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ORIGINAL RESEARCH

Using Interpretable Machine Learning with SHAP to Assess Dynapenic Abdominal Obesity as a Stroke Risk Predictor: A Prospective Cohort Study

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Background: Stroke is a major cause of mortality and disability worldwide, with a particularly high burden in China. While dynapenic abdominal obesity (DAO) is associated with adverse cardiometabolic outcomes, its relationship with stroke risk remains unclear. We examined whether DAO predicts stroke using interpretable machine learning in a nationally representative cohort of middle-aged and older Chinese adults.

Methods: We analysed prospective data from the China Health and Retirement Longitudinal Study, including 11,207 participants aged ≥ 45 years. Dynapenia was defined as a handgrip strength ≤ 28 kg (men)/≤ 18 kg (women); abdominal obesity was defined as a waist circumference ≥ 90 cm (men)/≥ 80 cm (women). Stroke events were identified via self-reported physician diagnoses. We employed logistic regression, subgroup analyses, multiple machine learning models, and Shapley additive explanations (SHAP) to assess the association and evaluate robustness.

Results: Over the 4-year follow-up period, 210 (1.9%) participants experienced stroke. DAO was significantly associated with increased stroke risk (adjusted OR = 1.58, 95% CI: 1.21–2.06). Subgroup analysis demonstrated consistent associations across all subgroups (all interaction p-values > 0.05). XGBoost demonstrated the highest predictive performance (AUC = 0.92, accuracy = 0.84). SHAP analysis ranked DAO as the fourth most important predictor after age, BMI, and residence.

Conclusion: DAO was independently associated with an increased risk of stroke, with an interpretable machine learning model further supporting its potential as a predictor. Maintaining muscle strength and managing abdominal obesity may reduce the risk of stroke in older adults. These findings suggest that DAO may serve as a potential risk marker for stroke. Future research, including external validation and implementation studies, is needed before any recommendations for screening or intervention can be made.

Keywords: dynapenic abdominal obesity, stroke, China health and retirement longitudinal study, CHARLS, machine learning, shapley additive explanations

Introduction

Stroke is a leading neurological disease causing death and disability worldwide. The World Health Organisation reports approximately 15 million new cases each year,[1] with one-third resulting in death and another third in disability.[2] *The Lancet Neurology* estimates that, without effective interventions, the global number of stroke deaths could reach 9.7 million per year by 2050, with economic losses up to 2.3 trillion US dollars.[3] China is among the countries with the heaviest stroke burden.[3–5] Global Burden of Disease data showed 4.09 million new cases of stroke in China in 2021, with an increasing incidence among younger individuals.[2,6] These figures highlight the need for targeted screening of modifiable risk factors, particularly in high-risk groups.

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Dynapenic abdominal obesity (DAO) refers to the combined presence of dynapenia (loss of skeletal muscle strength) and abdominal obesity (accumulation of visceral adipose tissue).[7] Recent studies associate DAO with physical impairment and adverse outcomes, including cognitive decline, falls, depressive symptoms, and increased mortality.[8–12] Each component independently increases cardiovascular risk. Greater muscle strength is associated with a lower risk of stroke in middle-aged and older adults,[13,14] while abdominal obesity is a recognised risk factor for cardiovascular diseases.[15–18] DAO may contribute to stroke through mechanisms such as chronic inflammation, insulin resistance, endothelial dysfunction, and increased oxidative stress, which promote atherosclerosis and vascular dysfunction.[19–23]

Despite these biological links and the individual risks of its components, direct epidemiological evidence on the association between DAO and incident stroke remains limited and inconsistent. Some cross-sectional studies, such as one involving older Brazilian adults, found no significant association between DAO and self-reported stroke,[24] possibly due to design limitations. In contrast, longitudinal data from the English Longitudinal Study of Ageing showed a higher prevalence of stroke at baseline and increased cardiovascular mortality risk with DAO,[25] though incident stroke was not specifically assessed. A recent Japanese prospective cohort study reported a significantly increased stroke risk in individuals with DAO,[26] indicating the need for further research. Notably, a study using the CHARLS data found an association between DAO and cardiovascular disease risk with traditional Cox regression,[27] but such methods may not capture complex, non-linear relationships. These inconsistencies and methodological limitations highlight a significant knowledge gap.

Machine learning models are effective at identifying complex patterns and nonlinear relationships among variables in epidemiological research.[28] However, there is a limit in interpretability, thus restricting the generalisation of results in empirical research and clinical decision-making.[29] Shapley additive explanations (SHAP), a leading explainable artificial intelligence (XAI) technique, quantifies each feature's contribution to model predictions, addressing interpretability challenges after model construction.[30] By combining machine learning with SHAP, this study examines the association between DAO and stroke using the CHARLS cohort data, aiming to promote brain health and healthy ageing.

Methods

Study Population

CHARLS is a nationally representative cohort study that employs a multistage probability sampling design to examine the socio-economic determinants and consequences of ageing in China. The baseline survey in 2011 included 17,708 participants, with subsequent biennial waves in 2013, 2015, 2018, and 2020. Participants are community-dwelling individuals aged 45 years or older from 450 villages in 28 provinces. Trained interviewers collect data through computer-assisted personal interviewing, covering demographic characteristics, health status, functional capacity, socio-economic conditions, and retirement information. A detailed description of the study design and methodology has been published previously.[31] As this study used publicly available, de-identified CHARLS data, the Ethics Committee of The First Affiliated Hospital of Nanchang University confirmed that no additional ethical approval was required. In accordance with national legislation guidelines (items 1 and 2 of Article 32 of the Measures for Ethical Review of Life Science and Medical Research Involving Human Subjects, February 18, 2023, China), this research is exempt from ethics review.

This study used data from CHARLS waves 1 (2011) and 3 (2015). Participants were included if they were aged 45 years or older, had complete baseline data on handgrip strength, waist circumference, and stroke status, had no history of stroke, and had stroke status recorded in 2015. As shown in Figure 1, of the 17,705 baseline participants, those who did not meet these criteria were excluded due to age, loss to follow-up, missing data, or prior stroke. The final sample included 11,027 individuals.

Assessment of Stroke

Participants' stroke status was assessed by asking, "Has a doctor ever told you that you have been diagnosed with stroke?" A positive response indicated a physician-confirmed stroke history. While this method is common in large cohort studies, it is vulnerable to recall bias and misclassification. CHARLS also gathers data on hospitalisation reasons and causes of death through exit interviews, but these rely on self- or proxy-reported data, lack independent medical

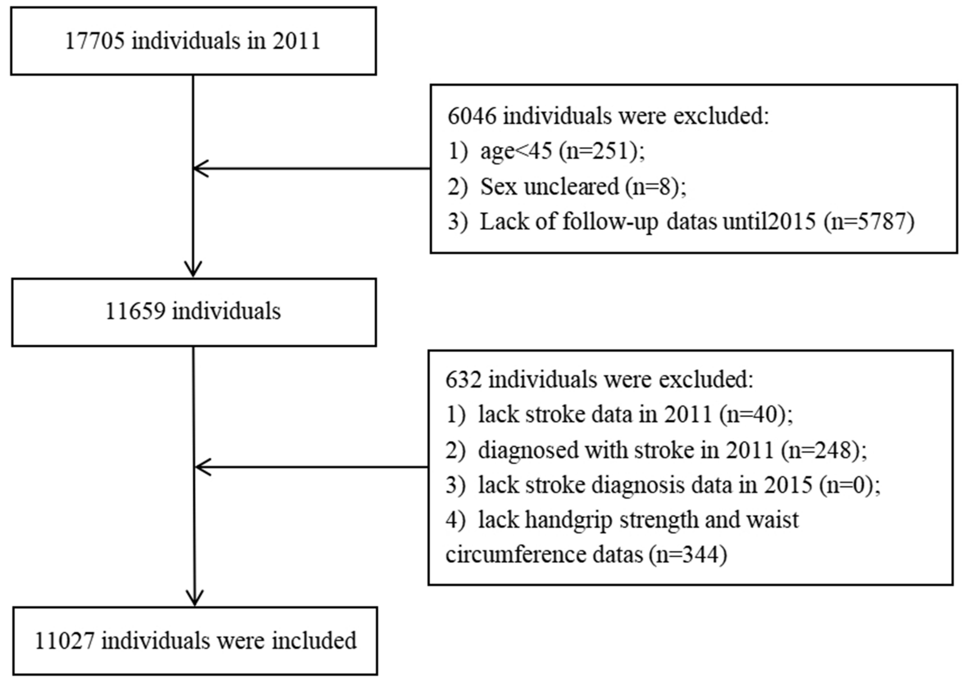

Figure 1 Flowchart of Participant Selection.

record verification, and are subject to similar recall and missing data issues. Hospital admission for stroke does not necessarily indicate an incident stroke, and the causes of death data only reflect fatal cases. As a result, these auxiliary variables do not serve as a diagnostic gold standard and cannot be used to rigorously validate or reclassify self-reported stroke outcomes. Due to these limitations, we did not conduct a quantitative sensitivity analysis using these sources.

Assessment of DAO

Participants' grip strength (in kilograms) was measured using a WL-1000 handheld dynamometer (Nantong Yuejian Physical Fitness Testing Equipment Co., Ltd., Jiangsu, China). Following the interviewer's demonstration, each participant performed the test while standing. They completed two trials with each hand, alternating between dominant and non-dominant sides, and received standardised verbal encouragement during measurement. During each trial, the dynamometer was held at 90°, and the maximum force was sustained for several seconds. The highest value from each hand was identified, and the average of these two maxima was recorded and used for analysis. Dynapenia was defined using Asian-specific grip strength cut-off values of ≤ 28 kg for men and ≤ 18 kg for women.[32]

Participants' waist circumferences were measured in centimetres using a standard tape measure. Following a demonstration, each participant stood upright while the tape was placed horizontally around the abdomen at the level of the umbilicus. Measurements were taken at the end of normal expiration, with the participant holding their breath momentarily to ensure consistency. Abdominal obesity was defined according to the World Health Organisation criteria as a waist circumference ≥ 90 cm for men and ≥ 80 cm for women.[33] Participants who met the requirements for both dynapenia and abdominal obesity were classified as having DAO. All participants were categorised into four groups based on their DAO status: no dynapenia and no abdominal obesity (ND/NAO), no dynapenia but abdominal obesity (ND/AO), dynapenia but no abdominal obesity (D/NAO), and dynapenia with abdominal obesity (D/AO).

Assessment of Covariates

In structured interviews, data on demographic characteristics [age, sex, marital status (living with a partner vs. living alone), residence (rural vs. urban) and education level (illiterate, junior high school or below, senior high school or above)] and health-related factors [lifestyle behaviours (non-smoker vs. smoker, non-drinker vs. drinker) and medical

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history (self-reported diagnoses of hypertension, dyslipidaemia, diabetes, cancer and heart disease)] were collected. BMIs were calculated as the weight (in kilograms) divided by the height (in metres) squared.

Statistical Analysis

Continuous variables with normal distributions are presented as means ± standard deviations, and those with skewed distributions are reported as medians (interquartile ranges). Group differences were assessed using one-way analysis of variance for normally distributed data and the Mann–Whitney *U*-test for non–normally distributed data. Categorical variables were reported as frequencies and percentages, and group comparisons were conducted using the chi-squared test or Fisher's exact test when expected cell counts were small.

Analysis of the Association Between DAO and Stroke

Binary logistic regression analysis was used to assess the association between DAO and stroke. An unadjusted model estimated the crude odds ratio (OR), followed by a multivariable-adjusted model to calculate the adjusted OR and 95% CI. Adjustment variables were selected based on a literature review and clinical relevance. To evaluate the effect of unmeasured confounding, a sensitivity analysis using the E-value was performed.[34,35] The E-value indicates the minimum strength of association an unmeasured confounder would need with both DAO and stroke to account for the observed association.

Subgroup Analysis and Interaction Test

To assess the robustness of the association between DAO and stroke across population subgroups, we conducted a pre-specified subgroup analysis. Variables used for stratification were the sex (male vs. female), hypertension (yes vs. no), hyperlipidaemia (yes vs. no), diabetes (yes vs. no), heart disease (yes vs. no), smoking status (smoker vs. non-smoker) and drinking status (drinker vs. non-drinker). The likelihood ratio test was used to assess the significance of the interaction between DAO and each subgroup variable.

Predictive Machine Learning Model–Based Analysis

To compare the predictive performance of traditional statistical methods with that of machine learning algorithms, the dataset was divided randomly into a training set (70%) and a test set (30%). Six models were developed using the training set: categorical boosting (CatBoost), extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), naive Bayes, reinforcement fine-tuning, and support vector machine. The best-performing model was evaluated on the training set using five-fold cross-validation. Model performance was evaluated using receiver operating characteristic (ROC) curves, decision curve analysis (DCA), calibration plots and precision-recall (PR) curves. Key metrics included accuracy, precision, recall, and F1 score.

We selected machine learning algorithms based on robustness, interpretability, and clinical relevance. To ensure our results reflect stable patterns rather than algorithm-specific artefacts, we used a range of models, including ensemble methods (CatBoost, XGBoost, LightGBM), support vector machines, naive Bayes, and reinforcement fine-tuning. XGBoost was included from the outset for its strong performance with tabular medical data, resistance to overfitting through regularisation, and compatibility with SHAP, which supports the interpretability required for clinical studies. Although newer architectures such as deep neural networks and transformers are available, they require larger datasets and offer less interpretability, making them less suitable for our goal of transparent, evidence-based assessment of DAO as a risk predictor in this cohort. Our comparison shows that the selected algorithms, especially XGBoost, delivered excellent predictive performance, supporting our methodological choices.

Model Output Interpretation and Feature Importance Analysis

SHAP values were used to interpret the predictions of the best-performing machine learning model. Mean absolute SHAP values were calculated to rank feature importance, enabling the identification of the most influential predictors in stroke risk classification.

Statistical Software and Significance Level

The statistical analyses were performed using R software (version 4.5.1; R Foundation for Statistical Computing, Vienna, Austria), IBM SPSS Statistics (version 25.0; IBM Corp., Armonk, NY, USA) and Python (version 3.8.2; Python Software Foundation). All hypothesis tests were two-sided, with the significance level set at $\alpha = 0.05$.

Results

Baseline Characteristics

A total of 11,207 participants were included in the final analysis. Of these, 620 (5.5%) were in the D/AO group, 4701 (41.9%) in the ND/NAO group, 763 (6.8%) in the D/NAO group, and 4943 (44.1%) in the ND/AO group. Baseline characteristics for the four groups are shown in Table 1. All variables differed significantly across groups ($p < 0.05$).

Table 1 Characteristics of Participants

Variable	Total	ND/NAO	D/NAO	ND/AO	D/AO	*p* value
Numbers	11027	4701	763	4943	620	
Age, mean (SD)	58.86 (9.20)	58.05 (8.59)	66.63 (9.80)	57.64 (8.67)	65.08 (9.93)	<0.001
BMI, mean (SD)	23.49 (3.86)	21.41 (2.69)	20.42 (2.76)	25.76 (3.48)	25 (4.03)	<0.001
Sex, n (%)						<0.001
Male	5180 (46.98)	3153 (67.07)	507 (66.45)	1402 (28.36)	118 (19.03)	
Female	5847 (53.02)	1548 (32.93)	256 (33.55)	3541 (71.64)	502 (80.97)	
Marital status, n (%)						<0.001
Living with a partner	9225 (83.66)	3992 (84.92)	573 (75.10)	4218 (85.33)	442 (71.29)	
Living alone	1802 (16.34)	709 (15.08)	190 (24.90)	725 (14.67)	178 (28.71)	
Education level, n (%)						<0.001
Illiterate	3094 (28.06)	1040 (22.12)	305 (39.97)	1426 (28.85)	323 (52.10)	
Junior high school or below	6812 (61.78)	3118 (66.33)	427 (55.96)	2999 (60.67)	268 (43.23)	
Senior high school or above	1121 (10.17)	543 (11.55)	31 (4.06)	518 (10.48)	29 (4.68)	
Residence, n (%)						<0.001
Rural	7227 (65.54)	3315 (70.52)	582 (76.28)	2948 (59.64)	382 (61.61)	
Urban	3800 (34.46)	1386 (29.48)	181 (23.72)	1995 (40.36)	238 (38.39)	
Hypertension, n (%)						<0.001
No	8478 (76.88)	4045 (86.05)	627 (82.18)	3431 (69.41)	375 (60.48)	
Yes	2549 (23.12)	656 (13.95)	136 (17.82)	1512 (30.59)	245 (39.52)	
Dyslipidemia, n (%)						<0.001
No	10081 (91.42)	4496 (95.64)	740 (96.99)	4312 (87.23)	533 (85.97)	
Yes	946 (8.58)	205 (4.36)	23 (3.01)	631 (12.77)	87 (14.03)	
Diabetes, n (%)						<0.001
No	10443 (94.70)	4572 (97.26)	735 (96.33)	4588 (92.82)	548 (88.39)	
Yes	584 (5.30)	129 (2.74)	28 (3.67)	355 (7.18)	72 (11.61)	
Cancer, n (%)						0.034
No	10947 (99.27)	4677 (99.49)	758 (99.34)	4901 (99.15)	611 (98.55)	
Yes	80 (0.73)	24 (0.51)	5 (0.66)	42 (0.85)	9 (1.45)	
Heart disease, n (%)						<0.001
No	9860 (89.42)	4359 (92.72)	693 (90.83)	4303 (87.05)	505 (81.45)	
Yes	1167 (10.58)	342 (7.28)	70 (9.17)	640 (12.95)	115 (18.55)	
Smoker, n (%)						<0.001
No	6706 (60.81)	2128 (45.27)	388 (50.85)	3712 (75.10)	478 (77.10)	
Yes	4321 (39.19)	2573 (54.73)	375 (49.15)	1231 (24.90)	142 (22.90)	
Drinker, n (%)						<0.001
No	6530 (59.22)	2252 (47.90)	413 (54.13)	3378 (68.34)	487 (78.55)	
Yes	4497 (40.78)	2449 (52.10)	350 (45.87)	1565 (31.66)	133 (21.45)	

(*Continued*)

Table 1 (Continued).

Variable	Total	ND/NAO	D/NAO	ND/AO	D/AO	*p* value
Grip strength, mean (SD)	31.32 (10.48)	34.96 (9.56)	19.97 (5.76)	31.60 (9.28)	15.54 (4.93)	<0.001
Waist circumference, mean (SD)	84.25 (12.54)	76.23 (11.21)	75.06 (10.21)	92.36 (7.72)	91.81 (8.13)	<0.001

Abbreviations: BMI, body mass index; SD, standard deviation; ND/NAO, no dynapenia and no abdominal obesity; D/NAO, dynapenia but no abdominal obesity; ND/AO, no dynapenia but abdominal obesity; D/AO, dynapenia with abdominal obesity.

Association Between DAO and Stroke

Over a 4-year follow-up period, 210 (1.9%) individuals experienced stroke. Stroke incidence rates were 1.57% in the ND/NAO group, 3.15% in the D/NAO group, 1.82% in the ND/AO group, and 3.55% in the D/AO group ($p < 0.001$). Logistic regression results are shown in Table 2. In the unadjusted model, the D/AO group had a significantly higher stroke risk than the ND/NAO group (OR = 2.323; 95% CI, 1.882–2.859; $p < 0.001$). This association remained significant after adjusting for demographic, medical, and lifestyle factors (OR = 1.578; 95% CI, 1.209–2.057; $p < 0.001$). The E-value for the point estimate (OR = 1.58) was 2.54, and for the lower limit of the 95% CI corresponding to an E-value of 1.71. D/NAO and ND/AO statuses were also significantly associated with stroke in both unadjusted and adjusted models (all $p < 0.05$).

Subgroup Associations with Stroke

Subgroup analyses revealed consistent associations between DAO and stroke across all stratified populations. No significant interaction effect was observed (Table 3).

Table 2 Logistic Regression Analysis for the Association Between D/AO and Stroke (OR, 95% CI)

Groups	Model 1	*p* value	Model 2	*p* value	Model 3	*p* value
ND/NAO	Reference		Reference		Reference	
D/NAO	1.332 (1.110~1.596)	0.002	1.290 (1.044~1.592)	0.017	1.293 (1.045~1.599)	0.018
ND/AO	1.805 (1.501~2.169)	<0.001	1.836 (1.524~2.211)	<0.001	1.325 (1.066~1.646)	0.011
D/AO	2.324 (1.883~2.859)	<0.001	2.227 (1.746~2.836)	<0.001	1.578[a] (1.209~2.057)	<0.001

Notes: Model 1: crude model. Model 2: adjusted for age, sex, residence, marital status and education level. Model 3: adjusted for the above combined with BMI, cancer, diabetes, hypertension, dyslipidemia, smoker and drinker. [a]E-value = 2.54.
Abbreviations: OR, odds ratio; CI, confidence interval; ND/NAO, no dynapenia and no abdominal obesity; D/NAO, dynapenia but no abdominal obesity; ND/AO, no dynapenia but abdominal obesity; D/AO, dynapenia with abdominal obesity.

Table 3 Subgroup Associations with Stroke (OR, 95% CI)

Variables	ND/NAO	D/NAO	ND/AO	D/AO	*p* Interaction
Sex					0.589
Male	Reference	1.474 (0.828~2.626)	1.103 (0.660~1.843)	1.835 (0.733~4.591)	
Female	Reference	1.041 (0.584~1.856)	0.708 (0.299~1.676)	1.345 (0.683~2.648)	
Hypertension					0.489
Yes	Reference	0.974 (0.538~1.762)	0.746 (0.380~1.464)	0.919 (0.457~1.848)	
No	Reference	1.011 (0.641~1.596)	1.107 (0.622~1.969)	1.306 (0.678~2.516)	
Dyslipidemia					0.122
Yes	Reference	0.734 (0.280~1.923)	0.391 (0.133~1.150)	0.617 (0.215~1.766)	
No	Reference	1.098 (0.743~1.622)	1.174 (0.729~1.889)	1.291 (0.756~2.204)	
Diabetes					0.542
Yes	Reference	0.357 (0.08~1.603)	2.027 (0.550~7.479)	1.117 (0.285~4.379)	
No	Reference	1.118 (0.770~1.624)	0.89 (0.555~1.426)	1.203 (0.725~1.997)	

(*Continued*)

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Table 3 (Continued).

Variables	ND/NAO	D/NAO	ND/AO	D/AO	*p* Interaction
Heart disease					0.708
Yes	Reference	0.657 (0.278~1.555)	0.759 (0.305~1.889)	0.871 (0.341~2.221)	
No	Reference	1.11 (0.746~1.652)	1.033 (0.624~1.713)	1.217 (0.694~2.136)	
Smoker					0.864
Yes	Reference	1.091 (0.591~2.016)	1.169 (0.635~2.154)	1.84 (0.780~4.342)	
No	Reference	1.127 (0.687~1.848)	0.938 (0.494~1.780)	1.224 (0.668~2.242)	
Drinker					0.622
Yes	Reference	1.255 (0.719~2.193)	1.056 (0.602~1.850)	0.888 (0.350~2.258)	
No	Reference	1.017 (0.619~1.671)	0.927 (0.469~1.835)	1.514 (0.822~2.787)	

Notes: Adjusted for age, marital status, education level, residence, cancer, and BMI as covariates.
Abbreviations: OR, odds ratio; CI, confidence interval; ND/NAO, no dynapenia and no abdominal obesity; D/NAO, dynapenia but no abdominal obesity; ND/AO, no dynapenia but abdominal obesity; D/AO, dynapenia with abdominal obesity.

Machine Learning Model Performance

The predictive performance of the machine learning models for stroke risk is summarised in Table 4. The XGBoost model had the highest area under the curve (AUC), indicating superior discrimination. DCA demonstrated its favourable clinical applicability, and calibration plots showed good agreement between predicted and observed probabilities. PR curve analysis confirmed this model's optimal performance with the training and test datasets. Overall, the XGBoost model outperformed other models and was selected as the best-performing model (Figure 2).

Optimal Model Performance

The average performance metrics for the XGBoost model were as follows: AUC = 0.912, accuracy = 0.845, precision = 0.843, recall = 0.907 and F1 score = 0.874. ROC, DCA, calibration, and PR curves further supported the model's robustness and reliability (Figure 3).

SHAP Analysis Results

SHAP analysis of the XGBoost model output identified age as the most influential predictor (mean absolute SHAP value = 0.784), followed by BMI (0.655), residence (0.306) and DAO (0.286; Figure 4).

Table 4 Comparison of the Performance of Machine Learning Models in Predicting Stroke

Models	ROC Curves	Accuracy	Precision	Recall	F1-Score
CatBoost	0.877	0.801	0.795	0.891	0.840
SVM	0.713	0.658	0.665	0.842	0.743
RFT	0.720	0.671	0.687	0.811	0.744
NB	0.604	0.592	0.650	0.666	0.658
XGBoost	0.916	0.847	0.843	0.909	0.875
LightGBM	0.905	0.827	0.825	0.896	0.859

Abbreviations: ROC, receiver operating characteristic; CatBoost, categorical boosting; XGBoost, extreme gradient boosting; LightGBM, light gradient boosting machine; NB, naive bayes; RFT, reinforcement fine-tuning; SVM, support vector machine.

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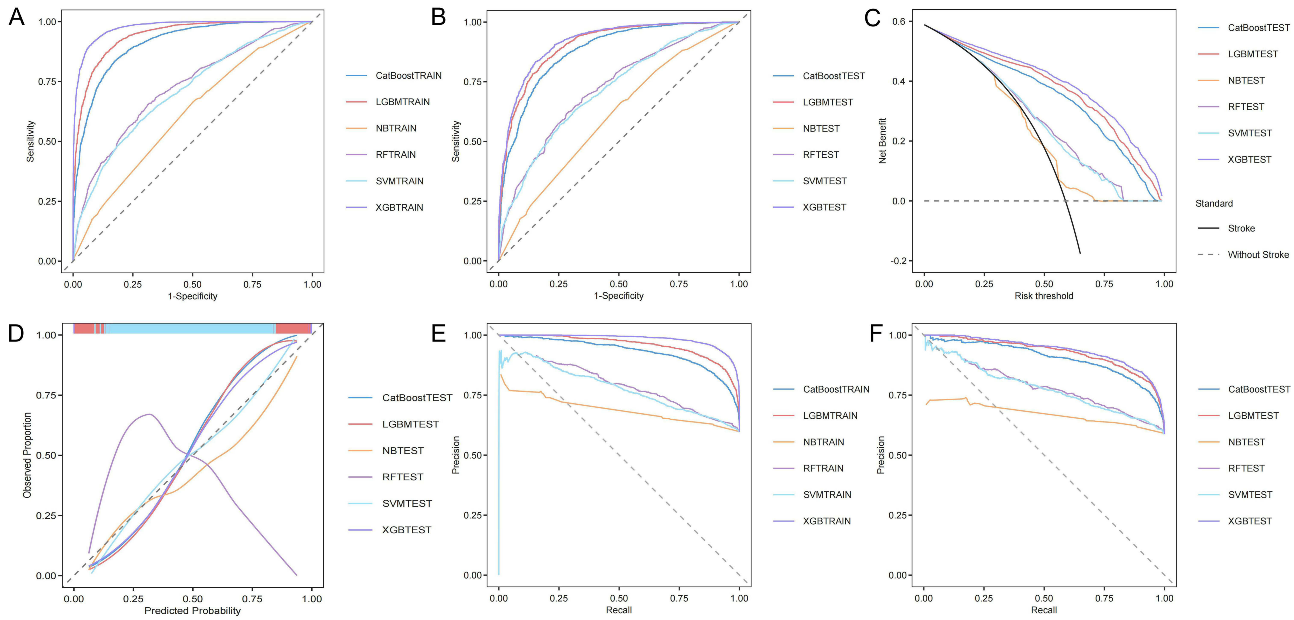

Figure 2 Comprehensive Analysis of Machine Learning. (**A**). ROC curve and AUC of the training set (CatBoostTRAIN: AUC = 0.908, LGBMTRAIN: AUC = 0.942, NBTRAIN: AUC = 0.61, RFTRAIN: AUC = 0.722, SVMTRAIN: AUC = 0.706, XGBTRAIN: AUC = 0.975). (**B**). ROC curve and AUC of the test set (CatBoostTEST: AUC = 0.877, LGBMTEST: AUC = 0.905, NBTEST: AUC = 0.604, RFTEST: AUC = 0.72, SVMTEST: AUC = 0.713, XGBTEST: AUC = 0.916). (**C**). DCA of the test set. (**D**). Calibration curve of the test set. (**E**). PR curve and Average Precision (AP) of the training set (CatBoostTRAIN: AUC = 0.931, LGBMTRAIN: AUC = 0.958, NBTRAIN: AUC = 0.686, RFTRAIN: AUC = 0.791, SVMTRAIN: AUC = 0.778, XGBTRAIN: AUC = 0.983). (**F**). PR curve and AP of the test set (CatBoostTEST: AUC = 0.904, LGBMTEST: AUC = 0.926, NBTEST: AUC = 0.668, RFTEST: AUC = 0.779, SVMTEST: AUC = 0.78, XGBTEST: AUC = 0.936).

Abbreviations: CatBoost, categorical boosting; XGBoost, extreme gradient boosting; LightGBM, light gradient boosting machine; NB, naive bayes; RFT, reinforcement fine-tuning; SVM, support vector machine.

Discussion

This study demonstrated that DAO was significantly associated with an increased stroke risk, even after adjusting for demographics, medical history, BMI, and lifestyle factors. All subgroups with low muscle strength and/or abdominal obesity showed higher stroke risks, with the highest incidence in the DAO group. Subgroup analyses confirmed this association across populations. The XGBoost model outperformed other machine learning methods, demonstrating strong predictive accuracy and clinical utility. SHAP-based analysis identified DAO as a prominent predictor of stroke, ranking fourth in feature importance. While our findings indicate an independent association between DAO and stroke risk, the observational design does not allow for causal inference. Therefore, we interpret these results as hypothesis-generating. Preserving muscle strength and managing abdominal obesity may be promising targets for future interventional studies on stroke prevention, rather than providing direct evidence for immediate clinical implementation.

Although an increasing number of studies have explored the independent links of dynapenia and abdominal obesity with cardiovascular diseases (including stroke), evidence regarding the association of both conditions (ie., DAO) on the stroke risk, particularly from longitudinal studies, remains limited and controversial. For instance, a cross-sectional analysis of the Survey on Health, Well-Being, and Ageing data found no significant association between DAO (defined as handgrip strength < 16 kg for women and <26 kg for men, and waist circumference > 88 cm for women and >102 cm for men) and self-reported stroke in 833 Brazilian older adults,[24] possibly due to the small sample size, cross-sectional design, and selection bias. Another study using eight years of follow-up from the English Longitudinal Study of Ageing cohort (7030 individuals aged 50 years and above) found a higher baseline prevalence of stroke in those with DAO and a significant association with increased cardiovascular mortality,[25] but did not directly assess the longitudinal association between DAO and stroke. A Japanese prospective cohort study reported a significantly increased stroke risk in the DAO group, particularly among individuals under 65 years old,[26] which is consistent with our findings. Although a recent study using CHARLS data established a positive association between DAO and cardiovascular disease risk,[27] the Cox regression model used could not capture non-linear interactions, limiting its clinical application. In our study, the

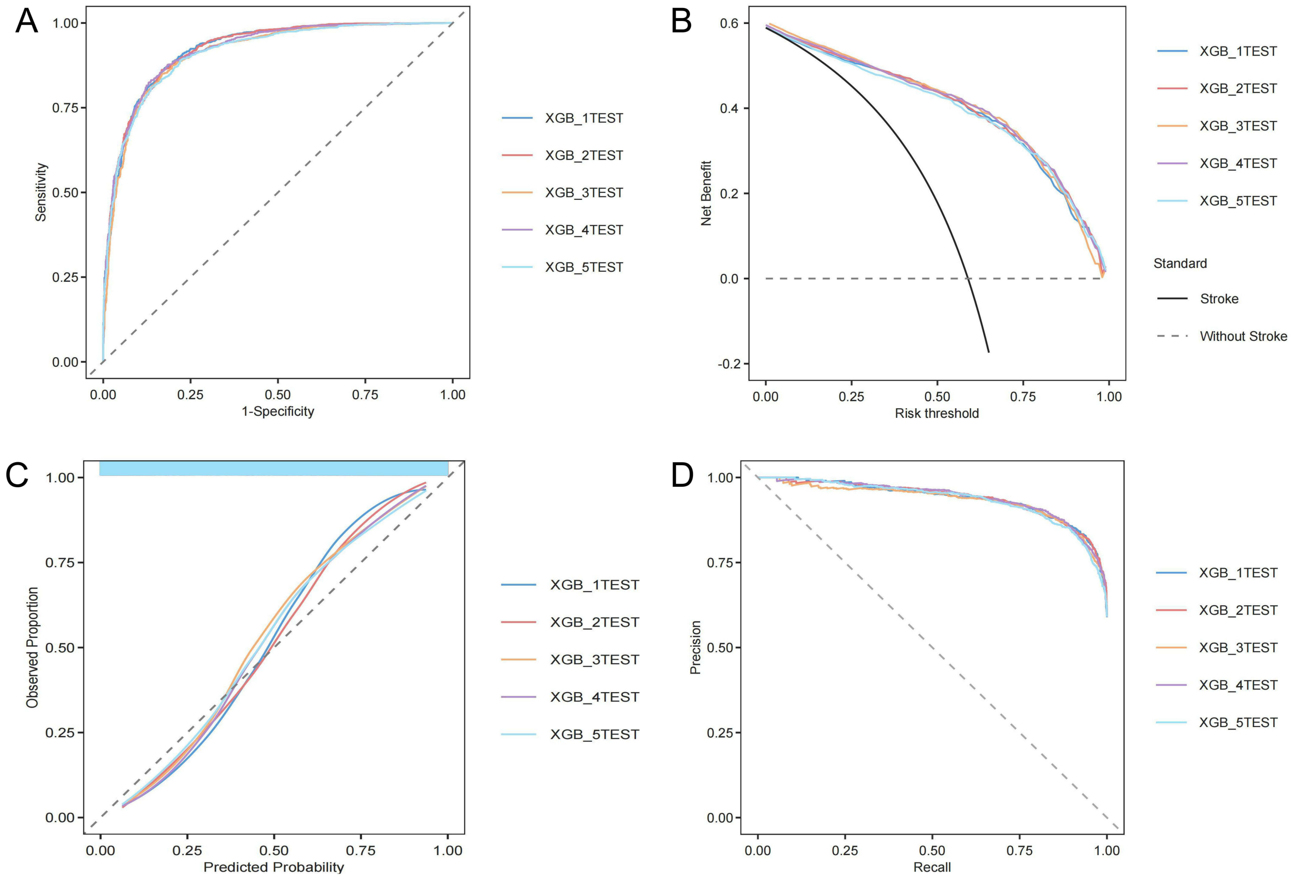

Figure 3 Evaluation of the XGBoost model. (**A**). ROC curve and AUC for the training set (XGB_1TEST: AUC = 0.92, XGB_2TEST: AUC = 0.922, XGB_3TEST: AUC = 0.911, XGB_4TEST: AUC = 0.919, XGB_5TEST: AUC = 0.912). (**B**). DCA for the training set. (**C**). Calibration curve for the training set. (**D**). PR curve and AP for the training set (XGB_1TEST: AUC = 0.938, XGB_2TEST: AUC = 0.939, XGB_3TEST: AUC = 0.932, XGB_4TEST: AUC = 0.94, XGB_5TEST: AUC = 0.934).

Abbreviation: XGB, extreme gradient boosting.

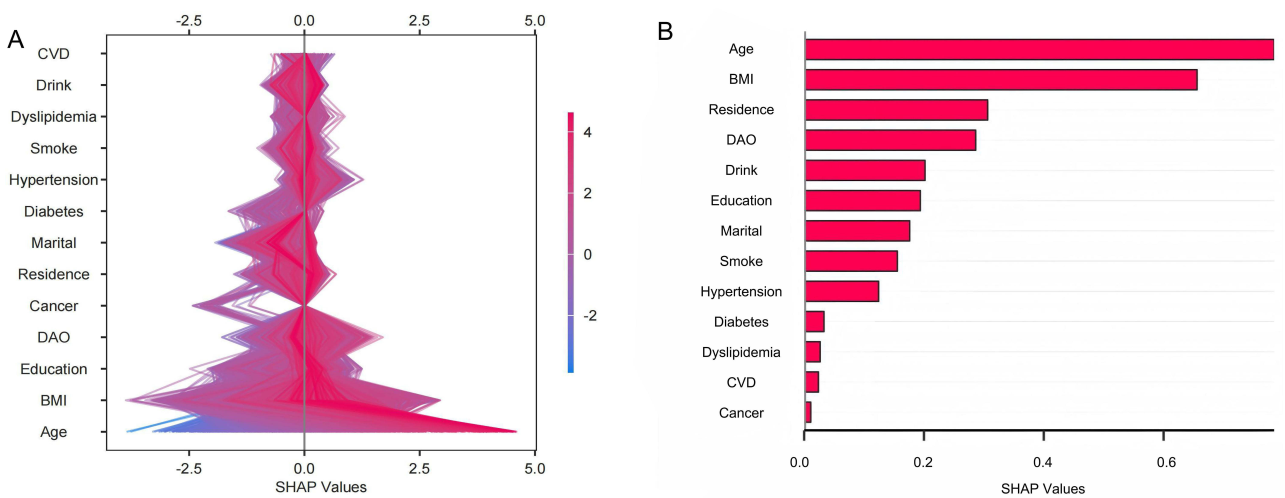

Figure 4 SHAP Visualisation Explanation of the Model. (**A**). SHAP Feature Attribution Plot, each curve represents a feature factor, with the horizontal coordinate being the SHAP value; Red lines represent higher feature values, and blue lines represent lower feature values. (**B**). Feature Factor Importance Ranking Based on SHAP Values, the matrix plot shows the importance of each variable in the construction of the final prediction model.

Abbreviations: SHAP, shapley additive explanations; CVD, cardiovascular disease; DAO, dynapenic abdominal obesity; BMI, body mass index.

significant association between DAO and stroke risk persisted after adjustment for a wide range of demographic characteristics. The consistency of results across subgroups further supports the potential role of DAO as a novel predictor across populations.

A key contribution of this study is the development of an interpretable machine learning model to assess the predictive value of DAO for stroke risk. The XGBoost model showed excellent discrimination and calibration, indicating strong clinical potential. These results support the use of advanced algorithms to improve chronic disease risk.[36–38] High predictive accuracy highlights the value of machine learning for identifying high-risk individuals and enabling early screening and targeted interventions. Interestingly, DAO ranked fourth in our SHAP analysis, surpassing traditional risk factors such as hypertension and diabetes. Several reasons may explain this. Firstly, DAO is associated with the loss of muscle strength and visceral fat accumulation, which can affect the vascular system through mechanisms like chronic inflammation, insulin resistance, endothelial dysfunction, and oxidative stress. As a result, DAO may have predictive value beyond a single disease. Secondly, the study population, middle-aged and older Chinese adults, commonly experience both abdominal obesity and dynapenia, conditions closely related to metabolic syndrome.[39,40] In this group, changes in the metabolism, muscle strength, and fat accumulation may better reflect overall risk than blood pressure or glucose alone, especially for multifactorial diseases like stroke. Thirdly, machine learning models such as XGBoost can capture complex nonlinear relationships and variable interactions, and SHAP values reflect the average marginal contribution of each feature. DAO may therefore carry greater predictive weight. Methodological factors may also play a role. Hypertension and diabetes were included as binary variables, which may not fully capture disease severity, while DAO is based on continuous, objectively measured grip strength and waist circumference, making it more sensitive to physiological changes. It should be noted that the higher ranking of DAO compared with hypertension and diabetes does not diminish the importance of established stroke risk factors. Instead, it suggests that assessing both muscle strength and abdominal obesity may provide additional risk information in middle-aged and older adults. This is especially relevant for individuals with well-controlled blood pressure and glucose who still have DAO, as their stroke risk may remain elevated. In summary, the prominent position of DAO in our model suggests that it may serve as a novel predictor. This finding supports further exploration of integrating assessments of muscle strength and abdominal obesity into stroke prevention strategies.

Another consideration is the potential influence of cardiovascular pharmacotherapy and non-pharmacological interventions on the observed associations. While the CHARLS database includes self-reported diagnoses of conditions such as hypertension, dyslipidemia, and diabetes, it lacked detailed information on the medication use, dosage, adherence, effectiveness and lifestyle interventions. This absence of treatment data may introduce unmeasured confounding. Participants with cardiovascular risk factors, such as those in the DAO group, may have been more likely to receive treatment, potentially reducing the observed association between DAO and stroke risk. Conversely, if treatments were unevenly distributed or ineffective, residual risk could remain. Our analysis adjusted for the presence of comorbidities, but not for treatment status or intensity. Future studies should include detailed treatment data to distinguish the role of medical interventions in DAO and stroke risk.

This study observed a significant and independent association between DAO and stroke risk. However, due to the observational design of CHARLS, causality cannot be established. Despite adjusting for a broad range of demographic, clinical, and lifestyle factors, residual confounding from unmeasured or imperfectly measured variables may remain. Factors such as detailed socioeconomic status, dietary patterns, physical activity, psychosocial stress, genetic predisposition, and early subclinical vascular disease could influence both DAO and stroke risk. Therefore, our findings demonstrate a robust association but do not confirm a direct causal relationship. The E-value for our point estimate (OR=1.58) is 2.54, indicating that an unmeasured confounder would need to be associated with both DAO and stroke by risk ratios of at least 2.54 each, beyond the measured covariates, to fully explain the observed association. While residual confounding cannot be ruled out, the association appears moderately robust. As a result, our findings do not support specific clinical interventions targeting DAO for stroke prevention at this time. Instead, DAO should be considered a novel risk marker that merits further investigation. Future research using quasi-experimental designs, such as Mendelian randomization, or ideally randomized controlled trials targeting muscle strength and abdominal obesity, is needed to clarify any causal relationship.

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Despite the XGBoost model performing well internally (AUC = 0.912), several key barriers must be addressed before it can be considered for clinical or public health screening. First, external validation in an independent, geographically or temporally distinct population is necessary to assess generalizability and identify potential overfitting. Since this was not feasible in our study, the model should be viewed as an exploratory proof-of-concept rather than a screening tool ready for implementation. Second, practical challenges exist for routine use. While all predictors (such as age, BMI, grip strength, and waist circumference) can be measured in community or primary care settings, grip strength measurement is not standardised across Chinese health facilities, and waist circumference protocols may differ. Additionally, although SHAP analysis provides interpretability at the individual level, communicating SHAP values to patients or clinicians without data science expertise remains challenging. Third, there is no established threshold for defining "high risk" based on model output. While decision curve analysis showed clinical net benefit across various risk thresholds, translating these into actionable screening or referral criteria will require further cost-effectiveness analysis, stakeholder agreement, and pilot studies. In summary, while our findings highlight the potential of machine learning to incorporate DAO into stroke risk stratification, substantial translational research, including external validation, implementation studies, and health economic evaluation, is needed before clinical adoption.

This study has several limitations. First, we did not include biochemical indicators such as inflammatory markers, lipid profiles, or blood glucose levels, which may have led to residual confounding. Second, the study population was limited to middle-aged and older Chinese adults, potentially restricting generalizability. Third, stroke events were self-reported, so misclassification bias cannot be excluded. Such non-differential misclassification typically biases effect estimates toward the null and may reduce the predictive performance of machine learning models. Although CHARLS collects data on hospitalisation and cause of death, these are self- or proxy-reported, lack independent adjudication, and may contain incomplete responses or recall errors. Additionally, diagnostic coding is not standardised, which further limits validity. Fourth, we did not account for competing risks from non-stroke mortality. While the proportion of non-stroke deaths was low and initial analysis suggested little impact on stroke incidence, the absence of a competing risk analysis remains a methodological limitation. As a result, our findings should be interpreted as measures of association rather than unbiased estimates of causal effect. Furthermore, hospitalisation for stroke is not equivalent to incident stroke, and cause-of-death data only cover fatal cases, making them unsuitable for validation or correction. We were therefore unable to conduct a rigorous quantitative sensitivity analysis using these variables. To partially address this, we calculated the E-value, suggesting a relatively strong unmeasured confounder would be needed to fully explain the observed effect; however, residual misclassification bias cannot be ruled out. Fifth, the machine learning model was developed and evaluated with only internal validation, with no external validation performed. This limits confidence in its generalizability and highlights an important gap for future studies using independent cohorts. While the XGBoost model performed well internally, its generalizability and robustness require further evaluation. In summary, future research should prioritize: (1) studies with longer follow-up and higher competing mortality using the Fine–Gray subdistribution hazard model or similar methods; (2) linkage to hospital discharge registers, neuroimaging reports, or validated death certificates for medically confirmed stroke outcomes; (3) external validation of predictive models; (4) inclusion of inflammatory and metabolic biomarkers; and (5) randomized controlled trials to assess interventions such as combining resistance training with weight management. Further research should also refine DAO assessment criteria and evaluate the feasibility of routine screening for targeted prevention strategies.

Conclusion

This study showed that DAO was independently associated with an increased risk of stroke in middle-aged and older Chinese adults. Interpretable machine learning identified DAO as a potentially informative predictor. However, due to the observational design, reliance on self-reported outcomes, and lack of external validation, these results should be considered exploratory. Future studies with adjudicated endpoints, longer follow-up, competing risk analysis, and independent external validation are needed to confirm the predictive value of DAO and to assess the feasibility of including muscle strength and abdominal obesity in stroke risk prediction.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declare no conflicts of interest in this work.

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