Original Article

Postoperative Blood Pressure Variability and Acute Kidney Injury after CABG: A MIMIC-IV Study

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Abstract

Background: **Blood pressure variability (BPV) has emerged as an important hemodynamic factor associated with adverse outcomes after cardiac surgery, including acute kidney injury (AKI). However, the prognostic value of postoperative BPV in patients undergoing coronary artery bypass grafting (CABG) remains insufficiently characterized.**

Objective: **To investigate the association between postoperative BPV and AKI after CABG and to evaluate the predictive value of early postoperative BPV for AKI.**

Methods: **We conducted a retrospective cohort study using data from 5,070 adult patients who underwent CABG in the Medical Information Mart for Intensive Care IV (MIMIC-IV) database. Systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (MAP) variability during the first 24 hours after ICU admission were quantified using average real variability (ARV), successive variation (SV), standard deviation (SD), and coefficient of variation (CV). Multivariable logistic regression and machine learning models, including XGBoost, logistic regression, support vector machine, random forest, and K-nearest neighbor, were developed to predict postoperative AKI. All statistical tests were two-sided, and a P value < 0.05 was considered statistically significant.**

Results: **After adjustment for relevant confounders, increased BPV and cumulative hypotension were independently associated with AKI. Higher BPV was significantly associated with AKI (OR, 1.005; 95% CI, 1.002–1.008), as was greater hypotension burden defined by area under MAP <65 mmHg (OR, 1.307; 95% CI, 1.220–1.400). Among all models, XGBoost demonstrated the best predictive performance.**

Conclusion: **Postoperative BPV within the first 24 hours is a significant predictor of AKI after CABG. Integrating BPV into predictive models may improve early risk stratification and support clinical decision-making.**

Keywords: **Myocardial Revascularization; Acute Kidney Injury; Machine Learning; Predictive Learning Models.**

Introduction

Acute kidney injury (AKI) is a common and severe complication following major surgeries, particularly in patients undergoing coronary artery bypass grafting (CABG). The incidence of AKI after CABG ranges from 10% to 30%,[1] with serious consequences, including prolonged hospital stays, increased morbidity, and higher mortality rates.[2] One of the primary factors influencing AKI in this population is hemodynamic instability, particularly fluctuations in blood pressure (BP), which are commonly observed during and after surgery.[3,4]

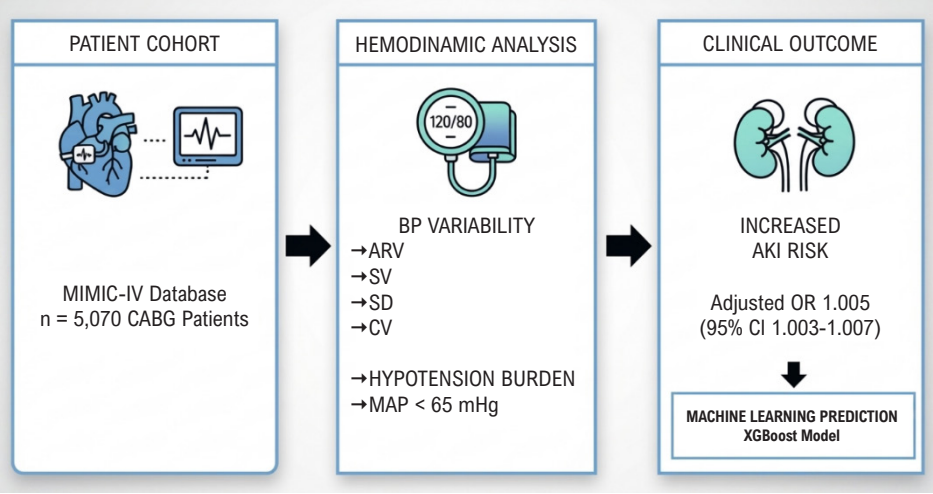
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Blood pressure variability (BPV) refers to the fluctuations in BP over time and is an important indicator of hemodynamic instability. Recent studies have highlighted the potential role of BPV in predicting adverse postoperative outcomes, including AKI, as it reflects the ability of the cardiovascular system to maintain stable perfusion during stress.[5,6] BPV is often quantified using several metrics, such as the standard deviation (SD), coefficient of variation (CV), and average real variability (ARV), each providing unique insights into the patterns and extent of BP fluctuations.[7,8] However, the relationship between BPV and AKI in the context of CABG surgery remains poorly understood, necessitating further investigation into how BPV affects renal outcomes in these patients.

The pathophysiology of AKI after CABG is multifactorial, involving ischemia-reperfusion injury, microcirculatory disturbances, and renal hypoperfusion.[9,10] Disruptions in BP homeostasis, particularly hypotension and wide fluctuations in BP, can lead to compromised renal perfusion and exacerbate renal injury.[11] Several studies have demonstrated a correlation

Central Illustration: Postoperative Blood Pressure Variability and Acute Kidney Injury after CABG: A MIMIC-IV Study



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between periods of low blood pressure, particularly systolic blood pressure (SBP) and mean arterial pressure (MAP) below certain thresholds, and the development of AKI.[12,13] BPV may further compound the risk by preventing the kidney from maintaining adequate perfusion pressure, resulting in renal hypoxia and ischemic injury.[14]

Given these concerns, this study aims to investigate the association between BPV and the incidence of AKI in patients undergoing CABG. By focusing on postoperative BPV in the first 24 hours, we seek to clarify whether BPV is an independent predictor of AKI in this high-risk population. Additionally, we explore the utility of machine learning models in predicting AKI based on BPV, which may provide valuable tools for early identification and targeted interventions to mitigate renal injury in this setting.[15,16]

The findings of this study could contribute to a deeper understanding of the hemodynamic factors involved in AKI after CABG surgery and may inform strategies for BP management to reduce the risk of AKI. Furthermore, by incorporating advanced predictive techniques such as machine learning, this research could pave the way for more personalized and effective management of high-risk patients in the postoperative period.

Materials and methods

Data source and study population

Data were obtained from the Medical Information Mart for Intensive Care IV version 1.0 (MIMIC-IV v1.0) database,[17] which is a multiparameter critical care database with information on critically ill patients at the Beth Israel Deaconess Medical Center (Boston, MA, USA) from 2001 to 2012. Our right to access the database was approved after completing the National Institutes of Health's (NIH) online training course (Record ID 45636271).

Patients who received CABG based on the ninth or tenth revision of the International Classification of Diseases (ICD-9/10) code[18] were screened and included in this study. AKI was defined according to the Kidney Disease: Improving Global Outcomes (KDIGO) criteria as an increase in serum creatinine by ≥0.3 mg/dL (≥26.5 μmol/L) within 48 hours or an increase to ≥1.5 times baseline within seven days.[19] Baseline creatinine was defined as the most recent preoperative measurement before surgery. Only the first ICU admission was included in this study. Patients who spent less than 48 hours in the ICU were excluded. Patients with end-stage kidney disease (ESKD) and who developed AKI before surgery were also excluded from this study.

In this study, we collected data from a consecutive series of 11,326 patients undergoing CABG between 2001 and 2012 in the MIMIC-IV database. The exclusion criteria were as follows: (1) missing BP measurement records (n = 274); (2) death within the first 24 h of postoperative ICU admission (n = 6); (3) length of ICU stay <24 h (n = 188); (4) BP measured <10 times within the first 24 h of postoperative ICU admission (n = 28); and (5) Patients with abnormal times (more than 1,000 times) of BP measurement (n = 2). Finally, a total of 5,070 patients were included in the study population (Figure 1).

3,396 patients were randomly selected to constitute the training set, including 824 AKI patients and 2,572 non-AKI patients. The remaining 1,674 patients constitute the test set, which contains 405 AKI patients and 1,296 non-AKI patients.

Feature extraction

In order to better distinguish AKI patients from non-AKI patients, we extracted 106 features, including (1) demographics: age, gender, height, weight, body mass index

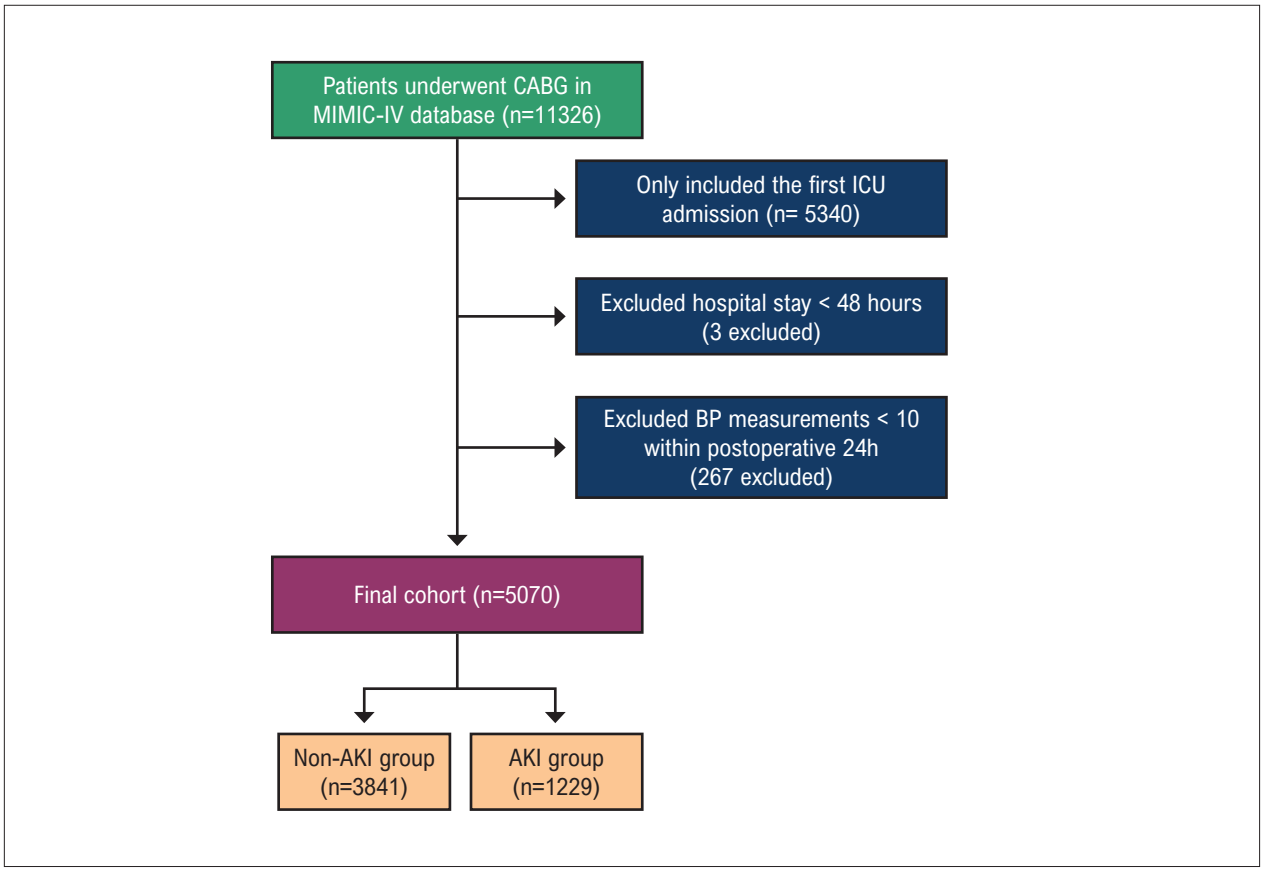


Figure 1 – *Data filtering flow chart: Data were collected from the MIMIC database and preprocessed to obtain 5,070 patients.*

(BMI), admission type, discharge location, language, marital status, and ethnicity; (2) comorbidities including myocardial infarct (MI), congestive heart failure (CHF), peripheral vascular disease, cerebrovascular disease, dementia, chronic pulmonary disease (COPD), rheumatic disease, peptic ulcer disease, mild liver disease, diabetes mellitus with or without complication, paraplegia, renal disease, malignant cancer, severe liver disease, metastatic solid tumor, acquired immunodeficiency syndrome (AIDS), and the calculated Charlson Comorbidity Index (CCI); (3) intensive care scores: Acute Physiology Score III (APS III), Oxford acute severity of illness score (OASIS), Simplified Acute Physiology Score II (SAPS II), and Sequential Organ Failure Assessment (SOFA); (4) vital signs after admitted to ICU within the first 24 hours: SBP, diastolic blood pressure (DBP), mean blood pressure (MBP), mean arterial pressure (MAP), heart rate (HR), respiratory rate (RR), and percutaneous oxygen saturation (SpO_2); (5) use of vasoactive agents including dobutamine, dopamine, epinephrine, norepinephrine, phenylephrine, and vasopressin; (6) mean laboratory data: hematocrit, hemoglobin, platelets, white blood cell (WBC), anion gap, bicarbonate, blood urea nitrogen (BUN), calcium, chloride, creatinine, glucose, sodium, potassium, basophils, eosinophils, lymphocytes, monocytes, neutrophils, fibrinogen, international normalized ratio (INR), prothrombin time (PT), partial thromboplastin time (PTT); and (7) continuous renal replacement therapy (CRRT), the length of hospital stay, length of ICU stay, and hospital mortality.

We calculated the BPV to evaluate the MAP, SBP, and DBP within the first 24 hours of ICU admission. BPV was evaluated using the following parameters: average real variability (ARV),[20] successive variation (SV),[21] standardized deviation (SD),[22] and coefficient of variation (CV),[23] These measures were defined as follows:

$$VRM = \left(\frac{1}{n-1}\right)\sum_{(i=1)}^{(n-1)}|PA_{i+1} - PA_i|,$$

$$VS = \sqrt{(1/(n-1))\sum_{(i=1)}^{(n-1)}(PA_{i+1} - PA_i)^2}$$

$$DP = \sqrt{\left(\frac{1}{n-1}\right)\sum_{(i=1)}^{(n)}(PA_i - PA_{mean})^2}$$

$$CV = \left(\frac{DP}{PA_{mean}}\right) * 100$$

The existence of hypotension was defined as SBP less than 100 mmHg and MAP less than 65 mmHg.[12,24] By comparing SBP-hypo and MAP-hypo, we explored which of the two different definitions of hypotension is more sensitive to AKI. Hypotension severity was also assessed by

measuring the area under the curve (AUC) of MAP below 65 mmHg and the duration of MAP below 65 mmHg, recorded as MAP-area. SBP-area was also measured under thresholds of 100 mmHg.

Statistical analysis methods

Data for continuous variables were expressed as the mean ± standard deviation (SD) or median [interquartile range (IQR)], as appropriate. The normality of continuous variables was assessed using the Shapiro–Wilk test. For normally distributed continuous variables, differences between groups were compared using the independent-samples (unpaired) Student's t-test, whereas the Mann–Whitney U test was used for non-normally distributed variables. Categorical variables were expressed as the number and percentage, and the chi-square test was used for comparisons between groups. The analyses above were conducted using IBM SPSS Statistics version 26.0 (IBM, Armonk, NY, USA). Statistical analyses were performed using two-sided tests, with a p value < 0.05 considered statistically significant.

Feature selection

As too-high feature dimension will lead to overfitting of the classifier, requiring feature selection to remove irrelevant and redundant features . Indeed, we adopted a two-step feature selection strategy to select features. In the first step, we ranked all features using the Random Forest (RF).[25] In the second step, we used sequential forward selection (SFS)[26] to obtain an optimal feature subset. We also compared the results with two common feature selection methods. These methods included the maximum relevance and minimum redundancy (mRMR) and SFS. Feature selection and model development were conducted strictly within the training dataset. The testing dataset was used only for final model evaluation.

Model building

The data were randomly divided, with 70% used for training and 30% for validation. We employed several supervised machine learning techniques to build predictive models, including XGBoost (XGB),[27] logistic regression (LR), support vector machine (SVM), random forest (RF), and K-Nearest Neighbor (KNN).[28]

XGB is an optimized distributed gradient boosting library designed to be highly efficient, flexible, and portable. It implements machine learning algorithms under the Gradient Boosting framework. We used the grid search method on the training set to tune parameters and obtain the optimal parameters of max_depth = 5, learning_rate = 0.01, n_estimators = 400, subsample = 0.8, min_child_weight = 1. To avoid data leakage, feature selection and hyperparameter tuning were performed exclusively on the training set. No information from the test set was used during model training or feature selection.

Evaluation criteria

We employed tenfold cross-validation on the training set for feature selection to obtain the best features.[29] We used several evaluation criteria, which comprise sensitivity (SEN), specificity (SPE), precision (PRE), F1 score (F1), accuracy (ACC), and Matthews correlation coefficient (MCC). These measures were defined as follows:

$$SEN = \frac{TP}{(TP + FN)}$$

$$ESP = \frac{TN}{(TN + FP)}$$

$$PRE = \frac{TP}{(TP + FP)}$$

$$F1 = \frac{2 \times SEN \times PRE}{SEN + PRE}$$

$$ACU = \frac{TP + TN}{TP + TN + FP + FN}$$

$$CCM = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

where TP, FP, TN, and FN represent the number of true positives (correctly predicted AKI patients), false positives (non-AKI patients incorrectly predicted as AKI), true negatives (correctly predicted non-AKI patients), and false negatives (AKI patients incorrectly predicted as non-AKI), respectively. For completeness, we also calculated the area of the ROC curve, called AUC, to evaluate our performance.

Results

Characteristics of the patients

As shown in Table 1, there were significant differences in gender, age, and CCI between the non-AKI group (n=3841) and the AKI group (n=1229). The mean HR, SBP, DBP, and MBP were significantly lower, and the levels of BPV were significantly higher among AKI patients within the first 24 hours of ICU admission. Severity-of-illness scores, including SAPS III, OASIS, SAPS II, and SOFA, were significantly higher in the AKI group than in the non-AKI group. Vasopressors and inotropes use were more common in the AKI group.

The occurrence of hypotension observed, whether defined by MAP $<$ 65mmHg or SBP $<$ 100mmHg, was significantly higher in the AKI group. As for the severity of hypotension, both SBP-area and MAP-area were notably elevated among patients in the AKI group ($p < 0.001$).

Both the length of hospital stay and ICU stay were significantly higher in the AKI group when compared with the non-AKI group.

Results of the univariable and multivariable logistic regression analysis

The results of the univariable logistic regression analysis for AKI are presented in Table 2, indicating that AKI group patients were associated with increased SBP-AVR (odds ratio

Table 1 – Characteristics of patients between non-AKI and AKI

	Non-AKI N = 3841	AKI N =1229	p value
Gender			
Male	3075(80.1%)	873(71.0%)	
Female	766(19.9%)	356(29.0%)	
Age (years)	67.82 ± 10.06	71.79 ± 9.91	< 0.001
BMI (kg/m²)	30.13 ± 5.52	30.40 ± 5.86	0.150
Charlson comorbidity index			
Comorbidities, n (%)	4.95 ± 1.97	6.38 ± 2.19	< 0.001
Myocardial infarct	1386/3841(36.1%)	535/1229(43.5%)	< 0.001
Congestive heart failure	698/3841(18.2%)	458/1229(37.3%)	< 0.001
Peripheral vascular disease	438/3841(11.4%)	212/1229(17.2%)	< 0.001
Cerebrovascular disease	345/3841(9.0%)	167/1229(13.6%)	< 0.001
Dementia	16/3841(0.4%)	8/1229(0.7%)	0.297
Chronic pulmonary disease	677/3841(17.6%)	275/1229(22.4%)	< 0.001
Rheumatic disease	100/3841(2.6%)	47/1229(3.8%)	0.026
Peptic ulcer disease	23/3841(0.6%)	13/1229(1.1%)	0.095
Mild liver disease	99/3841(2.6%)	62/1229(5.0%)	< 0.001
Diabetes without complications	1208/3841(31.5%)	417/1229(33.9%)	0.105
Diabetes with complications	390/3841(10.2%)	238/1229(19.4%)	< 0.001
Paraplegia	20/3841(0.5%)	14/1229(1.1%)	0.021
Renal disease	456/3841(11.9%)	406/1229(33.0%)	< 0.001
Cancer	94/3841(2.4%)	44/1229(3.6%)	0.034
Severe liver disease	4/3841(0.1%)	6/1229(0.5%)	0.017
Metastatic solid tumor	8/3841(0.2%)	5/1229(0.4%)	0.231
AIDS	2/3841(0.1%)	2/1229(0.2%)	0.249
heart_rate_mean	82.32 ± 9.09	81.64 ± 9.38	0.023
SBP_mean	112.19 ± 7.57	111.40 ± 8.63	0.002
DBP_mean	57.51 ± 6.29	55.19 ± 7.02	< 0.001
MBP_mean	74.69 ± 5.84	72.98 ± 6.58	< 0.001
Respiratory rate	17.42 (15.94, 19.07)	17.64 (16.05, 19.39)	0.005
Temperature	36.71 (36.56, 36.89)	36.71 (36.51, 36.82)	< 0.001
SpO_2	97.92 (97.00, 98.78)	98.00 (96.82, 98.94)	0.490
Glucose	128.55 (121.12, 137.31)	129.82 (121.60, 142.63)	< 0.001
apsiii	36.82 ± 17.48	47.98 ± 21.91	< 0.001
oasis	30.74 ± 7.21	34.86 ± 7.87	< 0.001
sapsii	35.82 ± 10.90	41.98 ± 12.25	< 0.001
SOFA	5.00 ± 2.42	6.86 ± 3.17	< 0.001
MAP-AVR	7.00 (6.00, 9.00)	7.00 (6.00, 9.00)	0.006
MAP-SV	9.97 (7.95, 12.76)	10.38 (8.35, 14.35)	< 0.001
MAP-SD	8.73 (7.22, 10.92)	9.56 (7.72, 12.40)	< 0.001
MAP-CV	11.75 (9.80, 14.52)	13.16 (10.85, 16.76)	< 0.001

SBP-AVR	11.62 ± 4.50	12.04 ± 3.56	0.003
SBP-SV	14.85 (12.20, 18.15)	15.58 (12.96, 18.93)	< 0.001
SBP-SD	12.94 (10.85, 15.36)	14.35(12.17, 16.98)	< 0.001
SBP-CV	11.93 ± 5.04	13.08 ± 3.39	< 0.001
DBP-AVR	5.36 (4.39, 6.62)	5.41(4.40, 6.64)	0.386
DBP-SV	7.36 (5.92, 9.27)	7.56 (6.08, 9.57)	0.003
DBP-SD	6.96 (5.74, 8.53)	7.52 (6.15, 0.15)	< 0.001
DBP-CV	12.31 (10.30, 15.00)	13.96 (11.56, 16.83)	< 0.001
creatinine_min	0.80 (0.70, 1.00)	0.90 (0.70, 1.30)	< 0.001
creatinine_max	0.90 (0.80, 1.10)	1.10 (0.90, 1.60)	< 0.001
Hospital mortality	9/3841(0.2%)	47/1229(3.8%)	< 0.001
CRRT	1/3841(0.0%)	81/1229(6.6%)	< 0.001
Mechanical ventilation	139/3841(3.6%)	78/1229(6.3%)	< 0.001
Dobutamine	16/3841(0.4%)	32/1229(2.6%)	< 0.001
Dopamine	12/3841(0.3%)	27/1229(2.2%)	< 0.001
Epinephrine	548/3841(14.3%)	395/1229(32.1%)	< 0.001
Norepinephrine	399/3841(10.4%)	326/1229(26.5%)	< 0.001
Phenylephrine	2709/3841(70.5%)	882/1229(71.8%)	0.406
Vasopressin	126/3841(3.3%)	166/1229(13.5%)	< 0.001
Glucose			< 0.001
<200	3815/3841(99.3%)	1200/1229(97.6%)	
≥200	26/3841(0.7%)	29/1229(2.4%)	
Anemia(hematocrit)	3797/3841(98.9%)	1193/1229(97.1%)	< 0.001
Anemia(hemoglobin)	3793/3841(98.8%)	1197/1229(97.4%)	< 0.001
Hematocrit	31.20 ± 3.91	30.13 ± 4.07	< 0.001
Hemoglobin	10.51 ± 1.39	10.04 ± 1.42	< 0.001
Platelets	157.50 (130.50, 190.50)	153.00 (124.25,137.31)	0.022
WBC	12.75 (10.25, 15.75)	12.80 (10.18, 16.20)	0.223
Aniongap	11.54 ± 2.25	12.59 ± 2.75	< 0.001
Bicarbonate	23.56 ± 2.03	22.75 ± 2.37	< 0.001
BUN	15.50 (12.50, 19.00)	19.00 (14.50, 26.50)	< 0.001
Calcium	8.36 ± 0.44	8.42 ± 0.54	< 0.001
Chloride	106.82 ± 3.15	106.88 ± 4.13	0.598
Sodium	138.11 ± 2.46	138.44 ± 2.85	< 0.001
Potassium	4.38 ± 0.38	4.50 ± 0.51	< 0.001
basophils	1.09 (0.04, 1.09)	1.09 (0.04, 1.09)	0.683
eosinophils	5.07 (0.14, 5.07)	5.07 (0.14, 5.07)	0.640
lymphocytes	63.73 (2.20, 63.73)	63.73 (2.20, 63.73)	0.378
monocytes	11.96 (0.51, 11.96)	11.96 (0.50, 11.96)	0.934
neutrophils	308.21 (10.34, 308.21)	308.21 (10.41, 308.21)	0.467
fibrinogen	220.00 (180.00,242.00)	221.15 (179.00, 249.00)	0.128
INR	1.31 ± 0.23	1.36 ± 0.26	< 0.001

PT	14.20 (13.35, 15.20)	14.55 (13.50, 15.85)	< 0.001
aPTT	30.85 (28.05, 36.78)	33.05 (29.05, 42.00)	< 0.001
Temperature (℃)			0.621
<37.2	3556/3841(92.6%)	1143/1229(93.0%)	
≥37.2	285/3841(7.4%)	86/1229(7.0%)	
SpO_2(%)			< 0.001
<95	72/3841(1.9%)	54/1229(4.4%)	
≥95	3769/3841(98.1%)	1175/1229(95.6%)	
Respiratory rate			0.026
<12	5/3841(0.1%)	2/1229(0.2%)	
12-20	3245/3841(84.5%)	998/1229(81.2%)	
>20	591/3841(15.4%)	229/1229(18.6%)	
Platelets			0.005
<150	1636/3841(42.6%)	580/1229(47.2%)	
150-400	2192/3841(57.1%)	641/1229(52.2%)	
>400	13/3841(0.3%)	8/1229(0.7%)	
WBC			0.460
<5	25/3841(0.7%)	5/1229(0.4%)	
5-10	860/3841(22.4%)	289/1229(23.5%)	
>10	2956/3841(77.0%)	935/1229(76.1%)	
Aniongap			< 0.001
<8	110/3841(2.9%)	16/1229(1.3%)	
8-16	3641/3841(94.8%)	1114/1229(90.6%)	
>16	90/3841(2.3%)	99/1229(8.1%)	
Bicarbonate			< 0.001
<23	1310/3841(34.1%)	619/1229(50.4%)	
23-30	2522/3841(65.7%)	607/1229(49.4%)	
>30	9/3841(0.2%)	3/1229(0.2%)	
BUN			< 0.001
<10	275/3841(7.2%)	50/1229(4.1%)	
10-20	2819/3841(73.4%)	622/1229(50.6%)	
>20	747/3841(19.4%)	557/1229(45.3%)	
Calcium			0.002
<9	3519/3841(91.6%)	1096/1229(89.2%)	
9-10.5	316/3841(8.2%)	125/1229(10.2%)	
>10.5	6/3841(0.2%)	8/1229(0.7%)	
Chloride			< 0.001
<95	10/3841(0.3%)	15/1229(1.2%)	
95-105	1104/3841(28.7%)	349/1229(28.4%)	
>105	2727/3841(71.0%)	865/1229(70.4%)	

Sodium			< 0.001
<135	275/3841(7.2%)	99/1229(8.1%)	
135-145	3560/3841(92.7%)	1119/1229(91.0%)	
>145	6/3841(0.2%)	11/1229(0.9%)	
Potassium			< 0.001
<3.5	17/3841(0.4%)	15/1229(1.2%)	
3.5-5	3608/3841(93.9%)	1054/1229(85.8%)	
>5	216/3841(5.6%)	160/1229(13.0 %)	
Basophils			0.275
0-0.5	1710/3841(44.5%)	569/1229(46.3%)	
>0.5	2131/3841(55.5%)	660/1229(53.7%)	
Eosinophils			0.442
0-0.5	16460/3841(42.9%)	542/1229(44.1%)	
>0.5	21950/3841(57.1%)	687/1229(55.9%)	
Lymphocytes			0.202
<0.77	43/3841(1.1%)	21/1229(1.7%)	
0.77-4.5	1568/3841(40.8%)	514/1229(41.8%)	
>4.5	2230/3841(58.1%)	694/1229(56.5%)	
Monocytes			0.013
<0.14	105/3841(2.7%)	54/1229(4.4%)	
0.14-1.3	1531/3841(39.9%)	473/1229(38.5%)	
>1.3	2205/3841(57.4%)	702/1229(57.1%)	
Neutrophils			0.677
<2.6	24/3841(0.6%)	9/1229(0.7%)	
2.6-8.5	634/3841(16.5%)	191/1229(15.5%)	
>8.5	3183/3841(82.9%)	1029/1229(83.7%)	
Fibrinogen			0.130
<200	1452/3841(37.8%)	444/1229(36.1%)	
200-400	2321/3841(60.4%)	753/1229(61.3%)	
>400	68/3841(1.8%)	32/1229(2.6%)	
INR			0.018
0.8-1.2	1171/3841(30.5%)	331/1229(26.9%)	
>1.2	2670/3841(69.5%)	898/1229(73.1%)	
PT			0.065
<11	10/3841(0.3%)	7/1229(0.6%)	
11-13	652/3841(17.0%)	183/1229(14.9%)	
>13	3179/3841(82.8%)	1039/1229(84.5%)	
aPTT			< 0.001
<60	3670/3841(95.5%)	1117/1229(90.9%)	
60-70	55/3841(1.4%)	45/1229(3.7%)	
>70	116/3841(3.0%)	67/1229(5.5%)	

Admission type			< 0.001
elective	305(7.9%)	127(10.3%)	
emergency	641(16.7%)	229(18.6%)	
surgical same day admission	1279(33.3%)	326(26.5%)	
urgent	1280(33.3%)	439(35.7%)	
observation admit	336(8.7%)	108(8.8%)	
Discharge location			< 0.001
home	2689 (70.0%)	493(40.1%)	
non-home	1143 (29.8%)	689(56.1%)	
died	9 (0.2%)	47(3.8%)	
Language			0.552
English	3485(90.7%)	1122(91.3%)	
non-English	356(9.3%)	107(8.7%)	
Marital status			< 0.001
single	541(14.1%)	193(15.7%)	
married	2745(71.5%)	801(65.2%)	
divorced	261(6.8%)	79(6.4%)	
widowed	294(7.7%)	156(12.7%)	
Ethnicity			0.081
White	2733(71.2%)	914(74.4%)	
Asian	91(2.4%)	23(1.9%)	
Other	1017(26.5%)	292(23.8%)	
SBPhypo	3520(91.6%)	1159(93.5%)	0.037
SBParea	6681.00 (2172.40, 14893.84)	8805.74 (3112.09, 17059.91)	< 0.001
MAPhypo	3128(81.4%)	1115(90.7%)	< 0.001
MAParea	225.31 (16.41, 886.26)	600.79 (114.27, 1833.01)	< 0.001
hours	9.78 (7.36, 13.06)	13.14 (9.18, 19.95)	< 0.001
LOS_hospital	6.80 (5.11, 9.07)	9.11 (6.38, 13.85)	< 0.001
LOS_icu	1.36 (1.18, 2.30)	3.25 (2.08, 5.54)	< 0.001

AIDS: acquired immunodeficiency syndrome; BUN: blood urea nitrogen; BMI: body mass index; CV: coefficient of variation; DBP: diastolic blood pressure; ICU: intensive care unit; IQR: interquartile range; MBP: mean blood pressure; MAP: mean arterial pressure; PT: prothrombin time; PTT: partial thromboplastin time; SBP: systolic blood pressure; SOFA: Sequential Organ Failure Assessment; SpO_2: percutaneous oxygen saturation; SV: successive variation; WBC: white blood cell.

Table 2 – Results of the Univariable Logistic Regression Analysis for AKI

Variable	OR	95% CI	p value
Gender			
Male	1		
Female	1.214	0.991-1.489	0.062
Age (years)	1.010	0.993-1.027	0.267
BMI (kg/m²)	1.008	0.993-1.023	0.286

Charlson comorbidity index	1.135	0.935-1.377	0.200
Comorbidities			
Myocardial infarct	0.889	0.688-1.150	0.371
Congestive heart failure	1.035	0.787-1.360	0.808
Peripheral vascular disease	0.932	0.696-1.249	0.639
Cerebrovascular disease	0.884	0.649-1.205	0.436
Dementia	1.044	0.392-2.780	0.931
Chronic pulmonary disease	0.873	0.665-1.147	0.330
Rheumatic disease	1.094	0.698-1.716	0.695
Peptic ulcer disease	0.682	0.278-1.674	0.404
Mild liver disease	1.23	0.788-1.920	0.362
Diabetes without complications	1.116	0.875-1.423	0.378
Diabetes with complications	1.026	0.678-1.554	0.903
Paraplegia	0.985	0.404-2.402	0.974
Renal disease	1.087	0.698-1.694	0.711
Cancer	1.067	0.599-1.901	0.826
Severe liver disease	1.821	0.349-9.512	0.477
Metastatic solid tumor	0.699	0.147-3.336	0.654
AIDS	8.081	0.693-94.201	0.095
heart_rate_mean	1.008	0.993-1.023	0.286
SBP_mean	0.996	0.986-1.005	0.396
DBP_mean	0.993	0.977-1.010	0.424
MBP_mean	1.009	0.986-1.033	0.456
Respiratory rate	0.992	0.962-1.022	0.590
Temperature	1.016	0.970-1.064	0.513
SpO_2	0.740	0.567-0.965	0.026
Glucose	0.952	0.887-1.022	0.178
apsiii	0.993	0.987-0.999	0.015
oasis	1.004	0.997-1.010	0.265
sapsii	1.032	1.017-1.046	< 0.001
SOFA	0.982	0.970-0.994	0.004
MAP-AVR	0.921	0.836-1.016	0.100
MAP-SV	1.017	0.969-1.067	0.496
MAP-SD	1.033	0.929-1.149	0.548
MAP-CV	0.981	0.903-1.066	0.657
SBP-AVR	1.106	1.024-1.195	0.010
SBP-SV	0.923	0.876-0.973	0.003
SBP-SD	1.048	0.987-1.112	0.126
SBP-CV	1.031	0.961-1.106	0.396
DBP-ARV	1.040	0.976-1.109	0.228
DBP-SV	0.981	0.938-1.027	0.415
DBP-SD	0.999	0.932-1.070	0.977
DBP-CV	1.029	1.010-1.048	0.003

Mechanical ventilation	1.007	0.688-1.475	0.970
Dobutamine	1.435	0.687-2.999	0.337
Dopamine	2.639	1.131-6.154	0.025
Epinephrine	1.090	0.872-1.363	0.449
Norepinephrine	1.042	0.804-1.353	0.754
Phenylephrine	1.216	1.000-1.477	0.050
Vasopressin	1.458	1.041-2.041	0.028
Glucose			
<200	1		
≥200	1.609	0.625-4.144	0.324
Anemia(hematocrit)	2.552	1.105-5.894	0.028
Anemia(hemoglobin)	2.113	1.344-3.320	0.001
Hematocrit	0.992	0.928-1.059	0.805
Hemoglobin	0.936	0.776-1.13	0.492
Platelets	1.001	0.998-1.003	0.550
WBC	1.001	0.987-1.016	0.856
Aniongap	1.076	1.019-1.136	0.008
Bicarbonate	0.941	0.874-1.013	0.106
BUN	1.008	0.995-1.02	0.234
Calcium	1.102	0.864-1.405	0.436
Chloride	1.013	0.958-1.071	0.648
Sodium	1.051	0.997-1.109	0.067
Potassium	1.529	1.178-1.985	0.001
basophils	1.016	0.953-1.083	0.631
eosinophils	0.998	0.985-1.011	0.713
lymphocytes	1.001	1.000-1.003	0.076
monocytes	0.998	0.989-1.006	0.583
neutrophils	1.000	0.999-1.000	0.454
fibrinogen	1.000	0.998-1.002	0.998
INR	1.103	0.406-2.995	0.848
PT	1.004	0.912-1.106	0.931
aPTT	1.005	0.995-1.016	0.312
Temperature (℃)			
<37.2	1		
≥37.2	1.239	0.859-1.786	0.252
SpO_2(%)			
<95			
≥95	0.581	0.349-0.967	0.037
Respiratory rate			0.523
<12	1		
12-20	0.612		0.581
>20	0.523		0.478

Platelets			0.824
<150	1		
150-400	0.935	0.746-1.172	0.562
>400	0.721	0.173-3.01	0.654
WBC			0.258
<5	1		
5-10	2.526	0.837-7.623	0.100
>10	2.484	0.817-7.553	0.109
Aniongap			0.600
<8	1		
8-16	1.34	0.723-2.484	0.352
>16	1.26	0.563-2.818	0.573
Bicarbonate			0.852
<23	1		
23-30	1.008	0.793-1.281	0.948
>30	0.611	0.098-3.824	0.599
BUN			0.008
<10	1		
10-20	0.972	0.681-1.388	0.878
>20	1.404	0.909-2.170	0.126
Calcium			0.556
<9	1		
9-10.5	0.823	0.574-1.178	0.287
>10.5	0.652	0.122-3.495	0.618
Chloride			0.065
<95	1		
95-105	0.273	0.092-0.812	0.020
>105	0.262	0.082-0.837	0.024
Sodium			0.217
<135	1		
135-145	0.835	0.583-1.196	0.325
>145	2.002	0.509-7.870	0.320
Potassium			0.023
<3.5	1		
3.5-5	0.287	0.113-0.733	0.009
>5	0.313	0.11-0.888	0.029
Basophils			
0-0.5	1		
>0.5	1.007	0.531-1.909	0.982
Eosinophils			
0-0.5	1		
>0.5	1.132	0.631-2.031	0.677

Lymphocytes			0.030
<0.77	1		
0.77-4.5	1.201	0.612-2.359	0.594
>4.5	0.52	0.208-1.299	0.162
Monocytes			0.091
<0.14	1		
0.14-1.3	0.737	0.475-1.143	0.173
>1.3	1.265	0.632-2.532	0.506
Neutrophils			0.420
<2.6	1		
2.6-8.5	1.185	0.471-2.981	0.718
>8.5	1.389	0.548-3.520	0.489
Fibrinogen			0.673
<200	1		
200-400	0.923	0.733-1.161	0.491
>400	1.009	0.457-2.229	0.983
INR			
0.8-1.2	1		
>1.2	0.953	0.744-1.222	0.705
PT			0.854
<11	1		
11-13	0.725	0.210-2.500	0.611
>13	0.755	0.216-2.644	0.661
aPTT			0.311
<60	1		
60-70	1.387	0.784-2.453	0.260
>70	0.868	0.455-1.655	0.668
Admission type			0.428
elective	1		
emergency	0.945	0.686-1.301	0.728
surgical same day admission	0.798	0.594-1.072	0.134
urgent	0.923	0.684-1.244	0.598
observation admit	0.813	0.553-1.194	0.291
Discharge location			< 0.001
home	1		
non-home	3.288	2.873-3.762	< 0.001
died	28.484	13.871-58.493	< 0.001
Language			
English	1		
non-English	0.945	0.713-1.252	0.693

Marital status			0.355
single	1		
married	0.855	0.687-1.065	0.162
divorced	0.753	0.530-1.070	0.114
widowed	0.921	0.674-1.259	0.607
Ethnicity			0.287
White	1		
Asian	0.843	0.485-1.467	0.546
Other	0.864	0.716-1.042	0.126
SBPhypo	0.249	0.128-0.484	< 0.001
lgSBParea	1.359	1.149-1.608	< 0.001
MAPhypo	0.874	0.592-1.290	0.498
lgMAParea	1.188	1.023-1.379	0.024
Hospital mortality	16.93	8.273-34.647	< 0.001
CRRT	270.941	37.667-1948.914	< 0.001
hours	1.090	1.080-1.101	< 0.001
LOS_hospital	1.133	1.117-1.148	< 0.001
LOS_icu	1.613	1.548-1.681	< 0.001

AIDS: acquired immunodeficiency syndrome; BUN: blood urea nitrogen; BMI: body mass index; CI: confidence index; CRRT: continuous renal replacement therapy; CV: coefficient of variation; DBP: diastolic blood pressure; ICU: intensive care unit; IQR: interquartile range; MBP: mean blood pressure; MAP: mean arterial pressure; OR: odds ratio; PT: prothrombin time; PTT: partial thromboplastin time; SBP: systolic blood pressure; SOFA: Sequential Organ Failure Assessment; SpO_2: percutaneous oxygen saturation; SV: successive variation; WBC: white blood cell.

[OR], 1.106; 95% confidence interval [CI], 1.024-1.195), DBP-CV (OR, 1.029; 95% CI, 1.010-1.048) and lg (SBP-area) (OR, 1.359; 95% CI 1.149-1.608). The variables that had a significant association with AKI, indicated by a p-value less than 0.1, were included in a multivariable backward stepwise logistic regression model (Table 3). As expected, both BPV represented by DBP-CV (OR, 1.005; 95% CI, 1.002-1.008) and hypotension severity defined by lg (MAP-area) (OR, 1.307; 95% CI, 1.220-1.400) were independently associated with AKI.

Features selected in models

Based on the analysis of feature contribution by the Random Forest classifier, we identified the top 20 most important features of the dataset. These included bun_mean, age, BMI, CCI, OASIS, SAPS II, SOFA, blood pressure (including SBP_mean, DBP_mean), BPV (represented by DBP-CV, SBP-SD, SBP-CV), and several serum markers. The feature importance is shown in Figure 2 and Table 4. A heat map was utilized to visually depict the interrelationship between features, as illustrated in Figure 3.

Model comparisons

We used five machine learning methods (XGB, LR, SVM, RF, KNN) with 20 variables to predict postoperative AKI. The AUCs were presented in Figure 4. In Table 5, the prediction efficiency of various models was compared.

Discussion

The main findings of this study are summarized in the Central Illustration. This study aimed to investigate the association between postoperative BPV and AKI in patients undergoing CABG. Our findings indicate that higher BPV during the first 24 hours after surgery was independently associated with an increased risk of postoperative AKI. In addition, greater hypotension burden, as reflected by the area under the MAP threshold of 65 mmHg, was also independently associated with AKI. These findings suggest that postoperative hemodynamic instability may contribute to the identification of patients at increased risk of AKI. However, given the retrospective observational design of this study, these associations should not be interpreted as evidence of a causal relationship. Additionally, we observed that hypotension severity, as indicated by the AUC for MAP and SBP below predefined thresholds, further enhances the predictive value for AKI.

The association between BPV and AKI has been explored in various surgical populations, with previous studies highlighting the detrimental effects of BP fluctuations on renal perfusion and tissue oxygenation.[5,6] The pathophysiological mechanisms underlying this association are complex but likely involve ischemia-reperfusion injury, renal hypoxia, and disrupted autoregulatory mechanisms that are particularly prevalent in critically ill patients.[9,10] Our study contributes to this body of literature by demonstrating the impact of postoperative BPV specifically in CABG patients, a group at high risk for both AKI and cardiovascular instability.[14]

Table 3 – Results of the Multivariable Logistic Regression Analysis for AKI

Variable	OR	95% CI	p value
DBPCV	1.005	1.002-1.008	0.004
Temperature	0.734	0.598-0.900	0.003
Oasis	1.029	1.018-1.040	< 0.001
SOFA	1.136	1.102-1.171	< 0.001
Aniongap	1.117	1.081-1.155	< 0.001
Sodium	1.033	1.001-1.067	0.046
Potassium	1.581	1.247-2.005	< 0.001
Dopamine	2.527	1.159-5.512	0.020
Vasopressin	1.863	1.393-2.491	< 0.001
Gender	1.485	1.255-1.758	< 0.001
BUN			< 0.001
<10	1		
10-20	1.072	0.770-1.495	0.680
>20	2.082	1.465-2.958	< 0.001
Chloride			0.029
<95	1		
95-105	0.315	0.120-0.827	0.019
>105	0.356	0.133-0.952	0.040
Potassium			0.004
<3.5	1		
3.5-5	0.254	0.107-0.605	0.002
>5	0.284	0.107-0.755	0.012
SpO_2	0.483	0.315-0.739	0.001
Anemia(hematocrit)	2.574	1.514-4.377	< 0.001
IgMAParea	1.307	1.220-1.400	< 0.001

BUN: blood urea nitrogen; CV: coefficient of variation; DBP: diastolic blood pressure; SOFA: Sequential Organ Failure Assessment; SpO_2: percutaneous oxygen saturation.

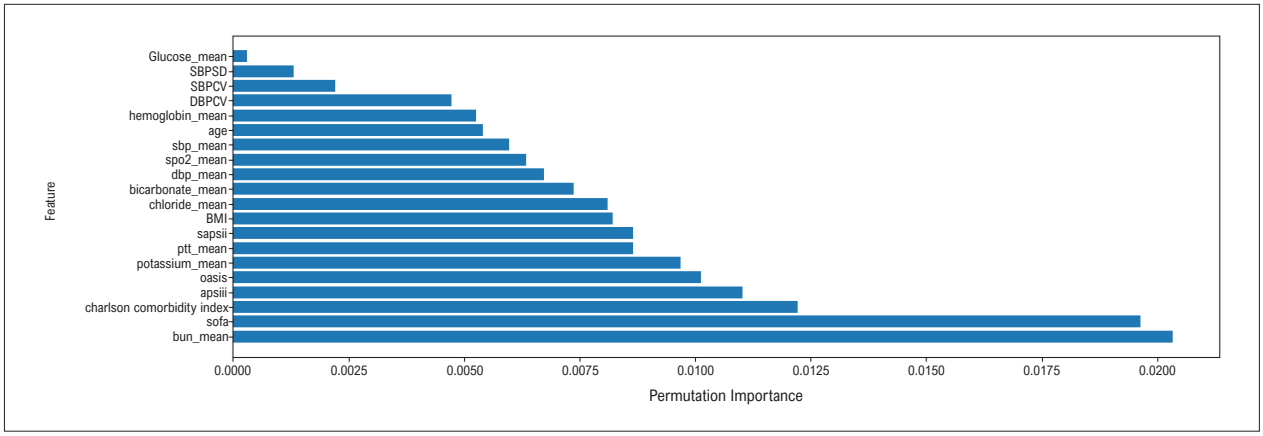


Figure 2 – *Feature Importance Plot. The length of the columns in the figure indicates the contribution degree of the feature to the model.*

Table 4 – Attribute data ranked by the weights (n = 20)

Attribute	Weight
1) apsiii	0.032715
2) bun_mean	0.031363
3) SOFA	0.025782
4) oasis	0.023938
5) SpO_2_mean	0.023863
6) sapsii	0.023449
7) age	0.021028
8) sbp_mean	0.020536
9) DBPCV	0.019943
10) bicarbonate_mean	0.019684
11) SBPSD	0.019534
12) glucose_mean	0.019443
13) SBPCV	0.019186
14)charlson_comorbidity_index	0.018627
15) ptt_mean	0.018598
16) potassium_mean	0.018222
17) hemoglobin_mean	0.018097
18) chloride_mean	0.018042
19) BMI	0.017987
20) dbp_mean	0.017646

BUN: blood urea nitrogen; BMI: body mass index; CV: coefficient of variation; DBP: diastolic blood pressure; MBP: mean blood pressure; MAP: mean arterial pressure; PTT: partial thromboplastin time; SBP: systolic blood pressure; SOFA: Sequential Organ Failure Assessment; SpO_2: percutaneous oxygen saturation.

The inclusion of BPV metrics such as ARV, SV, SD, and CV in this study provides a comprehensive approach to quantifying BP fluctuations.[7] Among these, we found that the CV of DBP was particularly predictive of AKI, in line with previous studies suggesting that variability in DBP is a key factor in renal outcomes.[6,22] These results underscore the importance of not only considering the mean blood pressure but also accounting for its variability when assessing postoperative risk.[8]

A potential concern in interpreting these findings is reverse causality. The diagnosis of AKI in this study was based on KDIGO criteria, which rely on serum creatinine changes that are inherently delayed relative to the onset of renal injury. As a result, early subclinical kidney injury may already be present during the initial postoperative period without yet fulfilling diagnostic thresholds. Consequently, some patients classified as non-AKI within the first 24 hours may have already experienced evolving renal dysfunction, which could itself contribute to hemodynamic instability and increased BPV. Although BPV was strictly calculated within the first 24 hours after ICU admission to preserve temporal precedence, reverse causality cannot be completely excluded in this retrospective design.

Machine learning techniques were employed to develop a predictive model for AKI, which demonstrated promising results.[30,31] Of the methods tested, XGBoost outperformed other models in terms of accuracy and predictive power, emphasizing the potential of advanced computational approaches in improving clinical decision-making. The model's ability to integrate a broad range of clinical and laboratory variables, including BPV, further enhances its clinical utility. The machine learning models developed in this study demonstrated promising predictive performance, suggesting that postoperative BPV may provide additional prognostic information for early risk stratification after CABG.[34] However, these models were developed and internally validated using a single retrospective database. Their clinical utility should therefore be interpreted with caution and require external validation and prospective evaluation before routine clinical application.

However, our study is not without limitations. First, although we utilized a large and diverse dataset from the MIMIC-IV database, the retrospective nature of the analysis introduces the possibility of unmeasured confounding factors. While we controlled several important covariates, there may be additional variables influencing the relationship between BPV and AKI that were not captured in the database. In addition, several important intraoperative variables known to influence the risk of cardiac surgery-associated AKI, including cardiopulmonary bypass duration, aortic cross-clamp time, intraoperative blood loss, and surgical bleeding, were not consistently available in the MIMIC-IV database and therefore could not be incorporated into our multivariable analyses. Although we adjusted for a broad range of demographic characteristics, comorbidities, illness severity scores, postoperative hemodynamic parameters, laboratory measurements, and vasoactive medication use, residual confounding from these unmeasured intraoperative factors cannot be excluded. Future studies using dedicated cardiac surgery registries or prospective datasets with comprehensive intraoperative information are warranted to further validate our findings. Additionally, while the use of machine learning models holds great promise, their application in clinical practice requires further validation and refinement, especially regarding their generalizability to other populations and settings. Moreover, BPV was assessed using data from only the first 24 hours postoperatively, and it is possible that variability later in the postoperative course could provide additional insights into AKI risk. Future studies could explore longer-term BPV trends and their potential impact on kidney function recovery and other postoperative outcomes. Additionally, while our study focused on BPV as a predictor, further research is needed to understand the underlying mechanisms by which BP fluctuations contribute to AKI and whether targeted interventions to stabilize BP variability could improve outcomes.

Conclusion

In conclusion, postoperative BPV was independently associated with AKI in patients undergoing CABG. These findings suggest that BPV may have potential value for early postoperative risk stratification. However, given the retrospective observational design of this study, causal inference cannot be established. Further prospective studies and external validation are needed before these findings can be translated into routine clinical practice.

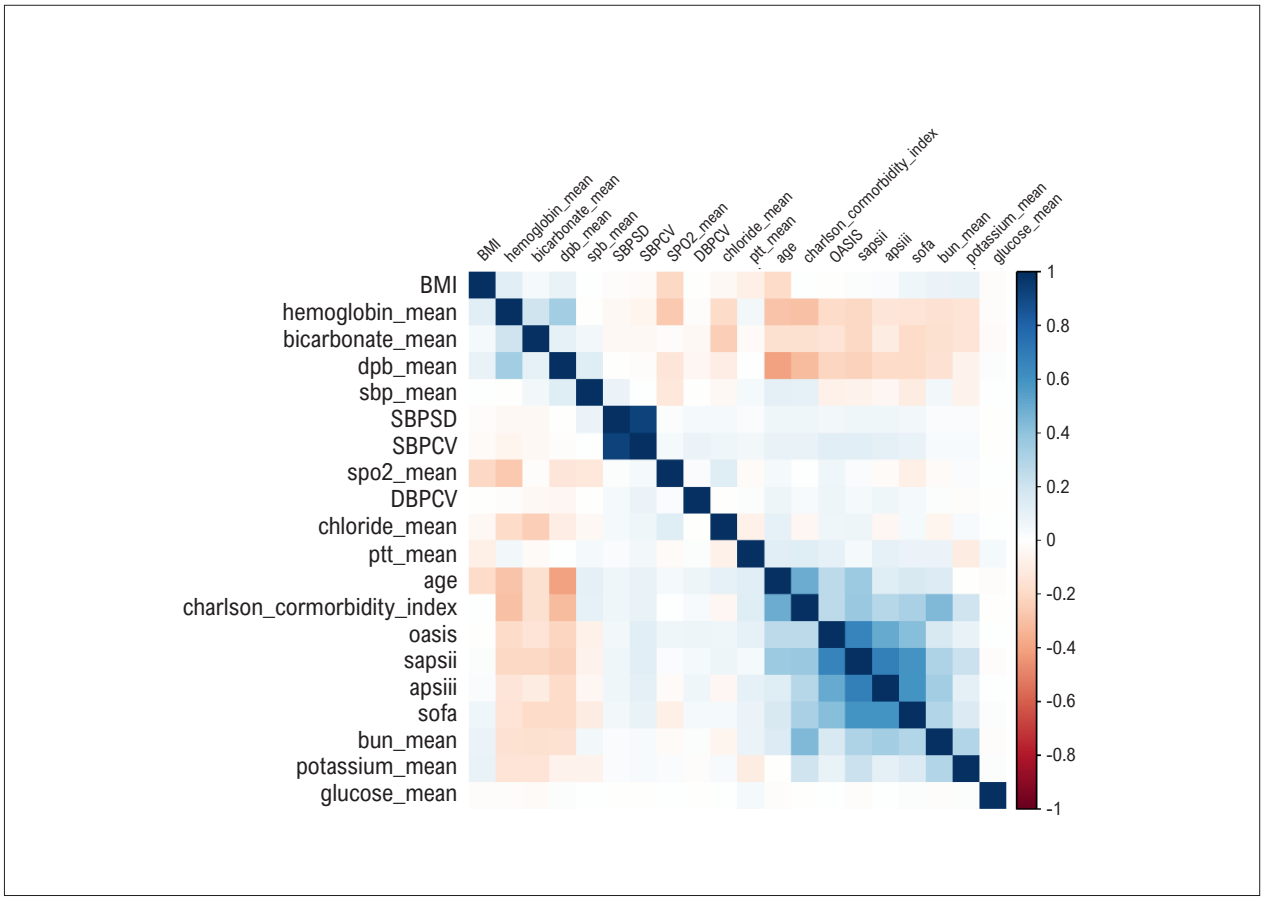


Figure 3 – *Feature correlation graph. Color indicates the degree of correlation between two features.*

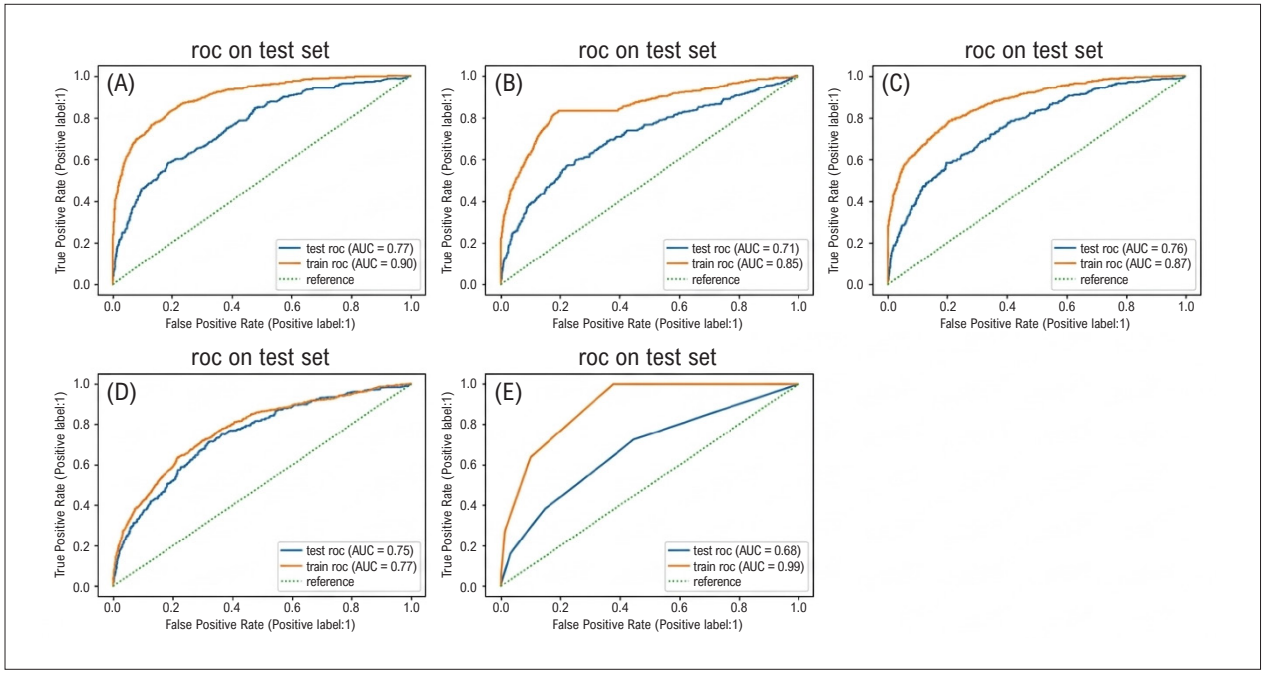


Figure 4 – *Train set results on different models. XGB (XGBoost), SVM (Support Vector Machine), RF (Random Forest), LR (Logistic Regression), KNN (K-Nearest Neighbor).*

Table 5 – Comparison of prediction efficiency among the different models

Model Name	SEN	SPE	PRE	F1	MCC	ACC	AUC	Confusion matrix
XGB	0.480	0.986	0.915	0.630	0.600	0.866	0.918	[1079 60; 269 113]
LR	0.316	0.949	0.658	0.428	0.355	0.798	0.776	[1079 60; 281 101]
SVM	0.365	0.982	0.865	0.513	0.482	0.835	0.850	[1101 38; 302 60]
RF	0.331	0.993	0.937	0.490	0.498	0.836	0.873	[1102 37; 296 86]
KNN	0.621	0.900	0.660	0.640	0.532	0.834	0.888	[1103 36; 320 62]

ACC: accuracy; AUC: area under the curve; F1: F1 score; KNN: K-Nearest Neighbor; LR: logistic regression; MCC: Matthews correlation coefficient; PRE: precision; RF: Random Forest; SEN: sensitivity; SPE: specificity; SVM: support vector machine; XGB: XGBoost.

Author Contributions

Conception and design of the research: Ling-Song Y, Yu-Chen D, Jie S, Yunfei B; Acquisition of data: Yu-Chen D; Analysis and interpretation of the data and Statistical analysis: Ling-Song Y; Funding acquisition: Yu-Chen D, Yunfei B; Writing of the manuscript: Ling-Song Y, Yu-Chen D; Critical revision of the manuscript for intellectual content: Qing-Ren L, Jie S, Yunfei B.

Potential Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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Study Association

This study is not associated with any thesis or dissertation work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants or animals performed by any of the authors.

Use of Artificial Intelligence

The authors did not use any artificial intelligence tools in the development of this work.

Availability of Research Data

All datasets supporting the results of this study are available upon request from the corresponding author.

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