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Development and Comparison of Machine Learning Models Incorporating the Weight-Adjusted Waist Index for Predicting Ischemic Stroke in Older Adults With Hypertension

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Development and Comparison of Machine Learning Models Incorporating the Weight-Adjusted Waist Index for Predicting Ischemic Stroke in Older Adults With Hypertension

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Abstract Objective: Ischemic stroke is a major cause of disability and mortality among elderly patients with hypertension. Identifying reliable and easily obtainable predictive indicators is essential for early risk stratification. The Weight-Adjusted

Waist Index (WWI), a novel marker of central obesity, has not been fully evaluated in stroke prediction models. This study aimed to develop and compare multiple machine learning models for predicting ischemic stroke in elderly hypertensive patients and to assess the predictive value of WWI.

Methods: A total of 1,070 elderly patients with hypertension were retrospectively enrolled. Feature selection was performed using Least Absolute Shrinkage and Selection Operator (LASSO) regression. Eight machine learning algorithms were developed, including decision tree (DT), k-nearest neighbors (KNN), random forest (RF), Light Gradient Boosting Machine (LightGBM), logistic regression (LR), multilayer perceptron (MLP), support vector machine (SVM), and extreme gradient boosting (XGBoost). Model performance was evaluated using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). SHapley Additive exPlanations (SHAP) were applied to interpret feature importance, and Decision Curve Analysis (DCA) was used to assess clinical utility.

Results: The LightGBM model demonstrated the best overall performance (accuracy: 0.857, recall: 0.905, F1-score: 0.915), with superior discrimination and calibration compared with the other models. DCA indicated that LightGBM and LR yielded the highest net benefits across a wide range of threshold probabilities. SHAP analysis identified a history of cardiac disease, age, and WWI as the most important predictors. Notably, WWI contributed more than BMI, suggesting a stronger association with abnormal fat distribution and cardiovascular risk.

Conclusion: WWI is a more effective anthropometric indicator than BMI for predicting ischemic stroke risk in elderly patients with hypertension. WWI showed substantial predictive contribution and may provide additional information beyond BMI for ischemic stroke risk assessment in older patients with hypertension.The LightGBM-based model demonstrates strong discriminative ability and clinical applicability, offering a promising tool for early screening and individualized intervention.

Keywords: Ischemic stroke; Weight-adjusted waist index; Elderly hypertension; Machine learning; Prediction model

Hypertension is one of the most prevalent chronic diseases worldwide, with an especially high incidence among the elderly population. [1] According to data from the Global Burden of Disease study, the number of individuals with hypertension worldwide increased from 648 million in 1990 to 1.278 billion in 2019, nearly doubling over the past three decades. [2] Hypertension is also a major risk factor for ischemic stroke. Prolonged elevated blood pressure can lead to vascular remodeling, increased arterial stiffness, and hemodynamic disturbances, thereby significantly increasing the risk of stroke. [3,4] Previous studies have shown that more than 60% of patients with acute stroke present with elevated blood pressure, and moderate to severe hypertension is closely associated with poor stroke prognosis. [5] Therefore, the development of an accurate predictive model for ischemic stroke is of considerable clinical significance for the early identification and intervention of high-risk populations.

Existing studies have primarily focused on conventional indicators, such as age, blood pressure, blood glucose, and body mass index (BMI), whereas the exploration of novel predictive markers remains limited. In recent years, the Weight-Adjusted Waist Index (WWI) has attracted increasing attention as a novel indicator of body fat distribution. [6] By integrating waist circumference with body weight, WWI more accurately reflects the degree of abdominal adiposity and provides a more comprehensive assessment of body composition and fat distribution. Moreover, WWI can effectively distinguish fat mass from muscle mass; elevated WWI levels indicate excessive fat accumulation accompanied by reduced muscle mass. [7,8] A 10-year cohort study demonstrated that, compared with waist circumference (WC) and BMI, both of which exhibit nonlinear relationships with stroke risk, WWI is a stronger predictor of stroke. Among adults aged 45 years and older, higher WWI levels were positively associated with an increased risk of new-onset stroke. [9] Another recent cohort study further reported a significant positive association between elevated WWI and stroke incidence in elderly patients with hypertension .[10] Therefore, the predictive role of WWI in ischemic stroke among elderly hypertensive patients warrants further investigation.

In this study, clinical data from 1,070 elderly patients with hypertension, including 160 patients with ischemic stroke, were retrospectively collected from Beihu Nanmian Community Hospital in Nanning. LASSO regression was used to select key features, and eight machine learning models (LR, RF, DT, KNN, LightGBM, MLP, SVM, and XGBoost) were constructed to predict stroke risk. The predictive value of

WWI was evaluated to provide scientific evidence for clinical decision-making, facilitate personalized interventions, improve stroke prevention, and ultimately enhance patient outcomes.

1 Study Population and Methods

1.1 Study Population

Clinical data were collected from elderly patients with hypertension who underwent health check-ups or visited Beihu Nanmian Community Health Service Center in Xixiangtang District, Nanning, from April 1, 2024 to April 1, 2025. The study protocol was approved by the Medical Ethics Committee of Ruikang Hospital Affiliated to Guangxi University of Chinese Medicine (approval No. KY2024-127), and written informed consent to participate was obtained from all participants prior to their inclusion in the study.

1.1.1 Inclusion criteria for the study group (elderly patients with primary hypertension complicated by ischemic stroke)

1. Age ≥ 65 years.

2. Primary hypertension meeting the diagnostic criteria of the *Chinese Guidelines for the Prevention and Treatment of Hypertension in the Elderly*: systolic blood pressure ≥ 140 mmHg and/or diastolic blood pressure ≥ 90 mmHg; or a self-reported history of hypertension with current use of antihypertensive medication.

3. First diagnosis of ischemic stroke during the study period, with no prior history of stroke.

4. Ischemic stroke confirmed by cranial CT or MRI.

1.1.2 Exclusion criteria for the study group

1. Ischemic stroke caused by arteritis, moyamoya disease, hematological disorders (e.g., polycythemia), connective tissue diseases, or other similar conditions.
2. Presence of other brain diseases besides ischemic stroke.
3. Concurrent secondary hypertension, severe infection, endocrine disorders, tub erculosis, cancer, or other malignant diseases.
4. Patients with severe cognitive impairment.

1.1.3 Inclusion criteria for the control group (elderly patients with primary hypertension without ischemic stroke)

1. Age ≥ 65 years.
2. Diagnosis of primary hypertension according to the *Chinese Guidelines for the Prevention and Treatment of Hypertension in the Elderly* (*2023 revised edition*).

1.1.4 Exclusion criteria for the control group

1. Secondary hypertension, severe infection, endocrine disorders, tuberculosis, malignancies, or other serious systemic diseases.
2. Severe cognitive impairment.

1.2 Data Collection

Based on a comprehensive literature review and relevant clinical guidelines, [11,12] a total of 65 candidate variables were initially extracted from health examination records. Variables with limited clinical relevance were excluded based on expert consensus and published evidence to ensure meaningful model contribution. Additionally, incorporating the practical experience of community clinicians

enhanced the clinical applicability of selected features.

Variables with a missing rate >30% were excluded to minimize bias. Ultimately, 21 variables were retained:

1. Demographic characteristics: age, sex, marital status, education level.

2. Clinical and laboratory indicators: body weight, waist circumference, BMI, WWI, smoking status, alcohol consumption, history of diabetes, history of cardiac disease, total cholesterol, LDL, HDL, triglycerides, blood glucose, white blood cell count, red blood cell count, platelet count, and hemoglobin.

1.3 Diagnostic Criteria and Definitions

1. BMI = weight (kg) / height² (m^2).

2. WWI = waist circumference (cm) / √ weight (kg).

3.Diabetes: prior diagnosis, or meeting diagnostic criteria (random glucose >11.1 mmol/L, fasting glucose ≥7.0 mmol/L, or 2hPG >11.1 mmol/L) [13] or current treatment.

4.Cardiac disease: coronary artery disease, heart failure, or atrial fibrillation.

5.Smoking: lifetime consumption of >100 cigarettes [14].

6.Alcohol consumption: ≥1 drinking episode per week in the past year. [15]

1.3 Data Cleaning

Data cleaning is a critical step in data preprocessing aimed at improving data quality by eliminating noise and handling incomplete data. This process ensures that machine learning models can learn meaningful patterns from reliable and well-structured datasets.

1.4 Handling of Missing Values

Missing data may occur for various reasons during data collection. In this study, missing values were handled using the following strategies:

1. When the proportion of missing data was low (<10%), mean or median imputation was applied for continuous variables.

2. When the proportion of missing data was relatively high, advanced imputation methods, such as multiple imputation, were employed.

3. For categorical variables, mode imputation (i.e., replacing with the most frequent value) was used.

If missing values for certain variables could not be reliably imputed, the corresponding samples were excluded from subsequent analyses to maintain the overall representativeness and integrity of the dataset.

1.5 Outlier Handling

Outliers may arise due to data entry errors or extreme physiological conditions. The following procedures were applied:

1. For numerical variables, outliers were identified using statistical methods (e.g., boxplot analysis), and decisions regarding their removal were based on the underlying data distribution.

2. Clinically plausible extreme values (e.g., markedly elevated blood glucose levels due to pathological conditions) were retained but flagged to account for their potential influence on model performance.

In addition, duplicate records—potentially resulting from repeated data entry—were

identified and removed using unique patient identifiers to ensure data independence. Data consistency checks were also performed to standardize variable formats and ensure consistent encoding of categorical variables across the dataset.

1.6 Data Transformation

In this study, a binary encoding method was applied to variables with binary attributes. Table 1 presents the coding scheme for these variables.

Table 1. Coding rules for categorical variables

No.	Variable	Coding
1	Sex	Male = 1, Female = 2
2	Education level	Primary school = 1, Junior high school = 2, Senior high school = 3, College or above = 4
3	Marital status	Married = 1, Widowed = 2, Divorced/Separated = 3
4	Smoking history	Yes = 1, No = 0
5	Alcohol consumption history	Yes = 1, No = 0
6	History of diabetes	Yes = 1, No = 0
7	History of cardiac disease	Yes = 1, No = 0
8	Ischemic stroke	Yes = 1, No = 0

1.7 Statistical Analysis

Least Absolute Shrinkage and Selection Operator (LASSO) regression was applied for feature selection to identify the most predictive variables among multiple clinical indicators, thereby improving model stability and predictive performance. The dataset was randomly divided into a training set and a validation set at a ratio of 7:3. The training set was used to develop the models, with features selected by

LASSO regression as input variables and the occurrence of ischemic stroke as the outcome variable.

Eight machine learning models—logistic regression (LR), random forest (RF), decision tree (DT), k-nearest neighbors (KNN), Light Gradient Boosting Machine (LightGBM), multilayer perceptron (MLP), support vector machine (SVM), and extreme gradient boosting (XGBoost)—were constructed using R software, and their predictive performance was compared.

Model performance was evaluated using accuracy, precision, recall, F1 score, and the area under the receiver operating characteristic curve (ROC–AUC).

2 Results

2.1 Dataset Description

A total of 1,070 elderly patients with hypertension were included in this study, among whom 160 (14.95%) were diagnosed with ischemic stroke and 910 (85.05%) had no history of stroke. The dataset comprised demographic characteristics, clinical indicators, lifestyle factors, and comorbidities, as summarized in Table 2.

Table 2. Baseline characteristics of study participants

Variable	Total (n = 1070)	No stroke (n = 910)	Stroke (n = 160)
Continuous variables (mean ± SD)			
Age (years)	70.31 ± 4.26	69.85 ± 3.94	72.92 ± 5.05
Total cholesterol (mmol/L)	4.83 ± 0.92	4.78 ± 0.91	5.09 ± 0.93
High-density lipoprotein (mmol/L)	1.50 ± 0.35	1.51 ± 0.35	1.43 ± 0.31
Low-density lipoprotein	2.17 ± 0.61	2.15 ± 0.61	2.32 ± 0.63

Variable	Total (n = 1070)	No stroke (n = 910)	Stroke (n = 160)
(mmol/L)			
Triglycerides (mmol/L)	1.46 ± 0.44	1.41 ± 0.40	1.76 ± 0.55
Fasting blood glucose (mmol/L)	5.28 ± 0.93	5.28 ± 0.91	5.29 ± 1.01
White blood cell count ($\times 10^9$/L)	6.36 ± 1.80	6.32 ± 1.76	6.54 ± 2.02
Platelet count ($\times 10^9$/L)	212.74 ± 65.84	212.10 ± 66.02	216.38 ± 64.90
Red blood cell count ($\times 10^{12}$/L)	4.26 ± 0.57	4.27 ± 0.58	4.25 ± 0.50
Hemoglobin (g/L)	143.87 ± 21.77	144.29 ± 22.03	141.46 ± 20.12
Body mass index (BMI, kg/m^2)	21.70 ± 2.93	21.58 ± 2.96	22.38 ± 2.66
Weight-adjusted waist index (WWI)	10.82 ± 0.71	10.80 ± 0.73	10.94 ± 0.55
Body weight (kg)	57.89 ± 9.09	57.44 ± 9.18	60.48 ± 8.11
Waist circumference (cm)	80.65 ± 7.46	80.49 ± 7.70	81.53 ± 5.84
Categorical variables, n (%)			
Sex			
Male	556 (51.96)	456 (50.11)	100 (62.50)
Female	514 (48.04)	454 (49.89)	60 (37.50)
Education level			
Primary school	159 (14.86)	134 (14.73)	25 (15.62)
Junior high school	412 (38.50)	336 (36.92)	76 (47.50)
Senior high school	425 (39.72)	374 (41.10)	51 (31.88)
College or above	74 (6.92)	66 (7.25)	8 (5.00)
Marital status			

Variable	Total (n = 1070)	No stroke (n = 910)	Stroke (n = 160)
Unmarried	42 (3.93)	32 (3.52)	10 (6.25)
Married	899 (84.02)	763 (83.85)	136 (85.00)
Divorced	65 (6.07)	58 (6.37)	7 (4.38)
Widowed	64 (5.98)	57 (6.26)	7 (4.38)
Alcohol consumption			
No	930 (86.92)	816 (89.67)	114 (71.25)
Yes	140 (13.08)	94 (10.33)	46 (28.75)
Smoking			
No	876 (81.87)	775 (85.16)	101 (63.12)
Yes	194 (18.13)	135 (14.84)	59 (36.88)
Diabetes			
No	913 (85.33)	782 (85.93)	131 (81.88)
Yes	157 (14.67)	128 (14.07)	29 (18.12)
History of cardiac disease			
No	907 (84.77)	803 (88.24)	104 (65.00)
Yes	163 (15.23)	107 (11.76)	56 (35.00)

Note: Continuous variables are presented as mean ± standard deviation (SD); categorical variables as number (%). Comparisons between groups used independent t-tests for continuous variables and chi-square tests for categorical variables.

2.2 Data Splitting

Data splitting and model development were performed using R software. To ensure reproducibility, a random seed of 1234 was set. The dataset was divided into training and test sets at a ratio of 7:3 using the initial_split function from the rsample package,

214 with stratified sampling applied to preserve the class distribution of the outcome
215 variable.
216 Balance testing between the training and test sets (Table 3) demonstrated no
217 significant differences, indicating that the data split was appropriate and that the
218 model was likely to generalize well to unseen data.

219 Table 3. Balance tests between the training and test sets

Variable	Total (n = 1070)	Test set (n = 321)	Training set (n = 749)	Statistic	P value
Continuous variables (mean ± SD)					
Age (years)	70.31 ± 4.26	70.10 ± 4.21	70.40 ± 4.29	t = -1.07	0.285
Total cholesterol (mmol/L)	4.83 ± 0.92	4.84 ± 0.95	4.82 ± 0.91	t = 0.17	0.866
High-density lipoprotein (mmol/L)	1.50 ± 0.35	1.50 ± 0.38	1.50 ± 0.33	t = 0.21	0.836
Low-density lipoprotein (mmol/L)	2.17 ± 0.61	2.14 ± 0.62	2.19 ± 0.61	t = -1.17	0.242
Triglycerides (mmol/L)	1.46 ± 0.44	1.51 ± 0.48	1.44 ± 0.42	t = 2.33	0.020
Fasting blood glucose (mmol/L)	5.28 ± 0.93	5.21 ± 0.90	5.31 ± 0.94	t = -1.66	0.097
White blood cell count ($\times 10^9$/L)	6.36 ± 1.80	6.35 ± 1.86	6.36 ± 1.78	t = -0.10	0.917
Platelet count ($\times 10^9$/L)	212.74 ± 65.84	215.02 ± 67.06	211.76 ± 65.33	t = 0.74	0.459

Variable	Total (n = 1070)	Test set (n = 321)	Training set (n = 749)	Statistic	P value
Red blood cell count (×10¹²/L)	4.26 ± 0.57	4.26 ± 0.60	4.26 ± 0.56	t = -0.20	0.839
Hemoglobin (g/L)	143.87 ± 21.77	143.83 ± 22.85	143.89 ± 21.30	t = -0.04	0.968
Body mass index (BMI, kg/m²)	21.73 ± 2.93	21.88 ± 3.07	21.66 ± 2.87	t = 1.10	0.272
Weight-adjusted waist index (WWI)	10.82 ± 0.71	10.88 ± 0.67	10.80 ± 0.72	t = 1.76	0.079
Body weight (kg)	57.89 ± 9.09	58.07 ± 9.27	57.82 ± 9.02	t = 0.41	0.681
Waist circumference (cm)	80.18 ± 7.61	80.59 ± 7.57	80.01 ± 7.62	t = 1.15	0.250
Categorical variables, n (%)					
Stroke				$\chi^2 = 0.03$	0.852
No	910 (85.05)	274 (85.36)	636 (84.91)		
Yes	160 (14.95)	47 (14.64)	113 (15.09)		
Sex				$\chi^2 = 4.68$	0.031
Male	556 (51.96)	183 (57.01)	373 (49.80)		
Female	514 (48.04)	138 (42.99)	376 (50.20)		
Education level				$\chi^2 = 1.63$	0.653
Primary school	159 (14.86)	44 (13.71)	115 (15.35)		
Junior high school	412 (38.50)	120 (37.38)	292		

Variable	Total (n = 1070)	Test set (n = 321)	Training set (n = 749)	Statistic	P value
			(38.99)		
Senior high school	425 (39.72)	131 (40.81)	294 (39.25)		
College or above	74 (6.92)	26 (8.10)	48 (6.41)		
Marital status				$\chi^2 = 4.35$	0.226
Unmarried	42 (3.93)	10 (3.12)	32 (4.27)		
Married	899 (84.02)	280 (87.23)	619 (82.64)		
Divorced	65 (6.07)	18 (5.61)	47 (6.28)		
Widowed	64 (5.98)	13 (4.05)	51 (6.81)		
Alcohol consumption				$\chi^2 = 0.35$	0.553
No	930 (86.92)	276 (85.98)	654 (87.32)		
Yes	140 (13.08)	45 (14.02)	95 (12.68)		
Smoking				$\chi^2 = 1.82$	0.177
No	876 (81.87)	255 (79.44)	621 (82.91)		
Yes	194 (18.13)	66 (20.56)	128 (17.09)		
Diabetes				$\chi^2 = 0.04$	0.836
No	913 (85.33)	275 (85.67)	638 (85.18)		
Yes	157 (14.67)	46 (14.33)	111 (14.82)		
History of cardiac				$\chi^2 = 0.01$	0.917

Variable	Total (n = 1070)	Test set (n = 321)	Training set (n = 749)	Statistic	P value
disease					
No	878 (82.06)	264 (82.24)	614 (81.98)		
Yes	192 (17.94)	57 (17.76)	135 (18.02)		

Note: Continuous variables are presented as mean ± standard deviation (SD); categorical variables as number (%). Comparisons between training and test sets used independent t-tests for continuous variables and chi-square tests for categorical variables. CVD stands for cardiovascular/cardiac disease.

2.3 Feature Selection

A total of 21 candidate variables were initially selected based on physical examination records, including demographic characteristics (age, sex, marital status, education level) and clinical/laboratory indicators (body weight, waist circumference [WC], body mass index [BMI], weight-adjusted waist index [WWI], smoking status, alcohol consumption, history of diabetes, history of cardiac disease, total cholesterol, low-density lipoprotein [LDL], high-density lipoprotein [HDL], triglycerides, blood glucose, white blood cell count, red blood cell count, platelet count, and hemoglobin). To improve model performance, reduce multicollinearity, and enhance model parsimony, LASSO regression was applied. Using 10-fold cross-validation, the optimal penalty parameter ($\lambda = 0.0252$) was selected based on the minimum prediction error.

Eight variables were identified as key predictors of ischemic stroke: age, history of

cardiac disease, BMI, WWI, total cholesterol, triglycerides, smoking, and alcohol consumption. These variables were included in subsequent model development. The LASSO coefficient path and cross-validation curves are shown in Figures 1 and 2.

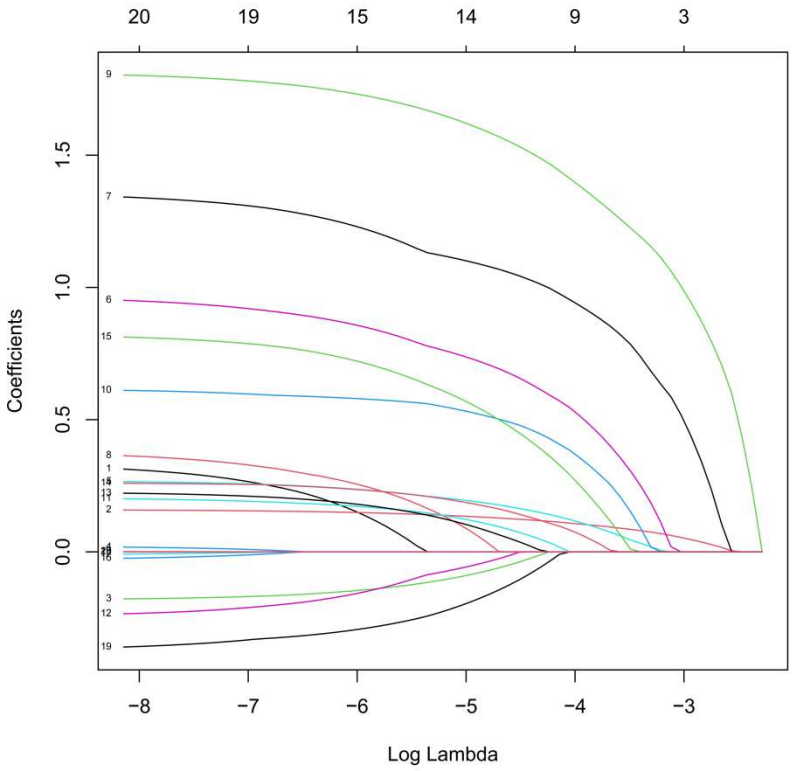


Figure 1. LASSO regression coefficient paths.

The horizontal axis represents log(λ), and the vertical axis represents the regression coefficients. The numbers at the top indicate the number of non-zero coefficients at each λ value.

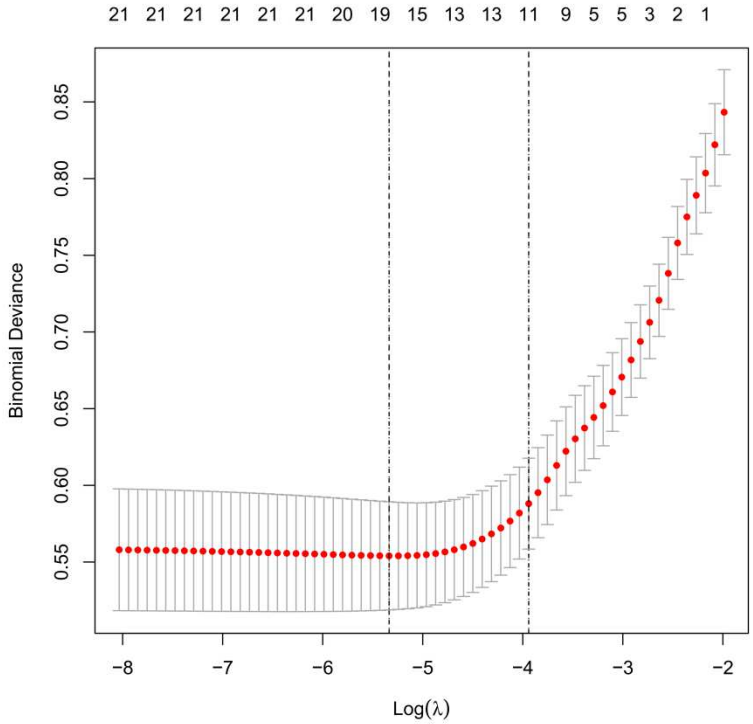


Figure 2. Cross-validation curve for LASSO regression.

The horizontal axis shows log(λ), and the vertical axis shows cross-validation error. The two vertical dashed lines represent λ.min (the λ with the minimum cross-validation error) and λ.1se (the largest λ within one standard error of the minimum).

2.4 Model Prediction Results

Internal validation of the eight models (LR, RF, DT, KNN, MLP, SVM, LightGBM, and XGBoost) was performed using the test set. Model performance was evaluated using accuracy, precision, recall, F1 score, area under the ROC curve (AUC), and calibration curves. Table 4, Figure 3, and Figure 4 present the performance of the eight models in internal validation.

Considering all evaluation metrics, the LightGBM model exhibited the best overall

performance, achieving the highest accuracy (0.857), indicating stronger generalization ability. It also achieved the best recall (0.905), demonstrating the strongest ability to identify positive samples (i.e., the lowest false negative rate), and the highest F1 score (0.915), representing the best harmonic mean of precision and recall and thus the optimal balance between exact identification and comprehensive coverage. The calibration curves showed that the LightGBM curve was the highest and most stable across nearly all threshold ranges, outperforming the other models.

Table 4. Internal validation performance of the eight models

Model	Accuracy	Precision	Recall	F1 score	ROC-AUC
Decision Tree (DT)	0.754	0.911	0.788	0.845	0.750
K-Nearest Neighbors (KNN)	0.769	0.959	0.762	0.849	0.847
LightGBM	0.857	0.925	0.905	0.915	0.845
Logistic Regression (LR)	0.816	0.931	0.846	0.887	0.860
Multilayer Perceptron (MLP)	0.801	0.934	0.824	0.875	0.861
Random Forest (RF)	0.776	0.943	0.784	0.856	0.846
Support Vector Machine (SVM)	0.816	0.931	0.846	0.887	0.856
XGBoost	0.754	0.937	0.762	0.840	0.856

Note: ROC-AUC = area under the receiver operating characteristic curve.

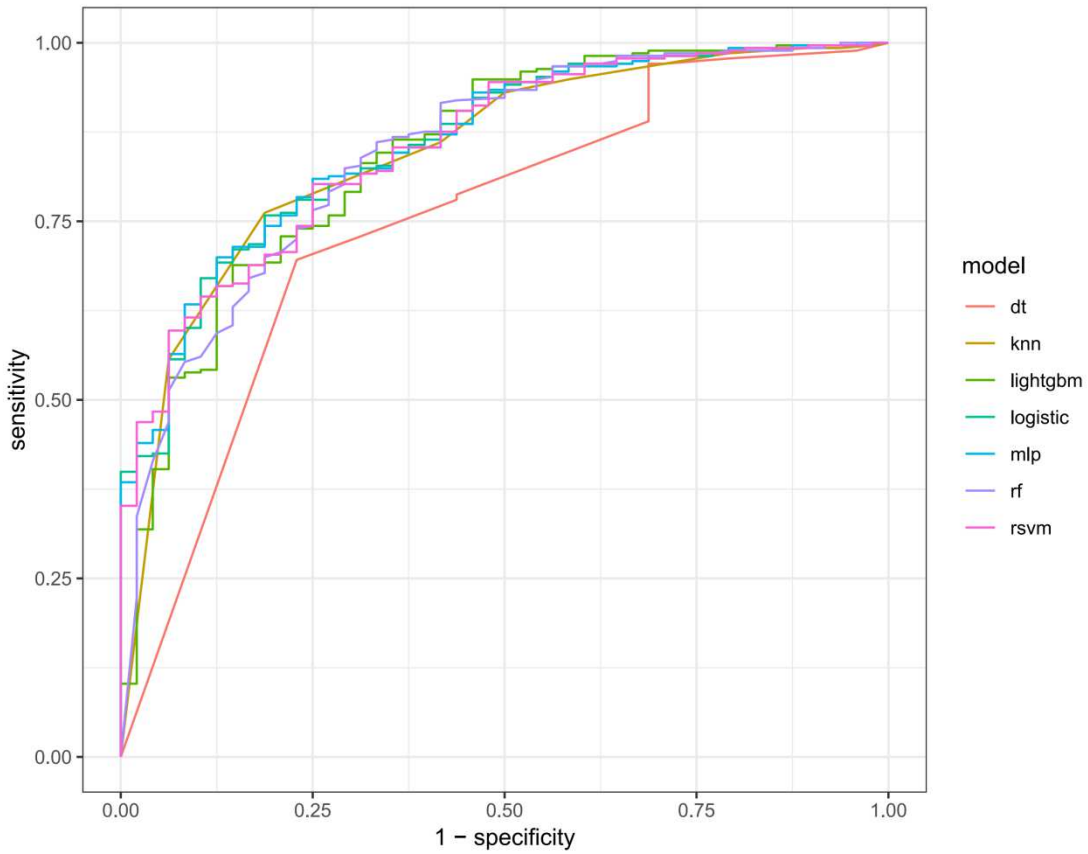


Figure 3. ROC curves of the eight models on the internal validation set (test set).

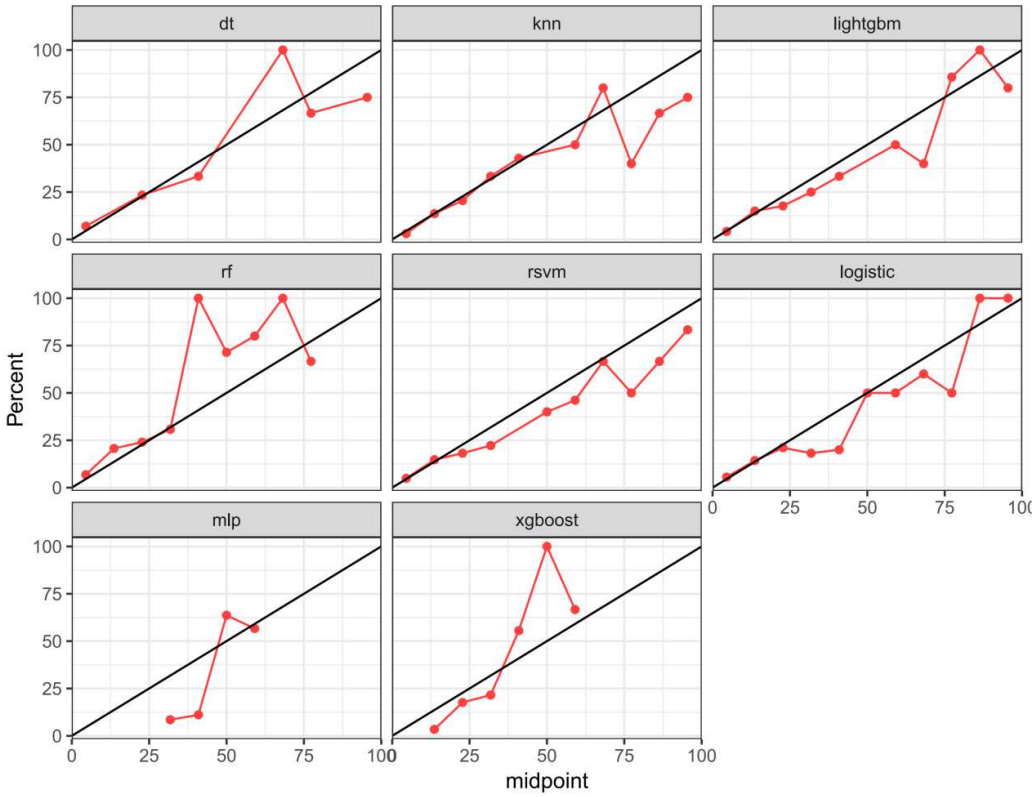


Figure 4. Calibration curves of the eight models.

2.5 Clinical Usability Evaluation of the Models

Machine learning models are increasingly applied in medicine, showing great potential in disease prediction, diagnostic assistance, and treatment optimization. However, even a model that performs excellently during the research phase has limited value if it cannot be reliably used in clinical practice. Therefore, evaluating the clinical usability of a model is essential to ensure its effective implementation. Traditional performance metrics (e.g., AUC, accuracy) alone are insufficient to fully assess a model's value in real-world clinical decision-making. [16] Thus, this study used decision curve analysis (DCA) to evaluate the net benefit of different models across various decision thresholds, thereby determining their clinical usability.As shown in the decision curve (Figure 5), the horizontal axis represents the decision threshold—the minimum predicted probability of ischemic stroke required for clinicians to consider intervention. When the model's predicted probability exceeds this threshold, the patient may receive further intervention; otherwise, no intervention is taken. The vertical axis represents net benefit, i.e, the additional benefit of using the model compared with "treating all" or "treating none." According to the overall trend of the decision curves (Figure 5), the LightGBM and LR models performed well across most threshold ranges, indicating that they have high clinical utility under different decision criteria.

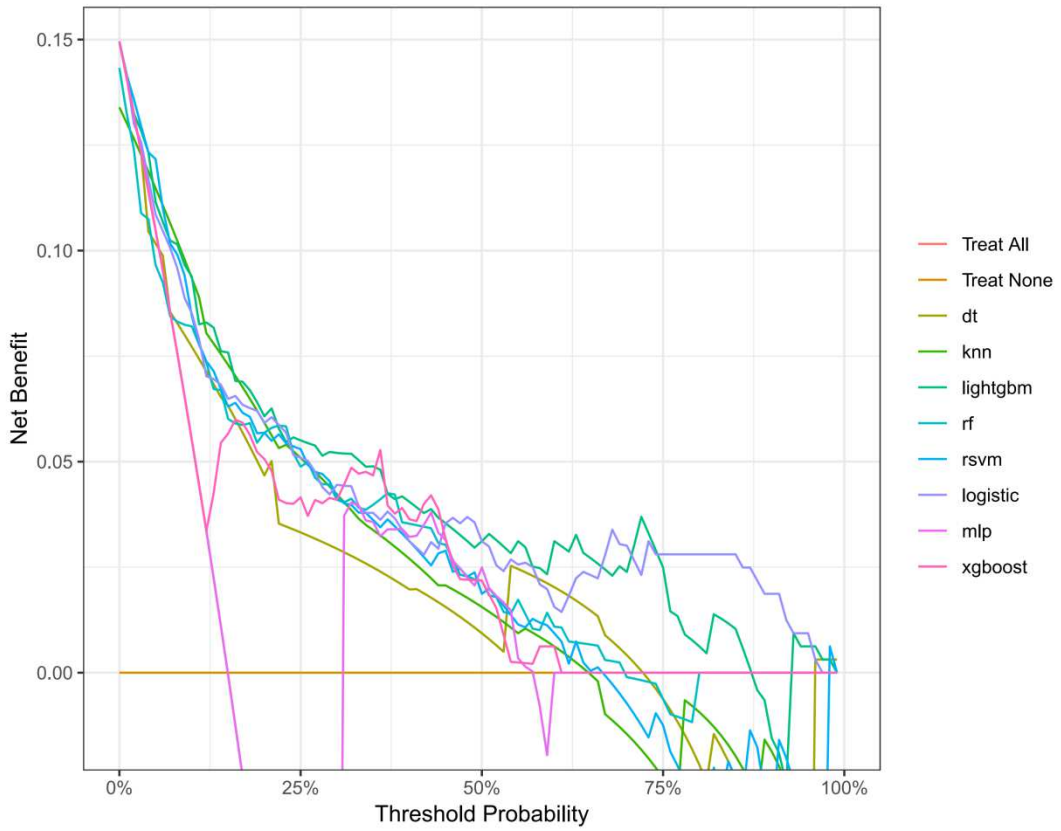


Figure 5. Clinical decision curves.

2.6 Model Interpretability

Machine learning is now widely applied across various fields, and model interpretability has become a crucial area of research. The "black-box" nature of models can lead to decision errors or loss of trust. SHAP (SHapley Additive exPlanations), a game-theory-based method, quantifies each feature's contribution to the model's predictions, thereby enhancing transparency and credibility. In this study, SHAP values were used to evaluate the contribution of each feature to the prediction of ischemic stroke risk.

The SHAP summary plot (Figure 6) shows SHAP values on the x-axis and features on the y-axis. Each point represents one sample, and the color indicates the feature value (red: high, blue: low). As shown in the figure, triglycerides (TAG) had the highest

importance, with a wide SHAP value distribution, indicating that TAG strongly drives predictions across many samples. Higher TAG values (red) were associated with a stronger positive prediction of stroke risk. The next most important features were history of cardiac disease and age, both of which significantly increased stroke prediction when present (e.g., history of cardiac disease = 1). Notably, the predictive contribution of WWI exceeded that of traditional BMI, with high WWI values markedly increasing stroke risk prediction, suggesting that WWI may better capture the cardiovascular and cerebrovascular risks associated with abnormal fat distribution. This finding is consistent with previous studies. [9,10,17,18]

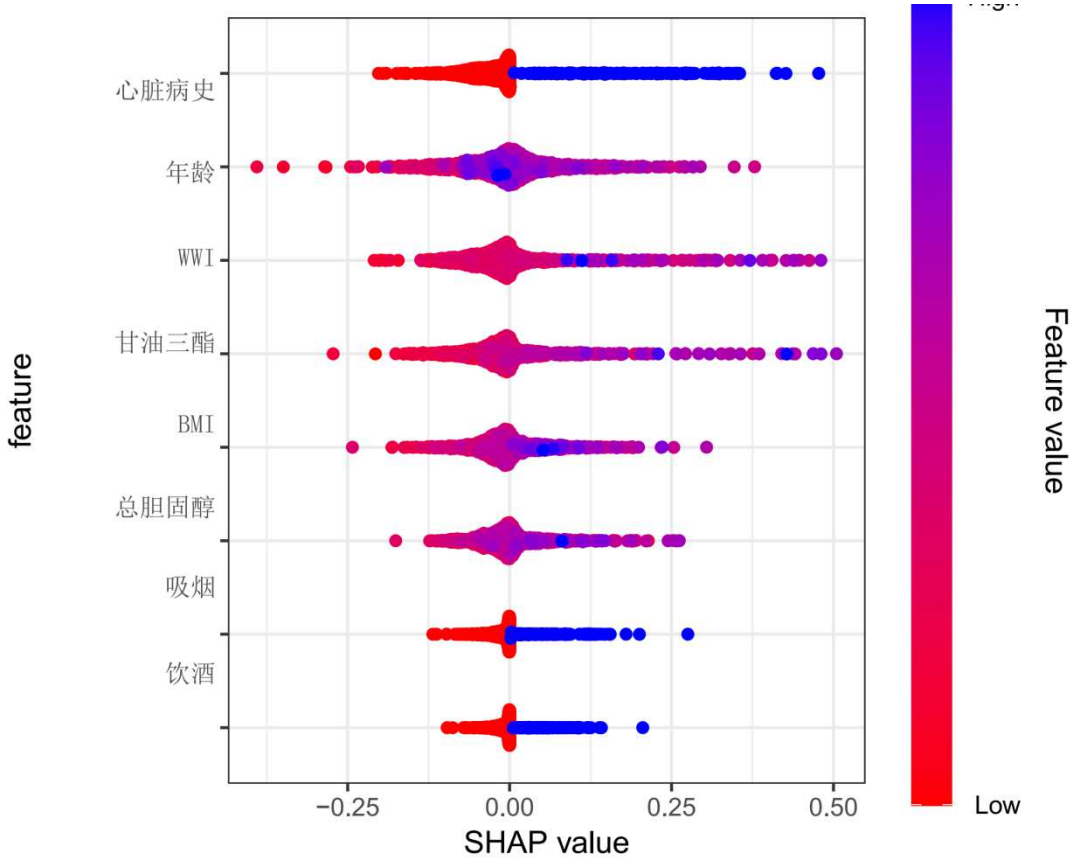


Figure 6. SHAP summary plot for the LightGBM model.

3 Discussion

Based on the clinical data of 1,070 elderly hypertensive patients, this study

systematically compared the performance of eight machine learning models in predicting ischemic stroke and specifically evaluated the incremental predictive value of a novel adiposity indicator: the Weight-Adjusted Waist Index (WWI). The results demonstrated that the LightGBM model achieved the best overall performance in the comprehensive evaluation. Notably, WWI exhibited a higher predictive contribution than traditional BMI and, together with established factors such as cardiac history, age, and lipid profiles, constituted key predictive features. The following discussion is organized into five aspects: model performance evaluation, the pathophysiological significance of key predictors, comparison with previous studies, clinical translation pathways, and study limitations.

3.1 Comprehensive Evaluation of Model Performance: Why LightGBM is More Suitable for Stroke Screening

Among the eight candidate models, the ROC-AUC of LightGBM was 0.845, slightly lower than that of Logistic Regression (0.860) and Multilayer Perceptron (0.861). However, this difference may not be clinically decisive. In the context of ischemic stroke primary prevention, Recall (Sensitivity) holds greater decision-making value than AUC. Missing a high-risk patient (false negative) can lead to irreversible neurological deficits. LightGBM achieved a Recall of 0.905, compared to 0.846 for Logistic Regression and 0.824 for MLP. This means that for every 100 actual stroke patients, LightGBM identifies approximately 6 additional cases. This improvement is of significant clinical importance for early screening in community-dwelling elderly populations.

Furthermore, LightGBM achieved the highest F1 Score (0.915), indicating an optimal balance between Precision and Recall. The calibration curves (Figure 4) showed that LightGBM's agreement between predicted probability and observed incidence was superior to other models across all threshold ranges. Decision Curve Analysis (Figure 5) further confirmed that LightGBM and Logistic Regression yielded the highest and comparable net benefits within a broad threshold range of 0.2 to 0.6.

The advantages of LightGBM are related to its algorithmic characteristics. Its Gradient-Boosted Decision Tree architecture can automatically capture non-linear interactions among features (e.g., the potential synergistic effect between WWI and Triglycerides). Additionally, employing histogram-based sparse feature optimization allows it to maintain robustness even with a relatively small number of stroke events (160 cases).

3.2 The Predictive Value of WWI: Mechanisms and Clinical Implications Beyond BMI

SHAP analysis (Figure 6) showed that WWI ranked third in its contribution to ischemic stroke prediction, following a history of cardiac disease and age, and exhibited a greater contribution than BMI within the present model. This finding suggests that WWI may capture clinically relevant information related to body composition and fat distribution that is not adequately reflected by BMI, particularly in older adults with hypertension. Because WWI incorporates waist circumference while adjusting for body weight, it may provide a more refined measure of abdominal adiposity than indices based primarily on overall body size.

Several biological mechanisms may help explain the observed association between elevated WWI and ischemic stroke risk. A higher WWI has been proposed to reflect a body-composition phenotype characterized by greater abdominal or visceral adiposity relative to body weight and, in some populations, lower lean mass. Visceral adipose tissue is metabolically active and contributes to chronic low-grade inflammation through the secretion of pro-inflammatory mediators, including interleukin-6 and tumor necrosis factor-α. These processes may promote endothelial dysfunction, oxidative stress, insulin resistance, and atherogenic lipid abnormalities, thereby facilitating the development and progression of atherosclerosis. In parallel, age-related loss of skeletal muscle may impair peripheral glucose and fatty-acid utilization and further aggravate metabolic dysregulation. In older individuals with hypertension, these metabolic disturbances may coexist with arterial stiffness, endothelial injury, and vascular remodeling, collectively creating a vascular environment that is more susceptible to cerebral ischemic events.

The SHAP dependence plot (Figure 6) further indicated that higher WWI values were associated with an increased predicted probability of ischemic stroke. The pattern appeared to suggest a possible non-linear relationship. However, because SHAP analysis primarily describes the contribution of a feature to model predictions rather than establishing an epidemiological dose-response relationship, the potential threshold or non-linear effect of WWI should be confirmed in future studies using approaches such as restricted cubic spline analysis or prospective cohort designs.

The greater contribution of WWI relative to BMI observed in our model may also be particularly relevant in geriatric populations. BMI does not distinguish adipose tissue from lean mass and provides limited information regarding fat distribution. These limitations become increasingly important with aging, as body weight and BMI may remain relatively stable despite progressive visceral fat accumulation and loss of skeletal muscle. Consequently, older adults with a normal or mildly elevated BMI may still have substantial central adiposity or sarcopenic obesity and therefore remain at increased cardiometabolic risk. In the present study, BMI was retained after LASSO feature selection, but its contribution in the SHAP analysis was considerably lower than that of WWI. This observation is consistent with previous studies indicating that WWI may provide clinically relevant information beyond conventional anthropometric indices in cardiovascular risk assessment. Li et al. [17] reported an association between WWI and all-cause mortality, whereas Wang et al. [18] demonstrated that WWI showed favorable performance in identifying coronary artery disease compared with BMI. Together with our findings, these observations support the hypothesis that anthropometric measures reflecting abdominal fat distribution may be more informative than overall body mass alone for vascular risk assessment.

Notably, several patients in our cohort had relatively high WWI values despite having BMI values within the conventional normal range and nevertheless experienced ischemic stroke (Table 2). This pattern illustrates the potential limitation of relying exclusively on BMI for risk stratification. However, because the present study did not formally compare nested prediction models with and without WWI using indices such

as changes in AUC, net reclassification improvement, or integrated discrimination improvement, these findings should be interpreted as evidence of the additional predictive contribution of WWI rather than definitive proof of incremental predictive value. Further prospective studies are warranted to determine whether incorporating WWI into existing stroke risk models meaningfully improves risk classification and clinical decision-making.

3.3 Clinical and Pathological Significance of Other Key Predictors

In addition to WWI, several established cardiovascular and metabolic factors showed substantial contributions to ischemic stroke prediction, reinforcing the multifactorial nature of stroke risk in older patients with hypertension.

History of cardiac disease. A history of cardiac disease showed the highest SHAP contribution among all included predictors. The prevalence of cardiac disease was substantially higher in the stroke group than in the non-stroke group (35.0% vs. 11.8%; Table 2). This finding is clinically plausible because several cardiac disorders are closely linked to ischemic stroke. Atrial fibrillation is an important cause of cardioembolic stroke, while coronary artery disease frequently coexists with systemic and cerebrovascular atherosclerosis because of shared risk factors and pathophysiological mechanisms. The strong predictive contribution of cardiac history in the present model therefore reflects the close interaction between cardiac and cerebrovascular disease in older hypertensive populations. These findings also underscore the importance of comprehensive cardiovascular assessment when evaluating stroke risk in elderly patients with hypertension.

Age was the second most influential predictor in the SHAP analysis. Patients with ischemic stroke were older than those without stroke (72.9 vs. 69.9 years; Table 2). Advancing age is accompanied by progressive arterial stiffening, endothelial dysfunction, vascular calcification, and impaired vascular repair, all of which may increase susceptibility to cerebral ischemia. Moreover, aging is frequently accompanied by multimorbidity, declining renal function, changes in body composition, and polypharmacy. Thus, the contribution of age likely reflects not only chronological aging itself but also the cumulative burden of vascular and systemic changes associated with aging.

Triglyceride levels were higher in the stroke group than in the non-stroke group (1.76 ± 0.55 vs. 1.41 ± 0.40 mmol/L; Table 2). Elevated triglycerides and triglyceride-rich remnant particles may contribute to atherosclerosis through cholesterol deposition, endothelial dysfunction, and vascular inflammation. The SHAP distribution further suggested that elevated triglycerides frequently coexisted with higher WWI values among individuals with increased predicted stroke risk. This observation raises the possibility that the combination of abdominal adiposity and triglyceride-related metabolic abnormalities may identify a metabolically unfavorable phenotype among older hypertensive patients. Nevertheless, whether an interaction exists between WWI and triglycerides requires formal statistical testing and should be explored in future studies.

Smoking and alcohol consumption were also more common among patients with ischemic stroke than among those without stroke (smoking: 36.88% vs. 14.84%;

449 alcohol consumption: 28.75% vs. 10.33%; Table 2). Smoking is a well-established
450 modifiable risk factor for ischemic stroke through its adverse effects on endothelial
451 function, oxidative stress, platelet activation, and atherosclerosis. The relationship
452 between alcohol consumption and stroke is more complex and may vary according to
453 the amount, frequency, and pattern of alcohol intake. Because detailed information on
454 alcohol exposure was not available in the present analysis, the observed association
455 should be interpreted cautiously. Nevertheless, assessment and modification of
456 lifestyle-related risk factors remain important components of stroke prevention in
457 older adults with hypertension.

458 **3.4 Comparison with Previous Studies on WWI**

459 In recent years, the predictive value of WWI in cardiovascular and cerebrovascular
460 diseases has gained increasing attention. Hu et al. [10] reported that in elderly
461 hypertensive individuals, each one-standard-deviation increase in WWI was
462 associated with a Hazard Ratio (HR) of 1.34 for stroke. Cao et al. [9] found a positive
463 association between WWI and new-onset stroke (Odds Ratio OR = 1.28) in adults
464 aged ≥45 years. Park et al. [6]reported that WWI showed greater prognostic utility than
465 BMI and waist circumference for cardiovascular mortality in a Korean population.
466 These findings suggest that WWI may capture aspects of adiposity distribution and
467 body composition that are relevant to vascular risk but are incompletely represented
468 by conventional anthropometric measures.

469 Our findings extend this evidence in several respects. Rather than examining WWI
470 solely as an exposure variable in a conventional regression framework, we evaluated

its contribution within multiple machine learning models developed specifically for ischemic stroke prediction in older adults with hypertension. In the SHAP analysis, WWI ranked third among all predictors and contributed more strongly to model predictions than BMI. Although effect estimates derived from conventional epidemiological models, such as hazard ratios and odds ratios, are not directly comparable with SHAP values, the direction of the findings is broadly consistent: higher WWI is associated with a less favorable cardiovascular and cerebrovascular risk profile.

The present study therefore provides complementary evidence supporting the potential role of WWI in stroke risk assessment among older hypertensive individuals. Importantly, our findings do not suggest that WWI should replace established clinical risk factors. Rather, WWI may serve as a simple and readily obtainable anthropometric marker that complements information derived from age, cardiovascular history, metabolic factors, and conventional anthropometric measures. Given that waist circumference and body weight are inexpensive and routinely available in clinical practice, WWI may have practical value for preliminary risk stratification, particularly in primary care and geriatric settings where more sophisticated assessments of visceral adiposity or body composition are not routinely feasible.

Nevertheless, external validation in independent populations is required before WWI can be incorporated into routine stroke risk prediction. Future prospective studies should determine whether adding WWI to established clinical models improves

discrimination, calibration, reclassification, and clinical net benefit, and whether clinically meaningful cut-off values can be identified for older adults with hypertension.

3.5 Clinical Applicability and Implementation Pathways

The LightGBM model developed in this study has high practical value, reflected in the following aspects:

1.Ease of Data Acquisition: The eight key variables selected by LASSO (age, cardiac history, WWI, BMI, total cholesterol, triglycerides, smoking, and alcohol consumption) are all part of routine physical examinations or clinical interviews at community hospitals.

2.Simple Calculation: WWI = waist circumference (cm) / √body weight (kg), which can be calculated instantly using a calculator or mobile app.

3.Decision Threshold Reference: According to DCA (Figure 5), LightGBM provides the highest net benefit across a broad threshold range (0.2–0.6). Clinicians may choose a threshold based on context; for example, patients with a predicted risk ≥0.3 could be recommended for further carotid ultrasound or referral.

4.Cost-Effectiveness: Utilizing already collected information incurs no additional costs, making it suitable for primary care settings.

Of course, implementation studies (e.g., physician acceptance, workflow integration) are still needed before clinical deployment.

3.6 Limitations and Future Directions

This study has several limitations:

1.Design Bias: The single-center retrospective design may introduce selection and recall bias. Future multicenter prospective cohort studies are planned for external validation.

2.Sample Size: With only 160 stroke cases, the sample size is relatively small for training eight machine learning models, and some models may be prone to overfitting. Future studies should expand the sample size.

3.Missing Variables: Key variables such as antihypertensive drug classes, detailed blood pressure control levels, and imaging data were not included. Subsequent studies will collect medication history and imaging data.

4.Generalizability: The model was validated only in a community-based elderly hypertensive population in Nanning. Future studies could attempt cross-regional validation.

5.Model Interpretability: Although SHAP was used, a simplified scoring system based on LightGBM's feature importance could be developed in the future for more intuitive clinical use.

Declaration of interest statement

All authors declare no conflict of interest.

Author Contributions

Jiaru Wang conceived and designed the study, collected and analyzed the data, and drafted the manuscript.

Yong Yang and Jiexia Cen contributed to data collection and preprocessing.

Yushi Chen and Liaofan Luo assisted in data analysis and interpretation.

Shiquan Yang supervised the study, reviewed and revised the manuscript, and approved the final version for publication.

Data availability statement

The data will be provided by the corresponding author upon reasonable request.

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Ethics approval and consent to participate

This study was approved by the Medical Ethics Committee of Ruikang Hospital Affiliated to Guangxi University of Chinese Medicine (approval No. KY2024-127). Written informed consent to participate was obtained from all participants prior to their inclusion in the study. All methods were performed in accordance with the relevant guidelines and regulations and the principles of the Declaration of Helsinki.

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