Cardiovascular Diabetology

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Association between the triglyceride glucose-Chinese visceral adiposity index and new-onset stroke risk: a national cohort study

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Abstract

Background Numerous studies have investigated the effect of an integrated index that combines the triglyceride–glucose (TyG) index with various obesity indicators on stroke incidence. However, how to use the TyG index and the Chinese Visceral Adiposity Index (CVAI) for stroke prevention remains unclear. This study examined the associations between dynamic changes in the TyG-CVAI index and cumulative, baseline, and new-onset stroke risk.

Methods Data from 3,769 participants in the China Health and Retirement Longitudinal Study(CHARLS) were analyzed, concentrating on the baseline TyG-CVAI, TyG-CVAI in 2015, and the cumulative TyG-CVAI derived from these. The fluctuations of the TyG-CVAI index were grouped into three clusters using K-means clustering analysis. Logistic regression models were used to examine the relationship between the TyG-CVAI index and new-onset stroke risk. Restricted cubic splines (RCS) were employed to investigate potential nonlinear relationships while assessing the predictive capability by receiver operating characteristic curve.

Results During the follow-up period, 181 participants experienced stroke events. The stroke incidence rates in Clusters 1, 2, and 3 were 2.42%, 8.72%, and 4.37%, respectively. After adjustment for confounding factors, Cluster 2 with high and increasing TyG-CVAI index (OR = 3.16, 95% CI 1.94–5.22), the Q3 group with high cumulative TyG-CVAI index (OR = 2.53, 95% CI 1.60–4.02), and the Q3 group with high baseline TyG-CVAI index (OR = 2.49, 95% CI 1.57–3.95),which were all correlated with an elevated risk of new-onset stroke. The RCS analysis disclosed a U-shaped relationship between cumulative and baseline TyG-CVAI index and stroke risk.

Conclusion The fluctuations in and baseline, and cumulative TyG–CVAI index are independently correlated with an increased risk of stroke. The TyG–CVAI index is anticipated to be a more efficient and significant indicator for evaluating early stroke.

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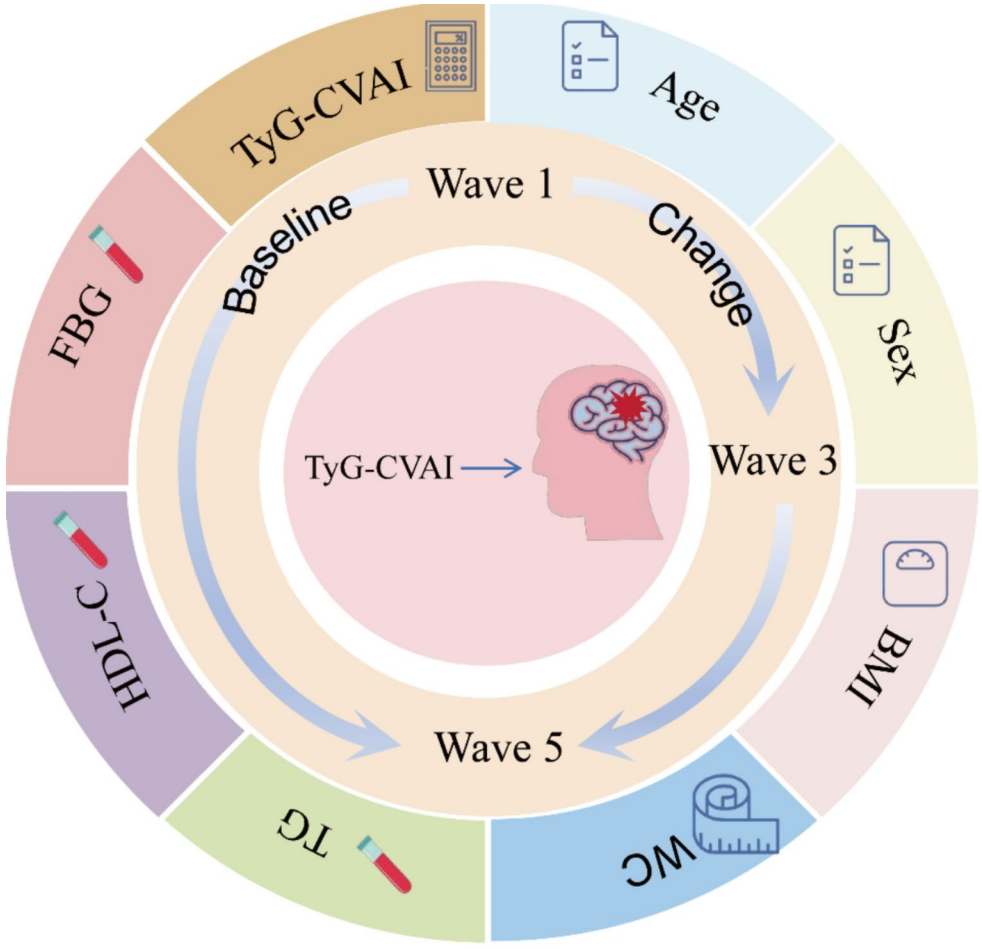
Graphical abstract



Introduction

The primary cause of disability is stroke, which raises incidence progressively globally and increases the risk of adverse outcomes [1, 2]. The detrimental effects of stroke include imposed significant burdens and economic strains on families as well as society. Previous studies have shown that factors increasing the risk of stroke are obesity and insulin resistance(IR) [3–5]. These factors are controllable and adjustable to a certain extent, highlighting the importance of identifying high-risk stroke individuals and taking targeted intervention measures to prevent and delay progression.

IR is a metabolic disorder that induces a spectrum of comorbidities—obesity, dyslipidemia, vascular damage, hypertension, and hyperglycemia—and can lead to the occurrence and progression of stroke [6, 7]. Numerous researchers are using the triglyceride-glucose (TyG) index as a marker of IR due to its simplicity and practicality. Moreover, substantial evidence supports its effectiveness in predicting diseases such as cardiovascular disease(CVD), hypertension, diabetes, and stroke [8–10]. Fat is classified as either visceral or subcutaneous, based on distribution, especially cumulative visceral fat, which is considered a risk factor for CVD and stroke [11, 12]. Visceral fat is difficult to assess visually, but advancements in medical technology—such as magnetic resonance imaging and ultrasound—have allowed for its evaluation [13, 14]. Despite this, implementation on a large scale is challenging because of high costs and radiation risks, highlighting the urgent need for a simple and feasible alternative [15]. Body Mass Index (BMI) and waist circumference (WC) are widely utilized indicators for assessing obesity; however, these indicators have limitations in accurately reflecting fat distribution [16]. Recently, the Chinese visceral adiposity index(CVAI) has emerged as a more effective alternative. Several studies have found that this index outperforms BMI and WC in predicting visceral fat and diseases, including diabetes

and stroke [17–19]. The CVAI is specifically tailored for the Chinese population through race-specific calculations [20].

Stroke is now understood to result from various factors, including IR and obesity, particularly abdominal obesity. Consequently, recent research has focused on the combined effects of the TyG index and various obesity indicators—BMI, WC, Waist-to-Height Ratio (WHTR), and Waist-to-Weight Index (WWI)—on stroke risk [21–23]. However, the impact of the combined index of TYG and CVAI on stroke remains inadequately explored. Although one study has investigated these two indices, it stratified the data by only the median and considered only baseline values [24]. However, the indices should be evaluated dynamically. This study aims to utilize the China Health and Retirement Longitudinal Study(CHRLS) data to explore the relationship between fluctuations in and cumulative and baseline TyG-CVAI index and new-onset stroke risk, thereby addressing this gap. The results may provide insights into stroke-targeted prevention strategies.

Methods

Study design and population

Our research data analysis was based on the CHARLS, a national survey in China designed to investigate aging-related issues. The first survey was conducted in 2011–2012 (wave 1) and participants are followed up every two to three years. Five waves had been conducted: 2013 (wave 2), 2015 (wave 3), 2018 (wave 4), and 2020 (wave 5). The survey sample includes 150 county-level and 450 village-level units, with participants aged 45 years and older. All participants provided informed consent. We included 11,847 participants who underwent blood tests at baseline(wave 1) because blood samples were only collected in waves 1 and 3. A total of 3,769 participants remained in the final study after the following exclusion criteria: age < 45 years; missing data on age, sex, triglycerides (TG), fasting blood glucose (FBG), high-density lipoprotein cholesterol(HDL-C), WC, and BMI in wave 1 and 3; history of stroke prior to 2015; lost to follow-up in 2020; missing relevant covariates data at baseline. Figure 1 depicts the specific screening process.

Exposures and outcome

We gathered the data regarding age, sex, TG, FBG, WC, BMI, and HDL-C from wave 1 and 3. Using previously established methods [25, 26], we calculated the following indices: (1) TyG = ln [TG(mg/dl) × FBG (mg/dl); (2) For male: CVAI = −67.93 + 0.68 × age (years) + 0.03 × BMI (kg/m^2) + 4.00 × WC(cm) + 22.00 × log10 (TG) (mmol/L) − 16.32 × HDL-C(mmol/L); For female: CVAI = -187.32 + 1.71 × age (years) + 4.23 × BMI (kg/m^2) + 1.12 × WC(cm) + 39.76 × log10 (TG) (mmol/L) − 11.66 × HDL-C (mmol/L); (3) TyG-CVAI = TyG × CVAI;4. Cumulative TyG-CVAI= (TyG-CVAI $_{wave1}$ +TyG-CVAI $_{wave3}$)/2×time (2015–2012). The stroke events that occurred between wave 4 and 5 of follow-up were considered the outcome, determined via the standardised questionnaire, which asked participants: "Have you been diagnosed with a stroke by a doctor?" or "Are you currently receiving any treatment (traditional Chinese medicine/Western medicine/physical therapy/acupuncture and moxibustion/occupational therapy) to control your stroke?".

Covariates

The following covariates have been selected. (1) sociodemographic aspects: age, sex (" Male", " Female"), marital status ("Married", "No"), education ("High school and above", " Below high school"), residence place ("Rural", "Urban"); (2) lifestyle and dietary habits: smoking ("Yes", "No"); drinking ("Yes", "No"); (3) Previous medical history: hypertension ("Yes", "No"); diabetes ("Yes", "No"); (4) Laboratory examinations included HDL-C, low-density lipoprotein cholesterol(LDL-C), and remnant cholesterol(RC); (5) Physical examinations contained BMI, WHTR, and WWI.

Statistical analysis

To classify the changing trends of the TyG-CVAI index from wave 1 to wave 3 and observe the effect on stroke in this study, we employed the K-means clustering analysis method founded on the "cluster" and "factoextra" packages. The K-means clustering algorithm is an iterative method for clustering data by calculating the within-cluster sum of squares (WSS) for each K value. The inflection point on the curve is considered the optimal number of clusters, representing the best division of the dataset. This algorithm has been extensively used in related analyses, such as the relationship between changes in the TyG index and CVD risk [27, 28]. Regarding our research, as shown in Fig. 2A, when K = 3, the curve tends to be steady, so the optimal number of clusters was 3. We divided the participants into three groups according to TyG-CVAI index changes (Fig. 2C): Cluster 1, low level with slightly increasing; the average TyG-CVAI index increased from 463.0238 in 2012 to 502.8473 in 2015; Cluster 2, high level, with a moderate increase, from 1358.2438 in 2012 to 1431.0151 in 2015; and Cluster 3, medium level, but with the fastest increase, from 853.4869 in 2012 to 965.2437 in 2015. Overall, Cluster 2 had the highest mean value, followed by Cluster 3, and Cluster 1 had the lowest mean value. Differences between the three groups were described using mean ± standard deviation or median (interquartile range) for continuous variables, and frequency (n) and percentage (%) for categorical variables.

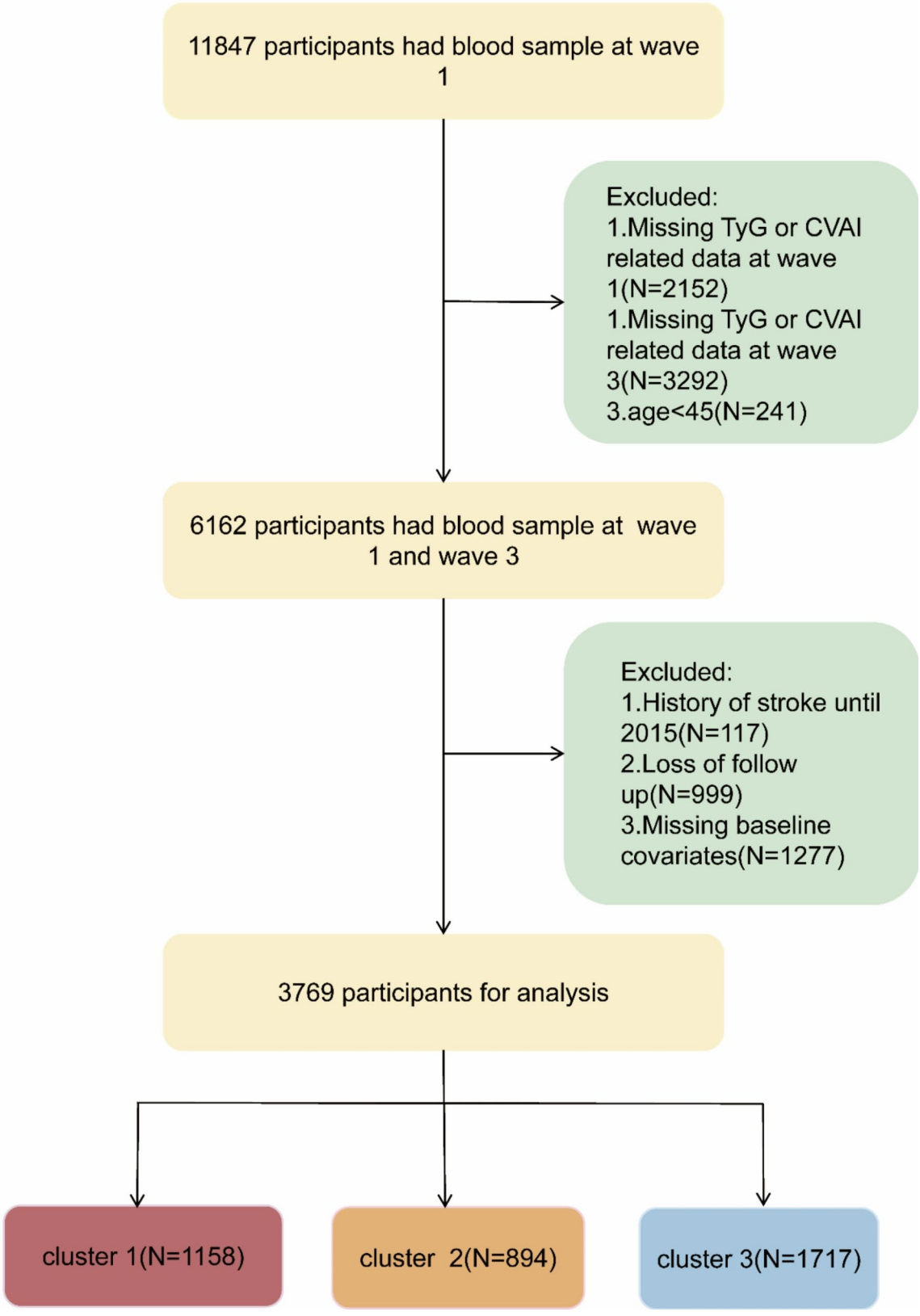


Fig. 1 Flow chart of the study population. TyG, triglyceride-glucose index; CVAI, Chinese visceral adiposity index

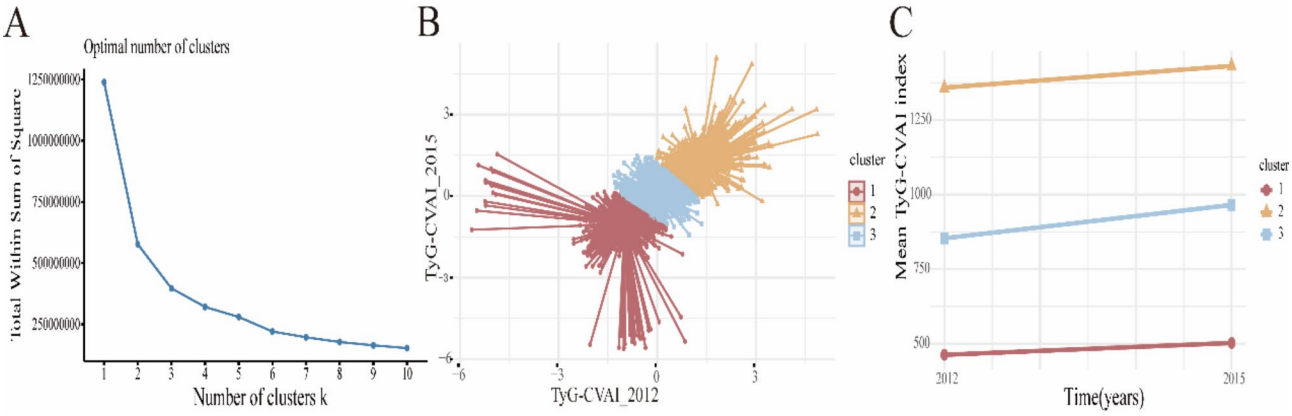


Fig. 2 Classification of change in the TyG-CVAI index from 2012 to 2015. (**A**) The optimal number of clusters of changes in TyG-CVAI was 3 using the K-means clustering algorithm; (**B**) Clustering diagrams for TyG-CVAI_2012 and TyG-CVAI_2015 in CHARLS; (**C**) Data visualization for the clusters of the change in the TyG-CVAI index from 2015 to 2015

Logistic regression models were performed to investigate the associations of the TyG-CVAI index (including its dynamic changes, baseline levels, and cumulative exposure) with stroke risk, with adjustment for the relevant variables in the model. The crude model did not adjust variables. Model 1 adjusted for age, sex, marital status, education, and residence place. Building on Model 1, Model 2 further adjusted for smoking, drinking, hypertension, diabetes, LDL-C, and RC. Following that, to explore the potential nonlinear relationship between the TyG-CVAI index and stroke risk, we applied the RCS analysis by the "rcssci" package. Finally, we conducted subgroup analyses to investigate whether the relationship between the TyG-CVAI index and stroke risk differed across different groups of potential risk covariates.

Several sensitivity analyses were performed to ensure the robustness of the findings. Firstly, in the intergroup analysis, We compared the differences in baseline characteristics between participants with and without missing TyG-CVAI in Wave 1 and Wave 3. The results showed that participants with and without missing TyG-CVAI showed similar distribution patterns in most baseline characteristics (Tables S2 and S3), indicating that the missing TyG-CVAI values in both survey waves were missing at random(MAR).The TyG-CVAI dynamic change groups and the cumulative TyG-CVAI tertiles were discussed. Secondly, to assess the robustness of the logistic regression results, we examined the relationship between TyG-CVAI change groups, cumulative TyG-CVAI tertiles, baseline TYG-CVAI tertiles, and new-onset stroke risk; further analyses were performed using complete data after multiple imputation. Additionally, The restricted cubic splines(RCS) analysis was used to explore the nonlinear relationship between stroke risk and the TyG-CVAI index (baseline and cumulative). In the subgroup and multiplicative interaction analysis, the effects of five TyG-CVAI statistical methods on stroke risk were examined across various stratifications: (1) dynamic change groups, (2)baseline tertiles, (3)cumulative tertiles, (4)baseline value as a continuous variable, (5)cumulative value as a continuous variable. Finally, The receiver operating characteristic(ROC) curve analysis was implemented to compare the predictive ability of the TyG-CVAI index and others on stroke, accounting for both the baseline value and the cumulative value of each index. All analyses were carried out using R (version 4.4.1). P-value < 0.05 was considered statistically significant.

Results

Baseline characteristics of participants

Table 1 shows that the study included 3769 participants, with an average age of 58.12 ± 8.47 years and a female-to-male ratio of slightly more than 2:1. At the end of the follow-up period, 181 participants experienced stroke, with cluster 2 (a high level and increasing) having the highest incidence rate, and the rates of cluster 1, 2, and 3 were 2.42%, 8.72%, and 4.37%, respectively. Cluster 2 was older than others, mostly female. The rates of smoking and drinking were lower, as were the levels of HDL-C and WWI; hypertension and diabetes were more prevalent, as were the levels of RC, LDL-C, BMI, TyG, WHTR, and cumulative TyG-CVAI. We also found the same pattern in cumulative TyG-CVAI tertiles; the stroke Incidence rates in Q1, Q2, and Q3 were 2.55%, 4.22%, and 7.64%, respectively (Table S1).

Correlation between dynamic changes, cumulative, baseline, and new-onset stroke risk of the TyG-CVAI index

To investigate the association between the TyG-CVAI index and stroke risk, logistic regression was performed to assess its between dynamic changes, cumulative

Table 1 Baseline characteristics of participants according to the classification of change in the TyG-CVAI index

Characteristics	Total	Cluster 1	Cluster 2	Cluster 3	*P* value
N	3769	1158	894	1717	
Age (years, M ± SD)	58.12 ± 8.47	56.67 ± 8.36	60.60 ± 8.48	57.81 ± 8.26	0.01
Sex, n(%)					< 0.0001
Female	2599(68.96%)	663(57.25%)	641(71.70%)	1295(75.42%)	
Male	1170(31.04%)	495(42.75%)	253(28.30%)	422(24.58%)	
Marital status, n(%)					0.08
Married	3380(89.68%)	1047(90.41%)	784(87.70%)	1549(90.22%)	
No	389(10.32%)	111(9.59%)	110(12.30%)	168(9.78%)	
Education, n(%)					0.68
High school and above	312(8.28%)	90(7.77%)	73(8.17%)	149(8.68%)	
Below high school	3457(91.72%)	1068(92.23%)	821(91.83%)	1568(91.32%)	
Residence place, n(%)					< 0.0001
Rural	2534(67.23%)	863(74.53%)	529(59.17%)	1142(66.51%)	
Urban	1235(32.77%)	295(25.47%)	365(40.83%)	575(33.49%)	
Smoking, n(%)					< 0.0001
Yes	976(25.90%)	406(35.06%)	204(22.82%)	366(21.32%)	
No	2793(74.10%)	752(64.94%)	690(77.18%)	1351(78.68%)	
Drinking, n(%)					< 0.001
Yes	681(18.07%)	246(21.24%)	169(18.90%)	266(15.49%)	
No	3088(81.93%)	912(78.76%)	725(81.10%)	1451(84.51%)	
Hypertension, n(%)					< 0.0001
Yes	891(23.64%)	140(12.09%)	374(41.83%)	377(21.96%)	
No	2878(76.36%)	1018(87.91%)	520(58.17%)	1340(78.04%)	
Diabetes, n(%)					< 0.0001
Yes	197(5.23%)	23(1.99%)	99(11.07%)	75(4.37%)	
No	3572(94.77%)	1135(98.01%)	795(88.93%)	1642(95.63%)	
Stroke, n(%)					< 0.0001
Yes	181(4.80%)	28(2.42%)	78(8.72%)	75(4.37%)	
No	3588(95.20%)	1130(97.58%)	816(91.28%)	1642(95.63%)	
HDL-C(mmol/L, M ± SD)	1.30 ± 0.37	1.50 ± 0.38	1.07 ± 0.29	1.29 ± 0.32	< 0.0001
LDL-C(mmol/L, M ± SD)	3.05 ± 0.89	2.88 ± 0.77	3.11 ± 1.05	3.13 ± 0.86	< 0.0001
RC(mmol/L, M ± SD)	0.66 ± 0.61	0.41 ± 0.29	1.08 ± 0.87	0.62 ± 0.48	< 0.0001
BMI(kg/m^2,M ± SD)	23.82 ± 3.89	20.73 ± 2.45	27.76 ± 3.82	23.84 ± 2.66	< 0.0001
WHTR(M ± SD)	0.54 ± 0.08	0.48 ± 0.07	0.62 ± 0.05	0.55 ± 0.06	< 0.0001
WWI(M ± SD)	20.68 ± 1.62	22.08 ± 1.27	19.10 ± 1.20	20.57 ± 1.13	< 0.0001
TyG(M ± SD)	8.68 ± 0.63	8.31 ± 0.47	9.20 ± 0.64	8.66 ± 0.53	< 0.0001
Cumulative TyG-CVAI(M ± SD)	297.82 ± 125.03	160.98 ± 64.33	464.88 ± 69.67	303.12 ± 42.49	< 0.0001

HDL-C: high-density lipoprotein cholesterol; LDL-C: low-density lipoprotein cholesterol; RC: remnant cholesterol; BMI: body mass index; WHTR: waist-to-height ratio; WWI: waist-to-weight index; TyG: triglyceride-glucose index; TyG-CVAI: triglyceride glucose-Chinese visceral adiposity index.

tertiles, baseline tertiles, and the risk of stroke by evaluating odds ratio (OR) and 95% confidence interval (95% CI). The results are shown in Fig. 3. After model adjustment, the OR value for cluster 2 decreased slightly but remained statistically significant [OR (95% CI): 3.86 (2.48-6.00) vs. 3.46 (2.20–5.46) vs. 3.16 (1.94–5.22)]. This suggests that the link between high TyG-CVAI levels and an increased risk of new-onset stroke remains relatively stable. The high score group of baseline and cumulative showed similar patterns of change. Interestingly, we observed the same tendency. Stroke risk was higher in the highest score group after adjusting for all confounders, regardless of dynamic changes, cumulative tertiles, or baseline tertiles [OR (95% CI): 3.16 (1.94–5.22) vs. 2.53 (1.60–4.02) vs. 2.49 (1.57–3.95)]. In general, a higher TyG-CVAI index trend, cumulative level, and baseline were all linked to an increased risk of stroke.Further analysis using complete data after multiple imputation led to the same conclusions as above (Table S4).

Analysis of the dose-response relationship cumulative and baseline TyG-CVAI index with stroke risk

The RCS analysis was performed to evaluate potential nonlinear associations of cumulative and baseline TyG-CVAI index with stroke risk, including analyses in the

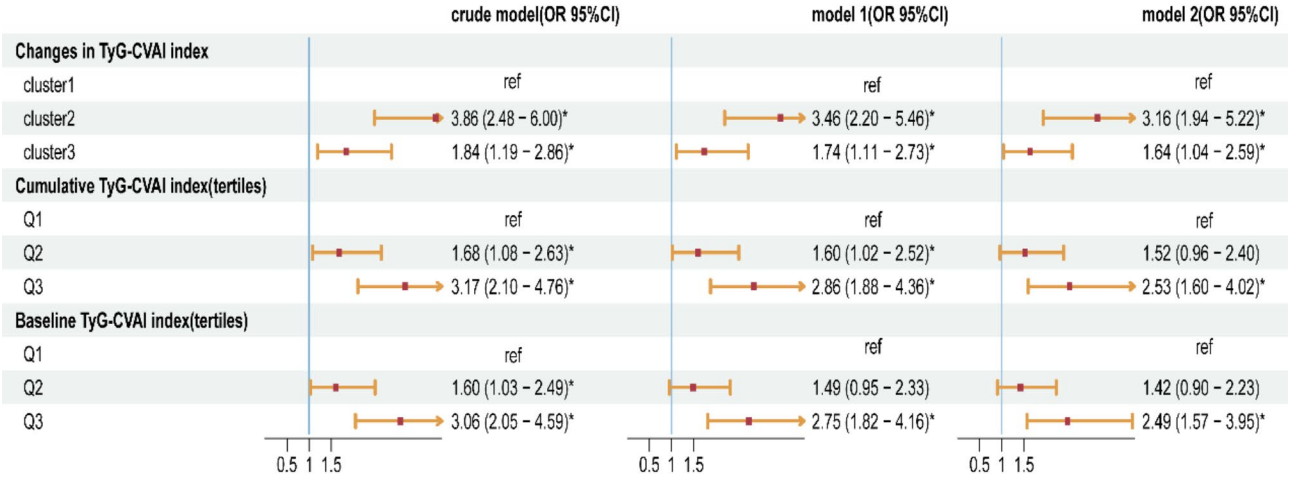


Fig. 3 Association between dynamic changes, cumulative tertiles, baseline tertiles, and the stroke risk of the TyG-CVAI index. Crude model: did not adjust variables; Model 1: Adjusted for age, sex, marital status, education, and residence place; Model 2: further adjusted for smoking, drinking, hypertension, diabetes, LDL-C, and RC. OR: Odds ratio; CI: Confidence interval; Q1: The lowest tertile; Q2: The middle tertile; Q3: The highest tertile; Ref: Reference; Asterisk (*) indicates $P < 0.05$

total population and subgroups stratified by dynamic change categories. Figure 4 and Fig. S1 illustrate the results, indicating that a U-shaped curve relationship was found between the cumulative (Fig. 4A) and baseline (Fig. S1A) TyG-CVAI index and the risk of stroke in the total population (P for non-linearity < 0.05), with inflection points of 198.536 and 525.209, respectively. However, no nonlinear relationship was discovered in the population with different categories (P for non-linearity > 0.05).

Stratified and interaction analyses

Subgroup analysis discovered that the associations between TyG-CVAI changes (Fig. 5), cumulative TyG-CVAI tertiles (Fig. S2), baseline TyG-CVAI tertiles (Fig. S3), continuous cumulative and baseline TyG-CVAI index (Table S5), and stroke risk were broadly consistent across stratification factors. Sex moderated the association between the continuous cumulative TyG-CVAI index and stroke (P for interaction = 0.039) (Table S5).

Predictive ability of TyG-CVAI index for stroke

The ROC analysis was utilized to compare the forecasting stroke risk capacity of the TyG-CVAI index with other indicators(TyG-WHTR, TyG-WC, TyG-BMI, and TyG-WWI). We also evaluated baseline and cumulative CVAI, baseline and cumulative TyG-CVAI, and other indicators(each with two conditions: baseline and cumulative). The findings revealed that baseline CVAI (Fig. 6A), cumulative CVAI (Fig. 6C), baseline TyG-CVAI (Fig. 6B), and cumulative TyG-CVAI (Fig. 6D) were the most effective predictors of stroke risk, with AUC values of 0.639, 0.632, 0.636, and 0.629, respectively.Net reclassification improvement (NRI) and integrated discrimination improvement (IDI) metrics were used to evaluate the predictive capacity of three TyG-CVAI index approaches (baseline values, dynamic changes, and cumulative values)for stroke risk. The results revealed that both cumulative and baseline TyG-CVAI values demonstrated statistically significant improvements in predictive performance compared to dynamic changes[NRI (95% CI): 0.4362 (0.2432–0.6291) vs. 0.3817 (0.1882 – 0.002); IDI (95% CI): 0.0054 (0.0024–0.0084) vs.0.0049 (0.002–0.0078); all P values < 0.001], with cumulative measurements showing the greatest enhancement(Table S6).

Discussion

The present study fills a gap in the literature regarding the relationship between the TyG-CVAI index and new-onset stroke risk by utilizing the CHARLS data. The main findings were as follows. First, dynamic changes, baseline, and cumulative of the TyG-CVAI index were independent risk factors for stroke, particularly dynamic changes. Next, a U-shaped relationship was discovered between cumulative and baseline TyG-CVAI and stroke risk. Noticeably, sex influenced the association between cumulative TyG-CVAI and stroke. Ultimately, for both the baseline and cumulative data, the TyG-CVAI index consistently outperformed other comprehensive indicators in terms of predicting stroke risk. Multiple sensitivity analyses supported our findings. The above results show that the TyG-CVAI index can be considered a powerful predictor of stroke risk, emphasizing the significance of dynamically monitoring TyG-CVAI for stroke identification, prevention, and intervention in clinical work, and that maintaining good body management and dietary habits can aid in prevention and treatment of stroke.

IR and visceral fat accumulation reinforce and influence each other. In individuals with IR, resistance to

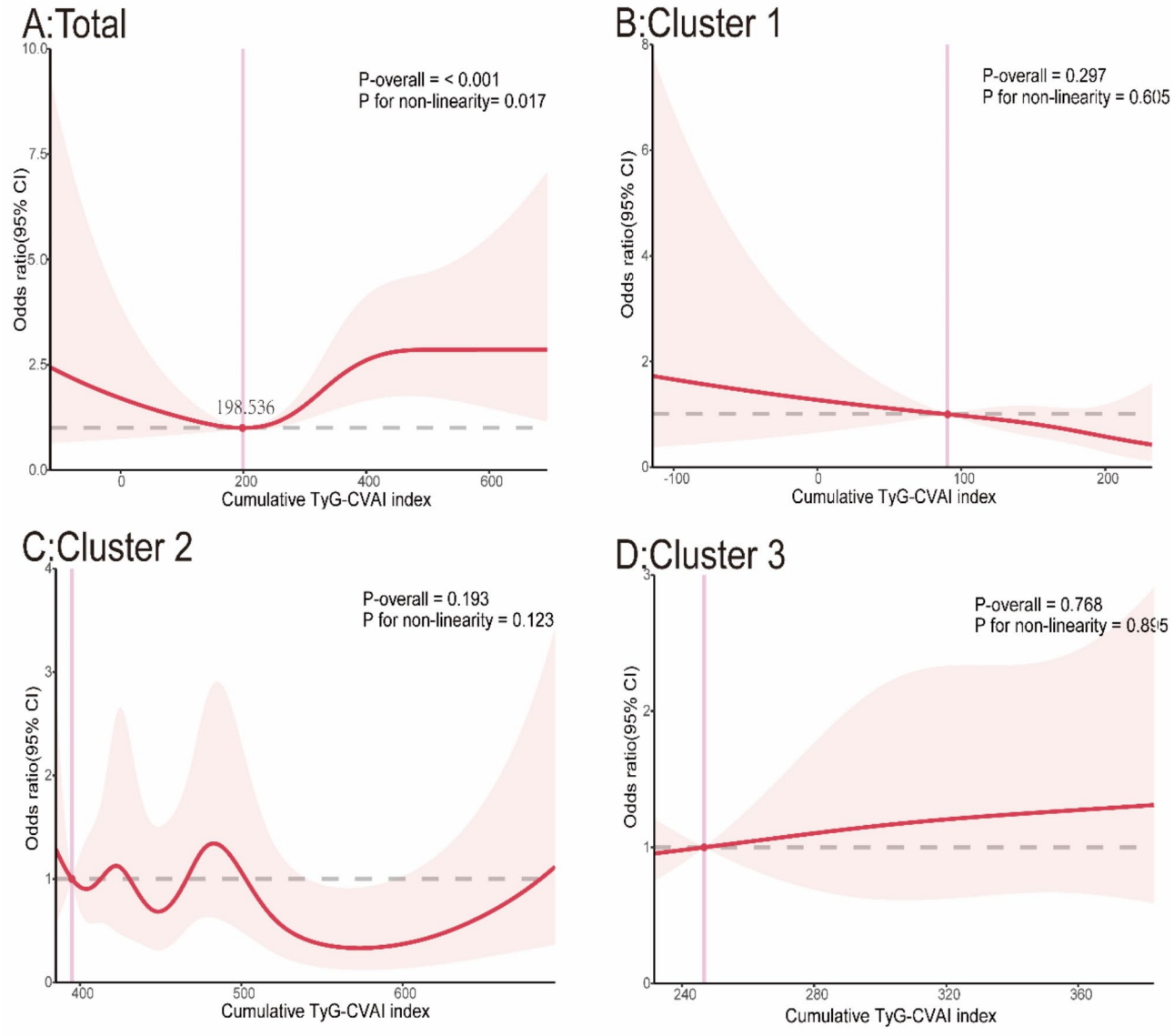


Fig. 4 Analysis of restricted cubic spline regression. (**A**) A U-shaped curve relationship between the cumulative TyG-CVAI index and stroke risk in the total population; (**B**) No nonlinear relationship between the cumulative TyG-CVAI index and stroke risk in the cluster 1 population; (**C**) No nonlinear relationship between the cumulative TyG-CVAI index and stroke risk in the cluster 2 population; (**D**) No nonlinear relationship between the cumulative TyG-CVAI index and stroke risk in the cluster 3 population.TyG-CVAI: Triglyceride glucose-Chinese visceral adiposity index; CI: Confidence interval

insulin prevents effective glucose uptake and utilization, resulting in the development of hyperinsulinemia and hyperglycemia over time [29]. Research has shown that IR is associated with low-grade chronic inflammation [30]. Elevated blood glucose increases the production of advanced glycation end products (AGEs), which are pro-inflammatory, pro-coagulant, and damage the vascular endothelium [31].Additionally, high insulin levels increase the risk of platelet aggregation, vasoconstriction, and thrombosis, affecting lipid metabolism, sympathetic nervous system activity, and renal sodium and water retention and contributing to hypertension, dyslipidaemia, and atherosclerosis [32]. Visceral fat accumulation produces inflammatory factors and free fatty acids, further exacerbating insulin resistance [33, 34]. Thus, IR and visceral fat accumulation form a vicious cycle that promotes stroke through multiple mechanisms, including inflammation, coagulation, vasoconstriction, thrombosis, atherosclerosis, and hypertension.

Current research hotspots are shifting from analyzing individual TyG or obesity indices to comprehensive indices that integrate both. Yao et al. conducted a cohort study in Chinese and British populations to compare the effects of a combined index of TyG and obesity index (BMI, WC, Body roundness Index, Fat mass index) with a simple index on stroke, showing that the combined index

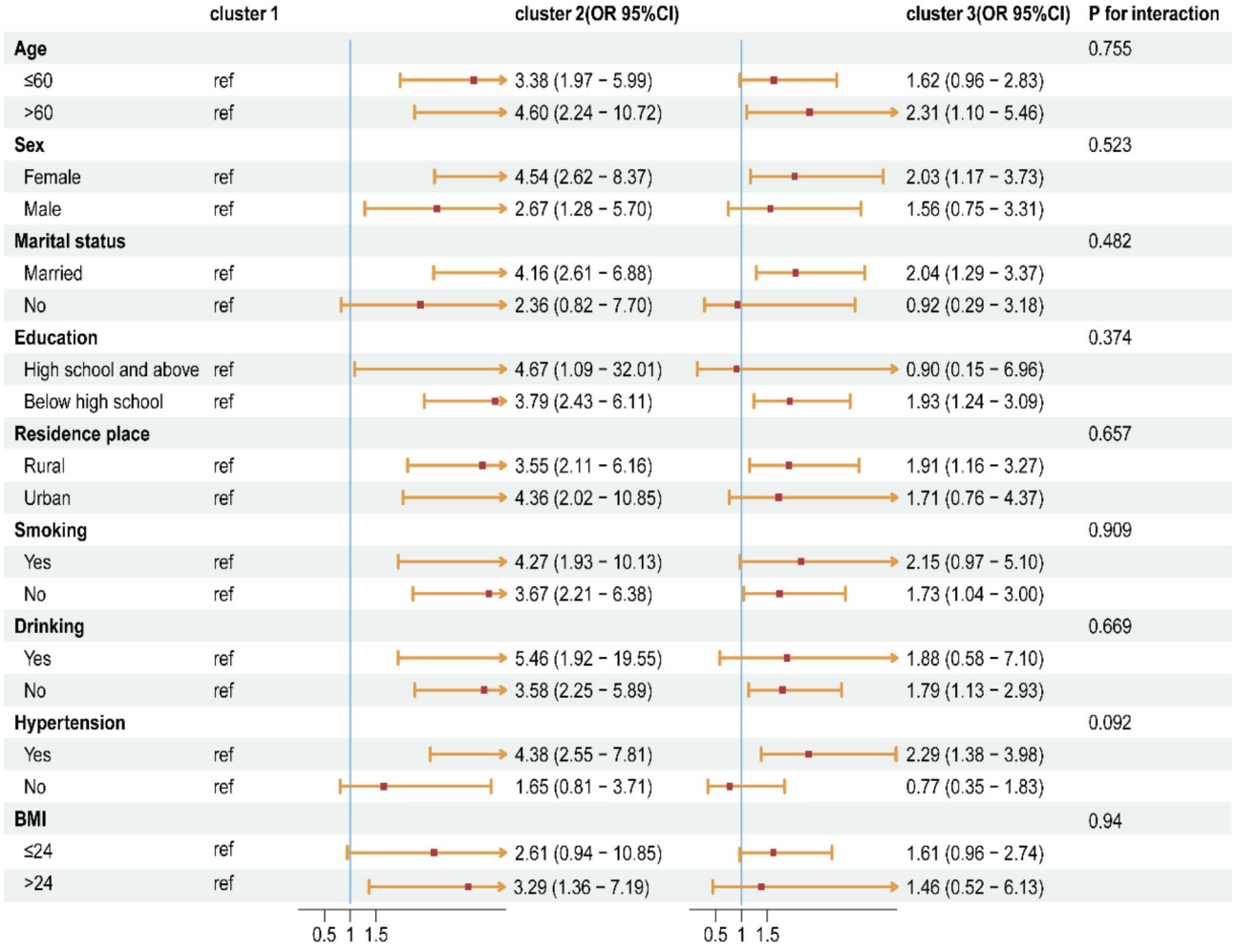


Fig. 5 Associations of the dynamic changes TyG-CVAI index with stroke risk stratified by different factors. Adjusted for age, sex, marital status, education, residence place, smoking, drinking, hypertension, diabetes, LDL-C, RC.OR: Odds ratio; CI: Confidence interval; Ref: Reference

was superior to the simple index in both significance and predictive ability [10]. A prospective cohort study in China further validated the reliability of the composite index (TyG-BMI, TyG-WC) in identifying individuals at high risk of stroke [35]. Indicators such as weight and WC are dynamic due to metabolism changes; more studies are examining the impact of these dynamic changes on disease [28, 36, 37]. Furthermore, the combined TyG-obesity index is widely used in disease research, including stroke, diabetes, hypertension, gout, CVD, non-alcoholic fatty liver disease, and depression [38–42]. Simple obesity indices such as BMI and WC are limited owing to the unique anatomical location of visceral fat. Fortunately, the CVAI index overcomes this limitation and has been widely validated for its effectiveness and stability in practice [43–45]. However, no studies have explored the impact of the TyG-CVAI index on disease. One study examined the effects of the TyG and CVAI indices on CVD but only grouped data by median and analyzed baseline data, which remains insufficient [24]. Our study is the first to investigate the influence of the TyG-CVAI index on new-onset stroke. We also examined dynamic changes and employed an objective grouping method (K-means clustering) that is widely used in disease analysis [28, 36, 37, 46]. Our results indicated that the dynamic changes, baseline, and cumulative TyG-CVAI index were strongly associated with new-onset stroke risk. Furthermore, TyG-CVAI demonstrated high sensitivity and specificity for stroke prediction, user-friendly and comprehensive, suggesting its potential as an effective stroke risk indicator. Easy to operate, low cost, can be calculated through simple indicators, and carried out in primary hospitals. In the future, clinicians could dynamically monitor to identify high-risk individuals, enabling more targeted interventions. This study also underscores the critical role of healthy lifestyles like exercise and weight loss in delaying stroke onset and progression.

Our study showed a U-shaped curve linking both cumulative and baseline TyG-CVAI levels with stroke risk, with inflection points at 198.536 and 525.209,

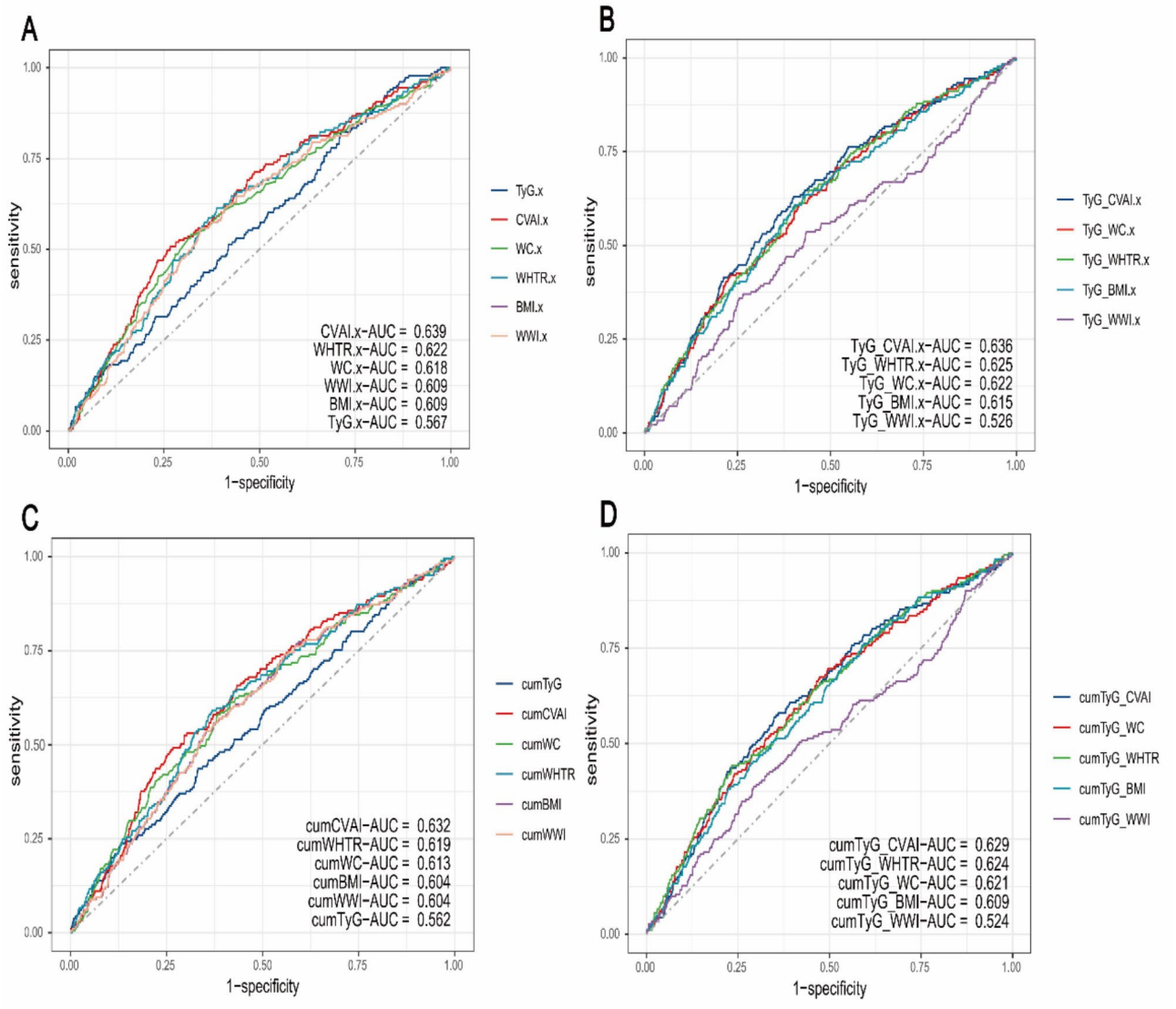


Fig. 6 Comparing the predictive ability of the TyG-CVAI index and others on stroke risk. (**A**) The AUC values for each indicator are as follows: baseline CVAI (AUC = 0.639), baseline WHTR (AUC = 0.622), baseline WC (AUC = 0.618), baseline WWI (AUC = 0.609), baseline BMI (AUC = 0.609), and baseline TyG index (AUC = 0.567). baseline CVAI index was the more effective predictor of stroke risk; (**B**) The AUC values for each indicator are as follows: baseline TyG-CVAI (AUC = 0.636), baseline TyG-WHTR (AUC = 0.625), baseline TyG-WC (AUC = 0.622), baseline TyG-WWI (AUC = 0.615),and baseline TyG-BMI (AUC = 0.526). baseline TyG-CVAI index was the more effective predictor of stroke risk; (**C**) The AUC values for each indicator are as follows: Cumulative CVAI (AUC = 0.632), cumulative WHTR (AUC = 0.619), cumulative WC (AUC = 0.613), Cumulative WWI (AUC = 0.604), cumulative BMI (AUC = 0.604), and cumulative TyG index (AUC = 0.562). Cumulative CVAI index was the more effective predictor of stroke risk; (**D**) The AUC values for each indicator are as follows: Cumulative TyG-CVAI (AUC = 0.629), cumulative TyG-WHTR (AUC = 0.624), cumulative TyG-WC(AUC = 0.621), cumulative TyG-WWI (AUC = 0.609), and cumulative TyG-BMI (AUC = 0.524). Cumulative TyG-CVAI index was the more effective predictors of stroke risk. cum: cumulative data;.x: Baseline data

respectively. However, it's important to note that while our analysis found significant nonlinear patterns (P for nonlinearity < 0.05), prior studies have reported linear associations between the TyG index and stroke risk [47, 48]. This finding may be due to combining the CVAI index, as both insufficient and excessive visceral fat have risks. Multicenter cohort studies will be needed to determine a safe and reliable range. Interestingly, sex influenced the relationship between cumulative TyG-CVAI and stroke (P for interaction = 0.039). Ding et al. suggested that the TyG index affects stroke risk regardless of sex [49]. This discrepancy may be related to the CVAI accounting for sex. Other studies reported that the effect of the CVAI index on stroke was not influenced by sex (P for interaction > 0.05) [50, 51],although they included only baseline CVAI data. These findings indirectly indicate the importance of dynamic index monitoring throughout the stroke disease process.

Our study has both strengths and limitations. The advantages include the following: (1) It is the first time

to investigate the relationship between the TyG-CVAI index and new-set stroke. (2) The data are derived from the CHARLS, a national study with a large sample size and extended follow-up. (3) The comprehensive data, incorporating baseline, cumulative, and dynamic change data, are grouped objectively. Multiple sensitivity analyses enhance the robustness and reliability of our findings. Moreover, the limitations are as follows: (1) Stroke definition was based on self-reported data, which may introduce reporting bias. Future research could combine medical records or imaging diagnostic data to validate these conclusions, which will help confirm the diagnosis and reduce the likelihood of misclassification. (2) Blood samples were only collected during wave 1 and wave 3, and additional follow-up data may be needed for a more in-depth analysis. (3) CVAI was developed using data from the Chinese population. Because of racial and geographical differences, further multicenter studies will be needed to adjust and validate the population-specific adjustment formula to ensure its applicability and specificity when applied to other national populations in the future. (4) The CHARLS data are sourced from the Chinese elderly population, primarily based on representative samples at the county and village levels. Therefore, there may be concerns regarding the representativeness of the sample, potentially introducing selection bias. Additionally, participant attrition due to death or migration could lead to non-random sample loss, further contributing to potential bias. However, despite these limitations, the CHARLS data remain broadly representative, owing to the broad geographic coverage across multiple counties and villages and the large sample size.

Conclusions

This study revealed that dynamic changes, baseline, and cumulative values of the TyG-CVAI index are independent risk factors for new-onset stroke. Our findings enhance early stroke-related prediction indicators by providing a more comprehensive and effective index, highlighting the importance of dynamic TyG-CVAI monitoring and maintaining a healthy weight for stroke prevention and management.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12933-025-02668-x .

Supplementary Material 1

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Author contributions
M-DW and FH designed this study. M-DW and BG collected data, analyzed statistics, and drew graphs. M-DW and BG drafted the manuscript. FH proofread the manuscript. All authors approved the final version of the manuscript.

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Data availability
The datasets used in this investigation are available in online repositories. Detailed descriptions of each survey and corresponding data have been published at http://charls.pku.edu.cn//.

Declarations

Ethics approval and consent to participate
The Biomedical Ethics Review Board of Peking University granted this program's ethical approval, with approval numbers IRB00001052-11015 and IRB00001052-11014.

Competing interest
The authors declare no competing interests.

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