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The Predictive Value of AI-Based FAI Combined with CT-FFR for Prognosis in Hyperuricemia Patients with Coronary Artery Stenosis

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Abstract

Background This study explores the evaluation and predictive value of AI based FAI combined with CT-FFR for adverse cardiovascular events (MACE) in hyperuricemia patients with concomitant coronary artery stenosis.

Methods A retrospective collection was conducted on 201 patients with hyperuricemia who were proposed diagnosis with coronary heart disease and had coronary artery stenosis detected by coronary CTA (CCTA) in our hospital from January 2021 to October 2025. According to the occurrence of MACE, they were divided into MACE group (n=52) and non MACE group (n=149). Measure, record, and compare the differences in relevant clinical baseline data between two groups. Use univariate and multivariate logistic regression analysis to identify the risk factors for MACE in patients with coronary artery stenosis and hyperuricemia. Compare the levels of coronary FAI and CT-FFR in hyperuricemia patients with different grades of coronary artery stenosis and plaque properties. Using receiver operating characteristic (ROC) curves to evaluate the diagnostic predictive value of various indicators and joint models, constructing nomogram, and analyzing and evaluating the predictive performance of the model using calibration curves and decision curves (DCA).

Results The grading of coronary artery stenosis, plaque properties, CT-FFR, and MAX-FAI were identified as risk factors for MACE in patients with coronary artery stenosis combine hyperuricemia ($P<0.05$); The overall differences in MAX-FAI and CT-FFR between hyperuricemia patients with different grades of coronary artery stenosis were statistically significant ($P<0.05$). The more severe the vascular stenosis, the higher the MAX-FAI level and the lower the CT-FFR level; The overall difference in MAX-FAI among hyperuricemia patients with different plaque properties was statistically significant ($P<0.05$), with mixed plaque patients having the highest MAX-FAI, while CT-FFR showed no significant difference among different plaque properties. The ROC curve analysis of various indicators and combined models showed that the AUC of coronary artery stenosis grading, plaque properties, CT-FFR, MAX-FAI, and CT-FFR combined with MAX-FAI for predicting MACE were 0.852, 0.836, 0.736, 0.924, and 0.950, respectively. The diagnostic efficacy of CT-FFR combined with MAX-FAI for MACE was better than using any indicator alone. The constructed nomogram model can intuitively and individualize the assessment of MACE risk in patients, and the decision curve shows that the model can provide higher clinical net benefits within a threshold probability range of about 0% -60%.

Conclusion The grading of coronary artery stenosis, plaque characteristics, CT-FFR, and MAX-FAI represent risk factors for major adverse cardiovascular events (MACE) in patients suffering from both coronary artery stenosis and hyperuricemia. The integration of CT-FFR and MAX-FAI significantly enhances the predictive capacity for MACE. The nomogram model, constructed based on the aforementioned imaging

features, demonstrates reliable calibration and offers a stable clinical net benefit, thereby serving as a noninvasive imaging tool for prognostic evaluation in this high-risk cohort and providing a valuable reference for precise prevention and treatment strategies.

Keywords Coronary artery disease,Artificial intelligence, Hyperuricemia, Coronary computed tomography angiography, CT fractional flow reserve, Fat attenuation index, Adverse cardiovascular events, Predictive value

Background

Coronary artery disease (CAD) has a high incidence rate, and patients are prone to multiple adverse cardiovascular events (MACE), which are important triggers of disease progression, readmission, and death [1-3]. Therefore, seeking cost-effective and early intervention and management methods is of great value for risk assessment and prevention of MACE in patients with coronary heart disease.

Hyperuricemia is an independent risk factor for coronary atherosclerosis, which can induce oxidative stress and vascular inflammation, damage coronary microvessels, and accelerate the progression of plaque and calcification[4-5]. Studies have confirmed that individuals with high uric acid levels have significantly higher risks of coronary artery disease and cardiovascular mortality, and there is a positive correlation between uric acid levels and cardiovascular mortality[6]. Therefore, patients with hyperuricemia should prevent the occurrence of CAD lesions.

Coronary computed tomography angiography (CCTA) is the preferred noninvasive screening method for coronary artery disease [7-8]. It not only avoids the

risks associated with invasive surgery but also provides a faster and more cost-effective visualization method for evaluating moderate-risk coronary artery disease. It is also the reference standard for assessing the degree of coronary artery stenosis[9]. However, due to the complex technical principles of CTA, the large amount of data, and the long post-processing and interpretation time, it not only increases the workload and risk of missed diagnoses for radiologists but also reduces work efficiency [10]. Artificial intelligence can optimize and quantitatively analyze CCTA images, compensate for the deficiencies of traditional diagnosis, and facilitate precise coronary artery assessment [11].

With the advancement of medical technology, various imaging examinations such as Optical Coherence Tomography (OCT) and Intravascular Ultrasound Imaging (IVUS) have made certain progress in predicting Major Adverse Cardiac Events (MACE) in patients with coronary heart disease. However, these examination methods are invasive procedures, which limit their clinical application and promotion[12]. Recently, the Computerized Tomography-Fractional Flow Reserve (CT-FFR) technology, based on conventional Coronary Computed Tomography Angiography (CCTA) images, has been introduced. This technology assesses coronary hemodynamics using a computer AI algorithm based on computational fluid dynamics. It can be applied to pre-existing CCTA images without requiring additional imaging, radiation dose, or additional medications. Through high-quality CCTA image analysis, it can obtain the Fractional Flow Reserve (FFR) value at any point on the coronary tree [13]. CT-FFR integrates anatomical and functional assessments, providing high diagnostic accuracy in

evaluating lesion-specific ischemia. It is highly consistent with invasive FFR and has superior predictive value for major adverse cardiovascular events compared to CCTA alone [14].

The perivascular fat attenuation index (FAI), derived from AI-assisted CCTA, is a novel imaging indicator. It can detect coronary artery inflammation by displaying changes in the density of perivascular adipose tissue and quantify the level of perivascular inflammation, offering high predictive value for future cardiovascular events[15-16]. Although both CT-FFR and FAI possess high predictive value for future cardiovascular events, currently, these two indicators are mostly studied separately, with rare joint application in the risk assessment of MACE in patients with hyperuricemia and coronary stenosis. This study explores the predictive value of their combination, providing a noninvasive imaging reference for early warning and individualized diagnosis and treatment of such high-risk patients.

Method

Study population and grouping

This study is a single-center retrospective study that enrolled 201 patients who visited our hospital from January 2021 to October 2025, were suspected of having coronary heart disease, underwent coronary computed tomography angiography (CCTA) examination, and had both coronary artery stenosis and hyperuricemia. The patients comprised 93 males and 108 females, with an age range of 28 to 89 years and an average age of 66 ± 11.20 years. According to whether major adverse cardiovascular events (MACE) occurred during the follow-up period, the patients were divided into

the MACE group and the non-MACE group. The definition of MACE includes: ①cardiac death (fatal myocardial infarction); ②non-fatal myocardial infarction; ③unstable angina requiring coronary revascularization therapy; ④recurrent hospitalization due to unstable angina.This study was approved by the hospital's Ethics Committee (Ethics approval reference number:KY-PJ-2025-016）.

Inclusion and exclusion criteria

Inclusion criteria: ①age > 18 years; ②clear CCTA image quality without severe artifacts, meeting the requirements for coronary artery disease assessment; ③complete clinical, laboratory, and follow-up data.

Exclusion criteria: ① patients with iodine contrast medium allergy; ②patients with a history of coronary artery surgery; ③patients with severe CCTA image artifacts, making it impossible to assess the disease; ④patients who were lost to follow-up or had incomplete data.

Diagnostic criteria for hyperuricemia

Venous blood samples were collected from all patients after fasting for blood uric acid detection. Diagnostic criteria for hyperuricemia: male blood uric acid > 420 μmol/L, female blood uric acid > 360 μmol/L.

Follow-up protocol and study endpoints

Starting from the day of the patient's CCTA examination, the follow-up period ended in December 2025. Prognostic follow-up was conducted through medical record review combined with telephone interviews. The study endpoint was the first occurrence of MACE in the patient. Patients without events were classified into the

non-MACE group for subsequent inter-group comparison.

Baseline clinical data and laboratory indicator testing

Collect baseline data such as patient age, gender, BMI, blood pressure, smoking history, and alcohol consumption history, as well as laboratory indicators such as fasting blood glucose, blood lipids, and blood uric acid. All fasting blood samples were uniformly tested by the hospital's laboratory department, and the data met clinical quality control standards.

CCTA scanning equipment and imaging parameters

The CCTA scan was performed using a GE Revolution 256-row helical CT scanner from the United States. The patient had metal foreign bodies removed and was trained to hold their breath. A nonionic iodinated contrast medium (1 mL/kg) was injected through the elbow vein at a flow rate of 5 mL/s. After the injection, 30 to 40 mL of saline was administered at the same flow rate to flush the catheter.Intelligent trigger scanning of the aortic root region of interest was employed, with unified scanning parameters: tube voltage of 120 kV, tube current of 300 mAs, slice thickness of 0.5 mm, matrix of 512×512, and field of view of 200 mm×200 mm. The raw scan images were automatically uploaded to the post-processing workstation for analysis.

Image post-processing and radiological evaluation process

All CCTA images underwent post-processing and quantitative analysis using the Shukun Intelligent Angiography Image Analysis Software (Shukun Technology, China). Two radiologists with over 3 years of experience independently assessed the degree of coronary stenosis and plaque characteristics, combining multiplanar reconstruction

images and AI results for comprehensive interpretation. In case of disagreement, a senior physician with more experience reviewed and confirmed the final diagnosis.

Evaluation criteria for the degree of coronary artery stenosis

Based on the 18-segment coronary artery segmentation method recommended by the American College of Cardiology, each visible segment of the left main artery, left anterior descending artery, left circumflex artery, and right coronary artery was assessed. The degree of coronary stenosis was calculated as the ratio of the diameter of the narrowest part of the lesion to the adjacent normal vessel lumen, expressed as a percentage.

According to the CAD-RADS standard grading: Grade 0 (no stenotic plaque); Grade 1 (0% to 24%); Grade 2 (25% to 49%); Grade 3 (50% to 69%); Grade 4 (70% to 99%); Grade 5 (100% occlusion). In this study, Grades 1 to 2 are classified as mild stenosis, Grade 3 as moderate stenosis, and Grades 4 to 5 as severe stenosis. Lumen stenosis ≥50% is defined as obstructive coronary stenosis.

Classification criteria for coronary plaque properties

Based on CT values, coronary plaques are categorized into three types: soft plaques (≤50 HU), fibrous plaques (50-120 HU), and calcified plaques (>120 HU). Soft plaques and fibrous plaques are collectively classified as non-calcified plaques, while plaques containing both calcified and non-calcified components are defined as mixed plaques.

Quantitative detection of pericoronary fat attenuation index (FAI)

The perivascular fat attenuation index (FAI) was automatically measured using the Shukun intelligent imaging analysis software (Shukun Technology, China), with a fat threshold set at -190 HU to -30 HU. The standardized measurement range was as follows: for the left anterior descending artery (LAD) and left circumflex artery (LCX), the interval from the vessel origin to 40 mm was taken; for the right coronary artery (RCA), the interval from the origin to 10-50 mm was taken. The average CT value of the 4 mm tubular fat area in the adventitia of the vessel was selected as the FAI result, and the data were summarized for subsequent statistical analysis.

Quantitative assessment of CT-FFR based on artificial intelligence

The Shukun intelligent imaging analysis software (Shukun Technology, China) was used to automatically calculate the CT-FFR values of each coronary segment. For patients with multivessel disease, the lowest CT-FFR value was taken as the final evaluation result. In this study, a CT-FFR value of ≤0.80 was used as the positive criterion for coronary functional ischemic stenosis.

Statistical analysis

Data were analyzed using R4.4.2 software. Continuous variables conforming to a normal distribution were expressed as mean 卤 standard deviation（x±S）, and independent sample t-tests were used for inter-group comparisons. Categorical variables were expressed as frequency (percentage) [n (%)], and tests or Fisher's exact test were used for inter-group comparisons. With MACE outcomes (0= not occurred, 1 = occurred) as the dependent variable, a univariate analysis was first conducted. To

screen variables and control for collinearity, LASSO regression was employed, and lambda.min was selected using 10-fold cross-validation to obtain retained variables and their coefficients. Subsequently, the variables selected by LASSO were incorporated into a multi-factor binary logistic regression. Receiver Operating Characteristic (ROC) curves were used to evaluate the diagnostic performance of each indicator and the combined model.Construct a nomogram,Calibration curves and Decision Curves Analysis (DCA) were used to analyze and evaluate the predictive performance of the model. $P < 0.05$ was considered statistically significant.

Result

Baseline clinical data

There were no statistically significant differences in gender, history of hypertension, alcohol consumption, smoking history, history of cerebral infarction, lesion extent, BMI, fasting blood glucose, total cholesterol, triglycerides, low-density lipoprotein, high-density lipoprotein, γ-GT, CK-MB, c-TnI, and calcification score between the two groups ($P > 0.05$), with CK-MB approaching marginal significance ($P = 0.054$). Significant differences were observed in plaque characteristics, CT-FFR, coronary artery stenosis grading, MAX-FAI, and age between the two groups ($P < 0.05$), as shown in Table 1.

Table 1 Comparison of baseline clinical data between the two groups

Name	MACE outcome		t/χ2 ·	*p-value*
	Non-MACE group 0.0(*n*=149)	MACE group 1.0(*n*=52)		
Gender (n,%)				
Male	68(45.64)	25(48.08)	0.092	0.761

Female	81(54.36)	27(51.92)		
History of hypertension(n,%)				
None	55(37.41)	17(32.69)	0.371	0.542
Have	92(62.59)	35(67.31)		
History of alcohol use(n,%)				
None	27(18.24)	7(13.73)		
Have	117(79.05)	43(84.31)	0.667	0.717
Abstain from alcohol	4(2.70)	1(1.96)		
History of smoking(n,%)				
None	48(32.43)	13(25.49)		
Have	92(62.16)	36(70.59)	1.181	0.554
Give up smoking	8(5.41)	2(3.92)		
History of cerebral infarction (n,%)				
None	113(75.84)	41(80.39)	0.445	0.505
Have	36(24.16)	10(19.61)		
Plaque characteristics(n,%)				
Mixed	18(12.08)	31(59.62)		
Calcification	46(30.87)	19(36.54)	61.318	0.000**
Non-calcification	85(57.05)	2(3.85)		
CT-FFR(n,%)				
＞0.80	119(79.87)	17(32.69)	39.204	0.000**
≤0.80	30(20.13)	35(67.31)		
Coronary artery lesion extent(n,%)				
Limitation	102(69.86)	31(59.62)		
Diffuse	14(9.59)	9(17.31)	2.682	0.262
Segmental	30(20.55)	12(23.08)		
Coronary artery stenosis grading(n,%)				
Grade 1	57(38.26)	2(3.85)		
Grade 2	61(40.94)	10(19.23)	82.733	0.000**
Grade 3	29(19.46)	16(30.77)		
Grade 4	2(1.34)	24(46.15)		
MAX-FAI（HU）	-84.23±8.99	-68.58±5.15	-15.261	0.000**
Age (years)	64.85±10.88	69.79±11.42	-2.781	0.006**

Body Mass Index (BMI,kg/m^2)	24.51±4.16	24.77±3.64	-0.392	0.695
Fasting blood glucose （GLU,mmol/L)	5.63±1.48	6.26±3.53	-1.185	0.242
Total Cholesterol （mmol/L）	4.56±1.15	4.56±1.32	-0.006	0.996
Triglyceride （mmol/L）	2.12±1.34	2.14±1.40	-0.104	0.917
Low-density lipoprotein (LDL) （mmol/L）	2.60±0.94	2.55±1.01	0.326	0.745
High-density lipoprotein （mmol/L）	1.01±0.27	0.98±0.27	0.700	0.485
γ-Glutamyltranspeptidase （γ-GT,U）	63.84±131.73	64.37±104.38	-0.026	0.979
Creatine kinase isoenzyme （U/L）	6.28±10.99	3.61±5.46	1.946	0.054
Troponin(μg/L)	0.43±3.06	0.59±3.36	-0.288	0.773
Calcium score	95.96±216.78	176.45±332.86	-1.622	0.109

** *P*<0.01，*Note*: *P*<0.05 indicates statistically significant differences

Analysis of MACE risk factors in patients with coronary artery stenosis and hyperuricemia

The variables with statistically significant differences in the baseline clinical data were included in the LASSO regression for further screening. As shown in Table 2, Figure 1, and Figure 2, the variables that were finally included in the model under the condition of lambda.min were: coronary artery stenosis grading, plaque properties, CT-FFR, MAX-FAI, and age. Multivariate binary logistic regression analysis was performed, and the results showed that coronary artery stenosis grading, plaque properties, CT-FFR, and MAX-FAI were risk factors for MACE in patients with coronary artery stenosis and hyperuricemia (P<0.05), as shown in Table 3.

Table 2 LASSO regression variable screening results (lambda.min)

Variable	Coefficients (β)	Type
Coronary artery stenosis grading	0.870	Continuous
Plaque characteristics（Reference: non-calcification）		
Calcification	−2.434	Dummy variable
Mixed	0.615	Dummy variable
CT-FFR	0.758	Dichotomous classification
MAX-FAI	0.174	Continuous
Age	0.004	Continuous
Constant term	9.836	—

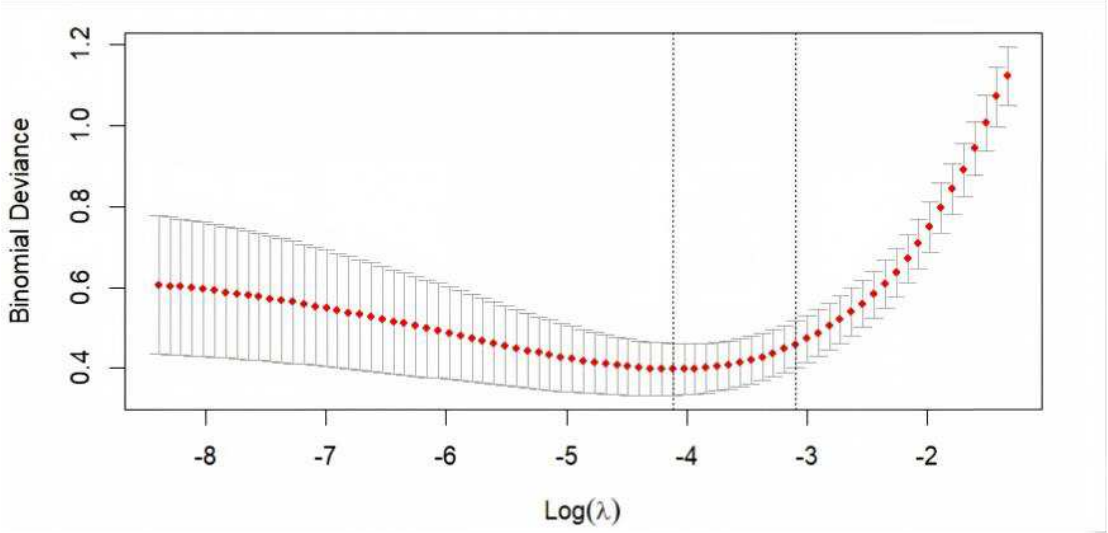


Fig. 1 10-fold cross-validation plot

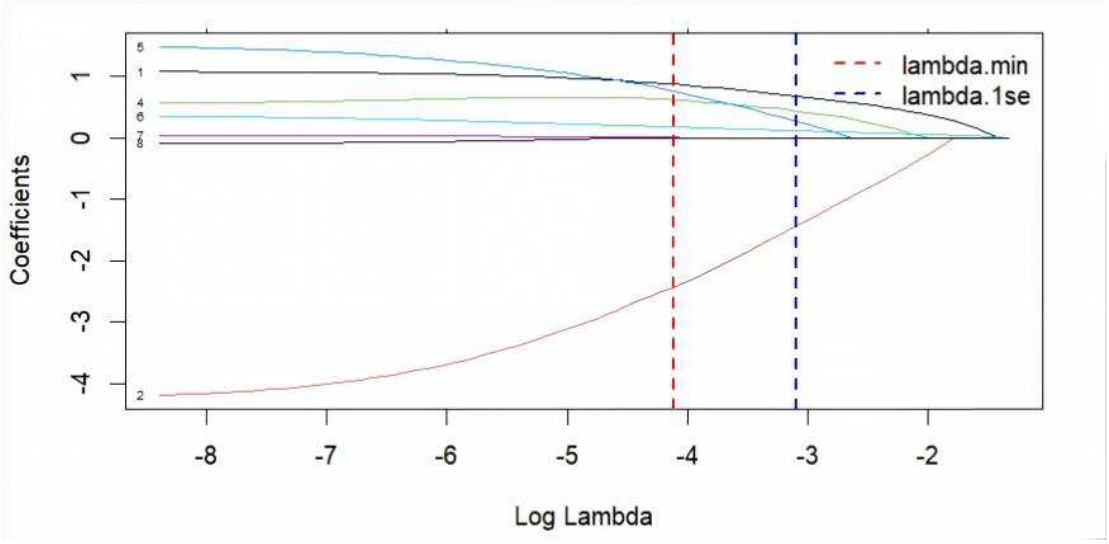


Fig.2 LASSO coefficient path plot

Table 3 Analysis of MACE risk factors in patients with coronary artery stenosis and hyperuricemia

Variable	β	SE	Wald χ^2	*p-value*	OR	95% CI
Coronary artery stenosis grading	1.421	0.466	3.050	0.002	4.140	1.850–12.160
Plaque characteristics (Reference: non-calcification)						
Calcification	3.701	1.378	2.687	0.007	40.500	3.910–954.380
Mixed	4.506	1.359	3.315	0.001	90.570	8.570–1982.29
CT-FFR	2.100	0.833	2.522	0.012	8.170	1.750–49.930
MAX-FAI	0.332	0.103	3.227	0.001	1.390	1.190–1.800
Age	0.048	0.039	1.221	0.222	1.050	0.970–1.140
Constant term	12.715	6.840	1.859	0.063	—	—

Comparison of MAX-FAI and CT-FFR in patients with hyperuricemia across different grades of coronary artery stenosis

Patients with hyperuricemia across different grades of coronary artery stenosis exhibited statistically significant differences in MAX-FAI and CT-FFR ($P<0.05$). As the grade of coronary artery stenosis increased from 1 to 4, MAX-FAI gradually increased, while CT-FFR gradually decreased, as shown in Table 4.

Table 4 Comparison of MAX-FAI and CT-FFR in patients with hyperuricemia across different grades of coronary artery stenosis ($x \pm S$)

Coronary artery stenosis grading	n	MAX-FAI	CT-FFR
Grade 1	59	-84.24±8.89	0.879±0.108
Grade 2	71	-82.00±10.11	0.852±0.118
Grade 3	45	-78.16±11.47	0.822±0.131
Grade 4	26	-69.50±5.96	0.810±0.124

F-value	—	15.548	2.963
p-value	—	<0.001	0.033

Comparison of MAX-FAI and CT-FFR in patients with hyperuricemia of different plaque properties

There was a statistically significant difference in MAX-FAI among patients with hyperuricemia of different plaque properties (P<0.05), with the mixed plaque group having the highest MAX-FAI. There was no statistically significant difference in CT-FFR among the groups (P>0.05), as shown in Table 5.

Table 5 Comparison of MAX-FAI and CT-FFR in patients with hyperuricemia of different plaque properties (x±S)

Plaque characteristics	n	MAX-FAI	CT-FFR
non-calcification	87	-83.53±9.15	0.852±0.116
Calcification	65	-79.66±11.28	0.851±0.135
Mixed	49	-74.92±10.28	0.836±0.112
F-value	—	11.399	0.327
p-value	—	<0.001	0.721

The predictive value of each indicator and the combination of CT-FFR and MAX-FAI

The ROC curve analysis of individual indicators and combined models revealed that the AUCs for predicting MACE occurrence were 0.852, 0.836, 0.736, and 0.924 for coronary artery stenosis grading, plaque properties, CT-FFR, and MAX-FAI, respectively. The sensitivities were 0.769, 0.962, 0.673, and 0.984, respectively, and the

specificities were 0.792, 0.570, 0.799, and 0.758, respectively. The AUC for predicting MACE occurrence using the combination of CT-FFR and MAX-FAI was 0.950, with a sensitivity of 0.904 and a specificity of 0.846. The AUC of this combined approach was higher than that of each individual indicator alone. Details are provided in Table 6, Figure 3, and Figure 4.

Table 6 Predictive value of each indicator and CT-FFR combined with MAX-FAI

Model	AUC	95% CI	Cutoff value	Sensitivity	Specificity
Coronary artery stenosis grading	0.852	0.792–0.912	0.287	0.769	0.792
Plaque characteristics	0.836	0.782–0.890	0.158	0.962	0.570
CT-FFR	0.736	0.664–0.808	0.332	0.673	0.799
MAX-FAI	0.924	0.891–0.958	0.167	0.984	0.758
CT-FFR + MAX-FAI	0.950	0.924–0.977	0.276	0.904	0.846

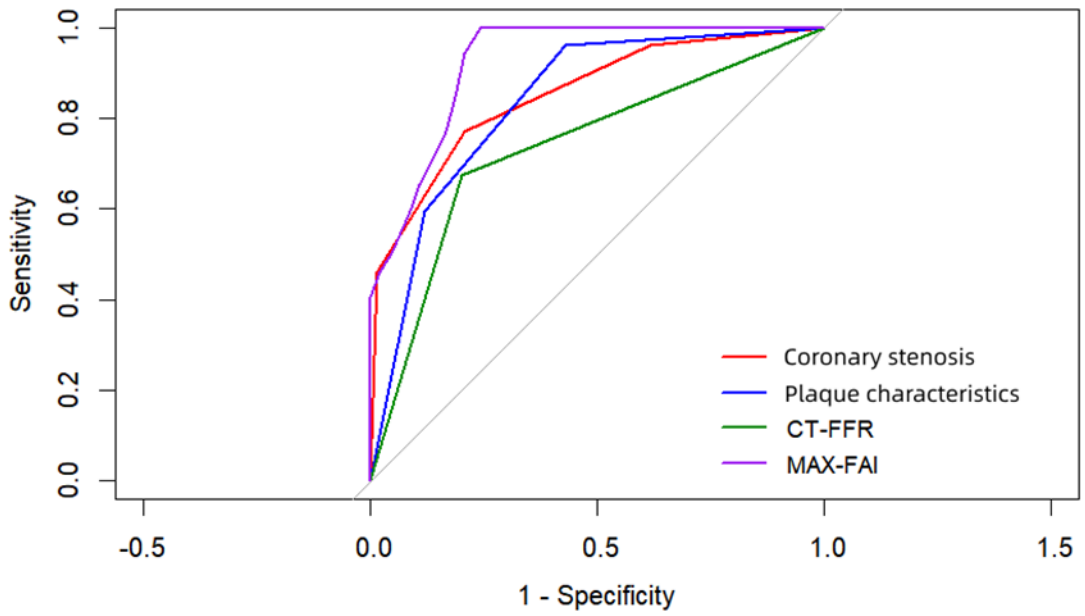


Fig. 3: Univariate ROC Curve

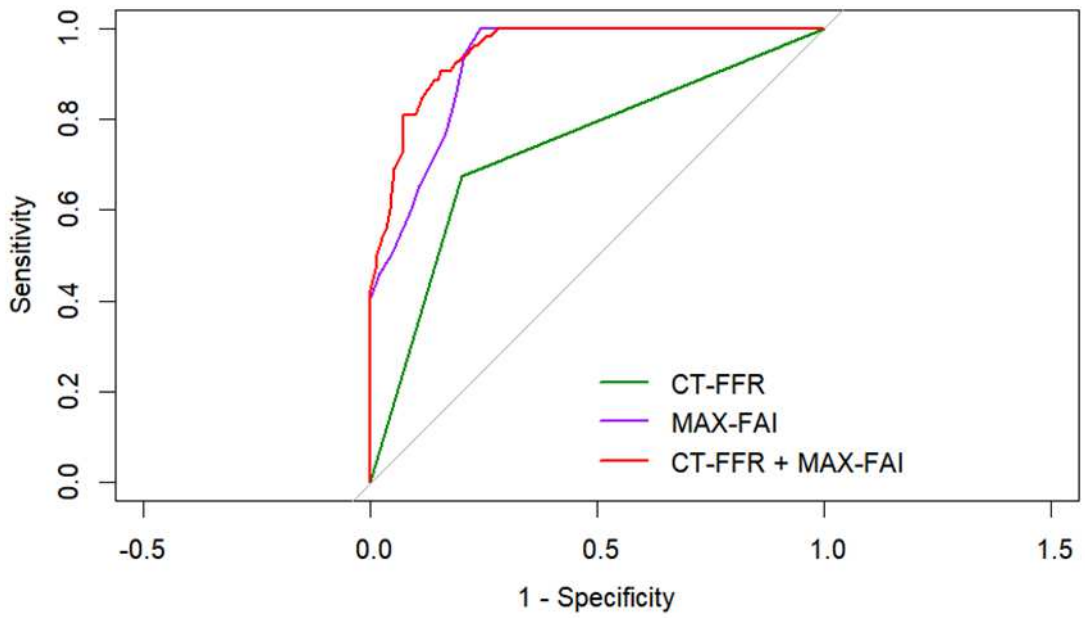


Fig. 4: ROC curve of combined diagnosis

Construction and validation of a nomogram model for predicting the risk of MACE

Incorporating four independent predictors: coronary artery stenosis grading, plaque nature, CT-FFR, and MAX-FAI, a nomogram model for predicting the risk of MACE (Figure 5) was constructed. The results indicated that patients with higher coronary artery stenosis grading, mixed or calcified plaque nature, CT-FFR ≤ 0.80, and a larger MAX-FAI (closer to -60) had a higher total score, corresponding to a greater risk of MACE. The calibration curve of this model demonstrated a good overall fit between observed and predicted values, with a mean absolute error of 0.013 (Figure 6). The decision curve analysis revealed that within a threshold probability range of approximately 0%–60%, it provided higher clinical net benefit (Figure 7).

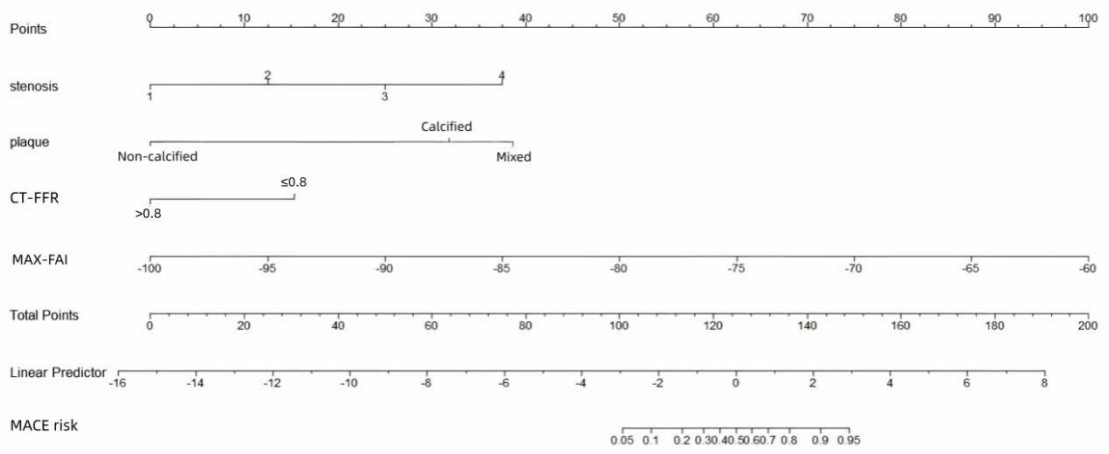


Fig.5: Nomogram prediction model for MACE occurrence risk

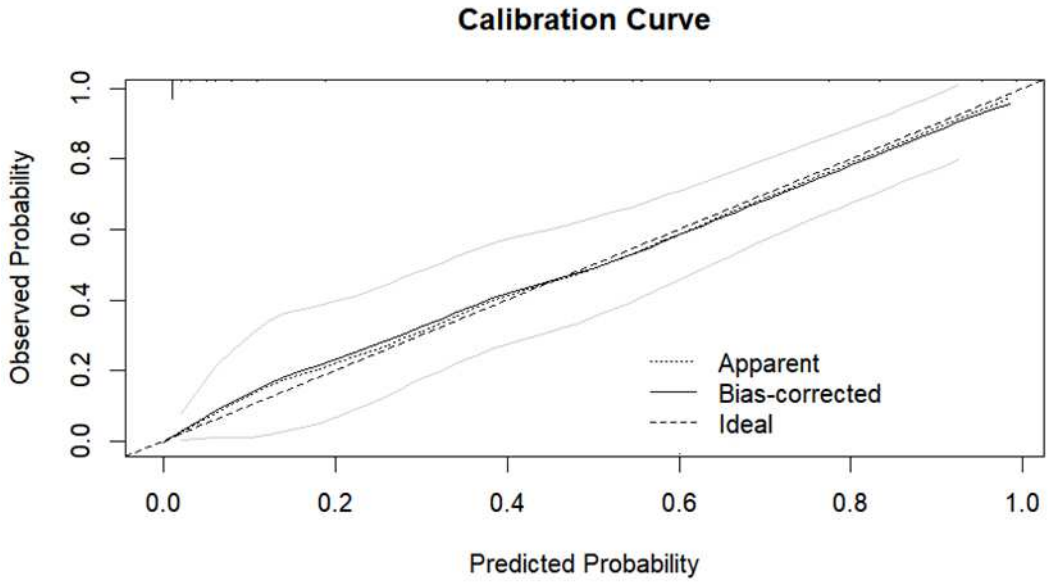


Fig.6 Calibration curve of the nomogram prediction model

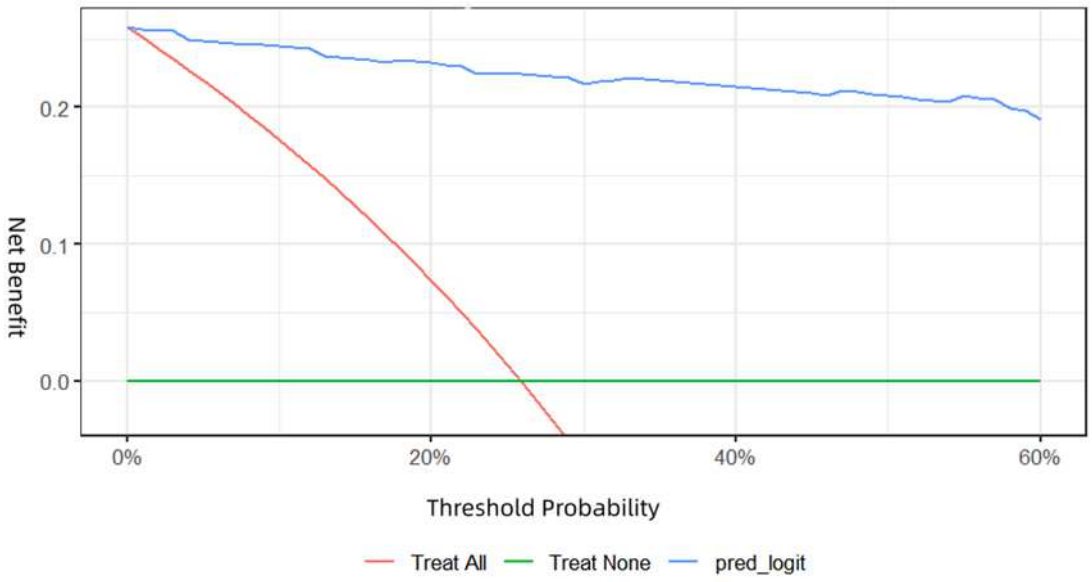


Fig.7 DCA decision curve of the nomogram prediction model

Discussion

The baseline data analysis results of this study showed no significant statistical differences in traditional cardiovascular risk factors (gender, blood pressure, smoking and alcohol history, blood glucose, blood lipids, myocardial enzyme indicators, and calcification scores) between the two patient groups. This suggests that the baseline confounding factors in this study cohort are well balanced, effectively eliminating the interference of conventional clinical indicators on prognostic outcomes. In this study, CK-MB showed a marginally significant trend, which is consistent with previous research conclusions: most patients with stable coronary heart disease maintain low baseline levels of myocardial injury markers, and only experience slight elevations during unstable plaque, recurrent micro-ischemia, or hemodynamic abnormalities. The independent predictive power of a single baseline myocardial enzyme indicator for long-term MACE is relatively limited [17]. However, the indicators ultimately selected

in this study with significant differences between groups focused on imaging quantification parameters, including coronary artery stenosis grading, plaque characteristics, CT-FFR, and MAX-FAI, further confirming that AI-assisted CCTA functional quantification indicators are more specific and sensitive for the prognostic assessment of patients with hyperuricemia and coronary artery stenosis compared to traditional clinical biochemical indicators.

This study, through the combination of LASSO regression and multi-factor binary logistic regression validation, confirmed that coronary artery stenosis grading, plaque properties, CT-FFR, and MAX-FAI are independent risk factors for the long-term occurrence of MACE in patients with hyperuricemia and coronary artery stenosis. Studies have reported that the degree of coronary artery stenosis is an important predictor of adverse cardiovascular events, and the higher the stenosis grading, the higher the risk of short-term adverse cardiovascular events [18]. This study is consistent with previous research, and the prognostic predictive value of stenosis grading remains stable in the hyperuricemia population. Simultaneously, this study found that plaque properties are closely related to the occurrence of MACE, with patients with mixed plaques and calcified plaques having a higher prognostic risk. Hyperuricemia can exacerbate plaque inflammatory infiltration, further increasing plaque instability, thereby promoting the occurrence of adverse cardiovascular events [19-20].

CT-FFR, as an imaging indicator for non-invasive assessment of coronary functional ischemia, can quantify the blood flow perfusion injury caused by coronary artery stenosis, compensating for the deficiency of solely relying on CCTA

morphological stenosis grading to assess lesions [21]. This study found that a decrease in CT-FFR is an independent risk factor for the occurrence of MACE, and as the grading of coronary artery stenosis increases, the CT-FFR value shows a progressive downward trend, consistent with previous clinical research conclusions [21-23]. Notably, this study innovatively discovered that there is no significant difference in CT-FFR values among different plaque property subgroups, suggesting that plaque morphology mainly affects plaque stability rather than immediate hemodynamic status. The long-term adverse events caused by plaques are primarily related to the risk of thrombus rupture, rather than pure myocardial ischemia[24-25]. This also explains the clinical phenomenon where some patients with mild to moderate stenosis and no significant blood flow restriction still experience MACE[26-27].

Pericoronary FAI is an emerging non-invasive quantitative indicator of adipose inflammation in recent years. It can reflect the level of perivascular inflammation and vascular remodeling status by detecting changes in the CT value of pericoronary fat. A higher CT value of fat indicates a more significant local inflammatory response and poorer plaque stability, which has high predictive value for future cardiovascular events [28-29]. The results of this study show that MAX-FAI gradually increases with the escalation of coronary stenosis grading, and MAX-FAI in the mixed plaque group is significantly higher than that in other plaque types, confirming that the more severe the stenosis and the more complex the plaque composition, the more active the pericoronary local inflammatory response[30].Hyperuricemia can activate inflammatory pathways and exacerbate pericoronary fat inflammatory infiltration,

further promoting the progression of coronary atherosclerosis and plaque instability. This also reveals the unique prognostic predictive value of MAX-FAI in hyperuricemia patients. Compared to single morphological indicators, MAX-FAI can supplement the risk assessment dimension of coronary heart disease from the micro-inflammatory level and is an effective complement to traditional imaging indicators.

The ROC curve analysis results confirmed that MAX-FAI, as a single indicator, exhibited the best predictive performance (AUC=0.924), significantly surpassing traditional coronary artery stenosis grading, plaque properties, and CT-FFR. This fully demonstrates the core advantage of pericoronary fat inflammation quantification indicators in the prognostic assessment of hyperuricemia patients. More importantly, the CT-FFR combined with MAX-FAI predictive model constructed in this study achieved an AUC of 0.950, with a sensitivity of 90.4% and a specificity of 84.6%, significantly outperforming each individual indicator. This confirms the good complementary effect between hemodynamic indicators and pericoronary inflammation indicators. CT-FFR reflects coronary functional ischemic injury, while MAX-FAI reflects perivascular microinflammation and plaque instability. The combination of the two can achieve precise assessment of MACE risk, which is also the core innovation of this study that distinguishes it from previous single imaging studies.

This study presents a nomogram prediction model constructed based on four independent risk factors, visually illustrating the contribution weights of each indicator to the risk of MACE (Major Adverse Cardiac Events). The model calibration curve

demonstrates a high degree of agreement between predicted and actual observed values, with an average absolute error of only 0.013, indicating excellent model fit and high prediction accuracy. The DCA (Decision Curve Analysis) further confirms that this combined model achieves good clinical net benefit across a wide threshold probability range of 0% to 60%, possessing strong clinical applicability and promotional value. It can provide a quantitative reference tool for stratified intervention and individualized diagnosis and treatment of high-risk patients in clinical settings.

This study has certain limitations. Firstly, it is a single-center, retrospective study, which inevitably introduces selection bias. The sample source is limited, and the extrapolation of the study results requires further verification through multi-center, large-sample cohort studies. Secondly, the follow-up duration is limited, and only the first MACE event during the follow-up period is counted. There is no continuous tracking of patients' long-term prognosis, recurrent adverse events, and disease progression. Furthermore, this study only incorporates quantitative indicators of CCTA imaging and routine clinical data, without adjusting for confounding factors such as medication use, lifestyle intervention, and subsequent treatment plans, which may slightly affect the accuracy of the risk model. Lastly, the AI quantitative indicators in this study rely on standardized CCTA scanning parameters. There may be slight differences in FAI and CT-FFR values across different devices and scanning protocols, and the cross-device applicability of the model still needs further verification.

In conclusion,coronary artery stenosis grading, plaque characteristics, CT-FFR, and MAX-FAI are risk factors for MACE in patients with coronary artery stenosis and

hyperuricemia. The combination of CT-FFR and MAX-FAI can significantly enhance the predictive efficacy of MACE. The nomogram model constructed based on the aforementioned imaging characteristics is reliable in calibration and stable in clinical net benefit, and can serve as an imaging tool for noninvasive prognostic assessment in this high-risk population, providing a reference for precise prevention and treatment.

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Author contributions

(I) Conception and design: Juanjuan Li,Zhengliang Li; (II) Funding acquisition: Juanjuan Li; (III) Collection and assembly of data: Biao Wang, Yazhu Zhao, Yujiao Cao; (IV) Data analysis and interpretation:Juanjuan Li, Zhou Zhou; (V) Manuscript writing: Juanjuan Li; (VI) Methodological support: Zhengliang Li, Zhou Zhou.(VII) Final approval of manuscript: All authors.

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Data availability

The datasets generated and/or analysed during the current study are not publicly available due to patient privacy and data protection regulations. However, they are available from the corresponding author on reasonable request, subject to approval by the institutional ethics committee.

Declarations

Ethics approval and consent to participate

This study was approved by the Xiangyun County People's Hospital Ethics Committee (Ethics approval reference number:KY-PJ-2025-016）, and informed consent from the participants was waived. All procedures involving human participants were conducted in accordance with the ethical standards of the institutional research committee and with the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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