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TyG-ABSI as a novel metabolic obesity indicator for carotid plaque: an explainable machine learning study using SHAP in low-income population

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Abstract

Background This investigation aimed to evaluate the relationship between a combined triglyceride-glucose (TyG)-adiposity index and carotid plaque within a low-income rural cohort, and to apply machine-learning models alongside SHapley Additive exPlanations (SHAP) for detailed interpretation.

Methods We conducted a cross-sectional analysis of 1,960 adults enrolled from documented low-income rural areas. Sociodemographic variables, lifestyle habits, anthropometric indices, and biochemical markers were systematically recorded. A binary logistic model served to predict carotid plaque, while restricted cubic splines (RCS) examined possible non-linear associations between the TyG-ABSI composite (triglyceride-glucose index combined with a body-shape index) and plaque risk. Next, ten machine-learning classifiers—Logistic Regression, Support Vector Machine (SVM), Gradient Boosting Machine (GBM), Neural Network, Random Forest, XGBoost, K-Nearest Neighbors (KNN), AdaBoost, LightGBM, and CatBoost—were trained and internally validated. Hierarchical 5-fold cross-validation was implemented in the training set to fine-tune the hyperparameters. Model performance was evaluated on both the training and validation sets using accuracy, sensitivity, specificity, precision, F1 score, and the area under the ROC curve (AUC). SHAP values were computed to quantify and visualize feature contributions.

Results Among 1,960 participants, the overall prevalence of carotid plaque was 48.3%, with 59.0% in men and 41.7% in women. In multivariable-adjusted logistic regression, sex, age, systolic blood pressure (SBP), and TyG-ABSI were independently associated with carotid plaque. Each one-unit increment in TyG-ABSI corresponded to a 20% higher

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odds of plaque presence (OR = 1.20; 95% CI 1.02–1.42; $P = 0.025$). RCS modelling revealed a non-linear relationship (P for non-linearity = 0.038), risk rose with TyG-ABSI up to = 7.75 and then declined, yielding an inverted-U trend around this inflection point. Among ML algorithms, logistic regression achieved the best generalization on the validation set (accuracy = 0.665, $F1 = 0.58$, AUC = 0.67). SHAP analysis confirmed the predictive importance of TyG-ABSI.

Conclusions In this cross-sectional study of a low-income rural population, the TyG-ABSI index demonstrated a significant nonlinear relationship with carotid plaque risk. Among the machine learning algorithms evaluated, logistic regression achieved the highest predictive accuracy. SHAP-based visualizations further revealed the key features driving this distinction. Future research is needed to validate causal associations through prospective studies.

Clinical trial number Not applicable.

Keywords Carotid plaque, TyG-ABSI, Machine learning, Rural population

Background

Cardiovascular disease (CVD) is now the foremost contributor to global disability and premature mortality, accounting for over 20 million deaths annually [1]. Projections indicate that by 2030 this figure will rise to approximately 23.6 million deaths per year [2]. Carotid plaque, a direct expression of atherosclerosis, induces luminal narrowing and thereby compromises cerebral perfusion [3]. Globally, carotid plaque affects 21.1% of adults [2] and its presence is strongly linked to incident CVD, elevating risks of coronary artery disease, myocardial infarction, and ischemic stroke [4]. The societal burden is substantial: among adults aged ≥ 55 years worldwide, age-standardized disability-adjusted life-years attributable to CVD reach 21,715.67, with the burden disproportionately concentrated in low-income populations [3].

Studies have shown that numerous factors influence carotid plaque formation, among which obesity and insulin resistance are key underlying contributors. Obesity is a widespread global health challenge, and its prevalence in rural, low-income populations deserves attention. Obesity not only modifies body shape but also induces metabolic disturbances—including dyslipidaemia, elevated blood glucose, and raised blood pressure—that foster atherosclerotic development and progression [5]. Insulin resistance, moreover, is a central pathophysiological mechanism of metabolic syndrome [6]. The triglyceride–glucose (TyG) index, a widely investigated and applied measure, reliably indicates the degree of insulin resistance. Evidence demonstrates a strong association between insulin resistance and atherosclerosis, probably mediated by endothelial dysfunction, inflammatory responses, and lipid metabolism derangements that encourage carotid plaque formation. For instance, a retrospective study revealed that the TyG index was closely linked to carotid plaque presence in patients with type 2 diabetes [7]. Another investigation observed a significant relationship between the TyG index and carotid plaque incidence, particularly among elderly men with dyslipidaemia, diabetes, or hypertension [8]. Relative to TyG

alone, combined indices incorporating TyG with obesity markers such as BMI and waist circumference exhibit superior predictive capacity [9]. Similarly, integrating the TyG index with the Body Roundness Index (BRI) has shown promise for stroke risk prediction, especially in rural populations [10].

However, evidence linking combined TyG–ABSI indices to carotid plaque in rural, low-income cohorts remains scarce, and conventional statistical approaches may struggle with such complex data. Machine learning—an advanced analytic framework—efficiently handles large, high-dimensional datasets and reveals latent non-linear patterns [11]. SHAP (SHapley Additive exPlanations) visualization further clarifies model predictions by quantifying each feature's contribution, thereby reinforcing clinical decision-making [12]. SHAP elucidates the critical role of input variables in the final predictions of “black box” models. A study based on the National Health and Nutrition Examination Survey (NHANES) employed machine learning and SHAP to demonstrate how these variables identify cardiovascular risk factors associated with heavy metal exposure [13], highlighting SHAP's pivotal role in interpreting such predictive models.

This study is based on the “Tianjin Brain Research” project, a longitudinal cohort study targeting low-income rural populations in 18 administrative villages of Yangjinzhuang Town, Jixian County, Tianjin City, China. The population is primarily composed of farmers with relatively low income and educational levels. Accordingly, we applied machine learning algorithms with integrated SHAP visualization to explain the importance of TyG-ABSI in predicting carotid plaque risk in low-income rural adults. Recent studies have combined conventional metabolic indicators with machine learning processes to achieve AUC >81% in the prediction of COVID-19 hospitalization [14], and $F1$ value of 0.84 in the screening of characteristics of type 2 diabetes [15], which provides external evidence for the design of this study. The innovation of this study is that TyG-ABSI is used as a predictor of carotid artery plaque for the first time, combined

with interpretable machine learning and SHAP visualization, and focuses on low-income rural populations with relatively poor medical resources. This approach deepens insight into the determinants of plaque formation within this demographic and furnishes an evidence base for tailored preventive strategies, thereby offering practical value for improving the health of low-income rural communities and reducing cerebrovascular disease incidence.

Methods

Study design and subjects

This population-based cross-sectional study originated from the Tianjin Cerebrovascular Disease Research Project, a longitudinal cohort study currently underway in China's Tianjin Municipality. It included 14,251 participants from 18 administrative villages in Yangjinzhuang Township, Jizhou District, Tianjin. The local population consists of farmers with relatively low income and educational levels, whose primary economic source is grain cultivation. In 1991, the per capita annual income was less than 100 yuan, which dropped further to below 1,000 yuan by 2010. The study cohort includes multiple data points such as carotid plaque, stroke, and cognition, with cognitive assessment involving the MMSE scale. However, the current study focuses on the relationship between carotid plaque and metabolic obesity indicators (such as TyG-ABSI) and does not utilize data from the MMSE score. Between 2018 and 2020, 2,869 residents underwent carotid ultrasound examinations. Fourteen participants younger than 45 years were excluded, leaving 2,855. We subsequently removed 43 individuals with prior myocardial infarction, 487 with coronary heart disease, and 365 with previous haemorrhagic or ischaemic stroke. The final analytic sample comprised 1,960 eligible adults.

The study protocol was approved by the Ethics Committee of Tianjin Medical University General Hospital and adhered to the Declaration of Helsinki; all participants provided written informed consent.

Data collection

Between 2018 and 2020, uniformly trained interviewers obtained sociodemographic and clinical data through face-to-face questionnaires that recorded sex, age, and prior diagnoses of diabetes and hypertension. Lifestyle variables included current smoking and alcohol consumption. Trained medical personnel used calibrated instruments to measure height, weight, waist circumference, and blood pressure; blood pressure was taken with a mercury sphygmomanometer, and the mean of two or three systolic (SBP) and diastolic (DBP) readings—collected by the same observer to minimize systematic bias—was documented. After an overnight fast of ≥ 12 h, morning blood samples were drawn; assays comprised

fasting blood glucose, triglycerides, total cholesterol, HDL-C, LDL-C, ALT, AST, BUN, creatinine, total bilirubin, red-cell count, white-cell count, platelet count, and hemoglobin. Experienced sonographers evaluated carotid plaque presence using B-mode ultrasonography of the carotid arteries.

Missing data handling

Missing observations were addressed via multiple imputation by chained equations (MICE). All preprocessing steps were conducted in R using the mice and tidyverse packages. Following assessment of the missing-data pattern, categorical variables were declared as factors and imputed with polytomous logistic regression (polyreg), whereas continuous variables were imputed through predictive mean matching (pmm). Imputed datasets were subsequently examined for face validity.

Variable definitions

Body-mass index (BMI) was determined as weight in kilograms divided by the square of height in meters. Smoking status was assigned to individuals who had smoked at least one cigarette per day for more than one year; alcohol consumption was considered positive when daily ethanol intake reached or exceeded 45 g during the preceding year. Hypertension was identified by systolic blood pressure ≥ 140 mmHg or diastolic blood pressure ≥ 90 mmHg, current use of antihypertensive medication, or a self-reported physician diagnosis. Diabetes mellitus was defined in accordance with the American Diabetes Association criteria: glycated hemoglobin $A1C \geq 6.5\%$, fasting plasma glucose ≥ 126 mg/dL, 2-hour oral glucose tolerance test value ≥ 200 mg/dL, use of glucose-lowering agents, or self-reported diabetes.

The triglyceride–glucose index (TyG) was computed as $\ln [TG \text{ (mg/dL)} \times FBG \text{ (mg/dL)} / 2]$. The A body shape index (ABSI) was derived as waist circumference (m) divided by $[BMI^{(2/3)} \times height^{(1/2)}]$. The waist-to-height ratio (WHtR) was defined as waist circumference divided by height. Composite indices—TyG-BMI, TyG-WHtR, TyG-WC, and TyG-ABSI—were generated by multiplying the TyG index by BMI, WHtR, waist circumference, and ABSI, respectively. Carotid plaque was identified as a focal structure encroaching ≥ 0.5 mm into the arterial lumen, $\geq 50\%$ thicker than adjacent intima-media thickness (IMT), or exhibiting an absolute thickness > 1.5 mm.

Statistical analysis

Continuous variables are summarized as mean $\pm$ SD, categorical variables as counts (%). Between-group differences were evaluated with Student's *t* test for continuous data and the χ^2 test for categorical data. Multivariable associations between TyG indices and carotid plaque

were examined using logistic regression, with results reported as odds ratios (ORs) and 95% confidence intervals (CIs). Analyses were performed in SPSS 25.0. To assess potential non-linearity, restricted cubic spline (RCS) regression was implemented with the rms package

in R 4.4.0, permitting evaluation of the TyG index–plaque relationship while accommodating non-linear effects.

SHAP-based machine-learning model construction and evaluation

Using the R caret package, the data set was randomly sampled and stratified according to the result variables. The data set was divided into training set and verification set in a one-time ratio of 7:3 to ensure that the proportion of the two categories was consistent with the original data and the data independence. To mitigate potential instability arising from a single train-test split, we performed stratified 5-fold cross-validation within the training set for model selection and hyperparameter tuning, ensuring a more robust performance estimate. Five fold cross-validation consists of four training and one verification, each of which calculates an AUC. Then the average value of these five AUCs is taken, and the performance is evaluated by a completely isolated 30% test set after hyperparameter tuning and selection of the optimal model. Variables retained after multivariable logistic regression were supplied to ten supervised classifiers: logistic regression, support-vector machine, gradient boosting machine, neural network, random forest, XGBoost, K-nearest neighbours, AdaBoost, LightGBM, and CatBoost. Model performance on both data partitions was assessed using accuracy, sensitivity, specificity, precision, F1-score, and the area under the receiver operating characteristic curve (AUC).

To enhance the interpretability of machine learning models, SHAP summary diagrams visually present distribution patterns, with colors and positions simultaneously indicating the magnitude and direction of influence. It is crucial to emphasize that SHAP does not identify direct correlations between input features and output results, but rather explains the importance of each input feature in shaping the model's final predictions. This proves particularly valuable for interpreting complex “black box” models, as their internal mechanisms are often opaque. By quantifying feature contributions, SHAP provides a unified framework for explaining model predictions, making the decision-making process more transparent and accessible.

All machine-learning analyses were conducted in R 4.4.0.

Results

Participant general characteristics

A total of 1,960 participants were enrolled in this study, including 749 males and 1,211 females. The average age of participants was 63.03 years. The overall prevalence of carotid plaque was 48.3%, among which the prevalence in males was 59.0% and in females was 41.7% (Table 1).

Table 1 Characteristics of participants

Characteristics	Male (n = 749)	Female (n = 1211)	Total (n = 1960)
Age, years, means ± SD	64.53 (8.44)	62.09 (7.83)	63.03 (8.15)
BMI, kg/m ² , means ± SD	24.74 (3.49)	25.59 (3.91)	25.27 (3.78)
SBP, mmHg, means ± SD	144.21 (20.05)	144.51 (19.95)	144.40 (19.98)
DBP, mmHg, means ± SD	83.97 (11.30)	80.25 (11.02)	81.67 (11.27)
FBG, mmol/L, means ± SD	5.85 (1.36)	5.99 (1.37)	5.94 (1.37)
TG, mmol/L, means ± SD	1.43 (1.52)	1.66 (1.14)	5.94 (1.37)
TC, mmol/L, means ± SD	5.02 (1.12)	5.47 (4.06)	5.30 (3.27)
LDL, mmol/L, means ± SD	2.49 (0.78)	2.71 (0.92)	2.63 (0.88)
HDL, mmol/L, means ± SD	1.49 (0.46)	1.51 (0.42)	1.50 (0.43)
ALT, U/L, means ± SD	5.69 (2.62)	20.62 (13.77)	20.53 (12.58)
BUN, mmol/L, means ± SD	21.99 (10.04)	5.69 (2.62)	5.86 (2.76)
AST, U/L, means ± SD	11.81 (5.61)	21.99 (10.04)	22.11 (9.67)
TB, μmol/L, means ± SD	14.39 (7.13)	11.81 (5.61)	12.79 (6.36)
Creatinine, mmol/L, means ± SD	79.17 (33.50)	64.49 (24.81)	70.10 (29.32)
WBC, ×10 ⁹ /L, means ± SD	7.59 (39.92)	6.91 (31.42)	7.17 (34.91)
RBC, ×10 ¹² /L, means ± SD	4.58 (0.42)	4.35 (0.39)	4.44 (0.42)
Hb, g/L, means ± SD	142.27 (12.45)	131.00 (12.41)	135.31 (13.58)
PLT, ×10 ⁹ /L, means ± SD	212.54 (52.94)	233.02 (59.68)	225.19 (58.04)
Smoking, n (%)			
Never smoking	138 (18.4)	1139 (94.1)	1277 (65.2)
Current smoking	378 (50.5)	30 (2.5)	408 (20.8)
Ever smoking	233 (31.3)	42 (3.5)	275 (14.0)
Alcohol consumption, n (%)			
Never drinking	198 (26.4)	1158 (95.6)	1356 (69.2)
Current drinking	421 (56.2)	25 (2.1)	446 (22.8)
Ever drinking	130 (17.4)	28 (2.3)	158 (8.1)
Hypertension, n (%)	571 (76.2)	966 (79.8)	1537 (78.4)
Diabetes, n (%)	113 (15.1)	243 (20.1)	356 (18.2)
WC, cm, means ± SD	88.65 (9.29)	86.19 (9.14)	87.13 (9.28)
WHtR, means ± SD	52.96 (5.40)	55.21 (5.80)	54.35 (5.76)
ABSI, means ± SD	0.81 (0.05)	0.80 (0.06)	0.80 (0.06)
TyG, means ± SD	8.56 (0.70)	8.79 (0.64)	8.70 (0.67)
TyG-BMI, means ± SD	212.67 (39.18)	225.68 (40.70)	220.71 (40.61)
TyG-WHtR, means ± SD	4.54 (0.67)	4.86 (0.67)	4.74 (0.69)
TyG-WC, means ± SD	760.88 (114.13)	759.27 (106.72)	759.88 (109.59)
TyG-ABSI, means ± SD	6.93 (0.70)	7.02 (0.72)	6.98 (0.71)
Carotid Plaque, n (%)	442 (59.0)	505 (41.7)	947 (48.3)

Univariable analysis results of carotid plaque occurrence in the training set

Univariable analysis results showed that gender, age, BMI, SBP, FBG, BUN, creatinine, platelet count, smoking history, drinking history, hypertension, diabetes, waist circumference, ABSI, and TyG-ABSI were associated with the occurrence of carotid plaque. Among them, male gender, older age, higher SBP, higher FBG, higher BUN, higher PLT, quitting smoking, quitting

Table 2 Univariate analysis of carotid plaque occurrence in the training set

Characteristics	Control (n = 710)	Carotid plaque (n = 663)	P
Gender, n (%)			< 0.001
Male	211 (40.6)	309 (59.4)	
Female	499 (70.3)	354 (53.4)	
Age, years, means ± SD	60.54 (7.46)	65.26 (8.03)	< 0.001
BMI, kg/m ² , means ± SD	25.52 (3.79)	24.99 (3.73)	0.008
SBP, mmHg, means ± SD	141.82 (18.42)	147.71 (21.31)	< 0.001
DBP, mmHg, means ± SD	82.18 (11.05)	81.28 (11.69)	0.140
FBG, mmol/L, means ± SD	5.81 (1.31)	6.06 (1.46)	< 0.001
TG, mmol/L, means ± SD	1.55 (1.08)	1.57 (1.50)	0.806
TC, mmol/L, means ± SD	5.15 (1.06)	5.15 (1.06)	0.058
LDL, mmol/L, means ± SD	2.62 (0.86)	2.62 (0.86)	0.330
HDL, mmol/L, means ± SD	1.50 (0.40)	1.51 (0.44)	0.558
ALT, U/L, means ± SD	20.41 (12.54)	20.03 (9.71)	0.535
BUN, mmol/L, means ± SD	5.65 (2.89)	6.04 (2.03)	0.004
AST, U/L, means ± SD	21.96 (9.80)	21.96 (8.58)	0.994
TB, μmol/L, means ± SD	12.39 (6.09)	13.01 (6.37)	0.065
Creatinine, mmol/L, means ± SD	13.01 (6.37)	73.34 (37.53)	0.002
WBC, ×10 ⁹ /L, means ± SD	7.56 (41.02)	7.71 (42.43)	0.946
RBC, ×10 ¹² /L, means ± SD	4.45 (0.42)	4.41 (0.42)	0.073
Hb, g/L, means ± SD	135.71 (13.76)	135.71 (13.76)	0.249
PLT, ×10 ⁹ /L, means ± SD	134.86 (13.52)	228.96 (58.28)	0.004
Smoke status, n (%)			< 0.001
Never smoking	516 (57.3)	384 (42.7)	
Current smoking	121 (42.8)	162 (57.2)	
Ever smoking	73 (38.4)	117 (61.6)	
Alcohol consumption, n (%)			< 0.001
Never drinking	530 (55.6)	424 (44.4)	
Current drinking	145 (46.0)	170 (54.0)	
Ever drinking	35 (33.7)	69 (66.3)	
Hypertension, n (%)	515 (47.8)	563 (52.2)	< 0.001
Diabetes, n (%)	102 (42.3)	139 (57.7)	0.001
WC, cm, means ± SD	86.60 (9.15)	87.58 (9.29)	0.048
WHtR, means ± SD	54.24 (5.72)	54.24 (5.72)	0.820
ABSI, means ± SD	0.79 (0.54)	0.81 (0.06)	< 0.001
TyG, means ± SD	8.69 (6.65)	8.71 (6.78)	0.540
TyG-BMI, means ± SD	222.49 (40.19)	218.46 (40.41)	0.064
TyG-WHtR, means ± SD	4.72 (0.68)	4.74 (0.70)	0.641
TyG-WC, means ± SD	754.14 (109.45)	754.14 (109.45)	0.082
TyG-ABSI, means ± SD	6.90 (0.71)	7.06 (0.72)	< 0.001

drinking, hypertension, diabetes, larger waist circumference, higher ABSI, and higher TyG-ABSI were associated with a higher incidence of carotid plaque. Lower BMI was associated with a higher incidence of carotid plaque. (Table 2)

Multivariable analysis results of carotid plaque occurrence in the training set

The multivariate analysis showed that after adjusting for multiple potential confounding factors, gender, age, systolic blood pressure (SBP), and TyG-ABSI were significantly associated with the occurrence of carotid plaque. Compared with females, the incidence of carotid plaque in males increased by 70% (OR = 1.70, 95% CI: 1.12–2.57, $P = 0.012$). For every 1-year increase in age, the incidence of carotid plaque increased by 7% (OR = 1.07, 95% CI: 1.05–1.08, $P < 0.001$). For every 1 mmHg increase in SBP, the incidence of carotid plaque increased by 1% (OR = 1.01, 95% CI: 1.01–1.02, $P < 0.001$). For every 1-unit increase in TyG-ABSI, the prevalence of carotid plaque increased by 20% (OR = 1.20, 95% CI: 1.02–1.42, $P = 0.025$) (Table 3).

Subgroup analysis results of multivariable analysis between TyG-ABSI and carotid plaque occurrence in the training set

Further subgroup analysis based on gender and BMI showed that, in the $24 \leq \text{BMI} < 28$ subgroup, TyG-ABSI was significantly positively associated with the occurrence of carotid plaque; for every 1-unit increase in TyG-ABSI, the incidence of carotid plaque increased by 39% (OR = 1.39, 95% CI: 1.06–1.82, $P = 0.017$). However, no significant associations between TyG-ABSI and carotid plaque occurrence were found in the male, female, BMI < 24, BMI ≥ 28, diabetes, or non-diabetes subgroups (all $P > 0.05$) (Table 4).

Non-linear relationship between TyG-ABSI index and carotid plaque risk

Through non-linear RCS analysis, we observed a significant non-linear relationship between TyG-ABSI and carotid plaque risk (P for nonlinear = 0.038). Figure 1 illustrates this relationship: when TyG-ABSI values were below 7.75, the risk of carotid plaque increased with increasing TyG-ABSI index. Around TyG-ABSI = 7.75, the risk reached a relative peak, and then began to decline with further increases in TyG-ABSI index, but remained above the baseline risk level (Fig. 1).

Determination of the best model and performance evaluation

The mean AUC and 95% confidence interval of each model on the 5-fold cross-validation of the training set are shown in Table 5; Fig. 2 shows the AUC distribution

Table 3 Multivariate analysis of carotid plaque occurrence in the training set

	References	OR (95%CI)	P
TyG-ABSI		1.20 (1.02, 1.42)	0.025
Male	Female	1.70 (1.12, 2.57)	0.012
Smoke status	Never smoking		
Current smoking		1.46 (0.95, 2.24)	0.083
Ever smoking		1.36 (0.87, 2.12)	0.176
Alcohol consumption	Never drinking		
Current drinking		0.70 (0.46, 1.06)	0.089
Ever drinking		1.15 (0.68, 1.94)	0.609
BUN		1.01 (0.96, 1.06)	0.766
Creatinine		1.00 (1.00, 1.01)	0.623
PLT		1.00 (1.00, 1.01)	0.358
age		1.07 (1.05, 1.08)	<0.001
SBP		1.01 (1.01, 1.02)	<0.001

Table 4 Subgroup analysis of multivariate results for carotid plaque occurrence in the training set

Subgroups	OR (95%CI)	P
Male	1.26 (0.97, 1.64)	0.086
Female	1.18 (0.96, 1.45)	0.121
BMI<24	/	
24 ≤ BMI<28	1.39 (1.06, 1.82)	0.017
BMI ≥ 28	/	
No Diabetes	/	
Diabetes	1.21 (1.00, 1.46)	0.052

Multivariable models adjusted for

Male: alcohol, SBP, Cr, Hb, age, TyG-ABSI; Female: SBP, Hb, age, TyG-ABSI; 24 ≤ BMI<28: sex, smoking, alcohol, SBP, BUN, PLT, age, TyG-ABSI; Diabetes: sex, smoking, alcohol, PLT, age, TyG-ABSI, SBP, BUN. Other subgroups were not analyzed due to the absence of a significant TyG-ABSI difference between cases and controls

of each model in 5-fold verification. The evaluation results of the training set demonstrated that although the CatBoost model exhibited a high AUC value (0.69) on the training set, indicating its excellent performance in fitting the training data, we further examined the models' performance on the validation set to consider their generalization ability and the importance of avoiding overfitting. After comprehensively evaluating the models' performance on both the training and validation sets, we selected Logistic Regression as the optimal model. Logistic Regression demonstrated the best generalization ability on the validation set, achieving an AUC of 0.67, accuracy of 0.64, sensitivity of 0.52, specificity of 0.75, precision of 0.66, and an F1 score of 0.58. (Fig. 3; Table 6) (Fig. 4; Table 7).

SHAP value analysis reveals the influence of logistic regression model features

Figure 5 presents a violin plot of SHAP values based on the Logistic Regression model, illustrating the importance of features in predicting carotid plaque risk. The plot's shape reflects the distribution of each feature's

influence on model predictions, where width indicates data density - wider widths indicate more frequent occurrence of the corresponding SHAP value. As shown, age and Tyg-ABSI index demonstrate the greatest predictive contribution to the model, with their positive impact on predictions increasing proportionally with higher feature values. In contrast, gender and systolic blood pressure show relatively smaller effects.

Figure 6 presents the individual SHAP values for one participant, illustrating how each logistic-regression feature contributes to the final prediction. Age exerts the strongest influence (SHAP = +0.356), driving the model toward a high-risk classification. Sex, SBP, TyG-ABSI also provide substantial positive contributions. The plot further indicates the model's overall expected value $E[f(x)] = 0.48$, reflecting an average moderate risk across the entire dataset. This granular SHAP breakdown clarifies the relative importance of each variable in the risk assessment for a single case.

Discussion

This cross-sectional investigation in Tianjin's rural, low-income adults examined the link between the composite TyG-ABSI index and carotid plaque. TyG-ABSI showed a significant positive association: each one-unit increase corresponded to a 20% rise in plaque prevalence. Restricted cubic spline analysis revealed a non-linear pattern, with risk peaking at a specific TyG-ABSI threshold. Machine-learning models confirmed this relationship; logistic regression achieved the best external performance, and SHAP analysis identified TyG-ABSI as an important predictor. These findings indicate that TyG-ABSI is a robust clinical marker for identifying individuals at elevated carotid plaque risk.

This study expands existing evidence in three key aspects: First, it provides the first validation of the novel index TyG-ABSI's inverted U-shaped association with carotid plaque in rural populations, an area previously under-researched. Second, it pioneers the use of SHAP (SHAP Explainable Machine Learning) to quantify the predictive weight of TyG-ABSI. Third, the findings highlight that this association is predominantly observed in overweight adults, offering immediate actionable priority targets for point-to-point screening at primary healthcare facilities.

TyG, an established marker of insulin resistance, has been repeatedly linked to carotid atherosclerosis. A meta-analysis of Asian cohorts showed that elevated TyG values heighten carotid-plaque risk [16]. In a cross-sectional study of 8,600 participants, higher TyG was significantly associated with carotid atherosclerosis and plaque, especially among men and hyperglycaemic individuals, and displayed a U-shaped non-linear pattern [17]. Similar non-linear associations were reported in patients with

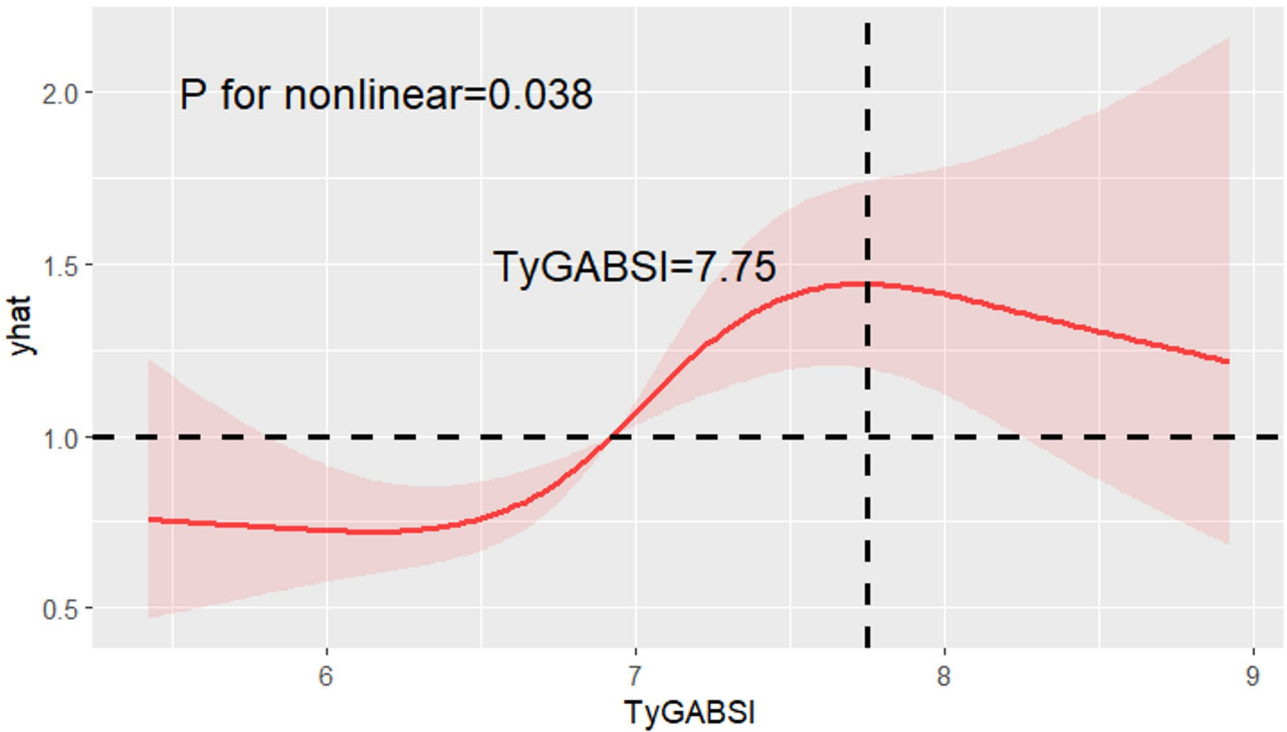


Fig. 1 Restricted cubic spline plot of the adjusted association between TyG-ABSI and carotid plaque risk. Illustrates the nonlinear relationship between TyG-ABSI and carotid plaque risk ($P=0.038$). The risk increases with elevated TyG-ABSI levels, peaks around 7.75, and subsequently shows a downward trend

Table 5 The AUC performance of different machine learning models in the 5-fold cross-validation of the training set

Model	Mean	SD	N	SE	95%low	95%up
CatBoost	0.694	0.041	5	0.018	0.659	0.730
Adaboost	0.691	0.039	5	0.017	0.657	0.725
Logistic	0.688	0.046	5	0.020	0.648	0.728
SVM	0.688	0.044	5	0.020	0.649	0.727
GBM	0.687	0.036	5	0.016	0.655	0.719
NeuralNet	0.686	0.038	5	0.017	0.652	0.719
XGBoost	0.683	0.039	5	0.017	0.650	0.718
LightGBM	0.682	0.035	5	0.016	0.652	0.712
KNN	0.644	0.038	5	0.017	0.611	0.678
RandomForest	0.642	0.047	5	0.021	0.601	0.683

type 2 diabetes [7]. Liu et al. observed that TyG correlated positively with multiple plaques but not with isolated carotid plaques in hypertensive patients [18]. These effects may arise because elevated TyG reflects increased triglyceride concentrations that foster endothelial dysfunction and arterial inflammation [19, 20]. Moreover, heightened TyG often signifies more pronounced insulin resistance, which triggers inflammatory cascades, endothelial injury, augmented sympathetic tone, and impaired autonomic regulation—mechanisms that collectively accelerate plaque formation [21, 22].

The A body shape index (ABSI)—a novel metric of abdominal adiposity derived from height, weight, and waist circumference—more accurately captures

individual fat distribution and visceral fat content than BMI [23–25]. Epidemiological studies consistently link elevated ABSI to carotid atherosclerotic disease. In a Spanish cohort, higher ABSI independently correlated with increased carotid intima-media thickness [26]. Among patients with type 2 diabetes, ABSI was strongly associated with carotid plaque and surpassed other adiposity measures in predictive performance [27]. Another investigation found that, after multivariable adjustment, only ABSI remained significantly and positively related to subclinical carotid atherosclerosis [28]. Mechanistically, obesity disrupts vascular homeostasis through chronic inflammation, altered adipokine secretion, and insulin resistance, collectively promoting endothelial

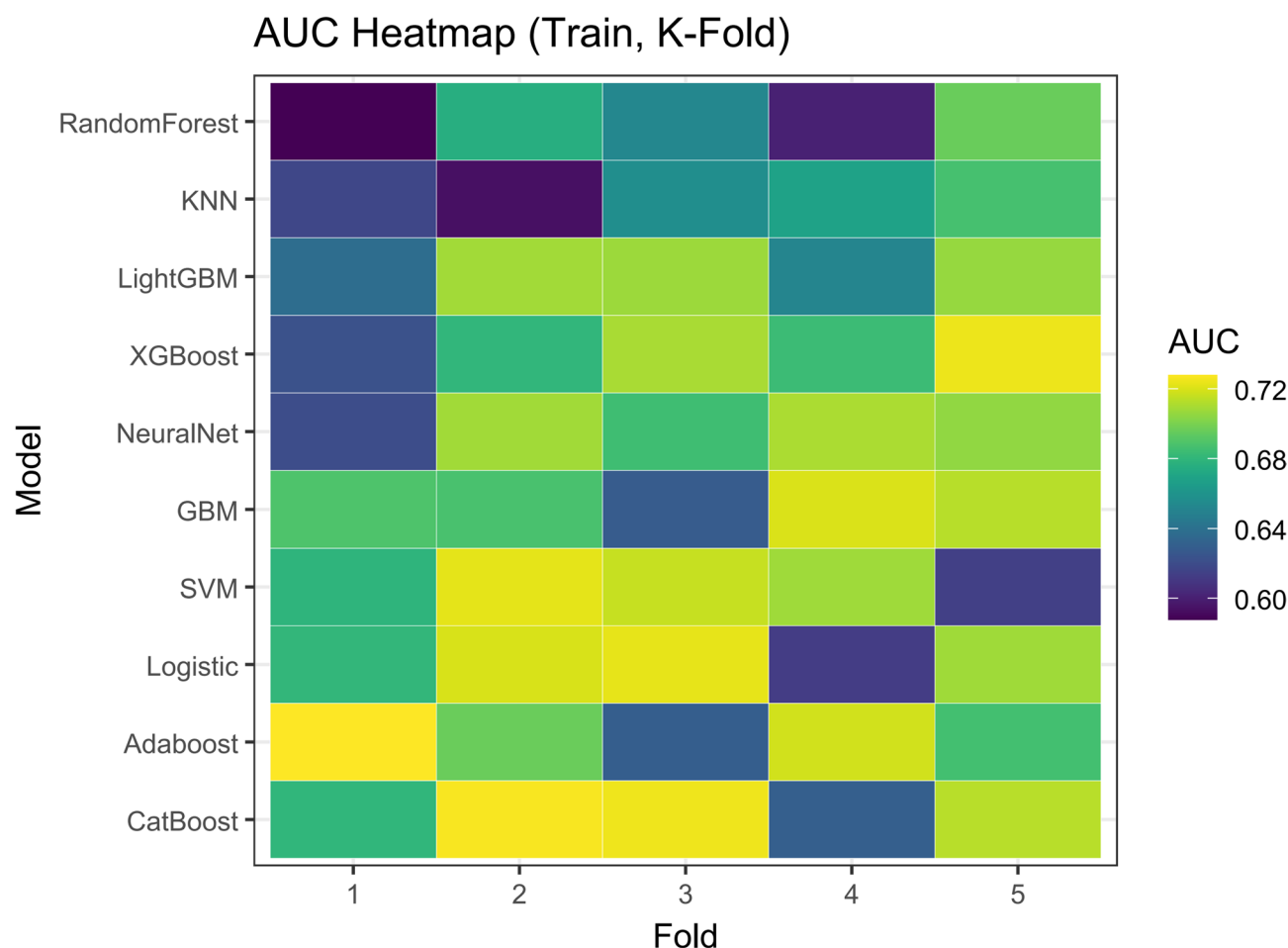


Fig. 2 k-fold cross-validation AUC heatmap across 10 models (k=5). Shows the AUC distribution of 10 models in 5-fold cross-validation. Each line represents one fold, and the color from blue to yellow indicates the AUC level

dysfunction [29]. Moreover, excess adiposity induces oxidative and inflammatory changes in perivascular adipose tissue, attenuating its anti-contractile capacity and further contributing to vascular disease [30].

An expanding body of literature has explored how indices combining the triglyceride–glucose (TyG) ratio with obesity metrics relate to cardiovascular risk; however, their specific association with incident carotid plaque has not yet been reported. NHANES-based research demonstrated that TyG–WC and TyG–WHtR improve the prediction of cardiovascular morbidity and mortality [31]. A rural cohort study indicated that TyG–BRI effectively forecasts ischemic stroke in such settings [10], while another investigation in rural elderly Chinese found TyG–WC positively correlated with MMSE scores, particularly among men and non-diabetic individuals [32]. A prospective cohort further revealed that combining TyG with ABSI outperforms either measure alone [33], and a separate analysis confirmed that TyG–ABSI surpasses other TyG–obesity composites in predicting cardiovascular death [34]. Nonetheless, the direct link

between TyG–ABSI and carotid plaque remains unclear. Our study closes this gap by demonstrating a significant association between TyG–ABSI and carotid-plaque risk, aligning with prior evidence that TyG–obesity indices are valuable novel predictors of cardiovascular disease. Two recent population cohort studies have further validated the predictive efficacy of the “metabolic markers + machine learning” strategy. Salehnasab et al. optimized hyperparameters using 20 algorithms on 207 COVID-19 patients, finding that XGBoost demonstrated the best risk prediction with an AUC of 81.3% [14]. Ghadarzadeh et al. screened T2DM characteristics using a filtering method, focusing on fasting blood glucose and fatty liver as core indicators, achieving 84% accuracy with logistic regression [15]. These findings confirm the feasibility of the metabolic-machine learning strategy employed in this study. Mechanistic work suggests that arterial stiffness mediates the relationship between elevated TyG–ABSI and increased cardiovascular mortality [34]. Activation of the epithelial sodium channel (ENaC) in obesity promotes endothelial stiffening, blunts

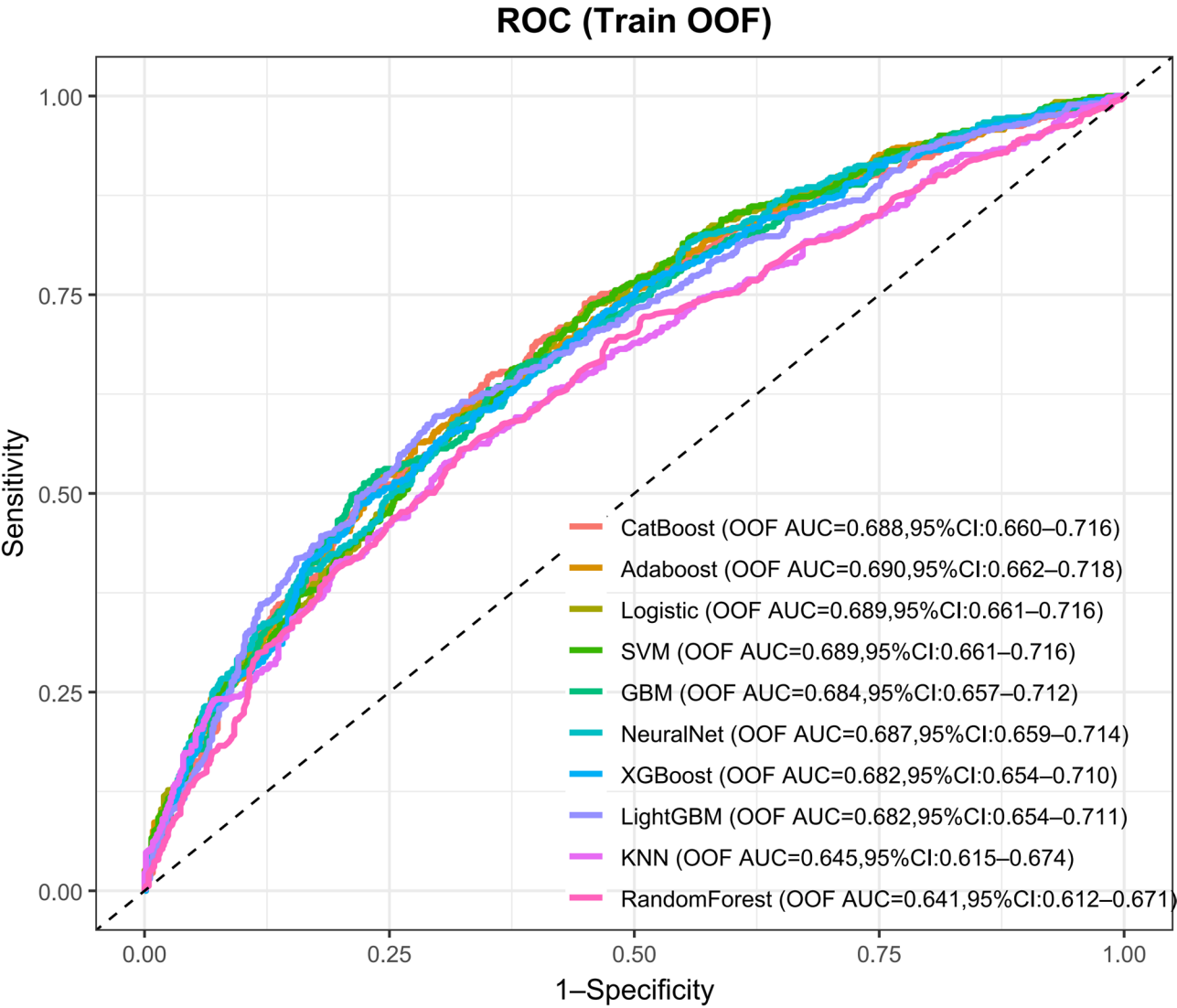


Fig. 3 ROC curves on the training set. Shows the ROC curve of the five-fold cross-validation of the training set. Logistic regression, SVM and CatBoost perform best, which provides a basis for model selection in subsequent external verification

Table 6 Overview of performance metrics for machine-learning models evaluated on the training set

Model	AUC (95%CI)	Threshold	Accuracy	Sensitivity	Specificity	Precision	F1
CatBoost	0.688 (0.660–0.716)	0.49	0.65	0.65	0.65	0.63	0.64
Adaboost	0.690 (0.662–0.718)	0.52	0.65	0.56	0.72	0.66	0.61
Logistic	0.689 (0.661–0.716)	0.43	0.64	0.73	0.55	0.60	0.66
SVM	0.689 (0.661–0.716)	0.5	0.64	0.66	0.63	0.62	0.64
GBM	0.684 (0.657–0.712)	0.55	0.65	0.53	0.76	0.67	0.59
NeuralNet	0.687 (0.659–0.714)	0.5	0.64	0.59	0.68	0.63	0.61
XGBoost	0.682 (0.654–0.710)	0.56	0.64	0.49	0.78	0.67	0.57
LightGBM	0.682 (0.654–0.711)	0.49	0.65	0.6	0.7	0.65	0.62
KNN	0.645 (0.615–0.674)	0.52	0.62	0.54	0.69	0.62	0.58
RandomForest	0.641 (0.612–0.671)	0.52	0.62	0.56	0.68	0.62	0.58

eNOS activation, induces aortic fibrosis and remodeling, and attenuates NO-mediated vasodilation, collectively precipitating endothelial dysfunction that can trigger carotid plaque formation [35]. These molecular events may partly explain the observed link between TyG-ABSI and plaque development, although definitive mechanistic studies are still warranted. Consistent with prior reports [7, 17], we observed a non-linear relationship: risk rose

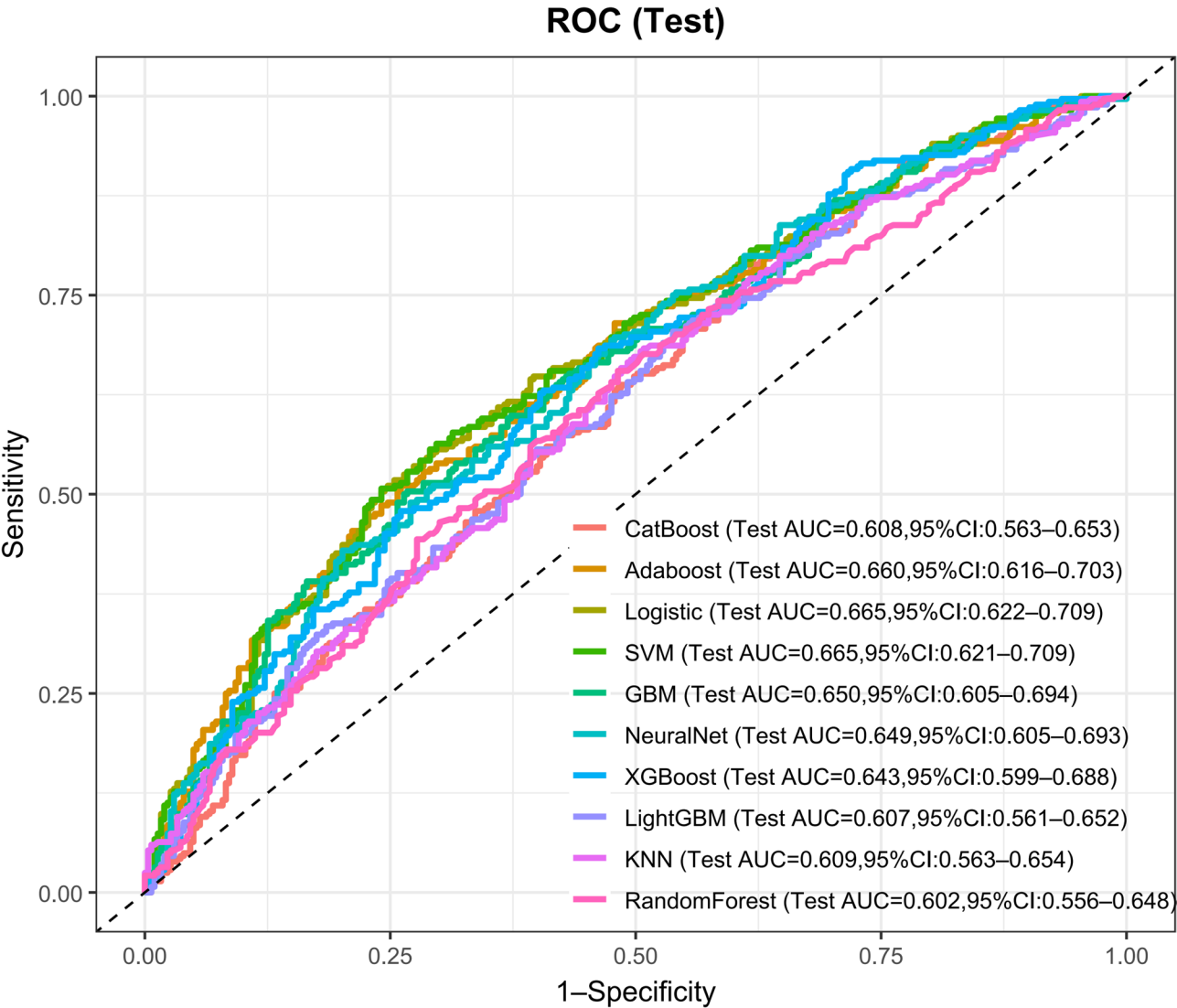


Fig. 4 ROC curves on the validation set. Shows the ROC curve for the independent validation set. Logistic regression and SVM performed best, indicating that the model has external discrimination ability

Table 7 Overview of performance metrics for machine-learning models evaluated on the validation set

Model	AUC (95%CI)	Threshold	Accuracy	Sensitivity	Specificity	Precision	F1
CatBoost	0.608 (0.563–0.653)	0.23	0.58	0.78	0.4	0.55	0.64
Adaboost	0.660 (0.616–0.703)	0.54	0.63	0.51	0.74	0.65	0.57
Logistic	0.665 (0.622–0.709)	0.53	0.64	0.52	0.75	0.66	0.58
SVM	0.665 (0.621–0.709)	0.54	0.64	0.56	0.7	0.64	0.6
GBM	0.650 (0.605–0.694)	0.54	0.62	0.5	0.73	0.64	0.56
NeuralNet	0.649 (0.605–0.693)	0.57	0.62	0.43	0.8	0.67	0.52
XGBoost	0.643 (0.599–0.688)	0.46	0.61	0.63	0.59	0.59	0.61
LightGBM	0.607 (0.561–0.652)	0.36	0.58	0.7	0.46	0.55	0.62
KNN	0.609 (0.563–0.654)	0.4	0.58	0.68	0.49	0.56	0.61
RandomForest	0.602 (0.556–0.648)	0.43	0.58	0.65	0.52	0.56	0.6

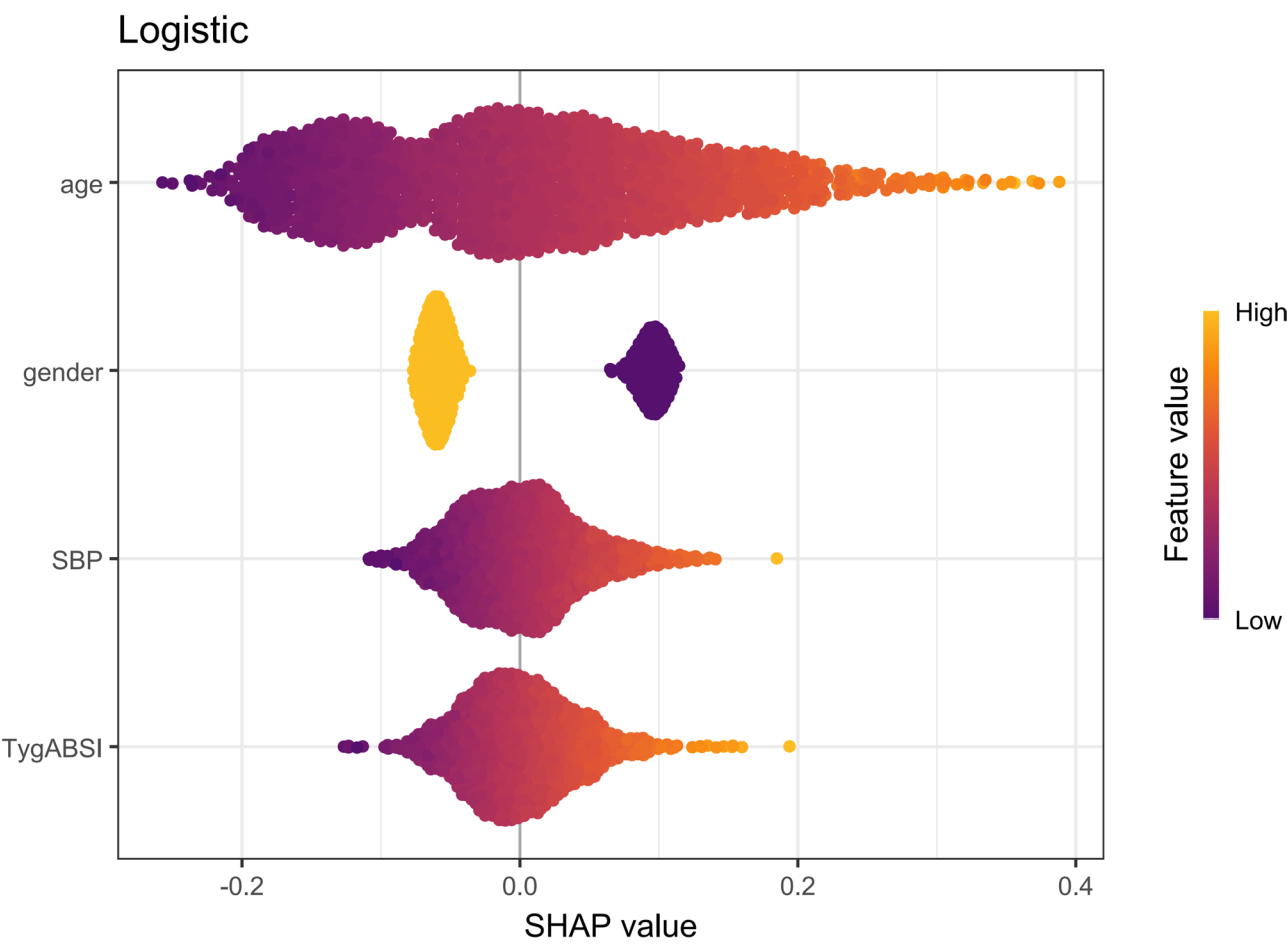


Fig. 5 SHAP summary plot for the logistic regression model on the validation set. Shows the summary of SHAP for the Logistic regression model in the validation set. Each point represents a subject, with the x-axis showing the SHAP value (direction and magnitude) of the feature, and color indicating the feature value level (red = high, blue = low). TyG-ABSI is the second most important predictor after age, and its elevated values make the model more inclined to higher plaque risk

Logistic – Force (row 6)

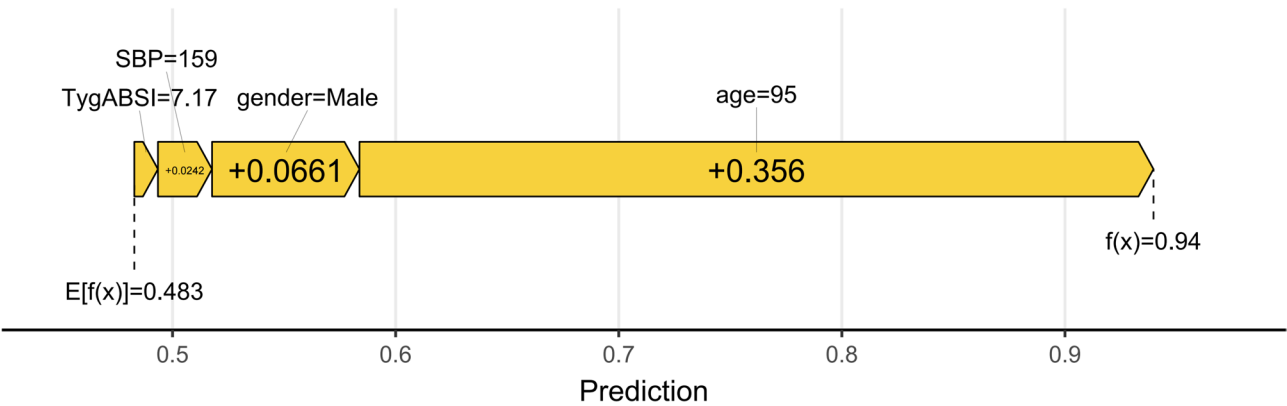


Fig. 6 SHAP force plot illustrating feature contributions for a high-risk individual. Shows the SHAP force plot of a high-risk individual in the validation set. The baseline prediction value $E[f(x)] = 0.48$; age contributed the most to the increase of prediction probability, TyG-ABSI, and gender and SBP also provided positive contribution. The final model output probability reached 0.94, indicating that the individual was at high plaque risk

steeply with increasing TyG-ABSI, peaked near 7.75, and then declined slightly yet remained above baseline. Moderately elevated TyG levels may heighten oxidative stress and chronic inflammation, thereby amplifying plaque risk; once TyG-ABSI surpasses a critical threshold, counter-regulatory pathways could attenuate these vascular insults. The precise biological circuitry underlying this inflection remains largely unexplored and merits dedicated investigation.

In the univariate analysis of this study, we found that smoking cessation and alcohol abstinence were associated with increased carotid plaque incidence. This finding appears to contradict previous understanding and requires comprehensive analysis. First, individuals who quit smoking or abstain from alcohol may be correlated with other confounding factors that could influence carotid plaque development. Therefore, after adjusting for other confounding factors (such as age, gender, and blood pressure) in multivariate analysis, the association between smoking cessation, alcohol abstinence, and carotid plaques became insignificant. Second, the status of smoking and alcohol use is based on participants' self-reported data, which may involve reporting biases or information distortion. Finally, there might be reverse causation—where the presence of carotid plaques could paradoxically increase an individual's tendency to quit smoking or abstain from alcohol. For example, patients diagnosed with carotid plaques might adopt health behaviors like quitting smoking or abstaining from alcohol to improve their health status. Future large-scale prospective studies are still needed to validate these conclusions.

Population-specific evidence linking TyG–obesity indices to incident carotid plaque remains sparse and highly heterogeneous. Li et al. reported that the TyG–atherosclerosis association was accentuated in overweight individuals [36], whereas a coronary-heart-disease cohort observed stronger relations among women, middle-aged adults, and diabetic patients [37]. Guo and colleagues further noted that the TyG–vascular link was most pronounced in younger participants, males, and those with hyperglycaemia [17]. In our rural sample, TyG-ABSI was significantly associated with carotid plaque only in the overweight stratum ($24 \leq \text{BMI} < 28$), aligning with Li et al.; however, no meaningful differences emerged across sex, diabetes status, or other BMI categories—findings that diverge from prior reports. These discrepancies likely reflect variations in population characteristics, sample size, and enrollment criteria. Large-scale, multi-ethnic studies are warranted to confirm the population-specific relevance of TyG-ABSI for carotid plaque prediction.

This study has several limitations. First, the cross-sectional design of our study limits our ability to infer causality between TyG-ABSI and carotid artery plaque.

Longitudinal cohort studies are required to clarify temporal sequences. Future longitudinal research is essential to explore the dynamic relationship between TyG-ABSI and plaque progression, which would provide stronger evidence for causal inference. Second, participants were recruited exclusively from rural Tianjin, restricting generalizability to urban or socioeconomically diverse populations; multi-region studies are needed to broaden external validity. Third, unmeasured confounders—including dietary habits, physical activity, and genetic factors—may bias observed associations; future work should comprehensively assess lifestyle and genetic variables to isolate TyG-ABSI's effect on plaque formation. Fourth, while the implementation of five fold cross-validation combined with grid parameter tuning (including tree depth and node size constraints) has significantly mitigated overfitting in Random Forest models, these models remain vulnerable to excessive noise capture when dealing with relatively limited sample sizes. Future efforts should focus on expanding training datasets or adopting regularization techniques, ensemble pruning strategies, and other approaches to continuously reduce overfitting risks and enhance generalization performance. Finally, smoking and alcohol data were self-reported, introducing recall and social-desirability bias; objective validation via biochemical markers and medical-record confirmation will enhance accuracy and reliability.

Conclusions

This cross-sectional study examined the TyG–obesity composite index (TyG-ABSI) and carotid plaque among low-income rural adults in Tianjin, China. TyG-ABSI was significantly linked to plaque presence and displayed a non-linear pattern: risk rose initially, peaked, and then declined as TyG-ABSI increased. The association was strongest in the overweight stratum ($24 \leq \text{BMI} < 28$). These findings highlight the predictive value of TyG-ABSI for carotid plaque and underscore the need for tailored, population-specific interventions to curb atherosclerotic disease and improve vascular health in resource-limited rural areas. However, the single cross-sectional design precludes causal or temporal inference; our conclusions need to be verified by prospective cohorts.

Abbreviations

CVD	Cardiovascular Disease
TyG	Triglyceride-Glucose index
ABSI	A Body Shape Index
TyG-ABSI	TyG index combined with ABSI
RCS	Restricted Cubic Spline
SBP	Systolic Blood Pressure
BMI	Body-Mass Index
WC	Waist Circumference
WtHr	Waist-to-Height Ratio
OR	Odds Ratio
CI	Confidence Interval
FBG	Fasting Blood Glucose

GBM	Gradient Boosting Machine
KNN	K-Nearest Neighbors
AUC	Area Under the Curve
PLT	Platelet Count
BUN	Blood Urea Nitrogen
IMT	Intima-Media Thickness

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Author contributions

YL, JW, and XN were involved in conception and design, and data interpretation for this article. JH, RC, DA, XL, YZ, LW, CF, CY were involved in data collection, case diagnosis and confirmation for this article. JH, RC, DA, and XL were involved in manuscript drafting. JW was involved in data analysis for this article. YL, JW, and XN were involved in critical review of this article.

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Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Ethics Committee of Tianjin Medical University General Hospital. Informed consent was obtained from all participants before enrollment in the study.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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