 vs 69.6±16.2 years, p<0.001) and more frequently male (65.0% vs 55.1%, p=0.008). Hemodynamic and respiratory parameters were more favorable among ROSC patients, who presented with higher systolic blood pressure (123.5±17.5 vs 118.9±20.1 mmHg, p=0.001), more stable body temperature (36.6±0.6 vs 36.0±1.0 °C, p<0.001), and higher oxygen saturation (96.7±3.5% vs 93.6±6.8%, p<0.001). Inflammatory burden was lower in the ROSC group, as reflected by reduced white blood cell count (9.99±4.96 vs 13.61±7.22×10^9/L, p<0.001) and neutrophil count (7.95±3.93 vs 10.38±4.69×10^9/L, p<0.001). Metabolic and organ function markers also showed clear differences: lactate levels were significantly lower (2.62±1.81 vs 5.02±3.77 mmol/L, p<0.001), bicarbonate was higher (24.5±4.4 vs 20.6±5.0 mmol/L, p<0.001), and renal function was more favorable, with lower BUN values (30.4±20.7 vs 37.4±25.2 mg/dL, p<0.001). Hepatic injury was less severe in the ROSC group, evidenced by significantly lower ALT, AST, and bilirubin levels (all p<0.01).

Clinically, ROSC patients required shorter ventilation duration (31.1±29.5 vs 44.8±52.9 hrs, p<0.001), maintained greater urine output (259.5±252.0 vs 195.8±170.7 ml/24 h, p<0.001), and had better neurological status (GCS score 14.5±1.1 vs 14.0±2.4, p=0.001). Importantly, their lower Acute Physiology Score III (APS III: 54.5±22.1 vs 80.6±29.2, p<0.001) indicated less severe overall illness and multi-organ dysfunction [16]. Taken together, these findings demonstrate that successful ROSC is associated with a constellation of favorable features – including preserved hemodynamic stability, lower systemic inflammation, balanced metabo-

Figure 1. Variable selection for ROSC prediction using LASSO regression analysis



lism, and better organ function – underscoring the value of integrating routinely available clinical and laboratory indicators into comprehensive risk stratification for cardiac arrest management (Table 1).

Variable selection for ROSC prediction using LASSO regression analysis

Our LASSO regression analysis reveals the process of variable selection for predicting ROSC outcomes. Figure 1A illustrates the coefficient paths of variables as the penalty parameter (λ) changes, with coefficients being shrunk towards zero as λ increases. Two critical λ values are highlighted by vertical dotted lines: one corresponding to the minimum error (λ.min), and another representing the most parsimonious model within one standard error (λ.1se). Figure 1B displays the binomial deviance curve with cross-validation error bars, where red dots indicate model deviance at different λ values. The analysis identified optimal model selection at approximately e^{-4}, striking a balance between model complexity and predictive performance. This regularization approach effectively helps identify the most significant predictors of ROSC while avoiding overfitting, thereby enhancing the model's generalizability for clinical application.

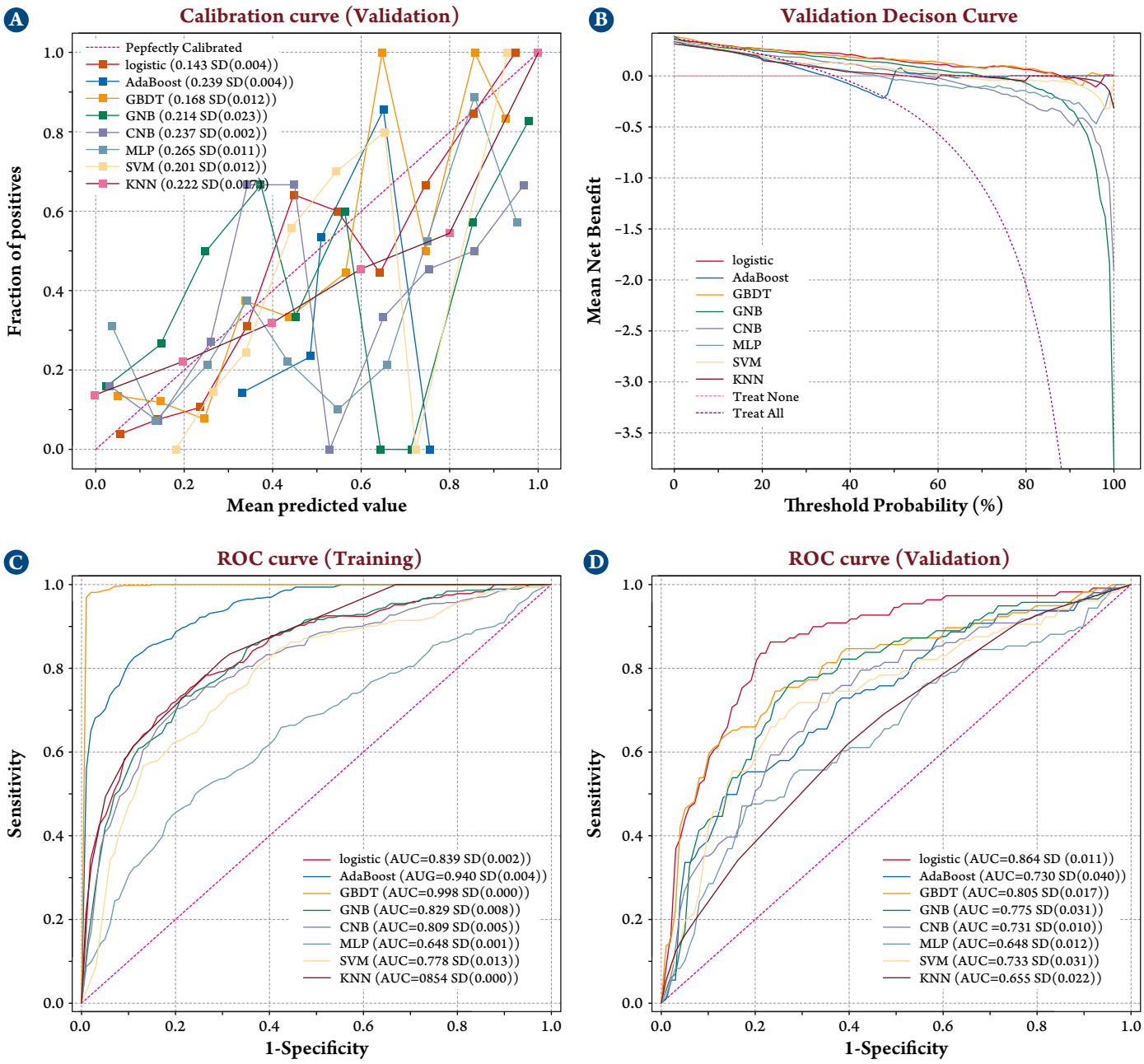
LASSO regression helps selection of the most important variables for predicting ROSC through the penalty parameter λ. As λ increases, the model shrinks the coefficients of less important variables close to zero. Through cross-validation, we determined the optimal model complexity to be approximately e^{-4}. The final model retained several independent predictors, including age, white blood cell count (WBC), serum lactate, Acute Physiology Score III (APS III), systolic blood pressure (SBP), heart rate, peripheral oxygen saturation (SpO_2), and serum bicarbonate. These variables were consistently associated with the likelihood of ROSC, highlighting their clinical relevance. This approach effectively identified key predictors while avoiding overfitting, thereby enhancing the reliability of the model in clinical applications.

Performance evaluation of machine learning models for predicting ROSC outcomes

Figure 2 summarizes the comparative performance of nine predictive models for ROSC. In the validation cohort, calibration curves (Panel **A**) showed that GBDT and logistic regression were closest to the ideal diagonal, indicating better agreement between predicted probabilities and observed outcomes. Decision curve analysis (Panel **B**) confirmed that these two models provided greater net clinical benefit than other algorithms across a range of threshold probabilities. The ROC curves in the training cohort (Panel **C**) demonstrated excellent discrimination for GBDT (AUC 0.998±0.000) and AdaBoost (AUC 0.940±0.004), both outperforming logistic regression (AUC 0.839±0.002). Other models such as GNB (AUC 0.829) and KNN (AUC 0.854) showed moderate performance, while MLP (AUC 0.648) performed poorly. In the validation cohort (Panel **D**), logistic regression (AUC 0.864±0.011) and GBDT (AUC 0.805±0.017) maintained reasonable predictive ability, whereas other models, including AdaBoost (AUC 0.730), GNB (AUC 0.775), and SVM (AUC 0.733), showed reduced performance. KNN (AUC 0.655) and MLP (AUC 0.648) demonstrated the lowest discrimination. Collectively, these results indicate that although GBDT achieved the best fit in the training set, logistic regression exhibited more stable and generalizable performance in the validation set. This

ISSN 0022-9040. Кардиология. 2025;65(10). DOI: 10.18087/cardio.2025.10.n2896

Figure 2. Performance evaluation of machine learning models for predicting ROSC outcomes



Panels **A-D**: The calibration curves show that models such as GBDT and LGBM have better calibration, with their predicted probabilities more closely aligned with the actual outcomes. The decision curves indicate that the GBDT and LGBM models have superior overall performance, providing higher net benefits. The ROC curves reflect the classification performance of the models on both the training and validation datasets, and GBDT and LGBM also demonstrate better results in these aspects.

suggests that traditional regression, when combined with appropriate feature selection, may provide a balance between predictive accuracy and robustness, while ensemble methods such as GBDT offer superior discrimination in training but risk overfitting.

Discussion

This study systematically analyzed 748 cardiac arrest patients and identified several key predictors of return of spontaneous circulation (ROSC), including age, white blood cell count, serum lactate, Acute Physiology Score III (APS III), systolic blood pressure, heart rate, peripheral oxygen saturation (SpO_2), and serum bicarbonate. While some of these indicators are consistent with previous clinical experience, our contribution lies in validating their prognostic value in a large, rigorously defined cohort and in demonstrating how advanced machine learning approaches can integrate these and other variables into robust predictive models. By evaluating multiple algorithms with calibration, decision curve, and ROC analyses, we found that gradient boosting models

(GBDT and LGBM) achieved superior calibration, discrimination, and clinical net benefit compared with traditional regression. These findings confirm the prognostic importance of classical clinical indicators while underscoring the added value of machine learning in enhancing prediction accuracy and supporting personalized risk stratification, thereby offering practical guidance for improving outcomes in cardiac arrest management.

The prognosis of cardiac arrest patients is influenced by multiple complex factors. This study systematically identified key predictive indicators across hemodynamics, metabolism, inflammation, and organ function. Among them, the lactate/albumin ratio (LAR) functions as an integrated indicator that reflects both metabolic status and the adequacy of tissue perfusion and organ function [17, 18]. In our cohort, lower LAR values were associated with higher ROSC rates, consistent with the notion that preserved metabolic reserve and perfusion capacity support tolerance to hypoxic – ischemic insults.

Hemodynamic indicators are well-recognized determinants of cardiac arrest prognosis, and our findings further substantiate this in a large cohort. In particular, systolic blood pressure within the range of 120–130 mmHg was significantly associated with higher ROSC rates, providing quantitative evidence that even modest deviations from this optimal window may reduce the likelihood of successful resuscitation. Similarly, oxygen saturation values >95% – a routinely monitored parameter – were consistently identified as independent predictors of ROSC. Beyond confirming established physiological principles, our analysis highlights that these common bedside measurements retain strong prognostic value when integrated into multivariable and machine learning models, underscoring their continued importance for real-time risk stratification and clinical decision-making [19–21]. Among inflammatory and metabolic indicators, the white blood cell count (WBC) provides critical information about the body's stress and metabolic balance [22]. WBC within the normal range suggest that the patient's inflammatory response and acid-base balance are relatively stable, forming an important physiological basis for successful ROSC.

Albumin is more than just a marker of nutritional status; it is a significant indicator of liver function and overall metabolic level. Higher albumin levels were significantly associated with better ROSC prognosis, potentially due to its unique advantages in regulating colloid osmotic pressure and resisting inflammation and oxidative stress. Renal function indicators, such as creatinine clearance, urea nitrogen, and electrolyte balance provide a comprehensive assessment of the patient's overall physiological state [23–25].

Cardiac rhythm and resuscitation-related indicators cannot be overlooked. Patients who presented with initial shockable rhythms, such as ventricular fibrillation or pulseless ventricular tachycardia, had significantly higher ROSC rates compared to those with non-shockable rhythms. This finding underscores the prognostic importance of the first documented rhythm at the time of cardiac arrest and highlights the critical role of early rhythm recognition and timely defibrillation in improving outcomes

[26, 27]. The time window from admission to CPR, CPR duration, and epinephrine administration strategies will directly impact patient survival probability. These indicators are interwoven, collectively forming a complex physiological landscape of cardiac arrest patient prognosis.

Notably, these predictive factors are not independent but part of a highly interconnected and mutually influential complex system. By analyzing these indicators systematically and multi-dimensionally, we can more accurately assess patient prognosis and develop personalized treatment strategies. Future research should further explore the potential interaction mechanisms of these indicators, establish more precise prediction models, and provide more targeted and precise treatment plans for cardiac arrest patients. This data-driven, individualized medical approach offers new hope and possibilities for improving survival rates and prognosis quality for cardiac arrest patients.

The study employed LASSO regression and machine learning models, particularly Gradient Boosting Decision Trees (GBDT) and Light Gradient Boosting Machine (LGBM), providing an innovative solution for clinical prognosis prediction. Model evaluation results demonstrated that GBDT and LGBM exhibited excellent performance across calibration curves, decision curves, and ROC curves. These models not only accurately predict patient outcomes but also help clinicians deeply understand the key clinical factors influencing ROSC, significantly enhancing model interpretability and clinical utility.

Comparison with existing research further validated the study's results. Previous studies similarly emphasized the impact of LAR, non-defibrillatable rhythms, and admission-to-CPR time on ROSC, while Zhao et al.'s research focused on CPR duration, epinephrine dosage, and initial rhythm. This multi-angle, multi-dimensional research perspective provides richer insights into understanding the prognosis mechanisms of cardiac arrest patients.

The research findings have significant clinical practice implications. By precisely identifying ROSC's key predictive factors, clinicians can more accurately assess patient prognosis and achieve precise resource allocation. Machine learning models, especially GBDT and LGBM, can provide real-time predictions and strong support for clinical decision-making. This data-driven approach aims to help identify patients more likely to achieve ROSC, optimize treatment strategies, and ultimately improve patient survival rates and prognosis quality.

ISSN 0022-9040. Кардиология. 2025;65(10). DOI: 10.18087/cardio.2025.10.n2896

Conclusion

This study systematically analyzed 748 patients with cardiac arrest and identified key predictors of return of spontaneous circulation (ROSC), including age, white blood cell count, serum lactate, Acute Physiology Score III (APS III), systolic blood pressure, heart rate, peripheral oxygen saturation (SpO_2), and serum bicarbonate. These routinely available clinical and laboratory indicators were consistently associated with ROSC, providing an evidence-based foundation for risk stratification. By integrating these predictors into machine learning models such as GBDT and LGBM, we achieved improved calibration, discrimination, and clinical net benefit compared with conventional regression methods. These findings confirm the prognostic importance of established clinical factors in a large cohort while demonstrating the added value of advanced machine learning for individualized risk assessment. Collectively, this work offers a practical and data-driven approach to guide clinical decision-making and may contribute to optimizing treatment strategies and improving survival outcomes in cardiac arrest patients.

No conflict of interest is reported.

The article was received on 07/02/2025

REFERENCES

1. Bakhsh A, Bakhashwain W, Alhazmi M, Bahwireth S, Binmahfooz S, Alghamdi R et al. Fever Prevention and Neurological Recovery in In-Hospital Cardiac Arrest Survivors at a Limited-Resource Setting. Therapeutic Hypothermia and Temperature Management. 2025; [Epub ahead of print]. DOI: 10.1089/ther.2024.0051
2. Jakobsen LK, Kjærulf V, Bray J, Olasveengen TM, Folke F. Drones delivering automated external defibrillators for out-of-hospital cardiac arrest: A scoping review. Resuscitation Plus. 2025;21:100841. DOI: 10.1016/j.resplu.2024.100841
3. Jeong D, Tak Lee G, Eun Park J, Yeon Hwang S, Gun Shin T, Do Shin S et al. Severity of metabolic derangement predicts survival after out-of-hospital cardiac arrest and the likelihood of benefiting from extracorporeal life support. Emergencias. 2024;36(6):408–16. DOI: 10.55633/s3me/093.2024
4. Motta F, Cerrato M, De Giorgio D, Salimbeni A, Merigo G, Magliocca A et al. Translational approach to assess brain injury after cardiac arrest in preclinical models: a narrative review. Intensive Care Medicine Experimental. 2025;13(1):3. DOI: 10.1186/s40635-024-00710-y
5. Breuer-Kaiser AFC, Lefering R, Weber TP, Gräsner J-T, Wnent J. Use of CPR feedback devices to treat out-of-hospital cardiac arrest in Germany: Associated with improved ROSC-rates, but infrequent usage, in a registry-based analysis of 107,548 cases. Resuscitation. 2024;110453. [Epub ahead of print]. DOI: 10.1016/j.resuscitation.2024.110453
6. Caputo ML, Baldi E, Burkart R, Wilmes A, Cresta R, Benvenuti C et al. Validation of Utstein-Based score to predict return of spontaneous circulation (UB-ROSC) in patients with out-of-hospital cardiac arrest. Resuscitation. 2024;197:110113. DOI: 10.1016/j.resuscitation.2024.110113
7. Dombrowski A, Curtis K, Wisniewski S, Nichols J, Irish L, Almahameed S et al. Post-ROSC Atrial fibrillation is not associated with rearrest but is associated with stroke and mortality following out of hospital cardiac arrest. Resuscitation. 2024;201:110270. DOI: 10.1016/j.resuscitation.2024.110270
8. Hubble MW, Martin MD, Kaplan GR, Houston SE, Taylor SE. The Route to ROSC: Evaluating the Impact of Route and Timing of Epinephrine Administration in Out-of-Hospital Cardiac Arrest Outcomes. Prehospital Emergency Care. 2025;29(6):826–34. DOI: 10.1080/10903127.2024.2414389
9. Choi H-J, Lee C, Chun J, Seol R, Lee YM, Son Y-J. Development of a Predictive Model for Survival Over Time in Patients With Out-of-Hospital Cardiac Arrest Using Ensemble-Based Machine Learning. Computers, Informatics, Nursing. 2024;42(5):388–95. DOI: 10.1097/CIN.0000000000001145
10. Kim YK, Seo W-D, Lee SJ, Koo JH, Kim GC, Song HS et al. Early Prediction of Cardiac Arrest in the Intensive Care Unit Using Explainable Machine Learning: Retrospective Study. Journal of Medical Internet Research. 2024;26:e62890. DOI: 10.2196/62890
11. Soundararajan K, Adams DJ, Nathanson BH, Mader TJ, Godwin RC, Melvin RL et al. Use of machine learning models to predict neurologically intact survival for advanced age adults following out-of-hospital cardiac arrest. Academic Emergency Medicine. 2025;32(2):169–71. DOI: 10.1111/acem.15018
12. Wu W, Kor C, Chou M, Hsieh H, Huang W, Huang W et al. Prediction model of in-hospital cardiac arrest using machine learning in the early phase of hospitalization. The Kaohsiung Journal of Medical Sciences. 2024;40(11):1029–35. DOI: 10.1002/kjm2.12895
13. Karatsu S, Hirano Y, Kondo Y, Okamoto K, Tanaka H. A Machine Learning Prediction Model for Non-cardiogenic Out-of-hospital Cardiac Arrest with Initial Non-shockable Rhythm. Juntendo Medical Journal. 2023;69(3):222–30. DOI: 10.14789/jmj.JMJ22-0035-OA
14. Lee H-Y, Kuo P-C, Qian F, Li C-H, Hu J-R, Hsu W-T et al. Prediction of In-Hospital Cardiac Arrest in the Intensive Care Unit: Machine Learning–Based Multimodal Approach. JMIR Medical Informatics. 2024;12:e49142. DOI: 10.2196/49142
15. Lee S, Lee K-S, Park S-H, Lee SW, Kim SJ. A Machine Learning-Based Decision Support System for the Prognostication of Neurological Outcomes in Successfully Resuscitated Out-of-Hospital Cardiac Arrest Patients. Journal of Clinical Medicine. 2024;13(24):7600. DOI: 10.3390/jcm13247600
16. Zheng X, Hu T, Liu T, Wang W. Simplified acute physiology score III is excellent for predicting in-hospital mortality in coronary care unit patients with acute myocardial infarction: A retrospective study. Frontiers in Cardiovascular Medicine. 2022;9:989561. DOI: 10.3389/fcvm.2022.989561
17. Kokulu K, Sert ET. The role of the lactate/albumin ratio in predicting survival outcomes in patients resuscitated after out-of-hospital cardiac arrest: A preliminary report. The American Journal of Emergency Medicine. 2021;50:670–4. DOI: 10.1016/j.ajem.2021.09.059
18. Kong T, Chung SP, Lee HS, Kim S, Lee J, Hwang SO et al. The Prognostic Usefulness of the Lactate/Albumin Ratio for Predicting Clinical Outcomes in Out-of-Hospital Cardiac Arrest: a Prospective, Multicenter Observational Study (koCARC) Study. Shock. 2020;53(4):442–51. DOI: 10.1097/SHK.0000000000001405
19. Beaulieu J, St-Onge M. Antidote use for cardiac arrest or hemodynamic instability due to cardiac glycoside poisoning: A narrative review. Resuscitation Plus. 2024;19:100690. DOI: 10.1016/j.resplu.2024.100690
20. Dogan B, Kudu E, Danış F, Ozturk Ince E, Karaca MA, Erbil B. Comparative Analysis of Perfusion Index and End-Tidal Carbon Dioxide in Cardiac Arrest Patients: Implications for Hemodynamic Monitoring and Resuscitation Outcomes. Cureus. 2023;15(2):e50818. DOI: 10.7759/cureus.50818
21. Linde L, Beske RP, Meyer MAS, Mølstrøm S, Grand J, Helgestad OKL et al. Hemodynamic Characteristics and Prognostic Implication of Modified Society for Cardiovascular Angiography and Interventions Shock Classification in Comatose Patients With Out-of-Hospital Cardiac Arrest. Journal of the American Heart Association. 2025;14(1):e036659. DOI: 10.1161/JAHA.124.036659
22. Seppä AMJ, Skrifvars MB, Vuopio H, Raj R, Reinikainen M, Pekkarinen PT. Association of white blood cell count with one-year mortal-

ity after cardiac arrest. Resuscitation Plus. 2024;20:100816. DOI: 10.1016/j.resplu.2024.100816
23. Szarpak L, Kurek K, Tomaszewska M, Pruc M. Lactate-to-albumin ratio in predicting neurological outcomes in patients who have survived cardiac arrest. The American Journal of Emergency Medicine. 2024;85:260–1. DOI: 10.1016/j.ajem.2024.08.002
24. Xiao L, Li F, Sheng Y, Hou X, Liao X, Zhou P et al. Predictive value analysis of albumin-related inflammatory markers for short-term outcomes in patients with In-hospital cardiac arrest. Expert Review of Clinical Immunology. 2025;21(2):249–57. DOI: 10.1080/1744666X.2024.2399700
25. Xie Y, Wang R. Enhancing neurological prognosis prediction in cardiac arrest survivors: Insights from lactate-to-albumin ratio and cholesterol levels. The American Journal of Emergency Medicine. 2024;85:258–9. DOI: 10.1016/j.ajem.2024.07.058
26. Drkic T, Sljivo A, Ljuhar K, Palikuca A, Knezevic A, Karamehic E et al. Outcomes of Out-of-Hospital Cardiac Arrest with Initial Shockable Rhythm: The Role of Bystander and Dispatch-Guided CPR in Sarajevo's Physician-Led Emergency Medical Teams. Materia Socio Medica. 2024;36(2):115–9. DOI: 10.5455/msm.2024.36.115-119
27. Simpson R, Dankiewicz J, Nielsen N, Pareek N, Keeble TR. Coronary artery disease and outcomes in Out of Hospital Cardiac arrest according to presenting rhythm – A post hoc analysis of the TTM-2 trial. Resuscitation. 2025;206:110457. DOI: 10.1016/j.resuscitation.2024.110457

ISSN 0022-9040. Кардиология. 2025;65(10). DOI: 10.18087/cardio.2025.10.n2896