Diabetology & Metabolic Syndrome

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The association of changes in the Chinese visceral adiposity index and cardiometabolic diseases: a cohort study

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Abstract

Objective The relationship between changes in Chinese visceral adiposity index (CVAI) and cardiometabolic diseases (CMD) in middle-aged and elderly individuals remains unclear. This study aimed to explore whether changes in the CVAI were associated with CMD incidence.

Methods This study included 3,243 individuals aged over 45 years from the China Health and Retirement Longitudinal Study. The exposures were changes in the CVAI and cumulative CVAI from 2012 to 2015. Changes in the CVAI were classified using K-means clustering analysis, and the cumulative CVAI was calculated as follows: $(CVAI_{2012}+CVAI_{2015})/2\times$time (2015–2012). Multivariable logistic regression models were used to assess the relationship between different CVAI change classes and CMD incidence. Restricted cubic splines regression was used to assess the dose–response relationship between cumulative CVAI and CMD incidence. To investigate the relationship between combined exposure to each component of CAVI and CMD incidence, a weighted quantile sum regression analysis was employed.

Results During the 5 years of follow-up, 776 (24%) incident CMD cases were identified. Changes in CVAI and cumulative CVAI were independently and positively associated with CMD. After adjusting for potential confounders, compared with Class 1, the adjusted ORs (95% CIs) for incident CMD were 1.18 (0.90–1.57) for Class 2, 1.40 (1.03–1.92) for Class 3, and 1.56 (1.04–2.34) for Class 4. When cumulative CVAI was categorized into quartiles, compared with Q1, the adjusted ORs (95% CIs) for incident CMD were 1.30 (1.00–1.70) for Q2, 1.34 (1.01–1.79) for Q3, and 1.63 (1.15–2.31) for Q4. In addition, cumulative CVAI in the overall population exhibited a linear association with CMD ($P_{overall}=0.012$, $P_{non\text{-}linearity}=0.287$), diabetes ($P_{overall}=0.022$, $P_{non\text{-}linearity}=0.188$), and stroke ($P_{overall}=0.002$, $P_{non\text{-}linearity}=0.978$), but showed no significant association with heart disease ($P_{overall}=0.619$, $P_{non\text{-}linearity}=0.442$).

Conclusion Participants with higher baseline CVAI level and a change of elevating CVAI level may suffer an increased incidence of CMD. Furthermore, our findings elucidate the underlying mechanisms of the CVAI by highlighting TG as the primary contributor to the observed associations. Long-term CVAI monitoring is of significant importance for early identification and prevention of CMD, with significant implications for clinical practice.

Keywords Chinese visceral adiposity index, Cardiometabolic diseases, Diabetes, Heart disease, Stroke

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Introduction

Cardiometabolic disease (CMD), a collective term for chronic conditions such as diabetes, cardiovascular disease (CVD), and stroke, shares common risk factors and leads to impaired quality of life and reduced life expectancy [1–3]. With the global population aging and lifestyle changes, the incidence of CMD has risen significantly in recent years [4]. In 2019, CVD was responsible for 17.9 million deaths, accounting for 32% of all global deaths [5]. Diabetes exacerbates morbidity and disability, with projections indicating its prevalence will reach 10.9% by 2045 [6]. Moreover, cardiometabolic multimorbidity (CMM), characterized by the presence of at least two CMDs simultaneously, substantially heightens mortality risk and further reduces life expectancy compared to having a single CMD [2]. CMD imposes a substantial burden on healthcare resources; hence, identifying potential risk factors for CMD is crucial for alleviating disease burden and promoting healthy aging.

Obesity affects approximately 36.9% of men and 38.0% of women globally and is a well-established predictor of ischemic heart disease, stroke, and premature death [7]. It significantly increases the risk of CMD, including insulin resistance (IR), dyslipidemia, fatty liver disease, hypertension, and coronary artery disease (CAD) [8–10]. Furthermore, accumulating evidence indicated that visceral adipose tissue distribution, rather than overall obesity, is an independent predictor of CMD [11–13]. Chinese researchers have developed the Chinese visceral adiposity index (CVAI), analogous to the visceral adiposity index (VAI) used in Western populations, derived from a sample of Chinese individuals using age, body mass index (BMI), waist circumference (WC), total triglycerides (TG), and high-density lipoprotein cholesterol (HDL-C) [14]. Studies have demonstrated that CVAI is a superior predictor of CMD compared to other adiposity indices such as BMI, WC, VAI, lipid accumulation product (LAP), triglyceride-glucose (TyG), and TyG-body mass index (TyG-BMI) [15–20].

Although existing studies have demonstrated a positive relationship between single-time CVAI levels and the risk of CMD, the relationship between cumulative CVAI—which considers both the CVAI level and the duration of exposure to a high CVAI—and the risk of CMD has not been fully elucidated. To address this gap, we utilized data from the China Health and Retirement Longitudinal Study (CHARLS), a prospective, nationwide, and representative cohort study, to clarify the association between cumulative CVAI and changes in CVAI with the risk of CMD. Furthermore, recognizing that age, sex, BMI, smoking, drinking, residence, education, and hypertension are significant conventional risk factors for CMD, we conducted subgroup analyses to refine the applicability and robustness of our findings.

Methods

Data source and study

The data were sourced from the CHARLS, an ongoing, nationally representative longitudinal survey in China initiated in 2011. In brief, CHARLS employed a multistage stratified probability-proportionate-to-size sampling approach to select individuals aged 45 and above from 28 provinces, covering 150 counties or districts and 450 villages. A total of 17,708 participants were recruited from June 2011 to March 2012. A standardized questionnaire was used to gather sociodemographic and lifestyle information, as well as health-related data. Following the baseline wave, subsequent follow-up surveys were scheduled at biennial intervals, occurring in 2013, 2015, 2018, and 2020 for Waves 2, 3, 4, and 5, respectively. Blood samples were obtained from participants at Wave 1 and 3. Detailed information about the study design of CHARLS has been previously documented [21].

Considering the available blood examination data, we extracted the datasets for Wave 1 (baseline, 2011) and Wave 3 (follow-up, 2015). Initially, 17,708 participants were included in Wave 1. The exclusion criteria were: (1) lack of information about age and sex (n = 175); (2) incomplete data on TG, HDL-C, BMI, WC, or CMD at Wave 1 (n = 8,059) or Wave 3 (n = 3,480); (3) individuals younger than 45 years (n = 198); (4) participants with an established diagnosis of CMD at Wave 1 (n = 1,112) or Wave 3 (n = 1,060); (5) participants lost follow up and missing CMD data (n = 403); (5) outliers of $CVAI_{2012}$ or $CVAI_{2015}$ (n = 64). Ultimately, 3,243 respondents who completed follow-ups in 2018 (Wave 4) and 2020 (Wave 5), corresponding to a follow-up period of approximately 5 years, were included in this analysis (Fig. 1).

The CHARLS study received approval from the Institutional Review Board of Peking University. Written informed consent was obtained from all participants. All procedures were conducted in accordance with the ethical guidelines of the 1975 Declaration of Helsinki, as well as the ethical standards of the responsible institutional and national committee on human experimentation. Additionally, this study adhered to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines [22].

Assessment of the change in CVAI

The exposures of this study were changes in the CVAI and cumulative CVAI from 2012 to 2015. The CVAI was calculated using the following formula [23]:

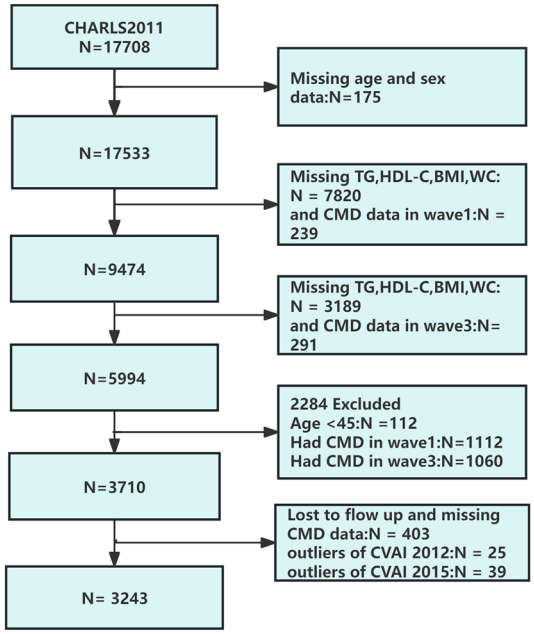

Fig. 1 Study Population Flow Chart. *CMD* Cardiometabolic Disease, *WC* waist circumference, *BMI* body mass index, *HDL-C* High-Density Lipoprotein Cholesterol, *TG* Triglyceride

Males:

$$\begin{aligned}\mathrm{CVAI} = &-267.93 + 0.68 \times \mathrm{age(y)} + 0.03 \times \mathrm{BMI}\left(\mathrm{kg/m^2}\right) \\ &+ 4.00 \times \mathrm{WC(cm)} + 22.00 \times \mathrm{LgTG(mmol/L)} \\ &- 16.32 \times \mathrm{HDL(mmol/L)}\end{aligned}$$

Females:

$$\begin{aligned}\mathrm{CVAI} = &-187.32 + 1.71 \times \mathrm{age(y)} \\ &+ 4.32 \times \mathrm{BMI}\left(\mathrm{kg/m^2}\right) \\ &+ 1.12 \times \mathrm{WC(cm)} \\ &+ 39.67 \times \mathrm{LgTG(mmol/L)} \\ &- 11.66 \times \mathrm{HDL(mmol/L)}\end{aligned}$$

We calculated the cumulative CVAI with reference to the cumulative TyG formula [24]: Cumulative $\mathrm{CVAI} = (\mathrm{CVAI}_{2012} + \mathrm{CVAI}_{2015})/2 \times \mathrm{time}\ (2015 - 2012)$.

Assessment of outcomes

The primary endpoint of this study was CMD, defined as the occurrence of any diabetes, stroke, or heart disease during the follow-up period. CMM was defined as the occurrence of two or more CMDs during the follow-up period. Diabetes mellitus (DM) was diagnosed based on one of the following criteria: (1) fasting plasma glucose level ≥ 126 mg/dL; (2) HbA1c ≥ 6.5%; (3) self-reported diagnosis by a physician ("Have you been diagnosed with DM?"); or (4) self-reported diabetes-related treatment, including traditional Chinese medicine, Western medicine, or insulin injections [25]. Heart disease was determined by a previous doctor's diagnosis (including heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems), regardless of whether related medication or other treatments were being received [26]. Stroke was similarly identified through self-report of a physician's diagnosis ("Have you been diagnosed with stroke?") [27].

Covariables

Trained interviewers equipped with measurement tools visited households to assess the respondents' health functioning and performance indicators. These included the anthropometric measurements of height, weight, BMI, WC, systolic blood pressure (SBP), and diastolic blood pressure (DBP). Sociodemographic characteristics and health-related information were gathered through a meticulously structured questionnaire administered by skilled interviewers. Sociodemographic data comprised variables such as age, sex (male/female), education level (junior high school and below, above junior high school), marital status (married/cohabiting, divorced/widowed/separated/single), and residence (rural, urban). Health-related information encompassed self-reported smoking and drinking behaviors (never, former, or current), as well as self-reported physician-diagnosed medical conditions, including hypertension and dyslipidemia, along with medication usage for these conditions. In this study, smoking behavior was categorized as "yes" (past or current smoker) and "no" (never smoked); drinking behavior was similarly categorized as "yes" (past or current drinker) and "no" (never drank). In 2012 and 2015, professional technicians collected venous blood samples from respondents after fasting for over 8 h to test for TC, HDL-C, low-density lipoprotein cholesterol (LDL-C), TG, fasting blood glucose (GLU), glycated hemoglobin A1c (HbA1c), uric acid (UA), creatinine (Cr), blood urea nitrogen (BUN), and C-reactive protein (CRP), among other indicators.

Hypertension was diagnosed in individuals who met any of the following criteria: (1) an average SBP ≥ 140 mmHg or DBP ≥ 90; (2) self-reported physician diagnosis; or (3) self-reported use of antihypertensive treatment [26]. Dyslipidemia was diagnosed based on one of the following criteria: (1) self-reported physician diagnosis; (2) self-report of antidyslipidemic treatment [28].

Statistical analysis

In this study, we utilized the "cluster" and "factoextra" packages to conduct a K-means cluster analysis on

the CVAI measurements from 2012 and 2015 to provide a basis for grouping the study subjects. During the data cleaning process, outliers in CVAI were identified using the 3σ rule, defining any CVAI < mean—3SD or CVAI > mean + 3SD as outliers, identifying a total of 25 outliers in $CVAI_{2012}$ and 39 outliers in $CVAI_{2015}$. To enhance clustering accuracy, these outliers were removed from the analysis. Subsequently, K-means clustering was performed on the refined data. Employing the elbow method (Figure S1), we identified four sample centers and then assigned the samples to the nearest cluster and updated the cluster center points (Fig. 2). This process was repeated until the cluster center points stabilized or a predetermined number of iterations was reached. Eventually, four cluster center points were obtained for 2012 and 2015 (41.35, 72.93, 103.96, 143.90, and 43.93, 82.65, 114.73, 151.59, respectively). Based on clinical situations and cluster center values, study subjects were categorized into four groups: "consistently low CVAI level" (Class 1), "moderate CVAI level with a slow rising trend" (Class 2), "high CVAI level with a slow rising trend" (Class 3), and "the highest CVAI level with a slow rising trend" (Class 4) (Fig. 2). When statistically describing the essential characteristics of these four groups of study subjects, categorical variables were presented as frequency (n) and percentage (%), with between-group differences compared using the chi-square test. For continuous variables following a normal distribution, they were described as mean ± standard deviation (SD) and between-group comparisons were made using one-way ANOVA. Continuous variables that did not follow a normal distribution were presented as median (interquartile range) M (Q1, Q3), and between-group comparisons were conducted using the Kruskal–Wallis test.

Additionally, in this study, cumulative CVAI was standardized using z-score before conducting multivariable analysis. We developed three multivariable logistic regression models to evaluate the relationship between CVAI changes and CMD. Model 1 did not adjust for any variables, while Model 2 adjusted for age and gender, and Model 3 further adjusted for multiple variables including education level, current marital status, residence, smoking and drinking behaviors, BMI_{2012}, SBP, DBP, dyslipidemia, TC, LDL-C, GLU, HbA1c, CRP, Cr, BUN, and UA.

Trend tests were employed to evaluate the trend relationship between CVAI changes and CMD, while subgroup analysis was conducted to explore the potential relationship between CVAI changes and CMD under different stratifications such as age, gender, smoking, and drinking behaviors, BMI, rural household registration, and hypertension. Restricted cubic splines (RCS) were utilized to assess whether there was a nonlinear

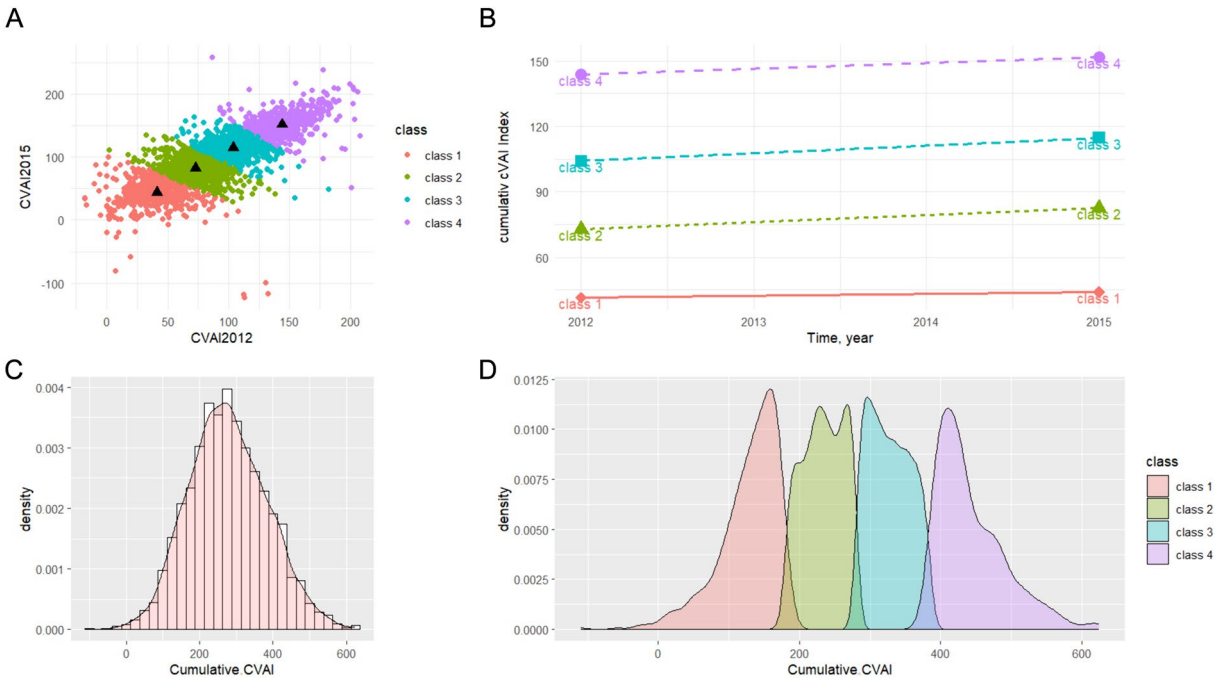

Fig. 2 **A** Clustering diagrams for $CVAI_{2012}$ and $CVAI_{2015}$; **B** Grouping diagram after k-means clustering; **C** Histogram and probability density plot of cumulative CVAI in the overall population, illustrating the data distribution of cumulative CVAI; **D** Histograms and probability density plots of cumulative CVAI for groups class 1–4, showing the data distribution of cumulative CVAI within these four groups. *CVAI* Chinese Visceral Adiposity Index

association between cumulative CVAI and CMD, with 4 knots selected at the 25th percentile, the 50th percentile, the 75th percentile, and the 95th percentile. Sensitivity analysis was employed to evaluate the stability of the relationship between CVAI changes and CMD. We used the "MatchIt" package for propensity score matching (PSM) to balance baseline data.

In addition, we employed a weighted quantile sum (WQS) regression model to elucidate the overall relationship between exposure to each component of CAVI (TG, age, HDL-C, WC, BMI) and CMD incidence and to establish the relative contribution of each component to CMD risk [29]. In the WQS regression, the weights assigned to exposure variables range from 0 to 1, with the total weights summing to 1. A higher weight value signifies a greater degree of contribution of the component exposure to the overall load. The WQS regression analysis was conducted to evaluate the relationship between combined exposure to each component of CAVI as a whole and CMD incidence. The exposure level of each component of CAVI was converted into an ordinal variable that was weighted and summed in interquartile form to obtain the sum of the weighted quartiles of all exposure elements (WQS index). The WQS index represents the overall exposure load of each component of CAVI and was combined with the covariates above in a regression model reflecting the effect of combined exposure on outcome [30].

In this study, a two-sided p-value < 0.05 was considered statistically significant. All statistical analyses were conducted using Stata software (version 18.0, StataCorp) and R software (version 4.2.2, http://www.R-project.org, The R Foundation).

Results

Intra-group comparison and distribution of CVAI-related indicators

The paired t-test was performed to assess the changes of CVAI withing each class: for Class 1 (n = 582), the CVAI ranged from 41.36 ± 19.68 in 2012 to 43.94 ± 23.70 in 2015 ($P = 0.051$), and the cumulative CVAI was 127.94 ± 42.70; for Class 2 (n = 1,139), the CVAI ranged from 72.93 ± 15.20 in 2012 to 82.66 ± 15.44 in 2015 ($P < 0.001$), and the cumulative CVAI was 233.38 ± 28.76; for Class 3 (n = 984), the CVAI ranged from 103.97 ± 15.08 in 2012 to 114.74 ± 14.22 in 2015 ($P < 0.001$), and the cumulative CVAI was 328.05 ± 29.71; for Class 4 (n = 538), the CVAI ranged from 143.90 ± 19.37 in 2012 to 151.60 ± 20.53 in 2015 ($P < 0.001$), and the cumulative CVAI was 443.25 ± 48.44 (Table 1, Figure S2). Histograms and probability density plots indicated that cumulative CVAI, $CVAI_{2012}$, and $CVAI_{2015}$ exhibited characteristics of a normal distribution in the overall population and in each subgroup (Figure S3).

Baseline data comparison

The investigation comprised 3,243 participants, with 46% male (1,482) and 54% female (1,761), averaging 57.49 ± 8.43 years old. The mean cumulative CVAI was 278.00 ± 106.33. By the end of the follow-up, 776 participants (24%) had developed CMD, and 118 participants (3.4%) had developed CMM. In class 4, age, hypertension, dyslipidemia, BMI_{2012}, BMI_{2015}, SBP, DBP, TC, GLU, Cr, UA, WC_{2012}, WC_{2015}, TG_{2012}, TG_{2015}, $CVAI_{2012}$, and $CVAI_{2015}$ were significantly elevated. Conversely, in rural residences, levels of HDL-C_{2012} and HDL-C_{2015} were lower in class 4. No significant differences were observed in education, marital status, HbA1c, CRP, and BUN across the four groups. Cumulative CVAI increased progressively from class 1 to class 4 (127.94 ± 42.70 vs. 233.38 ± 28.76 vs. 328.05 ± 29.71 vs. 443.25 ± 48.44, $P < 0.001$), as did the incidence of CMD (16% vs. 21% vs. 27% vs. 33%, $P < 0.001$) and CMM (1.8% vs. 2.8% vs. 4.1% vs. 6.5%, $P < 0.001$) (Table 1).

CMD risk analysis

After adjusting for potential confounders (in Model 3), compared with Class 1, the adjusted ORs (95% CIs) for incident CMD were 1.18 (0.90–1.57) for Class 2, 1.40 (1.03–1.92) for Class 3, and 1.56 (1.04–2.34) for Class 4. Trend tests indicated a significant increase in CMD incidence with rising CVAI levels ($P = 0.024$). When cumulative CVAI (per SD increase) was introduced as a continuous variable into the multivariate regression model, the result in model 3 was significant (OR 1.22, 95%CI 1.07–1.40, $P = 0.003$). Additionally, when cumulative CVAI was categorized into quartiles, compared with Q1, the adjusted ORs (95% CIs) for incident CMD were 1.30 (1.00–1.70) for Q2, 1.34 (1.01–1.79) for Q3, and 1.63 (1.15–2.31) for Q4. Trend tests also showed a significant increase in CMD incidence with higher cumulative CVAI ($P = 0.008$) (Table 2).

CMM risk analysis

Multivariable logistic regression analysis of CMM risk showed that compared to class 1, the risk was elevated in Class 4 (OR 2.12, 95%CI 0.85–5.60, $P = 0.115$), in Class 3 (OR 1.59, 95%CI 0.76–3.59, $P = 0.235$) and Class 2 (OR 1.31, 95%CI 0.65–2.84, $P = 0.468$) but not statistically significant in Model 3. Trend tests also revealed no statistically significant CMM incidence with higher CVAI levels ($P = 0.105$). However, when cumulative CVAI was introduced as a continuous variable into the multivariate regression model, Model 3 showed a significant

Table 1 Baseline characteristics of 3243 participants according to the change in the CVAI

Characteristic	Overall, N = 3,243	Class 1, N = 582	Class 2, N = 1,139	Class 3, N = 984	Class 4, N = 538	*P* value
Age (year)	57.49 ± 8.34	56.14 ± 8.11	56.47 ± 7.71	58.24 ± 8.55	59.72 ± 8.86	< 0.001
Male gender	1,482 (46.0%)	364 (63.0%)	477 (42.0%)	383 (39.0%)	258 (48.0%)	< 0.001
Rural residence	2,235 (69.0%)	437 (75.0%)	827 (73.0%)	660 (67.0%)	311 (58.0%)	< 0.001
Education						
Junior high school and below (low level)	2,966 (91.0%)	535 (92.0%)	1,049 (92.0%)	901 (92.0%)	481 (89.0%)	0.301
Junior high school and above (high level)	277 (8.5%)	47 (8.1%)	90 (7.9%)	83 (8.4%)	57 (11.0%)	
Married/cohabiting	2,955 (91.0%)	533 (92.0%)	1,045 (92.0%)	892 (91.0%)	485 (90.0%)	0.678
Drinking	1,248 (38.0%)	277 (48.0%)	418 (37.0%)	333 (34.0%)	220 (41.0%)	< 0.001
Smoking	1,214 (37.0%)	308 (53.0%)	399 (35.0%)	319 (32.0%)	188 (35.0%)	< 0.001
Hypertension	1,052 (33.0%)	106 (18.0%)	272 (24.0%)	375 (38.0%)	299 (56.0%)	< 0.001
Dyslipidemia	191 (6.0%)	9 (1.6%)	59 (5.3%)	55 (5.7%)	68 (13.0%)	< 0.001
BMI_{2012} (kg/m^2)	23.14 ± 3.57	19.85 ± 2.09	21.99 ± 2.51	24.07 ± 2.46	27.42 ± 3.62	< 0.001
BMI_{2015} ($kg/m^{2)}$	23.42 ± 3.62	19.99 ± 2.13	22.27 ± 2.58	24.51 ± 2.73	27.58 ± 3.36	< 0.001
TC (mg/dl)	191.80 ± 38.14	185.07 ± 33.94	189.11 ± 36.95	194.90 ± 37.23	199.11 ± 44.38	< 0.001
TG_{2012} (mg/dl)	100.00 (71.68, 144.26)	73.46 (57.53, 94.69)	88.50 (66.38, 122.13)	116.82 (83.19, 160.18)	148.68 (106.64, 211.29)	< 0.001
TG_{2015} (mg/dl)	108.85 (80.53, 160.18)	78.76 (63.94, 103.54)	98.23 (75.22, 133.63)	127.43 (94.69, 182.30)	166.37 (112.61, 235.40)	< 0.001
$HDL\text{-}C_{2012}$ (mg/dl)	52.23 ± 14.88	62.22 ± 16.48	54.70 ± 13.25	48.79 ± 12.86	42.48 ± 11.40	< 0.001
$HDL\text{-}C_{2015}$ (mg/dl)	52.38 ± 11.80	59.75 ± 14.14	53.96 ± 11.18	49.80 ± 9.48	45.76 ± 8.64	< 0.001
LDL-C (mg/dl)	115.32 ± 33.60	107.56 ± 29.21	115.74 ± 32.49	118.37 ± 34.57	117.27 ± 37.18	< 0.001
GLU (mg/dl)	102.88 ± 19.77	102.51 ± 27.13	100.53 ± 15.16	103.68 ± 18.86	106.80 ± 19.93	< 0.001
HbA1c (%)	5.09 ± 0.43	5.08 ± 0.55	5.08 ± 0.40	5.08 ± 0.39	5.15 ± 0.42	0.005
CRP (mg/dl)	2.24 ± 6.93	2.09 ± 8.78	2.06 ± 7.44	2.44 ± 6.21	2.42 ± 4.34	0.495
BUN (mg/dl)	15.66 ± 4.34	16.12 ± 4.56	15.50 ± 4.21	15.56 ± 4.43	15.69 ± 4.18	0.036
Cr (mg/dl)	0.76 ± 0.18	0.78 ± 0.18	0.75 ± 0.17	0.76 ± 0.19	0.79 ± 0.18	< 0.001
UA (mg/dl)	4.34 ± 1.20	4.32 ± 1.18	4.12 ± 1.12	4.34 ± 1.19	4.82 ± 1.28	< 0.001
DBP	74.21 ± 11.84	70.85 ± 10.92	72.45 ± 11.23	75.30 ± 11.75	79.63 ± 12.14	< 0.001
SBP	126.17 ± 19.97	119.99 ± 18.07	122.63 ± 18.15	128.60 ± 19.99	136.02 ± 21.22	< 0.001
WC_{2012} (cm)	83.36 ± 10.95	72.29 ± 9.50	79.62 ± 8.03	87.05 ± 7.03	96.51 ± 6.23	< 0.001
WC_{2015} (cm)	84.07 ± 11.79	71.16 ± 10.66	80.51 ± 8.59	88.52 ± 6.60	97.41 ± 7.58	< 0.001
$CVAI_{2012}$	88.46 ± 36.71	41.36 ± 19.68	72.93 ± 15.20	103.97 ± 15.08	143.90 ± 19.37	< 0.001
$CVAI_{2015}$	96.88 ± 38.51	43.94 ± 23.70	82.66 ± 15.44	114.74 ± 14.22	151.60 ± 20.53	< 0.001
Cumulative CVAI	278.00 ± 106.33	127.94 ± 42.70	233.38 ± 28.76	328.05 ± 29.71	443.25 ± 48.44	< 0.001
Stroke	233 (7.3%)	23 (4.0%)	65 (5.8%)	80 (8.2%)	65 (12.0%)	< 0.001
Heart disease	432 (13.0%)	56 (9.7%)	143 (13.0%)	142 (14.0%)	91 (17.0%)	0.002
Diabetes	236 (7.4%)	28 (4.8%)	64 (5.7%)	86 (8.8%)	58 (11.0%)	< 0.001
CMD	776 (24.0%)	96 (16.0%)	237 (21.0%)	266 (27.0%)	177 (33.0%)	< 0.001
CMM	118(3.4%)	11(1.8%)	32(2.8%)	40(4.1%)	35(6.5%)	< 0.001

Continuous variables are expressed as mean ± standard deviation or interquartile range, and categorical variables are expressed as frequencies (n) and percentages (%)

BMI Body Mass Index, *WC* waist circumference, *TC* Total Cholesterol, *TG* Triglyceride, *LDL-C* Low-Density Lipoprotein Cholesterol, *HDL-C* High-Density Lipoprotein Cholesterol, *UA* Uric Acid, *GLU* Glucose, *Cr* Creatinine, *BUN* Bilirubin, *HbA1c* Hemoglobin A1c, *CRP* C-Reactive Protein, *SBP* Systolic Blood Pressure, *DBP* Diastolic Blood Pressure, *CVAI* Chinese Visceral Adiposity Index

increase in CMM risk. The risk of CMM increased by 1.57 times per SD increase in cumulative CVAI (OR 1.57, 95%CI 1.15–2.18, $P = 0.004$). After categorizing cumulative CVAI into quartiles, the risk of CMM in the fourth quartile compared to the first was significantly higher in model 3 (OR 3.33, 95%CI 1.45–8.17, $P = 0.006$). Trend tests also indicated a significant rise in CMM incidence with increasing cumulative CVAI ($P < 0.001$) (Table 3).

Table 2 Associations of different classes of the CVAI with CMD incidence

	CMD, N (%)	Model 1		Model 2		Model 3	
		OR (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value
Change in the CVAI							
Class 1	96 (16.0%)	Reference		Reference		Reference	
Class 2	237 (21.0%)	1.33 (1.03–1.73)	0.032	1.29 (1.00–1.69)	0.056	1.18 (0.90–1.57)	0.234
Class 3	266 (27.0%)	1.88 (1.45–2.44)	< 0.001	1.75 (1.35–2.29)	< 0.001	1.40 (1.03–1.92)	0.032
Class 4	177 (33.0%)	2.48 (1.87–3.30)	< 0.001	2.28 (1.71–3.05)	< 0.001	1.56 (1.04–2.34)	0.033
P for trend			< 0.001		< 0.001		0.024
Cumulative CVAI (per SD)		1.37 (1.26–1.49)	< 0.001	1.33 (1.23–1.45)	< 0.001	1.22 (1.07–1.40)	0.003
Cumulative CVAI (quartiles)							
Q1 [−305,204.5]	126 (16.0%)	Reference		Reference		Reference	
Q2 (204.5,271.1]	183 (22.0%)	1.45 (1.13–1.87)	< 0.001	1.41 (1.10–1.83)	0.007	1.30 (1.00–1.70)	0.051
Q3 (271.1,350.6]	206 (25.0%)	1.70 (1.33–2.18)	< 0.001	1.62 (1.26–2.08)	< 0.001	1.34 (1.01–1.79)	0.043
Q4 (350.6,624.2]	261 (32.0%)	2.40 (1.89–3.06)	< 0.001	2.22 (1.74–2.84)	< 0.001	1.63 (1.15–2.31)	0.006
P for trend			< 0.001		< 0.001		0.008

Model 1: Unadjusted variables

Model 2: Adjusted for age, and gender

Model 3: In addition to the variables adjusted in Model 2 (age, gender), the following variables were added: education, current marital status, residence, smoking, drinking, BMI_{2012}, SBP, DBP, hypertension, dyslipidemia, TC, LDL-C, GLU, HbA1c, CRP, Cr, BUN, UA. Results are presented as Odds Ratios (OR) with 95% Confidence Intervals (CI)

CI Confidence Interval, *OR* Odds Ratio. The remaining abbreviations are the same as those in Table 1

Subgroup analysis results

Figure 3 illustrated subgroup analyses conducted to examine the relationships between cumulative CVAI and the incidence of CMD by age, gender, smoking, drinking, residence, BMI, education, and hypertension. These analyses revealed no significant interactions between subgroup variables and the relationship between changes in CVAI and cumulative CVAI with the incidence of CMD (all $P > 0.05$). This suggested that these subgroup factors—age, gender, smoking, drinking, residence, BMI, education, and hypertension—did not modify the relationship between changes in CVAI and cumulative CVAI with the incidence of CMD (Table 4).

Dose–response relationship analysis between cumulative CVAI and CMD

As depicted in Fig. 4, cumulative CVAI in the overall population exhibited a linear association with CMD ($P_{overall} = 0.012$, $P_{non\text{-}linearity} = 0.287$), diabetes ($P_{overall} = 0.022$, $P_{non\text{-}linearity} = 0.188$), and stroke ($P_{overall} = 0.002$, $P_{non\text{-}linearity} = 0.978$), but showed no significant association with heart disease ($P_{overall} = 0.619$, $P_{non\text{-}linearity} = 0.442$).

WQS analysis

An in-depth analysis of TG, age, HDL-C, WC, and BMI in the cumulative CVAI was conducted utilizing the WQS regression model. The model evaluated the relationship of cumulative TG, cumulative age, cumulative HDL-C, cumulative WC, and cumulative BMI exposures with CMD incidence. The WQS regression analysis revealed that cumulative TG had the highest relative contribution weight (0.367) among the five variables, followed by cumulative age (Fig. 5). The effect of the WQS index of mixed TG, age, HDL-C, WC, and BMI on CMD incidence was significant (OR = 1.76, 95% CI 1.31–2.36, $P < 0.001$). In addition, a significant association was observed between cumulative exposures to TG, age, WC, and BMI and the incidence of CMD (all $P < 0.001$). The association between cumulative HDL-C and CMD incidence was not significant ($P = 0.05$) (Table 5).

Sensitivity analysis

To assess the robustness of our findings, we initially divided the 3,243 participants into two groups: those with complete data and those with missing data. No significant differences in CMD were observed between the two groups (Table S1). We then applied the PSM method to categorize the data into two groups based on the median of cumulative CVAI, resulting in two groups, Q1-2 and Q3-4, and matched the data sets with the nearest neighbor method at a ratio of 1:1, with a caliper of 0.2, and finally matched 1,401 pairs of data sets (Table S2). Post-matching, there was no significant difference in the age of the two groups, and we conducted logistic regression analysis again. The results indicated a significant association between cumulative CVAI and CMD (OR 1.30, 95%

Table 3 Associations of different classes of the CVAI with CMM incidence

	CMM, N(%)	Model 1		Model 2		Model 3	
		OR (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value
Change in the CVAI							
Class 1	11(1.8%)	Reference		Reference		Reference	
Class 2	29(2.5%)	1.50 (0.77–3.14)	0.250	1.50 (0.77–3.16)	0.251	1.31 (0.65–2.84)	0.468
Class 3	38(3.8%)	2.20 (1.16–4.54)	0.022	2.13 (1.11–4.43)	0.030	1.59 (0.76–3.59)	0.235
Class 4	35(6.5%)	3.61 (1.87–7.53)	< 0.001	3.40 (1.75–7.13)	< 0.001	2.12 (0.85–5.60)	0.115
P for trend			< 0.001		< 0.001		0.105
Cumulative CVAI (per SD)		1.62 (1.35–1.94)	< 0.001	1.59 (1.32–1.91)	< 0.001	1.57 (1.15–2.18)	0.004
Cumulative CVAI (quartiles)							
Q1 [−305,204.5]	11(1.4%)	Reference		Reference		Reference	
Q2 (204.5,271.1]	28(3.4%)	2.42 (1.23–5.10)	0.014	2.42 (1.23–5.12)	0.014	2.29 (1.13–4.98)	0.026
Q3 (271.1,350.6]	29(3.5%)	2.51 (1.28–5.29)	0.010	2.48 (1.26–5.26)	0.011	2.08 (0.99–4.68)	0.063
Q4 (350.6,624.2]	50(6.2%)	4.50 (2.42–9.18)	< 0.001	4.27 (2.27–8.76)	< 0.001	3.33 (1.45–8.17)	0.006
P for trend			< 0.001		< 0.001		< 0.001

Model 1: Unadjusted variables

Model 2: Adjusted for age, and gender

Model 3: In addition to the variables adjusted in Model 2 (age, gender), the following variables were added: education, current marital status, residence, smoking, drinking, BMI_{2012}, SBP, DBP, hypertension, dyslipidemia, TC, LDL-C, GLU, HbA1c, CRP, Cr, BUN, UA

Results are presented as Odds Ratios (OR) with 95% Confidence Intervals (CI)

Abbreviations as in Table 1

CI 1.13–1.50, $P < 0.001$). The notable association included Class 3 vs. Class 1 (OR 1.48, 95% CI 1.06–2.08, $P = 0.021$), Class 4 vs. Class 1 (OR 1.75, 95% CI 1.14–2.70, $P = 0.011$), Q4 vs. Q1 (OR 1.85, 95% CI 1.29–2.68, $P < 0.001$), and Q3-4 vs. Q1-2 (OR 1.27, 95% CI 1.01–1.60, $P = 0.036$). Finally, based on the elbow graph, we identified three cluster centers for 2012 (49.17, 86.02, 133.57) and three for 2015 (52.87, 97.76, 141.38). Combined with the clinical situation and the cluster center values, the study subjects were classified into "consistently low CVAI level" (Class 1), "moderate CVAI level with a slow rising trend" (Class 2), and "high CVAI level with a slow rising trend" (Class 3) (Figure S4). We then re-evaluated the relationship between CVAI changes with CMD and CMM. Model 3 results showed that the relationship between the change of CVAI and CMD was stable, and the comparison between Class 3 and Class 1 (OR = 1.48, 95%CI 1.07–2.04, $P = 0.018$) was significant. Importantly, Model 3 results showed that the relationship between the changes in CVAI and CMM became more pronounced, and the comparison between class 3 and class 1 was significant (OR 3.26, 95%CI 1.49–7.51, $P = 0.004$) (Table S3).

Discussion

In this prospective, nationwide, longitudinal cohort study involving the population aged 45 years and above in China, encompassing 3,243 participants with a 5-year follow-up, we found: (1) 776 individuals (24%) developed CMD, and 118 individuals (3.4%) developed CMM by the end of the follow-up; (2) Participants with higher baseline CVAI level and a change of elevating CVAI level may suffer an increased incidence of CMD; (3) The fully adjusted RCS regression analysis displayed a positive, linear association between cumulative CVAI and the incidence of CMD, diabetes, and stroke, but no significant association with heart disease; (4) The WQS model demonstrated a mixed effect of combined TG, age, HDL-C, WC, and BMI exposures on outcomes, and the WQS index tended to correlate positively with the risk of CMD, with TG contributing the most. In summary, our findings suggested that cumulative CVAI could be a valuable tool for the early identification of individuals at heightened risk of CMD, emphasizing the importance of long-term CVAI monitoring in clinical practice.

This study employed the CVAI, which particularly reflects Chinese visceral adiposity scores, taking into account the components of metabolic syndrome, including age, BMI, WC, TG, and HDL-C. A study conducted on a population of 12,237 Chinese individuals, with a follow-up period of 6.01 years, found that the probability of developing T2DM was 20.43% greater in the highest CVAI quartile compared to the lowest quartile [15]. In the CHARLS cohort study, Zhang et al. examined 7,070 participants and observed that there was a 57% higher risk of stroke per interquartile range increment in CVAI [31]. A population-based study of 7,439 participants

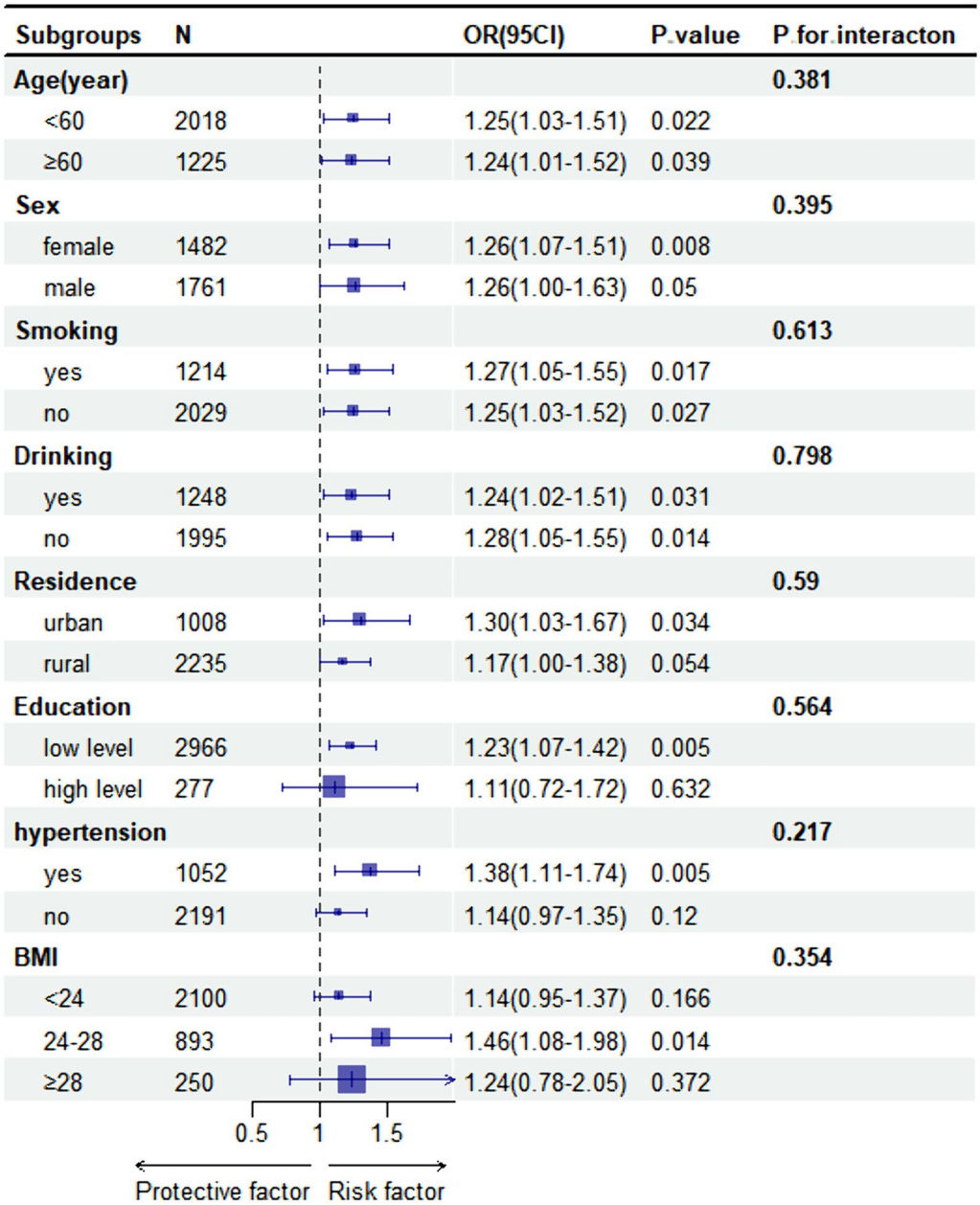

Fig. 3 Subgroup Analyses Between Cumulative CVAI and CMD. Results are presented as OR (95% CI). Adjustments were made for age, gender, education, current marital status, residence, smoking, drinking, BMI_{2012}, SBP, DBP, hypertension, dyslipidemia, TC, LDL-C, GLU, HbA1c, CRP, Cr, BUN, UA in the multivariable model, excluding the strata variables. *BMI* Body Mass Index, *CI* Confidence Interval, *TC* Total Cholesterol, *LDL-C* Low-Density Lipoprotein Cholesterol, *UA* Uric Acid, *GLU* Glucose, *Cr* Creatinine, *BUN* Bilirubin, *HbA1c* Hemoglobin A1c, *CRP* C-Reactive Protein, *DBP* Diastolic Blood Pressure, *CVAI* Chinese Visceral Adiposity Index

aged ≥ 45 years from CHARLS with 6.01 years of follow-up found that each SD increase in CVAI was associated with a 17% increased risk for CVD, a 12% increase for heart disease, and a 31% increase for stroke [17]. A study that included 34,732 participants from the REACTION study found that CVAI was significantly associated with hypertension and prehypertension in both men and women, even after adjusting for various biochemical and lifestyle risk factors [32]. A study analyzed 42,165 Chinese individuals over a median follow-up of 3.36 years discovered that the risk of CAD was considerably more significant in the fourth CVAI quartile than in the first [23]. An investigation involving 9,280 participants from Guizhou province found that women with high CVAI had a higher

Table 4 Analysis of the association between changes in CVAI and CMD subgroup

Subgroups	N	Class 1	Class 2 *OR (95% CI)*	Class 3 *OR (95% CI)*	Class 4 *OR (95% CI)*	*P for trend*	*P for ineraction*
Age							
< 60	2018	Ref	1.27(0.89–1.82)	1.54(1.03–2.34)	1.65(0.95–2.86)	0.057	0.883
> = 60	1225	Ref	1.12(0.71–1.76)	1.40(0.87–2.28)	1.82(1.00–3.34)	0.014	
Sex							
male	1482	Ref	1.11(0.76–1.63)	1.42(0.93–2.18)	1.90(1.10–3.29)	0.014	0.301
female	1761	Ref	1.32(0.85–2.09)	1.54(1.00–2.59)	1.51(0.76–3.04)	0.217	
Smoking							
yes	1214	Ref	1.28(0.86–1.94)	1.65(1.06–2.61)	1.50(0.84–2.73)	0.127	0.161
no	2029	Ref	1.25(0.83–1.88)	1.24(0.79–1.98)	2.09(1.16–3.85)	0.024	
Drinking							
yes	1248	Ref	1.24(0.85–1.83)	1.54(1.01–2.38)	1.56(0.88–2.79)	0.094	0.865
no	1995	Ref	1.22(0.81–1.87)	1.37(0.86–2.21)	1.85(1.01–3.42)	0.047	
Residence							
rural	2235	Ref	1.25(0.91–1.73)	1.47(1.02–2.13)	1.57(0.95–2.59)	0.061	0.943
urban	1008	Ref	0.96(0.56–1.70)	1.23(0.69–2.24)	1.43(0.71–2.96)	0.252	
BMI							
< 24	2100	Ref	1.18(0.90–1.57)	1.34(0.98–1.85)	1.43(0.76–2.60)	0.212	0.260
24–28	893	NA	Ref	1.34(1.00–2.16)	1.43(0.81–2.56)	0.049	
> = 28	250	NA	Ref	1.37(0.33–7.34)	1.44(0.38–7.08)	0.978	
Hypertension							
yes	1052	Ref	1.14(0.82–1.58)	1.36(0.94–1.99)	1.17(0.69–1.98)	0.033	0.443
no	2191	Ref	1.09(0.64–1.91)	1.32(0.76–2.35)	2.03(1.04–4.03)	0.425	
Education							
low level	2966	Ref	1.17(0.88–1.57)	1.38(1.00–1.92)	1.61(1.05–2.48)	0.022	0.814
high level	277	Ref	1.87(0.61–6.42)	2.03(0.63–7.20)	1.15(0.27–5.02)	0.827	

Adjustments were made for age, gender, education, current marital status, residence, smoking, drinking, BMI_{2012}, SBP, DBP, hypertension, dyslipidemia, TC, LDL-C, GLU, HbA1c, CRP, Cr, BUN, UA in the multivariable model, excluding the strata variables

Results are presented as Odds Ratios (OR) with 95% Confidence Intervals (CI)

Abbreviations as in Table 1

chance of having a stroke. However, this relationship was not observed in male participants [33]. In addition, research conducted on individuals from a community-dwelling population in Suzhou found no significant association between CVAI and the risk of incident stroke [34]. The disparities in these studies may arise from various factors: Initially, certain studies selected participants exclusively from one province instead of using a sample that represents the entire nation, leading to selection bias. Furthermore, certain studies exclusively focused on rural people, wherein disparities in income, quality of life, education, and medical accessibility between urban and rural regions could exert a substantial impact on the outcomes. In addition, the majority of studies based CVAI on single assessments, ignoring temporal changes, potentially causing regression dilution bias and affecting result accuracy. CVAI is calculated using TG and HDL-C, which show dynamic changes. Therefore, baseline CVAI evaluation often fails to adequately capture the intricate and enduring alterations linked to the advancement of the disease, which are essential for prognostic assessment and clinical application.

Unlike single baseline CVAI measurements, our study utilized cumulative CVAI to evaluate the relationship between CVAI exposure and incident CMD, leveraging long-term follow-up data. Compared to single baseline CVAI, cumulative CVAI had a more significant impact on outcomes, offering a more reliable assessment method, and yielding more robust and stable results. In this study, we found that cumulative CVAI was associated with an increased risk of developing CMD. The risk of CMD development was highest in individuals in the highest quartile group, with a multivariate-adjusted OR of 1.63. Additionally, this risk was not attenuated by additional adjustment for baseline CVAI. The cumulative effect appears to be independent of and superior to baseline

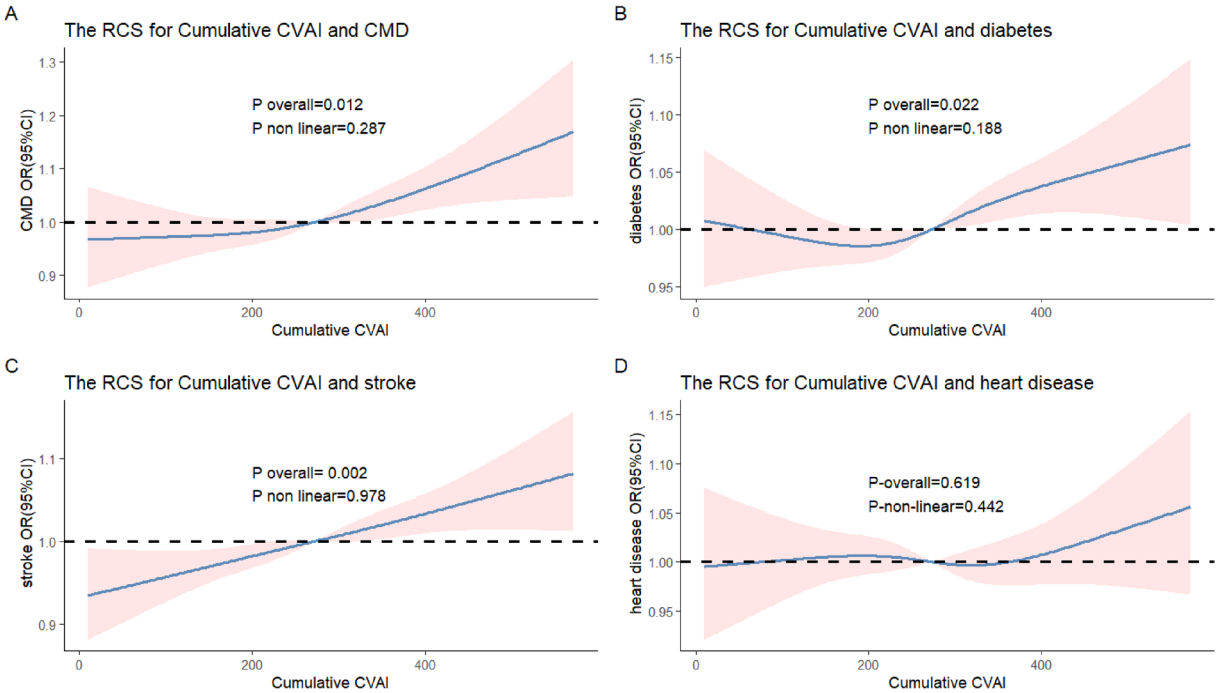

Fig. 4 Dose–Response Curves of Cumulative CVAI and CMD. Results are presented as OR (95% CI). **A**-**D** Represent the RCS curves of cumulative CVAI with CMD, diabetes, stroke, and heart disease. Abbreviations as in Fig. 3

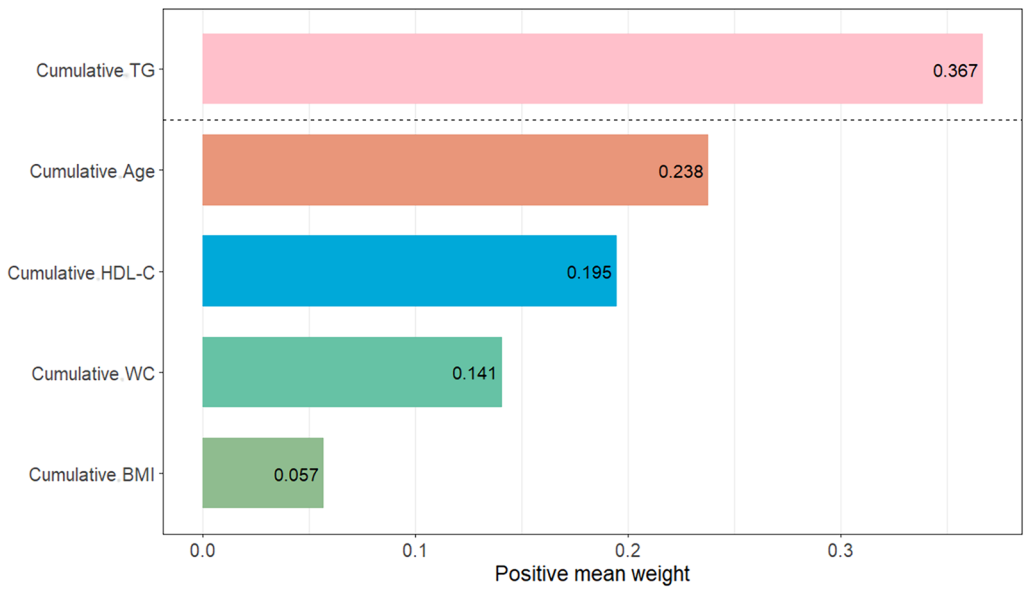

Fig. 5 WQS analysis. *TG* Triglyceride, *HDL-C* High-Density Lipoprotein Cholesterol, *WC* waist circumference, *BMI* body mass index

CVAI in the pathogenesis of CMD. Likewise, the longest exposure time was associated with the highest risk of CMD. These findings suggested that cumulative CVAI monitoring has substantial clinical potential, allowing for a more comprehensive evaluation of cardiovascular and metabolic changes in participants during follow-up, thereby aiding clinicians in better long-term health management and risk evaluation.

Our RCS model showed that cumulative CVAI was linearly associated with CMD, diabetes, and stroke but not

Table 5 WQS modeling to analyze the association between combined exposure to each component of CAVI and CMD risk

Exposures	CMD, n (%)	OR (95%CI)	*P* value
Cumulative TG	776 (24.0%)	1.14 (1.06–1.23)	< 0.001
Cumulative Age	776 (24.0%)	1.22 (1.13–1.32)	< 0.001
Cumulative HDL-C	776 (24.0%)	0.92 (0.85–1.00)	0.050
Cumulative WC	776 (24.0%)	1.27 (1.17–1.38)	< 0.001
Cumulative BMI	776 (24.0%)	1.22 (1.13–1.32)	< 0.001
Cumulative WQS index	776 (24.0%)	1.76 (1.31–2.36)	< 0.001

We adjusted for age, gender, education, current marital status, residence, smoking, drinking, BMI_{2012}, SBP, DBP, hypertension, dyslipidemia, TC, LDL-C, GLU, HbA1c, CRP, Cr, BUN, UA

Abbreviations as in Table 1

with heart disease. Consistent with our findings, linear associations between CVAI and stroke were observed in several prospective cohort studies [27, 29, 33]. A Mendelian randomization study also confirmed a positive association between CVAI and stroke risk, further supporting the linear relationship between CVAI and incident stroke [35]. Additionally, Pan et al. reported a nonlinear (U-shaped) relationship between CVAI and T2DM risk in the RCS model [36]. As CVAI increases, its influence on T2DM incidence tends to stabilize at higher values. This difference may be attributed to our use of cumulative CVAI, which more sensitively indicated that high cumulative CVAI significantly increased diabetes incidence. This suggested that in clinical management, early disease prediction and intervention for populations with high cumulative CVAI, rather than baseline indicators, may be more effective in reducing CMD risk. However, inconsistent with prior study [17], there was no significant association between cumulative CVAI and heart disease. These inconsistent results on the association may be attributable to the sample size, the length of follow-up, the method of statistical analysis, the adjusted covariables, environment, or other factors. Prospective studies with a longer duration of follow-up and larger sample size are needed in future for an in-depth evaluation of the association between CVAI and CVD.

Another notable point was that TG was the primary contributor to the observed association between cumulative CVAI and CMD risk from the WQS regression model. Consistent with our findings, Huo et al. elucidated the underlying mechanisms of the TyG-BMI by highlighting TG as the primary contributor to the observed association between cumulative TyG-BMI and stroke risk [37]. The potential mechanisms linking increased CMD risk with elevated TG levels may be explained by chronic inflammation, insulin resistance, and endothelial dysfunction. In addition, age also identified an essential contributor to the observed association between cumulative CVAI and CMD risk, which suggested the importance of monitoring long-term CVAI changes in the middle-aged and elderly population.

The exact physiological mechanisms explaining the association between CVAI and CMD remain unclear, but several hypotheses have been proposed. First, visceral adiposity induces a systemic inflammatory state, particularly evident in vascular inflammation, by increasing the expression of interleukin-6, tumor necrosis factor-a, and high-sensitivity C-reactive protein, leading to CMD [12, 38]. Second, visceral obesity exacerbates the production of inflammatory markers and adipocytokines while reducing the production of adiponectin, leading to IR and consequently increasing the incidence of CMD [39, 40]. Third, visceral adiposity could lead to renal cytokine imbalance and damage to the glomerular basement membrane, initiating metabolic dysfunction in the kidneys [41]. Then excessive reactive oxygen species and reactive nitrogen species were produced, which induced oxidative stress, presenting as oxidized low-density lipoprotein, 8-hydroxylated deoxyguanosine, malondialdehyde, thioredoxin, and advanced oxidation protein products [42]. Oxidative stress induces a vicious cycle of endothelial dysfunction, inflammation, and fibroblast proliferation and affects arteries through stenosis and occlusion, leading to CMD incidence [39]. Last, in addition to inherited genetic factors, we found that individuals with high cumulative CVAI had high SBP, DBP, TC, TG, GLU, Cr, UA, BMI, and WC values, and the majority had hypertension or dyslipidemia, which were primary CMD risk factors. However, biologically meaningful effects might not have been completely eliminated, even with adjustment for the above confounders. Consequently, the risk of CMD was obviously elevated under high cumulative CVAI exposure, which could have been due to the synergistic effects of these factors.

The present findings have significant value for the prevention and management of CMD among the middle-aged and elderly Chinese population. Currently, the CVAI is widely used clinically as a surrogate indicator of visceral obesity, further refining the assessment of CMD risk. More attention should be given to the long-term hazards associated with the cumulative exposure and long duration of high CVAI values rather than focusing on only a single CVAI measurement during routine clinical evaluation. Using data from electronic medical records, CVAI values were automatically generated from traditional indicators, and we utilized repeated measurement data at different time points to capture the dynamic cumulative changes. Thus, measures for implementing electronic medical record information management and popularizing personal dynamic monitoring devices will provide future directions for the primary prevention of

CMD. Importantly, considering that the lifetime CMD risk depends on early cumulative exposure to risk factors, identification of high-risk individuals and timely intervention to reduce cardiovascular symptoms and events have relevant practical implications.

The strengths of this study include: (1) The current study is comprised of the abundant, credible medical data of CHARLS, and the prospective nationwide cohort has extended follow-up. Moreover, the CHARLS study adopted a standardized protocol for multiple potential confounders, including anthropometric measurements, lifestyle behaviors, and laboratory indicators, to ensure the quality of data collection; (2) The use of a scientific machine learning method (K-means clustering) to explore the relationship between changes in CVAI and CMD, instead of baseline CVAI, which could represent the longstanding status of IR. To the best of our knowledge, this was the first study to undertake such an assessment; (3) We adjusted for underlying confounding factors in analyses where possible and conducted subgroup and sensitivity analyses to control for bias to guarantee the robustness of the results; 4) We have provided new evidence for the primary prevention of CMD, with an expectation of lowering the incident rate of CMD via early recognition and intervention in populations with high CVAI exposure.

However, this study also had limitations: (1) Akin to challenges encountered in similar studies, some CMD diagnoses were based on self-reports from participants, which may underestimate the actual prevalence and also cannot distinguish specific types of heart disease. The CHARLS lacked medical records, precluding the validation of these self-reported CMD cases, highlighting a gap that future large-scale, randomized controlled trials could aim to fill; (2) Despite efforts to encompass a wide range of potential confounders, other relevant factors, such as environmental changes and genetic susceptibility, were not considered owing to the limitations of the study design; (3) Due to the expansive scale of the cohort and budgetary constraints, MRI and CT scans—the gold standards for visceral fat assessment—were not employed to verify coherence with the actual amount of visceral fat and the cumulative CVAI values; (4) The study subjects were middle-aged and elderly Chinese individuals, and the conclusions may mainly apply to East Asian populations, with applicability to people under 45 years of age still unclear; (5)Although this study found an independent positive relationship between CVAI and CMD and CMM, it did not further explore the conversion model between CMD and CMM and the prognosis of CMM patients, which will be the focus of subsequent research.

Conclusion

This nationwide prospective cohort study involving 3,243 Chinese adults aged 45 and above found that participants with higher baseline CVAI level and a change of elevating CVAI level may suffer an increased incidence of CMD, especially diabetes and stroke, but not heart disease. Furthermore, our findings elucidated the underlying mechanisms of the CVAI by highlighting TG as the primary contributor to the observed associations. This study highlighted the importance of long-term CVAI monitoring for early identification and prevention of CMD, with significant implications for clinical practice. However, given the relatively small sample size of this study, more multicenter, large-sample cohort studies are needed in the future to further explore the relationship between CVAI and CMD.

Abbreviations

CVAI	Chinese visceral adiposity index
CMD	Cardiometabolic disease
CMM	Cardiometabolic multimorbidity
CHARLS	China health and retirement longitudinal study
IR	Insulin resistance
TG	Triglyceride
GLU	Glucose
BMI	Body mass index
RCS	Restricted cubic spline
SD	Standard deviation
OR	Odds ratio
CI	Confidence interval
SBP	Systolic blood pressure
DBP	Diastolic blood pressure
HbA1c	Glycosylated hemoglobin
TC	Total cholesterol
HDL-C	High-density lipoprotein cholesterol
LDL-C	Low-density lipoprotein cholesterol
CRP	C-reactive protein
UA	Uric acid
Cr	Creatinine
BUN	Blood urea nitrogen

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13098-024-01460-3.

Additional file 1: Figure S1: Elbow graph. Figure S2: Paired T-tests between $CVAI_{2012}$ and $CVAI_{2015}$. A: Box plots of paired T-tests between $CVAI_{2012}$ and $CVAI_{2015}$ for group Class 1. B: Box plots of paired T-tests between $CVAI_{2012}$ and $CVAI_{2015}$ for group Class 2. C: Box plots of paired T-tests between $CVAI_{2012}$ and $CVAI_{2015}$ for group Class 3. D: Box plots of paired T-tests between $CVAI_{2012}$ and $CVAI_{2015}$ for group Class 4. ns: no significance; ****: < 0.001. Figure S3: The data distribution within groups Class 1-4 of CVAI. A: Histograms and probability density plots of $CVAI_{2012}$ for groups Class 1-4, illustrating the data distribution within these groups. B: Histograms and probability density plots of $CVAI_{2015}$ for groups Class 1-4, illustrating the data distribution within these groups. Figure S4: A: Clustering diagrams for $CVAI_{2012}$ and $CVAI_{2015}$ with three cluster centers; B: Grouping diagram after k-means clustering; C: Histogram and probability density plot of cumulative CVAI in the overall population, illustrating the data distribution of cumulative CVAI; D: Histograms and probability density plots of cumulative CVAI for groups Class1-3, showing the data distribution of cumulative CVAI within these three groups.

Additional file 2: Table S1: Comparison of CMD between missing value groups and complete data groups. Table S2: Results of propensity matching analysis. Results are presented as Odds Ratios (OR) with 95% Confidence Intervals (CI). Abbreviations as in Table 2. Table S3: Associations Between Different Classes of the CVAI (3 Classes) and Incidence of CMD. Results are presented as Odds Ratios (OR) with 95% Confidence Intervals (CI). Abbreviations as in Table 2.

Acknowledgements
We would like to express our sincere gratitude to the China Health and Retirement Longitudinal Study (CHARLS) team for providing the data that made this research possible.

Author contributions
Xingjie Huang, Song Wen, Zehan Huang, and Yuqing Huang designed this study. Xingjie Huang, Xinjie Zhang, and Zehan Huang performed the statistical analysis. Song Wen, Xingjie Huang and Chang Dai wrote the manuscript. Shubo Chen, Bin Zhang, and Yuqing Huang revised the manuscript. All authors read and approved the final manuscript.

Funding
This study was supported by the following scientific research funds: (1) National Natural Science Foundation of China (82103910); (2) Guangdong Basic and Applied Basic Research Foundation-Provincial Enterprise Joint Fund (2022A1515220113), (3) Guangxi Natural Science Foundation (2022JJA140023); (4) Guangxi Medical and Healthcare Appropriate Technology Development and Popularization and Application Project (S2022146); (5) Guangxi Clinical Key Specialty Construction Project.

Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Ethical approval for CHARLS was granted by the Ethical Review Committee at the Peking University, including anthropometrics (IRB00001052-11015) and biomarker collection (IRB00001052-11014), with all participants providing informed consent.

Competing interests
The authors declare no competing interests.

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Received: 31 May 2024 Accepted: 29 August 2024
Published online: 14 September 2024

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