RESEARCH ARTICLE

Machine Learning for Predicting the Development of Postoperative Acute Kidney Injury After Coronary Artery Bypass Grafting Without Extracorporeal Circulation

Sai Zheng[1,a], Yugui Li[1,a], Cheng Luo[1], Fang Chen[1], Guoxing Ling[1] and Baoshi Zheng[1]

[1]*The First Affiliated Hospital of Guangxi Medical University, Cardiac Surgery, Nanning, Guangxi, China*

Abstract

Background: Cardiac surgery-associated acute kidney injury (CSA-AKI) is a major complication that increases morbidity and mortality after cardiac surgery. Most established predictive models are limited to the analysis of nonlinear relationships and do not adequately consider intraoperative variables and early postoperative variables. Nonextracorporeal circulation coronary artery bypass grafting (off-pump CABG) remains the procedure of choice for most coronary surgeries, and refined CSA-AKI predictive models for off-pump CABG are notably lacking. Therefore, this study used an artificial intelligence-based machine learning approach to predict CSA-AKI from comprehensive perioperative data.

Methods: In total, 293 variables were analysed in the clinical data of patients undergoing off-pump CABG in the Department of Cardiac Surgery at the First Affiliated Hospital of Guangxi Medical University between 2012 and 2021. According to the KDIGO criteria, postoperative AKI was defined by an elevation of at least 50% within 7 days, or 0.3 mg/dL within 48 hours, with respect to the reference serum creatinine level. Five machine learning algorithms—a simple decision tree, random forest, support vector machine, extreme gradient boosting and gradient boosting decision tree (GBDT)—were used to construct the CSA-AKI predictive model. The performance of these models was evaluated with the area under the receiver operating characteristic curve (AUC). Shapley additive explanation (SHAP) values were used to explain the predictive model.

Results: The three most influential features in the importance matrix plot were 1-day postoperative serum potassium concentration, 1-day postoperative serum magnesium ion concentration, and 1-day postoperative serum creatine phosphokinase concentration.

Conclusion: GBDT exhibited the largest AUC (0.87) and can be used to predict the risk of AKI development after surgery, thus enabling clinicians to optimise treatment strategies and minimise postoperative complications.

Keywords: Machine learning; CSA-AKI; off-pump CABG

[a]Sai Zheng and Yugui Li contributed equally to this work.
Correspondence: Baoshi Zheng, The First Affiliated Hospital of Guangxi Medical University, Department of Cardiac Surgery, No 6 Shuangyong Road, Nanning, Guangxi, China, Tel.: +86-13977189015, E-mail: zhengbs25@vip.sina.com

Introduction

Cardiac surgery-associated acute kidney injury (CSA-AKI) is a complication after cardiac surgery that is associated with increased morbidity and

mortality, hospital stays and health care costs [1, 2]. A meta-analysis investigating the global incidence and prognosis of CSA-AKI over the period from 2004 to 2014 has indicated that the incidence of all stages of AKI is approximately 22%, and the combined short-term and long-term mortality rates are 10.7% and 30%, respectively [3, 4]. The two main types of surgical treatment for coronary artery disease are coronary artery bypass grafting with extracorporeal circulation and nonexternal circulation coronary artery bypass grafting (on-pump and off-pump CABG). Previously, off-pump CABG was believed to avoid the second strike of extracorporeal circulation in high-risk patients, and to decrease perioperative complication rates and mortality [5].

However, in recent years, several large randomised controlled studies have concluded that off-pump CABG has no significant advantage over on-pump CABG in terms of perioperative complications and mortality [6]. The pathophysiological mechanisms underlying CSA-AKI are not fully understood and may involve a variety of factors that act in different ways, and to different degrees, in different patients. The development of CSA-AKI may involve several major pathways of injury, including underperfusion, ischaemia-reperfusion injury, neurohumoural activation, inflammation, oxidative stress, nephrotoxins and mechanical factors [7, 8]. The main risk assessment systems currently available for cardiac surgery are the Chinese Cardiac Surgical Risk Evaluation System (SinoSCORE), the new European Cardiac Surgical Risk Evaluation System (EuroSCORE II) and the Society of Thoracic Surgeons Adult Cardiac Surgery Risk Calculator (STSscore) [9]. However, a targeted off-pump CABG perioperative risk predictive model is lacking. Accurate prediction of patients at risk of CSA-AKI would facilitate interventions to prevent or minimise the consequences of CSA-AKI [10].

Machine learning has been applied to medical fields such as outcome prediction, diagnosis, medical image interpretation and treatment [11, 12]. Machine learning techniques do not require assumptions regarding input variables and their relationships with outputs. Moreover, models built by machine learning methods enable early dynamic monitoring based on all available patient datasets, thus saving clinicians time [13]. Fan's team has collected data on approximately 600 cardiac surgery patients and successfully built a CSA-AKI risk predictive model

with a machine learning approach [14]. Therefore, in this study, we applied machine learning methods to develop a more targeted off-pump CABG perioperative risk predictive model that accurately predicts CSA-AKI. Preoperative variables and intraoperative time series physiological data were used to optimise the predictive model. With the high computing power of today's computers and a variety of novel algorithms, machine learning can learn and analyse big medical data to discover potential connections within data, thereby increasing models' predictive and generalisation capabilities [15].

Methods

Study Population

In this retrospective cohort study, we analysed 477 patients who underwent off-pump CABG in the Department of Cardiac Surgery at the First Affiliated Hospital of Guangxi Medical University (No. 6 Shuangcang Road, Nanning, Guangxi Zhuang Autonomous Region, China) between 2012 and 2021. The exclusion criteria were as follows: 1. other concomitant surgical procedures, such as surgery combining valve and coronary artery bypass; 2. death within 48 hours after surgery; 3. emergency surgery; and 4. preoperative renal replacement therapy and renal transplantation.

Data Collection

We collected data on demographic characteristics, clinical status, preoperative biochemistry, preoperative medications, intraoperative blood product transfusions, intraoperative medication use, and postoperative biochemistry, such as weight, blood cell infusion, total adrenaline, pre-WBC, emergency postoperative-HCT and 1 day postoperative-MONO%.

Definition of Cardiac Surgery–Associated Acute Kidney Injury

The development of postoperative AKI was defined according to the KDIGO criteria during the first 7 days after surgery. Postoperative AKI was defined by an elevation of at least 50% within 7 days, or 0.3 mg/dL within 48 hours, with respect

to the reference serum creatinine level, with the preoperative serum creatinine level as the reference value [16].

Data Preprocessing

The following data preprocessing protocol was performed before data analysis: 1) data cleaning to identify missing values, outliers and duplicates, with missing values interpolated with the mean value, and 2) feature selection and extraction, in which the features (feature selection) or combinations of features (feature extraction) that were most useful/relevant for predictive model building were identified in the dataset.

Model Construction and Validation

The dataset was constructed from 477 patients and 293 variables. A total of 70% of the data was used for training, and 30% was used for validation. All analyses were developed in Python (version 3.5). The following machine learning methods were used to develop predictive models: logistic regression, simple decision trees, random forests, support vector machines, extreme gradient boosting and gradient boosted decision trees (GBDT). To evaluate the prediction and accuracy of the various machine learning models, we calculated and compared the area under the ROC curve enclosed by the coordinate axes (AUC). We used the Shapley additive expansion (SHAP) values for each predictive model [17] in each feature to provide consistent and locally accurate imputation values. This unified approach can be used for explaining the outcome of any machine learning model.

Results

Patients' demographic data and perioperative variables are listed in Table 1 (with abbreviations explained in the Table footnotes). Among 477 admitted patients, 88 had a CSA-AKI event within 7 days postoperatively (18.45%) cases. The following variables were more common in the CSA-AKI group than the non-AKI group: higher post-operative transfusion of red blood cells or plasma, longer duration of ventilator use and higher levosimendan dosage.

The predictive models' AUC curves are shown in Figure 1. GBDT exhibited the largest AUC (0.87). The main risk factors for predicting CSA-AKI were analysed with SHAP values to assess the characteristics' contributions to the GBDT model. Figure 2 illustrates the top ten features in the SHAP bar chart, according to the mean SHAP values, ranked from largest to smallest, and their mean magnitude of influence on the model output. The top ten variables that significantly influenced the model runs were 1-day postoperative K ion concentration, 1-day postoperative Mg ion concentration, 1-day postoperative CK, preoperative AST, total dopamine use, preoperative FT4, preoperative lymphocyte ratio, postoperative basophils, preoperative glucose and 1-day postoperative prothrombin activity, all of which were measured in serum. To identify the features with the greatest influence on the predictive model, we used a SHAP summary plot (Figure 3) and the top 20 features of the predictive model. This plot relates high and low feature values to SHAP values in the training dataset. According to the predictive model, the higher the SHAP value of a feature, the more likely AKI is to occur. The colours represent the feature values (The higher the SHAP value of a feature, the higher the probability of postoperative acute kidney injury development. Red represents high feature values, blue represents low feature values). The red direction on the right indicates that the feature has a positive influence on the model's prediction results, and the blue has a negative influence.

Discussion

In this retrospective cohort study, we developed and validated machine learning algorithms to predict CSA-AKI, based on 293 preoperative, intraoperative and postoperative features. The GBDT model had the largest AUC among the models tested. The most important variables are presented in SHAP bar charts, and each variable is described with SHAP summary plots. This study demonstrated the value of not only preoperative variables but also intraoperative and early postoperative data in predicting CSA-AKI. Our findings suggest that intraoperative medication affects early renal function decline after cardiac surgery and demonstrate additional early postoperative variables for predicting the occurrence of CSA-AKI.

Table 1 General Patient Characteristics and Perioperative Variables.[a]

Variables	Non-AKI	AKI	z/χ2	P
Sex (n, %)	320 (83.551)	73 (82.955)	0.02	0.892
Diabetes (n, %)	281 (73.368)	68 (77.273)	0.57	0.451
Hypertension (n, %)	165 (43.081)	30 (34.091)	2.38	0.123
Smoking history (n, %)	198 (51.832)	49 (55.682)	0.43	0.514
History of alcohol consumption (n, %)	277 (72.324)	59 (67.045)	0.98	0.323
Postoperative atrial fibrillation (n, %)	375 (97.911)	81 (92.045)	7.99	0.005**
CRRT (n, %)	379 (98.956)	76 (86.364)	34.58	0.000***
Secondary surgery (n, %)	373 (97.389)	83 (94.318)	2.19	0.139
Age (years, Md [IQR])	61.000 (55.000, 66.000)	63.000 (57.250, 67.000)	−2.12	0.034*
Height (cm, Md [IQR])	165.000 (160.000, 170.000)	163.000 (158.000, 169.000)	−1.55	0.120
Weight (kg, Md [IQR])	64.000 (57.000, 72.000)	63.000 (55.000, 69.750)	−1.38	0.169
Intraoperative red blood cell infusion (U, Md [IQR])	4.000 (3.000, 6.000)	4.000 (3.000, 6.000)	−0.41	0.682
Intraoperative plasma transfusion (mL, Md [IQR])	400.000 (190.000, 600.000)	400.000 (262.500, 600.000)	−0.90	0.370
Postoperative plasma transfusion (mL, Md [IQR])	400.000 (0.000, 700.000)	600.000 (200.000, 1050.000)	−3.63	0.000***
Ventilator use time (h, Md [IQR])	23.488 (19.830, 32.500)	26.580 (20.270, 73.348)	−2.57	0.010*
Total dopamine (mg, Md [IQR])	1100.000 (660.000, 1680.000)	1090.000 (490.000, 2260.000)	−0.90	0.368
Total adrenaline (mg, Md [IQR])	1.000 (0.250, 3.000)	1.000 (0.250, 3.000)	−1.61	0.108
Total norepinephrine (mg, Md [IQR])	2.000 (0.000, 4.000)	4.000 (2.000, 15.075)	−5.26	0.000***
Time of IABP (h, Md [IQR])	0.000 (0.000, 29.000)	33.500(0.000, 72.000)	−4.72	0.000***
Pre-WBC (L^{-1}, $\times 10^9$, Md [IQR])	6.740 (5.730, 7.880)	6.760 (5.635, 8.287)	−0.40	0.693
Pre-RBC (L^{-1}, $\times 10^9$, Md [IQR])	4.460 (4.060, 4.800)	4.290 (4.022, 4.625)	−2.13	0.033*
Pre-HG ($g \cdot L^{-1}$, Md [IQR])	131.400 (119.400, 139.800)	130.300 (116.100, 137.750)	−1.21	0.225
Pre-PLT (L^{-1}, $\times 10^9$, Md [IQR])	226.000 (183.100, 263.100)	222.350 (182.675, 273.525)	−0.12	0.908
Pre-N% (%, Md [IQR])	0.579 (0.522, 0.645)	0.643 (0.544, 0.700)	−3.71	0.000***
Pre-L% (%, Md [IQR])	0.293 (0.238, 0.344)	0.246 (0.196, 0.329)	−2.47	0.013*
Pre-MONO% (%, Md [IQR])	0.086 (0.072, 0.105)	0.086 (0.072, 0.100)	−0.58	0.561
Pre-EO% (%, Md [IQR])	0.038 (0.023, 0.062)	0.034 (0.021, 0.071)	−0.32	0.752
Pre-BASO% (%, Md [IQR])	0.005 (0.004, 0.007)	0.005 (0.004, 0.008)	−0.01	0.990
Pre-N (L^{-1}, $\times 10^9$, Md [IQR])	3.830 (3.060, 4.900)	4.065 (3.163, 5.045)	−0.89	0.373
Pre-L (L^{-1}, $\times 10^9$, Md [IQR])	1.950 (1.550, 2.370)	1.600 (1.130, 2.165)	−3.81	0.000***
Pre-MONO (L^{-1}, $\times 10^9$, Md [IQR])	0.570 (0.460, 0.710)	0.530 (0.460, 0.700)	−1.07	0.285
Pre-EOS (L^{-1}, $\times 10^9$, Md [IQR])	0.240 (0.140, 0.400)	0.210 (0.103, 0.367)	−1.74	0.081
Pre-BASO (L^{-1}, $\times 10^9$, Md [IQR])	0.040 (0.020, 0.050)	0.030 (0.020, 0.050)	−1.91	0.056
Pre-MCV (fL, Md [IQR])	89.610 (86.030, 92.730)	90.495 (85.472, 93.450)	−0.89	0.373

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ2	P
Pre-MCHpg, Md [IQR]	29.790 (28.400, 30.850)	29.770 (28.157, 31.098)	−0.52	0.604
Pre-MCHC (g·L⁻¹, Md [IQR])	330.000 (322.800, 336.300)	329.100 (324.200, 333.950)	−0.82	0.413
Pre-HCT (L·L⁻¹, Md [IQR])	0.393 (0.351, 0.419)	0.381 (0.328, 0.416)	−1.25	0.212
Pre-RDWCV (%, Md [IQR])	0.140 (0.130, 0.150)	0.140 (0.130, 0.150)	−0.30	0.762
Pre-PDW (fL, Md [IQR])	0.160 (0.160, 0.170)	0.160 (0.160, 0.170)	−0.90	0.368
Pre-PCT (%, Md [IQR])	0.190 (0.160, 0.220)	0.180 (0.161, 0.220)	−0.21	0.835
Pre-MPV (fL, Md [IQR])	8.500 (7.700, 9.160)	8.420 (7.500, 9.398)	−0.46	0.649
Pre-TBiL (umol·L⁻¹, Md [IQR])	9.100 (6.600, 12.300)	8.750 (6.800, 12.900)	−0.18	0.856
Pre-Dbil (umol·L⁻¹, Md [IQR])	2.900 (2.100, 3.800)	2.800 (2.125, 3.700)	−0.30	0.763
Pre-Ibil (umol·L⁻¹, Md [IQR])	6.200 (4.300, 8.600)	6.050 (4.500, 9.200)	−0.47	0.636
Pre-DB/TB (%, Md [IQR])	0.300 (0.300, 0.400)	0.300 (0.300, 0.400)	−1.09	0.275
Pre-TP (g·L⁻¹, Md [IQR])	66.700 (62.900, 70.400)	65.200 (61.025, 69.450)	−2.28	0.022*
Pre-ALB (g·L⁻¹, Md [IQR])	39.700 (37.200, 41.900)	39.400 (36.250, 41.525)	−1.36	0.174
Pre-GLO (g·L⁻¹, Md [IQR])	26.800 (24.300, 30.300)	26.600 (24.150, 29.150)	−0.63	0.530
Pre-A/G (%, Md [IQR])	1.500 (1.300, 1.700)	1.400 (1.300, 1.700)	−0.38	0.702
Pre-GGT (U·L⁻¹, Md [IQR])	35.000 (24.000, 56.000)	32.500 (22.000, 41.000)	−1.42	0.155
Pre-TBA (umol·L⁻¹, Md [IQR])	4.600 (2.900, 7.600)	4.700 (2.500, 8.525)	−0.31	0.759
Pre-AST (U·L⁻¹, Md [IQR])	23.000 (19.000, 30.000)	25.500 (20.000, 33.750)	−1.63	0.102
Pre-ALT (U·L⁻¹, Md [IQR])	24.000 (17.000, 37.000)	24.000 (16.250, 36.750)	−0.31	0.757
Pre-AST/ALT (Md [IQR])	0.900 (0.700, 1.200)	1.000 (0.725, 1.400)	−1.31	0.192
Pre-ALP (U·L⁻¹, Md [IQR])	75.000 (60.000, 92.000)	72.500 (62.250, 92.000)	−0.74	0.462
Pre-PA (mg·L⁻¹, Md [IQR])	248.400 (214.800, 283.400)	221.300 (190.475, 274.350)	−2.94	0.003**
Pre-CHE (U·L⁻¹, Md [IQR])	8074.000 (7128.000, 9114.000)	7704.500 (6282.750, 8657.250)	−2.48	0.013*
Pre-CREA (umol·L⁻¹, Md [IQR])	87.000 (76.000, 103.000)	87.500 (69.000, 104.000)	−0.73	0.467
Pre-T*CHO (mmol·L⁻¹, Md [IQR])	4.130 (3.310, 4.940)	4.360 (3.792, 5.105)	−1.54	0.125
Pre-TG (mmol·L⁻¹, Md [IQR])	1.300 (0.950, 1.960)	1.305 (0.925, 1.780)	−0.42	0.676
Pre-HDL*C (mmol·L⁻¹, Md [IQR])	0.990 (0.790, 1.220)	1.000 (0.742, 1.198)	−0.41	0.679
Pre-LDL*C (mmol·L⁻¹, Md [IQR])	2.370 (1.740, 2.990)	2.755 (2.032, 3.213)	−2.36	0.018*
Pre-GLU (mmol·L⁻¹, Md [IQR])	4.640 (3.830, 5.290)	4.770 (4.150, 5.338)	−0.80	0.425
Pre-K (mmol·L⁻¹, Md [IQR])	4.050 (3.790, 4.320)	4.015 (3.790, 4.268)	−0.45	0.654
Pre-Na (mmol·L⁻¹, Md [IQR])	140.300 (138.500, 141.800)	139.750 (138.300, 141.500)	−0.98	0.325
Pre-CL (mmol·L⁻¹, Md [IQR])	104.500 (102.100, 106.400)	105.050 (102.300, 107.000)	−1.23	0.219
Pre-Ca (mmol·L⁻¹, Md [IQR])	2.259 (2.177, 2.320)	2.268 (2.174, 2.330)	−0.80	0.426
Pre-Mg (mmol·L⁻¹, Md [IQR])	0.880 (0.810, 0.940)	0.880 (0.820, 0.927)	−0.08	0.937

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ2	P
Pre-P (mmol·L⁻¹, Md [IQR])	0.000 (0.000, 1.070)	0.885 (0.000, 1.098)	-1.42	0.157
Pre-CK (U·L⁻¹, Md [IQR])	76.000 (56.000, 104.000)	83.000 (58.500, 115.250)	-1.28	0.200
Pre-CK*MB (U·L⁻¹, Md [IQR])	14.000 (11.000, 17.000)	13.000 (10.000, 17.750)	-1.12	0.263
Pre-LD (U·L⁻¹, Md [IQR])	185.000 (159.000, 219.000)	190.000 (163.250, 212.750)	-0.84	0.400
Pre-LD1 (U·L⁻¹, Md [IQR])	47.000 (36.000, 57.000)	47.000 (35.250, 61.000)	-0.68	0.494
Pre-HBD (U·L⁻¹, Md [IQR])	130.000 (114.000, 150.000)	138.500 (119.000, 157.000)	-1.82	0.069
Pre-CK*MB/CK (%, Md [IQR])	0.180 (0.120, 0.250)	0.175 (0.100, 0.270)	-0.77	0.439
Pre-PT (s, Md [IQR])	10.900 (10.400, 11.600)	11.000 (10.500, 11.775)	-1.62	0.104
Pre-INR (%, Md [IQR])	0.920 (0.880, 0.980)	0.930 (0.890, 0.980)	-0.97	0.335
Pre-PTA (%, Md [IQR])	91.000 (2.780, 109.000)	78.500 (3.712, 108.000)	-0.44	0.661
Pre-FIB (g·L⁻¹, Md [IQR])	4.110 (3.440, 5.120)	4.310 (3.542, 7.688)	-1.02	0.309
Pre-APTT (s, Md [IQR])	32.300 (27.700, 35.600)	31.300 (13.400, 35.175)	-1.44	0.150
Pre-TT (s, Md [IQR])	12.400 (11.600, 13.900)	13.050 (12.100, 96.500)	-2.75	0.006**
Pre-Urine Specific gravity (%, Md [IQR])	1.020 (1.015, 1.025)	1.020 (1.015, 4.008)	-0.40	0.691
Pre-Urine PH(Md [IQR])	5.500 (5.000, 6.000)	5.500 (1.020, 6.500)	-0.33	0.744
Pre-TnI (u·L⁻¹, Md [IQR])	0.010 (0.002, 0.028)	0.010 (0.003, 0.034)	-0.48	0.631
Pre-T3 (nmol·L⁻¹, Md [IQR])	1.620 (1.100, 1.900)	1.620 (1.065, 1.938)	-0.13	0.894
Pre-T4 (nmol·L⁻¹, Md [IQR])	98.980 (70.130, 121.160)	91.665 (74.363, 109.780)	-1.61	0.107
Pre-FT3 (pmol·L⁻¹, Md [IQR])	4.270 (3.530, 4.790)	4.260 (3.700, 4.643)	-0.27	0.791
Pre-FT4 (mIU·L⁻¹, Md [IQR])	10.190 (7.600, 12.050)	10.010 (7.867, 11.787)	-0.17	0.863
Pre-TSH (pmol·L⁻¹, Md [IQR])	1.530 (0.470, 2.650)	1.780 (0.715, 2.410)	-0.58	0.565
Emergency postoperative-WBC (L⁻¹, ×10⁹, Md [IQR])	13.910 (11.050, 16.600)	13.265 (11.140, 16.047)	-0.77	0.439
Emergency postoperative-RBC (L⁻¹, ×10⁹, Md [IQR])	4.230 (3.720, 4.610)	4.000 (3.627, 4.400)	-1.77	0.077
Emergency postoperative-HG (g·L⁻¹, Md [IQR])	122.800 (108.800, 132.300)	118.500 (106.900, 128.800)	-1.39	0.166
Emergency postoperative-PLT	167.200 (128.300, 200.900)	156.150 (94.733, 189.175)	-2.14	0.032*
Emergency postoperative-N% (%, Md [IQR])	0.873 (0.841, 0.905)	0.867 (0.833, 0.895)	-1.23	0.219
Emergency postoperative-L% (%, Md [IQR])	0.058 (0.042, 0.093)	0.063 (0.047, 0.133)	-2.24	0.025*
Emergency postoperative-MONO% (%, Md [IQR])	0.064 (0.044, 0.083)	0.063 (0.045, 0.089)	-0.84	0.399
Emergency postoperative-N (L⁻¹, ×10⁹, Md [IQR])	11.710 (9.160, 14.170)	11.010 (8.727, 13.273)	-1.99	0.047*
Emergency postoperative-L (L⁻¹, ×10⁹, Md [IQR])	0.790 (0.580, 1.140)	0.905 (0.620, 1.475)	-2.30	0.021*
Emergency postoperative-MONO (L⁻¹, ×10⁹, Md [IQR])	0.820 (0.530, 1.160)	0.790 (0.497, 1.008)	-1.10	0.273
Emergency postoperative-BASO (L⁻¹, ×10⁹, Md [IQR])	0.010 (0.000, 0.010)	0.010 (0.000, 0.030)	-1.38	0.167
Emergency postoperative-MCV (fL, Md [IQR])	88.250 (85.000, 90.770)	88.400 (82.425, 91.448)	-0.03	0.974
Emergency postoperative-MCH (pg, Md [IQR])	29.370 (28.040, 30.400)	29.000 (26.762, 30.635)	-0.84	0.401

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ2	P
Emergency postoperative-MCHC (g·L⁻¹, Md [IQR])	330.700 (324.300, 337.800)	329.400 (318.925, 336.500)	−1.51	0.130
Emergency postoperative-HCT (L·L⁻¹, Md [IQR])	0.365 (0.320, 0.400)	0.345 (0.300, 0.380)	−2.59	0.010**
Emergency postoperative-RDWCV (%, Md [IQR])	0.150 (0.140, 0.170)	0.150 (0.140, 0.170)	−0.53	0.596
Emergency postoperative-PDW (fL, Md [IQR])	0.160 (0.160, 0.170)	0.170 (0.160, 0.170)	−1.90	0.058
Emergency postoperative-PCT (%, Md [IQR])	0.150 (0.120, 0.180)	0.140 (0.112, 0.178)	−0.85	0.396
Emergency postoperative-MPV (fL, Md [IQR])	8.600 (7.970, 9.320)	8.495 (7.603, 9.200)	−1.45	0.148
Emergency postoperative-TBiL (umol·L⁻¹, Md [IQR])	14.800 (10.900, 19.700)	14.250 (9.500, 18.750)	−1.53	0.126
Emergency postoperative-Dbil (umol·L⁻¹, Md [IQR])	5.300 (3.900, 7.600)	4.700 (3.100, 8.125)	−1.13	0.260
Emergency postoperative-Ibil (umol·L⁻¹, Md [IQR])	9.000 (6.800, 12.700)	8.250 (5.500, 12.200)	−1.91	0.056
Emergency postoperative-DB/TB (%, Md [IQR])	0.400 (0.300, 0.400)	0.400 (0.300, 0.420)	−1.20	0.231
Emergency postoperative-TP (g·L⁻¹, Md [IQR])	59.800 (54.300, 65.200)	58.400 (48.300, 63.950)	−1.52	0.128
Emergency postoperative-ALB (g·L⁻¹, Md [IQR])	36.900 (33.900, 40.300)	36.500 (31.625, 38.875)	−2.38	0.017*
Emergency postoperative-GLO (g·L⁻¹, Md [IQR])	22.500 (19.400, 25.800)	21.550 (18.000, 26.250)	−0.91	0.363
Emergency postoperative-A/G (%, Md [IQR])	1.600 (1.400, 1.800)	1.600 (1.400, 1.800)	−0.86	0.390
Emergency postoperative-GGT (U·L⁻¹, Md [IQR])	32.000 (24.000, 50.000)	32.000 (20.250, 45.000)	−0.94	0.345
Emergency postoperative-TBA (umol·L⁻¹, Md [IQR])	0.700 (0.400, 1.100)	0.800 (0.425, 1.400)	−1.55	0.122
Emergency postoperative-AST (U·L⁻¹, Md [IQR])	32.000 (23.000, 47.000)	32.500 (27.250, 40.750)	−0.64	0.523
Emergency postoperative-ALT (U·L⁻¹, Md [IQR])	31.000 (22.000, 46.000)	30.000 (19.000, 43.000)	−1.16	0.246
Emergency postoperative-AST/ALT (Md [IQR])	1.000 (0.800, 1.400)	1.200 (0.900, 1.500)	−2.73	0.006**
Emergency postoperative-ALP (U·L⁻¹, Md [IQR])	62.000 (49.000, 78.000)	63.000 (47.250, 75.000)	−0.06	0.956
Emergency postoperative-PA (mg·L⁻¹, Md [IQR])	208.900 (177.700, 237.900)	191.950 (154.050, 227.575)	−1.84	0.065
Emergency postoperative-CHE (U·L⁻¹, Md [IQR])	7062.000 (6115.000, 8045.000)	6386.500 (5657.000, 7979.500)	−1.72	0.086
Emergency postoperative-CREA (umol·L⁻¹, Md [IQR])	85.000 (72.000, 103.000)	106.000 (80.000, 142.000)	−4.84	0.000***
Emergency postoperative-K (mmol·L⁻¹, Md [IQR])	4.430 (4.140, 4.690)	4.500 (4.070, 4.880)	−1.54	0.124
Emergency postoperative-Na	140.500 (138.400, 142.600)	140.800 (138.525, 144.025)	−2.12	0.034*
Emergency postoperative-CL (mmol·L⁻¹, Md [IQR])	104.400 (101.400, 107.300)	105.300 (103.050, 107.800)	−2.16	0.031*
Emergency postoperative-Ca (mmol·L⁻¹, Md [IQR])	2.150 (2.030, 2.245)	2.160 (2.083, 2.238)	−0.97	0.331
Emergency postoperative-Mg (mmol·L⁻¹, Md [IQR])	1.090 (0.950, 1.250)	1.195 (1.000, 1.460)	−3.38	0.001***
Emergency postoperative-P (mmol·L⁻¹, Md [IQR])	0.000 (0.000, 1.190)	0.835 (0.000, 1.270)	−2.11	0.035*
Emergency postoperative-CK (U·L⁻¹, Md [IQR])	212.000 (0.000, 404.000)	209.500 (100.000, 358.750)	−0.40	0.693
Emergency postoperative-CK*MB (U·L⁻¹, Md [IQR])	16.000 (0.000, 24.000)	18.000 (11.000, 24.000)	−1.86	0.062
Emergency postoperative-LD (U·L⁻¹, Md [IQR])	232.000 (0.000, 304.000)	233.000 (185.000, 316.000)	−1.36	0.175
Emergency postoperative-LD1 (U·L⁻¹, Md [IQR])	44.000 (0.000, 63.000)	52.000 (25.000, 78.000)	−2.50	0.012*
Emergency postoperative-HBD (U·L⁻¹, Md [IQR])	152.000 (0.000, 202.000)	161.000 (124.500, 214.750)	−1.60	0.109

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ^2	P
Emergency postoperative-CK*MB/CK (%, Md [IQR])	0.050 (0.000, 0.080)	0.075 (0.030, 0.110)	−3.37	0.001***
Emergency postoperative-RBP (mg/L, Md [IQR])	0.000 (0.000, 34.600)	20.850 (0.000, 36.900)	−1.95	0.051
Emergency postoperative-PT (s, Md [IQR])	11.900 (11.000, 12.800)	12.000 (11.400, 13.500)	−1.89	0.059
Emergency postoperative-INR (%, Md [IQR])	1.000 (0.930, 1.070)	1.000 (0.962, 1.075)	−0.56	0.578
Emergency postoperative-PTA (%, Md [IQR])	80.000 (2.250, 98.000)	80.000 (4.183, 97.750)	−0.72	0.474
Emergency postoperative-FIB (g·L⁻¹, Md [IQR])	4.940 (3.990, 6.110)	4.830 (3.025, 5.735)	−1.60	0.110
Emergency postoperative-APTT (s, Md [IQR])	31.100 (16.600, 36.200)	31.000 (12.900, 36.000)	−0.43	0.667
Emergency postoperative-TT (s, Md [IQR])	12.000 (10.700, 15.000)	13.200 (11.600, 73.250)	−2.88	0.004**
Postoperative serum troponin I (u·L⁻¹, Md [IQR])	0.000 (0.000, 0.229)	0.000 (0.000, 0.447)	−0.87	0.387
1 day postoperative-WBC (L⁻¹, ×10⁹, Md [IQR])	15.160 (11.990, 18.750)	15.810 (13.050, 19.170)	−1.13	0.260
1 day postoperative-RBC (L⁻¹, ×10⁹, Md [IQR])	3.770 (3.280, 4.250)	3.535 (3.107, 3.917)	−2.96	0.003**
1 day postoperative-HG (g·L⁻¹, Md [IQR])	109.000 (97.000, 122.100)	103.450 (92.000, 115.650)	−2.39	0.017*
1 day postoperative-PLT (L⁻¹, ×10⁹, Md [IQR])	149.200 (108.400, 187.300)	133.400 (93.530, 175.800)	−1.74	0.081
1 day postoperative-N% (%, Md [IQR])	0.883 (0.855, 0.907)	0.888 (0.851, 0.919)	−1.35	0.177
1 day postoperative-L% (%, Md [IQR])	0.049 (0.035, 0.067)	0.058 (0.037, 0.077)	−2.62	0.009**
1 day postoperative-MONO% (%, Md [IQR])	0.067 (0.050, 0.082)	0.071 (0.051, 0.101)	−1.86	0.063
1 day postoperative-EO% (%, Md [IQR])	0.000 (0.000, 0.000)	0.000 (0.000, 0.001)	−2.16	0.030*
1 day postoperative-BASO% (%, Md [IQR])	0.000 (0.000, 0.001)	0.001 (0.000, 0.001)	−1.88	0.061
1 day postoperative-N (L⁻¹, ×10⁹, Md [IQR])	13.100 (9.840, 16.640)	12.570 (9.105, 16.670)	−0.45	0.657
1 day postoperative-L (L⁻¹, ×10⁹, Md [IQR])	0.710 (0.510, 0.960)	0.790 (0.590, 1.070)	−2.29	0.022*
1 day postoperative-MONO (L⁻¹, ×10⁹, Md [IQR])	0.960 (0.660, 1.270)	1.005 (0.615, 1.360)	−0.30	0.767
1 day postoperative-EOS (L⁻¹, ×10⁹, Md [IQR])	0.000 (0.000, 0.010)	0.000 (0.000, 0.010)	−2.61	0.009**
1 day postoperative-BASO (L⁻¹, ×10⁹, Md [IQR])	0.000 (0.000, 0.010)	0.010 (0.000, 0.018)	−2.03	0.042*
1 day postoperative-MCV (fL, Md [IQR])	88.400 (84.590, 91.000)	88.015 (84.710, 92.203)	−0.16	0.873
1 day postoperative-MCH (pg, Md [IQR])	29.480 (28.100, 30.430)	29.460 (27.320, 30.565)	−0.21	0.837
1 day postoperative-MCHC (g·L⁻¹, Md [IQR])	330.830 (323.600, 336.200)	331.150 (322.375, 336.550)	−0.03	0.977
1 day postoperative-HCT (L·L⁻¹, Md [IQR])	0.330 (0.285, 0.370)	0.302 (0.249, 0.340)	−3.61	0.000***
1 day postoperative-RDWCV (%, Md [IQR])	0.150 (0.140, 0.170)	0.150 (0.140, 0.170)	−1.14	0.256
1 day postoperative-PDW (fL, Md [IQR])	0.160 (0.160, 0.170)	0.170 (0.160, 0.170)	−2.44	0.015*
1 day postoperative-PCT (%, Md [IQR])	0.140 (0.110, 0.172)	0.142 (0.107, 0.177)	−0.04	0.965
1 day postoperative-MPV (fL, Md [IQR])	8.900 (8.140, 9.580)	8.830 (7.978, 9.800)	−0.23	0.819
1 day postoperative-TBiL (umol·L⁻¹, Md [IQR])	11.100 (7.600, 16.100)	12.800 (8.650, 16.675)	−1.36	0.173
1 day postoperative-Dbil (umol·L⁻¹, Md [IQR])	4.400 (3.000, 6.300)	5.100 (2.925, 7.600)	−1.84	0.065
1 day postoperative-Ibil (umol·L⁻¹, Md [IQR])	4.400 (0.000, 8.300)	4.900 (0.000, 7.975)	−0.14	0.891

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ2	P
1 day postoperative-DB/TB (%, Md [IQR])	0.300 (0.000, 0.400)	0.000 (0.000, 0.400)	−0.80	0.425
1 day postoperative-TP (g·L⁻¹, Md [IQR])	0.000 (0.000, 58.800)	0.000 (0.000, 53.200)	−1.58	0.114
1 day postoperative-ALB (g·L⁻¹, Md [IQR])	38.500 (35.100, 41.400)	38.750 (35.825, 40.875)	−0.61	0.544
1 day postoperative-GLO (g·L⁻¹, Md [IQR])	0.000 (0.000, 22.300)	0.000 (0.000, 18.075)	−1.35	0.178
1 day postoperative-A/G (%, Md [IQR])	0.000 (0.000, 1.300)	0.000 (0.000, 1.125)	−1.52	0.128
1 day postoperative-GGT (U·L⁻¹, Md [IQR])	0.000 (0.000, 24.000)	0.000 (0.000, 21.750)	−1.10	0.271
1 day postoperative-TBA (umol·L⁻¹, Md [IQR])	0.000 (0.000, 0.700)	0.000 (0.000, 0.525)	−1.25	0.211
1 day postoperative-AST (U·L⁻¹, Md [IQR])	0.000 (0.000, 29.000)	0.000 (0.000, 33.750)	−0.06	0.952
1 day postoperative-ALT (U·L⁻¹, Md [IQR])	22.000 (0.000, 34.000)	19.000 (0.000, 32.500)	−1.62	0.106
1 day postoperative-AST/ALT (Md [IQR])	0.000 (0.000, 0.900)	0.000 (0.000, 0.675)	−1.04	0.296
1 day postoperative-ALP (U·L⁻¹, Md [IQR])	0.000 (0.000, 51.000)	0.000 (0.000, 37.750)	−1.31	0.192
1 day postoperative-PA (mg·L⁻¹, Md [IQR])	0.000 (0.000, 149.700)	0.000 (0.000, 141.000)	−1.35	0.178
1 day postoperative-CHE (U·L⁻¹, Md [IQR])	0.000 (0.000, 5964.000)	0.000 (0.000, 4474.000)	−1.86	0.064
1 day postoperative-CREA (umol·L⁻¹, Md [IQR])	90.000 (72.000, 111.000)	154.500 (113.000, 204.000)	−10.27	0.000***
1 day postoperative-K (mmol·L⁻¹, Md [IQR])	4.460 (4.160, 4.710)	4.640 (4.245, 4.908)	−3.44	0.001***
1 day postoperative-Na (mmol·L⁻¹, Md [IQR])	139.700 (137.000, 142.500)	140.300 (138.575, 144.275)	−2.23	0.026*
1 day postoperative-CL	102.600 (99.200, 105.100)	101.700 (99.600, 105.525)	−0.42	0.673
1 day postoperative-Ca (mmol·L⁻¹, Md [IQR])	2.197 (2.089, 2.292)	2.240 (2.131, 2.359)	−2.86	0.004**
1 day postoperative-Mg (mmol·L⁻¹, Md [IQR])	1.110 (0.960, 1.280)	1.250 (1.090, 1.417)	−4.81	0.000***
1 day postoperative-P (mmol·L⁻¹, Md [IQR])	0.000 (0.000, 1.000)	0.795 (0.000, 1.212)	−2.81	0.005**
1 day postoperative-CK (mmol·L⁻¹, Md [IQR])	262.000 (0.000, 624.000)	342.000 (0.000, 922.750)	−2.13	0.033*
1 day postoperative-CK*MB (U·L⁻¹, Md [IQR])	13.000 (0.000, 22.000)	15.000 (0.000, 25.000)	−1.79	0.074
1 day postoperative-LD (U·L⁻¹, Md [IQR])	226.000 (0.000, 307.000)	269.000 (0.000, 355.500)	−2.51	0.012*
1 day postoperative-LD1 (U·L⁻¹, Md [IQR])	43.000 (0.000, 72.000)	54.000 (0.000, 83.250)	−1.50	0.133
1 day postoperative-HBD (U·L⁻¹, Md [IQR])	151.000 (0.000, 211.000)	182.000 (0.000, 251.250)	−2.58	0.010*
1 day postoperative-CK*MB/CK (%, Md [IQR])	0.020 (0.000, 0.040)	0.030 (0.000, 0.040)	−0.45	0.653
1 day postoperative-PT (s, Md [IQR])	11.000 (9.200, 11.800)	11.250 (10.225, 12.650)	−2.72	0.007**
1 day postoperative-INR (%, Md [IQR])	0.930 (0.810, 1.010)	0.960 (0.903, 1.075)	−2.81	0.005**
1 day postoperative-PTA (%, Md [IQR])	4.880 (0.000, 100.000)	73.500 (4.610, 99.750)	−2.76	0.006**
1 day postoperative-FIB (g·L⁻¹, Md [IQR])	5.460 (0.000, 7.210)	5.785 (3.590, 7.070)	−0.85	0.395
1 day postoperative-TT (s, Md [IQR])	0.000 (0.000, 12.600)	9.550 (0.000, 43.000)	−1.19	0.235
Predischarge WBC (L⁻¹, ×10⁹, Md [IQR])	11.580 (9.540, 13.430)	11.335 (9.258, 14.240)	−0.28	0.782
Predischarge RBC (L⁻¹, ×10⁹, Md [IQR])	3.700 (3.210, 4.250)	3.270 (2.955, 3.790)	−4.20	0.000***
Predischarge HG (g·L⁻¹, Md [IQR])	107.000 (93.400, 121.500)	95.150 (86.350, 109.925)	−4.11	0.000***

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ2	P
Predischarge PLT (L⁻¹, ×10⁹, Md [IQR])	272.000 (204.200, 349.600)	240.150 (136.525, 319.500)	−2.58	0.010**
Predischarge N% (%, Md [IQR])	0.733 (0.670, 0.786)	0.758(0.696, 0.857)	−2.90	0.004**
Predischarge L% (%, Md [IQR])	0.159 (0.122, 0.214)	0.149 (0.093, 0.207)	−1.02	0.309
Predischarge MONO% (%, Md [IQR])	0.082 (0.064, 0.100)	0.083 (0.062, 0.105)	−0.09	0.926
Predischarge EO% (%, Md [IQR])	0.026 (0.012, 0.044)	0.036 (0.012, 0.058)	−1.98	0.048*
Predischarge BASO% (%, Md [IQR])	0.003 (0.001, 0.004)	0.003 (0.001, 0.005)	−0.07	0.947
Predischarge N (L⁻¹, ×10⁹, Md [IQR])	8.000 (6.470, 10.070)	7.455 (5.980, 11.020)	−0.32	0.749
Predischarge L (L⁻¹, ×10⁹, Md [IQR])	1.700 (1.230, 2.250)	1.550 (1.022, 2.100)	−2.13	0.033*
Predischarge MONO (L⁻¹, ×10⁹, Md [IQR])	0.900 (0.650, 1.100)	0.795 (0.510, 1.008)	−2.26	0.024*
Predischarge EOS (L⁻¹, ×10⁹, Md [IQR])	0.280 (0.130, 0.460)	0.340 (0.133, 0.607)	−1.87	0.062
Predischarge BASO (L⁻¹, ×10⁹, Md [IQR])	0.030 (0.010, 0.050)	0.030 (0.010, 0.050)	−0.41	0.679
Predischarge MCV (fL, Md [IQR])	89.290 (85.780, 92.100)	89.880 (85.175, 92.892)	−0.62	0.536
Predischarge MCH (pg, Md [IQR])	29.400 (28.040, 30.280)	29.400 (27.700, 30.590)	−0.28	0.783
Predischarge MCHC (g·L⁻¹, Md [IQR])	328.000 (322.000, 334.000)	325.250 (316.225, 331.525)	−2.59	0.010**
Predischarge HCT (L·L⁻¹, Md [IQR])	0.323 (0.279, 0.370)	0.280 (0.250, 0.332)	−4.13	0.000***
Predischarge RDWCV (%, Md [IQR])	0.150 (0.140, 0.170)	0.160 (0.140, 0.190)	−3.45	0.001***
Predischarge PDW (fL, Md [IQR])	0.170 (0.160, 0.170)	0.170 (0.160, 0.180)	−3.60	0.000***
Predischarge PCT (%, Md [IQR])	0.233 (0.184, 0.300)	0.229 (0.175, 0.299)	−0.74	0.461
Predischarge MPV (fL, Md [IQR])	8.260 (7.520, 9.090)	8.275 (7.490, 9.085)	−0.09	0.931
Predischarge TBiL (umol·L⁻¹, Md [IQR])	11.900 (8.400, 17.300)	13.400 (8.425, 17.625)	−0.76	0.446
Predischarge Dbil (umol·L⁻¹, Md [IQR])	4.000 (2.900, 6.000)	4.550 (2.700, 7.100)	−0.79	0.432
Predischarge Ibil (umol·L⁻¹, Md [IQR])	8.000 (5.000, 10.900)	8.450 (4.975, 10.575)	−0.67	0.500
Predischarge DB/TB (%, Md [IQR])	0.300 (0.300, 0.400)	0.340 (0.240, 0.400)	−0.13	0.899
Predischarge TP(g·L⁻¹, Md [IQR])	62.900 (58.100, 67.500)	61.500 (52.575, 65.525)	−3.11	0.002**
Predischarge ALB	36.300 (33.100, 39.500)	35.250 (31.325, 38.600)	−1.43	0.152
Predischarge GLO (g·L⁻¹, Md [IQR])	26.000 (22.700, 29.900)	23.800 (20.050, 27.375)	−3.25	0.001**
Predischarge A/G (%, Md [IQR])	1.300 (1.100, 1.500)	1.300 (1.000, 1.600)	−0.25	0.806
Predischarge GGT (U·L⁻¹, Md [IQR])	52.000 (33.000, 118.000)	41.000 (17.250, 93.000)	−2.72	0.007**
Predischarge TBA (umol·L⁻¹, Md [IQR])	2.200 (1.300, 4.500)	1.800 (0.900, 4.550)	−1.38	0.168
Predischarge AST (U·L⁻¹, Md [IQR])	28.000 (18.000, 38.000)	26.000 (18.000, 42.000)	−0.15	0.883
Predischarge ALT (U·L⁻¹, Md [IQR])	31.000 (18.000, 55.000)	25.000 (15.000, 62.000)	−0.80	0.427
Predischarge AST/ALT (Md [IQR])	0.800 (0.500, 1.200)	0.900 (0.400, 1.375)	−0.73	0.468
Predischarge ALP (U·L⁻¹, Md [IQR])	78.000 (58.000, 103.000)	71.500 (47.750, 91.750)	−2.21	0.027*
Predischarge PA (mg·L⁻¹, Md [IQR])	190.400 (148.200, 230.400)	160.700 (123.575, 214.500)	−2.85	0.004**

Table 1 (continued)

Variables	Non-AKI	AKI	z/χ2	P
Predischarge CHE (U·L⁻¹, Md [IQR])	5979.000 (4957.000, 7050.000)	5326.000 (3006.500, 6447.000)	−3.693	0.000***
Predischarge UREA (umol·L⁻¹, Md [IQR])	9.950 (6.680, 12.860)	12.215 (8.770, 16.300)	−3.879	0.000***
Predischarge CREA (umol·L⁻¹, Md [IQR])	92.000 (71.000, 117.000)	123.000 (91.000, 164.000)	−5.726	0.000***
Predischarge UA (umol·L⁻¹, Md [IQR])	308.000 (203.000, 392.000)	282.500 (198.000, 424.250)	−0.015	0.988
Predischarge HCO3 (umol·L⁻¹, Md [IQR])	25.500 (22.200, 27.800)	23.500 (20.200, 27.350)	−2.199	0.028*
Predischarge CCR	60.000 (42.000, 78.000)	46.200 (20.750, 64.750)	−3.806	0.000***
Predischarge CysC (mg·L⁻¹, Md [IQR])	1.116 (0.862, 1.403)	1.263 (0.957, 1.726)	−2.514	0.012*
Predischarge K (mmol·L⁻¹, Md [IQR])	4.340 (3.960, 4.630)	4.440 (3.990, 4.982)	−2.575	0.010*
Predischarge Na (mmol·L⁻¹, Md [IQR])	136.700 (134.000, 139.300)	137.200 (134.700, 139.425)	−1.428	0.153
Predischarge CL (mmol·L⁻¹, Md [IQR])	99.500 (96.200, 102.800)	100.900 (96.925, 103.275)	−1.438	0.150
Predischarge Ca (mmol·L⁻¹, Md [IQR])	2.178 (2.078, 2.260)	2.183 (2.085, 2.363)	−1.387	0.166
Predischarge Mg (mmol·L⁻¹, Md [IQR])	0.920 (0.830, 1.050)	0.980 (0.883, 1.182)	−3.147	0.002**
Predischarge P (mmol·L⁻¹, Md [IQR])	0.000 (0.000, 1.020)	0.875 (0.000, 1.152)	−2.728	0.006**
Predischarge RBP (mg/L, Md [IQR])	0.000 (0.000, 42.300)	26.000 (0.000, 48.800)	−2.156	0.031*
Predischarge PT (s, Md [IQR])	11.200 (10.000, 12.200)	12.000 (11.000, 14.225)	−4.219	0.000***
Predischarge INR (%, Md [IQR])	0.940 (0.860, 1.030)	0.980 (0.930, 1.140)	−4.121	0.000***
Predischarge PTA (%, Md [IQR])	6.610 (0.000, 97.000)	8.315 (0.000, 91.000)	−0.067	0.947
Predischarge FIB (g·L⁻¹, Md [IQR])	5.870 (3.780, 7.020)	5.580 (3.735, 6.893)	−0.581	0.561
Predischarge APTT (s, Md [IQR])	0.000 (0.000, 27.200)	11.000 (0.000, 30.100)	−1.617	0.106
Predischarge TT (s, Md [IQR])	9.700 (0.000, 12.500)	11.500 (0.000, 14.300)	1.993	0.046*

*P < 0.05, **P < 0.01, ***P < 0.001.

ᵃAbbreviations: ALB, serum albumin; ALP, serum alkaline phosphatase; ALT, glutamic-pyruvic transaminase; APTT, activated partial thromboplastin time; AST, glutamic oxalacetic transaminase; BASO, basophil; BASO%, basophil percentage; CHE, cholinesterase; CK*MB, creatine kinase isoenzyme; CK, creatine phosphokinase; CREA, creatinine; CRRT, continuous renal replacement therapy; Dbil, direct bilirubin; EO%, percentage of eosinophils; EO, eosinophils; FIB, fibrinogen; GGT, gamma-glutamyl transpeptidase; GLO, globulin; GLU, glucose; HBD, hydroxybutyrate dehydrogenase; HCT, red blood cell specific volume; HDL*C, high density lipoprotein cholesterol; HG, haemoglobin; Ibil, indirect bilirubin; INR, international normalised ratio; L%, lymphocyte percentage; L, lymphocyte; LD, serum lactate dehydrogenase; LDL*C, low density lipoprotein cholesterol; MCH, mean corpuscular hemoglobin; MCHC, mean corpuscular hemoglobin concentration; MCV, mean corpuscular volume; MONO%, monocyte percentage; MONO, monocyte; MPV, mean platelet volume; N%, neutrophilic granulocyte percentage; N, neutrophilic granulocyte; PA, proserum protein; PCT, platelet specific volume; PDW, platelet distribution width; PLT, platelet; Pre, preoperative; PT, prothrombin time; PTA, prothrombin activity; RBC, red blood cell; RBP, vitamin A binding protein; RDWCV, coefficient of variation of erythrocyte width; T*CHO, total cholesterol; TBA, serum total bile acid; TBiL, total bilirubin; TG, triglyceride; TnI, troponin; TP, total protein; TT, thrombin time; WBC, white blood cell.
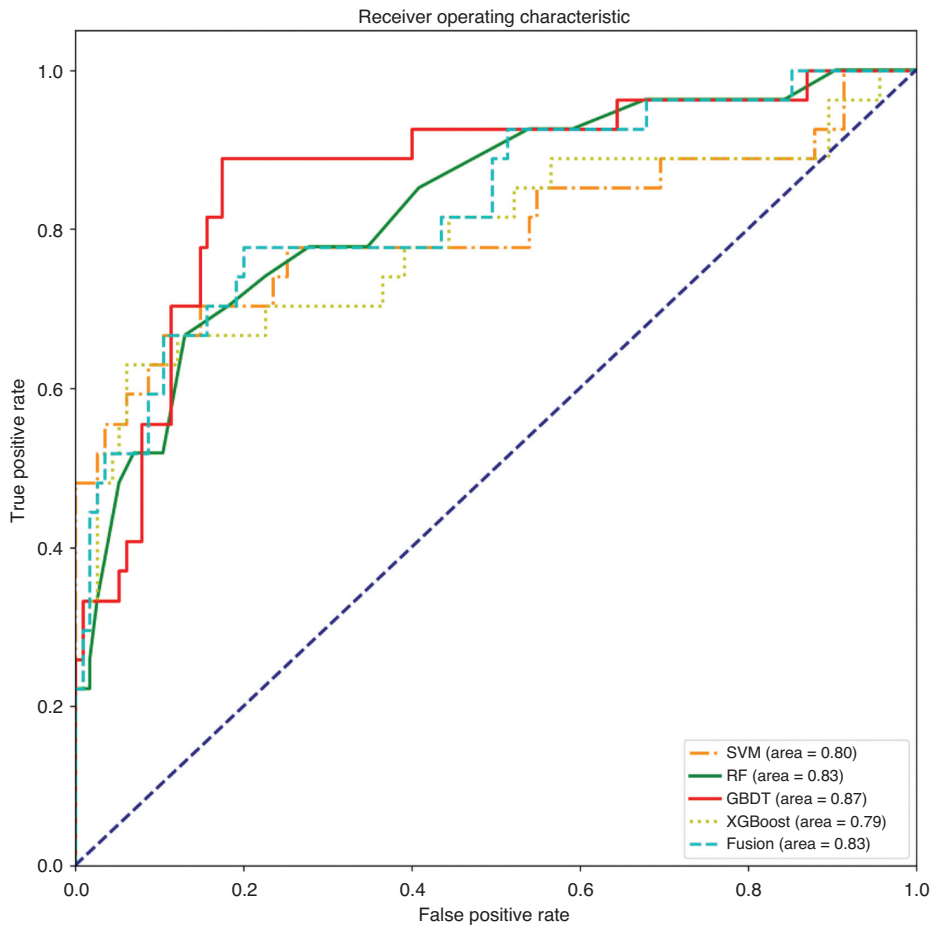
Figure 1 Receiver Operating Characteristic Curves for Machine Learning Models.

The earlier and better known prediction scores for CSA-AKI, such as the Cleveland Clinic score [18] and the Mehta score, use logistic regression, and ignore the predictive value of intraoperative and early postoperative variables. Most prior studies have used the multivariable logistic regression method, and the AUC has ranged from 0.76 to 0.84 [19]. Flechet et al. have used serum creatinine and other patient information (age, diabetes and admission information) to calculate the risk of AKI during the first week of the ICU stay after admission (stage 2 or 3) [20]. Other data (Acute Physiology and Chronic Health Evaluation [APACHE] II score, bilirubin, maximum lactate level, etc.) are also available. More data from the early postoperative period could be added to the findings from this study to achieve more refined and accurate prediction. Lee et al. were early adopters of machine learning methods for the prediction of CSA-AKI and they have reported that extreme gradient boosting (0.78, 95% CI 0.75–0.80) achieved the best AUC [21].

According to that study, machine learning models performed significantly better than traditional logistic regression models in predicting AKI after cardiac surgery. Our study built on these findings by creating SHAP summary plots showing the risk indexes of the important predictors in the final model.

Several risk factors have been predicted in previous risk scoring models, such as preoperative renal function, age, time to surgery, left ventricular ejection fraction, body mass index, hypertension, preoperative haemoglobin and creatinine clearance [18, 22]. However, these familiar risk factors were not significant in the current study; instead, early postoperative variables for CSA-AKI had high predictive power, possibly because previous studies focused less on the prediction of CSA-AKI in the off-pump CABG procedure. The pathophysiology of CSA-AKI may explain why intraoperative features are critical in the prediction of AKI. Although the pathogenesis of AKI is not fully understood, renal hypoperfusion is known to be produced by
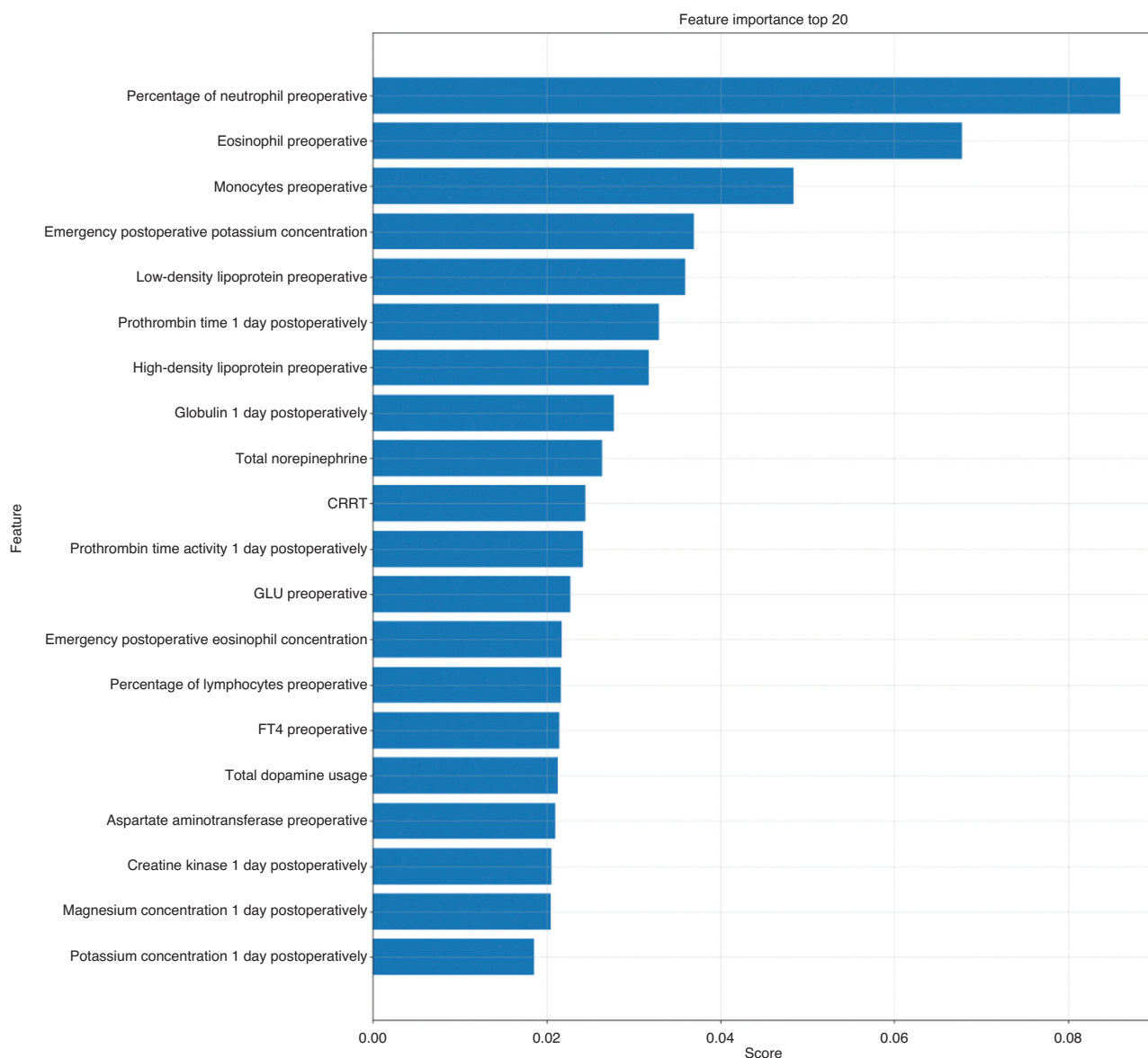
Figure 2 Importance Matrix Diagram for the GBDT Model.
This importance matrix diagram depicts the importance of each covariate in the development of the final predictive model.

low flow, low pressure and haemodilution. In addition, rapid nuclear hypothermia due to extracorporeal circulation, bleeding complications and inflammatory responses all play important roles in the development of CSA-AKI. The early postoperative variables identified by machine learning in this study have not been reported in the literature, and our team will pursue these findings in future research. Nonetheless, early postoperative variables can give clinicians sufficient warning to intervene in CSA-AKI with relevant treatment.

Models built by machine learning methods can be based on datasets from all available patients to enable early dynamic monitoring, thus saving clinicians time. Artificial intelligence and machine learning have already yielded many achievements in clinical medicine research, such as the assessment of postoperative patient outcomes [12] in cardiovascular imaging [23] and the prediction of death in chronic kidney disease [24]. In addition, machine learning has been applied to critical care/intensive care medicine [25], emergency medicine [26] and neurology [27]. With the expansion of electronic health records in the era of big data, the intersection of large amounts of electronic health record data and artificial intelligence has increased
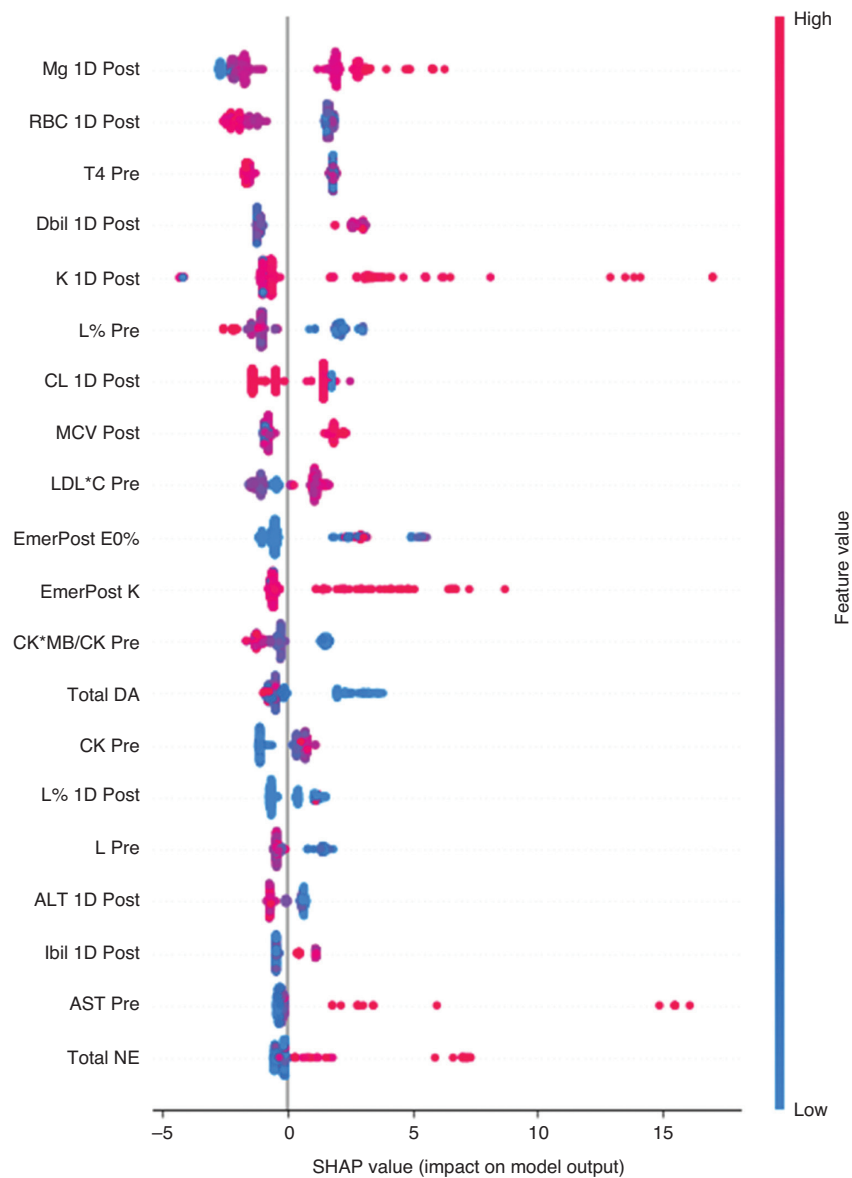
Figure 3 Summary Graph of SHAP for Each Feature.
The higher the SHAP value of a feature, the higher the likelihood of postoperative acute kidney injury. A dot is created for each feature attribute value of the model for each patient, and a dot for each patient is shown on the line for each feature. Dots are coloured according to the respective patient's feature values, and their vertical accumulation indicates the density. Red indicates higher feature values, and blue indicates lower feature values.

the importance of machine learning in AKI clinical research; AI tools are now effective in the diagnosis and prediction of AKI [28]. In this study, the risk of AKI after cardiac surgery was determined by the preoperative health condition–related susceptibility to acute stress and large dynamic physiological responses intraoperatively, thus reflecting the ongoing response to surgery. Therefore, software may be developed that can identify high-risk patients who are prone to AKI for the optimisation of treatment strategies after cardiac surgery.

This study has several limitations: 1) The study analysis used only single-centre data with a relatively small number of cases. The performance of the machine learning algorithm may vary depending on patient characteristics with different distributions and larger datasets from different institutions. Therefore, external validation is required to prevent overfitting. 2) Because the dataset was manually implemented by physicians, some hidden variable relationships might have been be lost because of human error. 3) Whether the risk predictive models

constructed will translate into actual clinical benefits for patients in clinical practice is unclear; therefore, prospective multicentre studies are required. 4) The data were mostly manually entered, and owing to the relatively large volume of data, some input errors were inevitable.

In summary, we developed a machine learning method that can be used to predict the risk of AKI development after surgery. The results of this study show that early postoperative variables are critical in AKI prediction. As research continues, a machine learning-based real-time patient monitoring system may assist clinicians in providing valuable clinical decision support, and decreasing the mortality and incidence of CSA-AKI. This system would not only reveal the complex relationships between predictors but also assess the risk of CSA-AKI events in patients postoperatively. Consequently, physicians would be able to identify patients at higher risk and to use protective strategies that improve patient prognosis, and decrease the length of stay and hospital costs.

Acknowledgements

Conflicts of Interests

The authors have no financial or personal conflicts of interests to declare.

REFERENCES

1. Hu J, Chen R, Liu S, Yu X, Zou J, Ding X. Global incidence and outcomes of adult patients with acute kidney injury after cardiac surgery: a systematic review and meta-analysis. J Cardiothorac Vasc Anesth. 2016;30(1):82–9.

2. Dong Y, Liu JE, Song L. Risk factors for intraoperative pressure injury in aortic surgery: a nested case-control study. Cardiovasc Innov Appl. 2021;5(3):173–81.

3. Vandenberghe W, Gevaert S, Kellum JA, Bagshaw SM, Peperstraete H, Herck I, et al. Acute kidney injury in cardiorenal syndrome type 1 patients: a systematic review and meta-analysis. Cardiorenal Med. 2015;6(2):116–28.

4. Erdogan T, Duman H, Etin MC, Ozer S, Cinier G, Usta E, et al. Impact of postdilation on intervention success and long-term major adverse cardiovascular events(MACE) among patients with acute coronary syndromes. Cardiovasc Innov Appl. 2020;4(3):185–93.

5. Sabik JF. On-pump coronary revascularization should be our preferred surgical revascularization strategy. J Thorac Cardiovasc Surg. 2014;148(6):2472–4.

6. Nicolini F, Fortuna D, Contini GA, Pacini D, Gabbieri D, Zussa C, et al. Comparison between off- and on-pump coronary artery bypass grafting: long-term results of a real-world registry. Eur J Cardiothorac Surg. 2016;50(3):528–35.

7. Wang Y, Bellomo R. Cardiac surgery-associated acute kidney injury: risk factors, pathophysiology and treatment. Nat Rev Nephrol. 2017;13(11):697–711.

8. Karauzum I, Karauzum K, Acar B, Hanci K, Bildirici H, Kilic T, et al. Predictive value of lymphocyte-to-monocyte ratio in patients with contrast-induced nephropathy after percutaneous coronary intervention for acute coronary syndrome. J Transl Intern Med. 2021;9(2):123–30.

9. Hu S, Zheng Z. An overview of risk assessment of coronary artery bypass grafting in Chinese population. Chin J Thor Cardiovasc Surg. 2011;27(2):2.

10. Penny-Dimri JC, Cochrane AD, Perry LA, Smith JA. Characterising the role of perioperative erythropoietin for preventing acute kidney injury after cardiac surgery: systematic review and meta-analysis. Heart Lung Circ. 2016;25(11):1067–76.

11. Li Q, Fan Q-L, Han Q-X, Geng W-J, Zhao H-H, Ding X-N, et al. Machine learning in nephrology: scratching the surface. Chin Med J (Engl). 2020;(6):687–98.

12. Voglis S, Niftrik CHBV, Staartjes VE, Brandi G, Serra C. Feasibility of machine learning based predictive modelling of postoperative hyponatremia after pituitary surgery. Pituitary. 2020;23(6):543–51.

13. Fei J, Yong J, Hui Z, Yi D, Hao L, Ma S, et al. Artificial intelligence in healthcare: past, present and future. Stroke Vasc Neurol. 2017;2(4):230.

14. Fan Y. Prediction of acute kidney injury following cardiac surgery by machine learning. Acad J Plant Postgrad Med School. 2022;(043-002):168.

15. Steyerberg EW, Tjeerd V, Calster BV. Risk prediction with machine learning and regression methods. Biom J. 2014;56(4):601–6.

16. Thomas ME, Blaine C, Dawnay A, Devonald MA, Ftouh S, Laing C, et al. The definition of acute kidney injury and its use in practice. Kidney Int. 2015;87(1):62–73.

17. Lundberg SM, Erion GG, Lee SI. Consistent individualized feature

attribution for tree ensembles. 2018. https://arxiv.org/abs/1802.03888.

18. Thakar CV, Arrigain S, Worley S, Yared JP, Paganini EP. A clinical score to predict acute renal failure after cardiac surgery. J Am Soc Nephrol JASN. 2005;16(1):162.

19. Mehta RH, Grab JD, O'Brien SM, Bridges CR, Gammie JS, Haan CK, et al. Bedside tool for predicting the risk of postoperative dialysis in patients undergoing cardiac surgery. Circulation. 2006;114(21):220.

20. Flechet M, Falini S, Bonetti C, Güiza F, Schetz M, Berghe GVD, et al. Machine learning versus physicians' prediction of acute kidney injury in critically ill adults: a prospective evaluation of the AKI predictor. Crit Care. 2019;23:282.

21. Lee HC, Yoon HK, Nam K, Cho Y, Kim T, Kim W, et al. Derivation and validation of machine learning approaches to predict acute kidney injury after cardiac surgery. J Clin Med. 2018;7(10):322.

22. Wijeysundera DN, Karkouti K, Dupuis JY, Rao V, Chan CT, Granton JT, et al. Derivation and validation of a simplified predictive index for renal replacement therapy after cardiac surgery. JAMA. 2007;297(16):1801–9.

23. Seetharam K, Min JK. Artificial intelligence and machine learning in cardiovascular imaging. Methodist DeBakey Cardiovasc J. 2020;16(4):263–71.

24. Ibeas J, Galles O, Monill N, Macias E, Morell A, Serrano J, et al. MO463: machine learning-based prediction of mortality and risk factors in patients with chronic kidney disease developed with data from 10000 patients over 11 years. Nephrol Dial Transpl. 2022;37 Suppl 3:gfac070.077. https://doi.org/10.1093/ndt/gfac070.077.

25. Hever G, Cohen L, O'Connor M, Matot I, Lerner B, Bitan Y. Machine learning applied to multi-sensor information to reduce false alarm rate in the ICU. J Clin Monitor Comput. 2019;34(2):339–52.

26. Lee S, Mohr NM, Street WN, Nadkarni P. Machine learning in relation to emergency medicine clinical and operational scenarios: an overview. West J Emerg Med. 2019 Mar;20(2):219–27.

27. Glaser JI, Benjamin AS, Farhoodi R, Kording KP. The roles of supervised machine learning in systems neuroscience. *Prog Neurobiol.* 2019;175:126–37.

28. Song X, Waitman LR, Hu Y, Luo B, Li F, Liu M. The impact of medical big data anonymization on early acute kidney injury risk prediction. AMIA Jt Summits Transl Sci Proc. 2020;2020:617–25.