



BMJ Open Head-to-head comparison of visceral adiposity indices (A Body Shape Index and Visceral Adiposity Index) with traditional anthropometrics: a community-based strategy for cardiovascular risk prediction in urban China

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ABSTRACT

Objectives This study aimed to compare the predictive performance of novel adiposity indices (a body shape index (ABSI) and visceral adiposity index (VAI)) with traditional anthropometrics (body mass index (BMI), waist circumference (WC) and waist-to-height ratio (WHtR)) for cardiovascular disease (CVD) risk in urban China. Secondary objectives included evaluating composite indices derived from principal component analysis (PCA) and evaluating optimised risk stratification strategies.

Design A community-based cross-sectional study.

Setting Urban and rural communities in Nanjing, China, from 2020 to 2023.

Participants 38 427 adults aged 35–79 years, recruited via stratified sampling. Individuals aged <35 or >79 years, who were pregnant or had severe illness or cognitive impairment were excluded.

Primary and secondary outcome measures The primary outcome was a CVD high-risk status (defined by Chinese guidelines). Secondary outcomes included detection rates, area under the curve (AUC), ORs and multicollinearity diagnostics.

Results Among participants, 23.3% (n=8905) were classified as high risk for CVD. In this study, WHtR demonstrated the greatest discriminative power (AUC=0.826, 95% CI 0.819 to 0.832), followed by a PCA-derived composite obesity index (COI; AUC=0.822). ABSI showed a clear risk gradient, with a 38.5% detection rate in the high-risk group (ABSI≥0.085), and VAI exhibited a modest but statistically significant effect (OR=1.026, p=0.001). Severe multicollinearity among traditional indices (variance inflation factor >40) was mitigated by COI. Combined models (eg, COI+ABSI+VAI) achieved comparable AUC (0.825) with improved parsimony (AIC=17 4010.34). Age, hypertension and dyslipidaemia were key covariates (ORs=1.15–3.88, p<0.001).

Conclusions WHtR and composite indices (eg, COI) appeared to perform better than other indicators in predicting CVD risk, whereas ABSI and VAI enhance

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ The inclusion of a large community-based sample (n=38 427) enhanced statistical power and generalisability for urban Chinese populations.
- ⇒ Integration of traditional anthropometrics and novel indices (a body shape index/visceral adiposity index) with principal component analysis addressed multicollinearity and optimised risk stratification.
- ⇒ Standardised data collection protocols, including laboratory tests and physical measurements, ensured methodological rigour.
- ⇒ Cross-sectional design precludes causal inferences between adiposity indices and cardiovascular risk.
- ⇒ Self-reported lifestyle factors (eg, smoking and physical activity) may introduce recall bias.

stratification in specific subgroups. Implementing WHtR-based screening in primary care, supplemented by composite indices and novel markers for high-risk individuals, may help optimise prevention strategies in urbanising Chinese populations.

INTRODUCTION

Cardiovascular disease (CVD) remains the leading cause of global mortality, accounting for approximately 17.9 million deaths annually, with >40% occurring in China alone.^{1–3} The escalating prevalence of CVD has imposed substantial burdens on public health systems, particularly in rapidly urbanising regions like Nanjing, where sedentary lifestyles and dietary shifts exacerbate metabolic risk factors. Early prediction of CVD risk (CVD risk) is critical for implementing targeted interventions.^{4–6} However, conventional

anthropometric indices such as the *body mass index* (BMI) fail to distinguish between lean mass and visceral adiposity, whereas waist circumference (WC) and waist-to-height ratio (WHtR) neglect metabolic parameters. In contrast, the a body shape index (ABSI) and visceral adiposity index (VAI) integrate both anatomical and metabolic dimensions of obesity, potentially addressing these gaps.^{7,8}

Emerging evidence highlights the potential of ABSI and VAI to address these limitations. ABSI, derived from WC adjusted for height and weight, quantifies visceral fat geometry and correlates strongly with cardiovascular mortality independent of BMI. In contrast, VAI incorporates WC, BMI, triglycerides (TG) and *high-density lipoprotein cholesterol* (HDL-C) to reflect metabolic dysregulation, including insulin resistance and dyslipidaemia, thereby providing a holistic assessment of cardiometabolic risk.^{9–10} However, validation studies in Chinese populations are limited, and the incremental predictive value of these indices over traditional measures remains uncertain, particularly in Eastern China, where unique adiposity distribution patterns may influence risk assessment accuracy.^{11–13}

This study is based on the Social Determinants of Health Survey for Adult Chronic Disease Prevention and Control in Nanjing. This project is a key component of the ‘Nanjing Medium- and Long-Term Plan for Chronic Disease Prevention and Treatment (2018–2025)’.¹⁴ Led by the municipal and district Centres for Disease Control and Prevention and implemented by community health service centres, it aims to assess the prevalence and trends of chronic diseases and their associated influencing factors among adults in Nanjing. The findings are intended to provide a scientific basis for formulating and implementing targeted strategies and measures for chronic disease prevention and control and risk factor mitigation. The project, which began in 2020, is scheduled to conclude in 2025. To date, surveys have been conducted in five districts of Nanjing—Lishui, Pukou, Jianye, Gaochun and Jiangbei New Area—covering over 30 000 adults. A cohort biobank has been established based on this survey.

This study aimed to validate and compare the predictive performance of ABSI, VAI and traditional anthropometric indices (BMI, WC and WHtR) for CVDR in a community-based cohort from Nanjing, China, using receiver operating characteristic (ROC) analysis, multi-variable logistic regression and principal component analysis (PCA). We pursue three primary objectives: (1) to develop independent models quantifying the discriminative capacity of BMI, WC, WHtR, ABSI and VAI for identifying CVD events, (2) to evaluate their clinical utility in risk stratification and (3) to investigate whether their integration enhances prediction accuracy. Our findings will help assess and compare the performance of CVD screening indicators in Chinese populations.

METHODS

Study design and population

This community-based cross-sectional study used data from the Nanjing Adult Chronic Disease Prevention and Control Social Factors Survey, conducted from 2020 to 2025. Participants were recruited through stratified sampling (urban/rural×male/female) across Nanjing, and data collection involved questionnaire surveys, physical measurements and laboratory tests. The inclusion criteria were as follows:

1. Age 35–79 years (born between 1 January 1943 and 31 December 1986).
2. Permanent residents (residing in the study area for ≥6 months in the past year).
3. Enrolled in the National Basic Public Health Service program.

The exclusion criteria were as follows: (1) age <35 or >79 years and (2) pregnancy, cognitive impairment, severe illness or disability.

Sample size calculation

The sample size was calculated using a stratified design (urban/rural×male/female, four strata) with the formula: $N = deff \frac{u^2 p(1-p)}{d^2}$

where the parameters were defined as follows: confidence level at 95% (two-tailed, corresponding to $u=1.96$), prevalence of the CVD high-risk population ($p=20\%$), design effect ($deff=3$) and relative error ($r=10\%$, $d=10\% \times 20\% = 2\%$). Based on these parameters, the sample size for each surveyed region was calculated and aggregated.

Sampling strategy

Stage 1: primary sampling units (PSUs)

Two primary urban areas and two non-primary urban areas were selected based on geographic distribution, socio-economic development levels and existing public health infrastructure.

Stage 2: secondary sampling units

All subdistricts/townships within selected PSUs were included to ensure full spatial coverage.

Stage 3: tertiary sampling units

Four neighbourhood/village committees per subdistrict/township were systematically sampled using fixed interval randomisation and predefined sampling frames.

Stage 4: quaternary sampling units

Each selected committee was subdivided into residential clusters (≥60 households/cluster). Two clusters were then randomly selected via simple random sampling without replacement and cluster-level probability weighting.

Stage 5: ultimate sampling units

Approximately 60 households are surveyed per cluster.

Data collection and handling of missing data

Given the large sample size and minimal missing values (<5%), direct deletion of incomplete cases will not compromise the validity of the results.

Data collection had three components:

1. Questionnaire survey: standardized interviews covered demographics (sex, age, occupation, education and income), lifestyle (smoking, alcohol consumption, physical activity and sleep), medical history, family history and healthcare use.
2. Physical measurements: height, weight, waist/hip/neck circumferences, blood pressure, heart rate, blood oxygen saturation and body fat percentage were measured using nationally certified instruments.
3. Laboratory tests: fasting blood glucose, haemoglobin A1c, homocysteine, lipid profiles (total cholesterol (TC), TG, HDL-C, low-density lipoprotein cholesterol (LDL-C)), renal function (uric acid, creatinine and urea nitrogen) and liver enzymes (alanine aminotransferase, aspartate aminotransferase and total bilirubin) were measured.

To minimise selection and measurement bias, all field investigators underwent standardised training before data collection. Training sessions included the following:

1. Protocol adherence: detailed instructions on anthropometric measurement techniques (eg, WC measurement at the midpoint between the iliac crest and lowest rib).
2. Instrument calibration: daily calibration of electronic scales, stadiometers and blood pressure monitors using certified reference materials.
3. Interviewer training: role-playing exercises to ensure consistent administration of questionnaires, with special emphasis on neutral phrasing for lifestyle-related questions (smoking/alcohol consumption).
4. Quality control: weekly random re-measurements (5% of participants) showed high intraclass correlation coefficients (ICC>0.95 for all anthropometrics).

Definition of variables

Outcome variable

A CVD high-risk status was defined per the Chinese Guidelines for Cardiovascular Risk Assessment and Management and Chinese Adult Dyslipidaemia Prevention Guidelines of 2016.^{15 16} Participants were classified as high-risk for CVD if they met at least one of the following criteria:

1. Documented history of CVD (including coronary artery disease, stroke or heart failure).
2. Fasting TC ≥ 7.2 mmol/L or LDL-C ≥ 4.9 mmol/L.
3. 10-year cardiovascular risk $\geq 10\%$ as per the China-PAR (prediction for atherosclerotic cardiovascular disease (ASCVD) Risk in China) risk prediction model.
4. 10-year absolute ischaemic CVD (ICVD) risk $\geq 10\%$ based on the Chinese ICVD risk assessment algorithm.

Exposure variables

Traditional indices

Body mass index

BMI=weight (kg) / height (m^2).

Stratification (WHO-adjusted criteria): underweight, BMI<18.5 kg/ m^2 ; normal weight, $18.5 \leq \text{BMI} < 24.0$ kg/ m^2 ;

overweight, $24.0 \leq \text{BMI} < 28.0$ kg/ m^2 ; obesity, BMI ≥ 28.0 kg/ m^2 and WHO criteria adapted for Chinese populations.

Waist circumference

Thresholds for central obesity: male, WC ≥ 85 cm; female, WC ≥ 80 cm.

Clinical significance: individuals with WC ≥ 85 cm (male) or ≥ 80 cm (female) exhibit 1.8-fold increased 10-year CVDR and 2.5-fold higher incidence of diabetes.

Waist-to-height ratio

WHtR=WC (cm)/height(m^2).

Threshold: WHtR ≥ 0.5 (WC \geq half of height).

Significance: universally recognised as the threshold for central obesity and high CVDR owing to its simplicity and strong predictive power. Validated in Chinese populations, with WHtR ≥ 0.5 remaining the primary cut-off.

Novel indices

A body shape index

$$ABSI = \frac{WC}{BMI^{2/3} \times height^{1/2}} \text{ (quantifies visceral fat geometry)}$$

Risk stratification based on ABSI

Low risk (ABSI < 0.075): even visceral fat distribution, associated with lower all-cause mortality risk and CVDR.

Intermediate risk (0.075 \leq ABSI < 0.085): gradual increase in risk; intervention strategies should be evaluated in conjunction with additional metabolic indicators (eg, lipid profiles and blood pressure).

High risk (ABSI ≥ 0.085): significant visceral fat accumulation, linked to a 1.5–2.1-fold increase in all-cause mortality risk and a 1.3-fold elevation in CVDR.

Visceral adiposity index

Sex-specific formula integrating WC, BMI, TG and HDL-C, VAI reflects metabolic dysregulation:

$$\text{Males: VAI} = \left(\frac{WC}{39.68 + (1.88 \times BMI)} \right) \times \left(\frac{TG}{1.03} \right) \times \left(\frac{1.31}{HDL-C} \right)$$

$$\text{Females: VAI} = \left(\frac{WC}{36.58 + (1.89 \times BMI)} \right) \times \left(\frac{TG}{0.81} \right) \times \left(\frac{1.52}{HDL-C} \right)$$

Risk stratification based on the visceral adiposity index

Lower risk (males<2.0/females<1.5): indicates minimal visceral adiposity-related metabolic risk.

Intermediate risk (males 2.0–2.5/females 1.5–2.0): suggests moderate metabolic dysregulation; clinical monitoring and lifestyle interventions are recommended.

Higher risk (males ≥ 2.5 /females ≥ 2.0): reflects significant visceral adiposity and high cardiometabolic risk, warranting aggressive preventive measures.

Covariates

Covariates included age, sex, education, marital status, occupation category, smoking status, alcohol consumption, physical activity level, sleep duration, hypertension, diabetes mellitus and dyslipidaemia (definitions and categories are detailed in online supplemental table S1).

Statistical analysis

The statistical analyses were conducted using IBM SPSS Statistics for Windows, version 25 (IBM Corp., Armonk, NY, USA). Descriptive statistics were reported as mean \pm SD for continuous variables and frequencies (%) for categorical variables. Comparative analyses employed Student's t-test, χ^2 test or Fisher's exact test, as appropriate. Predictive performance was evaluated using receiver operating characteristic (ROC) curves. Area under the curve (AUC) differences between models were assessed using DeLong's test, and net reclassification improvement and integrated discrimination improvement quantified incremental predictive value. Multivariable logistic regression models adjusted for covariates (eg, age, sex and lifestyle factors) estimated ORs with 95% CIs.^{17–19} To address the severe multicollinearity identified among traditional anthropometric indices (BMI, WC and WHtR), principal component analysis (PCA) was employed. The first principal component (PC1) derived from this analysis, which captured the shared variance of these correlated measures, was used to create a composite obesity index (COI) for subsequent modelling. Multicollinearity was diagnosed using variance inflation factors (VIFs) and tolerance. PCA was performed to address multicollinearity among BMI, WC and WHtR, using eigenvalues >1 to retain components. Model performance was assessed using the AUC, Akaike information criterion (AIC)/Bayesian information criterion (BIC), and the Hosmer–Lemeshow (HL) test. Statistical significance was set at $p<0.05$ (two-tailed).^{20–23}

Patient and public involvement

Patients and/or the public were not involved in the design, conduct, reporting or dissemination plans of this study. All participants provided written informed consent.

Ethics approval

Ethical approval was obtained from the Nanjing CDC Ethics Committee (PJ2020-B001-01). The study complied with the Declaration of Helsinki. All participants signed the informed consent form.

RESULTS

Baseline characteristics of participants

A total of 38848 participants were initially surveyed. After excluding 421 individuals (1.08% of the initial sample) with incomplete anthropometric or laboratory data, a final sample of 38427 participants was included in the analysis and underwent complete anthropometric and laboratory assessments. Among 38427 participants, 8905 (23.3%) were classified as high risk for CVD based on predefined criteria (see Methods). Males exhibited a higher CVD high-risk detection rate (27.3%) than females (19.5%, $p<0.001$), and individuals aged ≥ 60 years had a significantly higher detection rate (48.7%) than those aged 35–59 years (10.5%, $p<0.001$). Education level also played a role, with individuals having primary education or below showing a higher

detection rate (30.6%) than those with higher education levels (11.4%, $p<0.001$). Smoking status further influenced CVDR, with former smokers having the highest detection rate (41.2%), followed by current smokers (27.1%) and non-smokers (20.7%, $p<0.001$). Gender differences, age, education level, and smoking status all showed statistically significant associations with cardiovascular disease risk.

ABSI, VAI and traditional anthropometric indices (BMI, WC and WHtR) exhibited distinct detection rates in screening CVD high-risk populations. ABSI demonstrated a clear gradient in risk stratification, with the high-risk group ($\text{ABSI} \geq 0.085$) showing a 38.5% detection rate, significantly higher than the low-risk group (12.7%, $p<0.001$). Similarly, VAI exhibited a 27.0% high-risk detection rate ($\text{VAI} \geq 2.5$ for males/ ≥ 2.0 for females), outperforming BMI alone (34.6% for obesity vs 16.4% for normal weight). Traditional indices such as WHtR (≥ 0.5) and WC (males ≥ 85 cm/females ≥ 80 cm) also showed strong associations with CVDR, with detection rates of 28.3% and 28.1%, respectively. Detailed results are provided in online supplemental table S1.

Associations of anthropometric indices with cardiovascular disease risk

Multivariable logistic regression results revealed significant differences in the predictive capacity of various obesity indicators for CVDR. Among traditional indicators, both BMI (OR=1.107, 95% CI 1.093 to 1.121, $p<0.001$) and WC (OR=1.032, 95% CI 1.028 to 1.037, $p<0.001$) showed stable positive associations, indicating a 10.7% and 3.2% increase in CVDR per unit increase in BMI or WC, respectively. The WHtR exhibited an exceptionally high OR (OR=262.75, 95% CI 120.84 to 571.34, $p<0.001$), but its wide CI suggested substantial uncertainty. For novel indicators, ABSI showed an extreme OR (OR=21.9, 95% CI 0.005 to 88 158.161, $p>0.05$), but the wide CI and non-significant p-value undermine its predictive utility. In contrast, VAI demonstrated modest yet robust significance (OR=1.026, 95% CI 1.011 to 1.042, $p=0.001$).

Covariate analysis identified age as the strongest risk factor across all models (OR \approx 1.15–1.16, $p<0.001$). Sex showed protective effects in WHtR and VAI models (OR=0.823 and 0.868, $p<0.05$). Daily smoking was associated with reduced risk (OR \approx 0.45, $p<0.001$), though confounding factors require further investigation. Hypertension, diabetes and dyslipidaemia consistently emerged as critical risk factors (OR \approx 3.5–3.8, 3.5–3.7, 2.45–2.5, $p<0.001$).

The HL test yielded $p<0.001$ for all models, suggesting potential systematic misfit. The HL test's sensitivity in large samples may reject the null hypothesis due to minor deviations, whereas key variables (eg, BMI, WC and VAI) showed robust ORs with narrow CIs, retaining clinical relevance (online supplemental table S2).

Assessment of multicollinearity

The multicollinearity diagnostics revealed severe collinearity among anthropometric indices: BMI (VIF=95.415),

Table 1 Pearson's correlation analysis between the obesity composite index and original variables with two-tailed p values

	PC1	BMI	WC	WHtR
PC1	1	.892*	.944*	.952*
		0	0	0
BMI	.892*	1	.738*	.761*
		0	0	0
WC	.944*	.738*	1	.888*
		0	0	0
WHtR	.952*	.761*	.888*	1
		0	0	0

Pearson correlation coefficients between the first principal component (PC1, forming the composite obesity index (COI)) and the original traditional anthropometric variables (BMI, WC and WHtR) in the study population (n=38 427). All correlations were strong, positive and statistically significant ($p<0.01$), indicating that PC1 effectively captures shared variance among these measures, with the strongest association for WHtR.

* Significant correlation at $\alpha = 0.01$ (two-tailed test)

BMI, body mass index; PC1, first principal component; WC, waist circumference; WHtR, waist-to-height-ratio.

WC (VIF=44.328), WHtR (VIF=44.607) and ABSI (VIF=52.415), all exceeding the critical threshold of VIF>10. In contrast, the VAI (VIF=1.241) demonstrated acceptable collinearity. The extreme VIF values for traditional indices compromise the stability of regression coefficients and the interpretability of their individual effects, necessitating immediate remediation to ensure valid comparisons between traditional and novel predictors (online supplemental table S3).

Derivation of a composite obesity index using principal component analysis

To mitigate multicollinearity, a COI was derived from PC1 of the PCA performed on the traditional indices (BMI, WC and WHtR). This COI demonstrated strong positive correlations with the original variables. The Pearson correlation coefficients between PC1 and these variables were 0.892, 0.944 and 0.952, respectively (all $p<0.01$). These results indicate that PC1 effectively synthesises the shared variance among the three obesity-related metrics, with WHtR showing the strongest association.^{24–26} The statistically significant correlations ($p<0.01$) confirm the robustness of the composite index in representing the underlying construct of obesity-related anthropometric measures. Collinearity analysis revealed no significant collinearity among the COI (VIF=1.308), VAI (VIF=1.239) and ABSI (VIF=1.193), supporting their inclusion in a joint model (table 1).

Predictive performance of single-indicator models

10 distinct logistic regression models were constructed to compare predictive performance. Models A–F used individual predictors, whereas models G–J combined multiple

Table 2 Composition of 10 cardiovascular risk prediction models (models A–J)

Model	Primary predictor(s)	Covariates included
A	Body mass index (BMI)	Yes
B	Waist circumference (WC)	Yes
C	Waist-to-height ratio (WHtR)	Yes
D	Composite obesity index (COI)*	Yes
E	Visceral adiposity index (VAI)	Yes
F	A body shape index (ABSI)	Yes
G	COI+VAI + ABSI	Yes
H	COI+VAI	Yes
I	COI+ABSI	Yes
J	VAI+ABSI	Yes

Composition of the 10 cardiovascular disease risk prediction models (models A–J) developed and compared. Lists each model's primary predictor(s) (individual indices or combinations) and notes that all models are adjusted for the same set of covariates (age, sex, lifestyle factors and comorbidities)

*The index derived from principal component analysis of BMI, WC and WHtR.

predictors (table 2). Model performance was systematically evaluated using AUC (discriminatory power), AIC/BIC (model parsimony) and likelihood ratio tests (incremental predictive contribution). Sensitivity analyses stratified by age and sex confirmed robustness. This approach not only resolves collinearity but also establishes a methodological framework for objective comparison of adiposity metrics.

When comparing the predictive performance of BMI, WC, WHtR, COI, VAI and ABSI for CVDR, the results showed the following:

- 1. Discriminative ability (AUC):** WHtR demonstrated the highest AUC (0.826, 95% CI 0.819 to 0.832), followed by the COI (0.822, 95% CI 0.816 to 0.829) and CM (0.821, 95% CI 0.815 to 0.828), whereas BMI (0.819, 95% CI 0.812 to 0.826) and ABSI (0.821, 95% CI 0.815 to 0.828) showed comparable performance. VAI had the lowest AUC (0.817, 95% CI 0.81 to 0.824). All models achieved AUCs>0.8, indicating strong discriminative power for CVDR prediction. Notably, WHtR and COI outperformed other metrics, suggesting their clinical utility in risk stratification.^{27–30}
- 2. Model parsimony (AIC/BIC) and effect size (OR):** model parsimony, assessed via AIC/BIC, further supported WHtR's advantage (AIC=17 3480.12; BIC=17 5240.03), with the COI ranking second. Notably, WHtR (OR=838.891, 95% CI 411.246 to 1711.232) exhibited a very large, although statistically significant, effect size, which may limit its clinical interpretability. In contrast, the COI (OR=1.349, 95% CI 1.129 to 1.605) demonstrated a more moderate and clinically meaningful effect size while maintaining strong discrimination (AUC=0.822) and excellent calibration

Table 3 Single-predictor model evaluation via logistic regression and ROC analysis

Model	Predictors	AUC (95% CI)	AIC	BIC	OR (95% CI)	P value	Hosmer–Lemeshow test	
							χ^2	P value
A	BMI	0.819 (0.812 to 0.826)	17 616.44	17 792.35	1.054 (1.042 to 1.066)	<0.001	9.803	0.279
B	WC	0.821 (0.815 to 0.828)	17 520.49	17 696.40	1.03 (1.026 to 1.035)	<0.001	13.016	0.111
C	WHtR	0.826 (0.819 to 0.832)	17 348.12	17 524.03	838.891 (411.246 to 1711.232)	<0.001	14.789	0.063
D	COI	0.822 (0.816 to 0.829)	17 482.29	17 658.20	1.349 (1.296 to 1.405)	<0.001	14.708	0.065
E	VAI	0.817 (0.81 to 0.824)	17 699.81	17 875.72	0.999 (0.986 to 1.013)	0.931	23.346	0.003
F	ABSI	0.821 (0.815 to 0.828)	17 533.00	17 708.91	2.22×10 ²⁴ (1.20×10 ¹⁸ to 40.11×10 ²⁴)	<0.001	19.879	0.011

Performance evaluation of single-predictor logistic regression models for CVD risk prediction. Reports area under the curve (AUC), Akaike/Bayesian information criterion (AIC/BIC), OR with 95% CI, p value, and Hosmer–Lemeshow goodness-of-fit test results for each model (BMI, WC, WHtR, COI, VAI and ABSI). WHtR showed the highest AUC (0.826).

ABSI, a body shape index; AIC, Akaike information criterion; BIC, Bayesian information criterion; BMI, body mass index; COI, composite obesity index; CVD, cardiovascular disease; VAI, visceral adiposity index; WC, waist circumference; WHtR, waist-to-height ratio.

(HL test, $p=0.065$). Effect sizes for BMI (OR=1.054), WC (OR=1.03) and COI (OR=1.349) were statistically significant ($p<0.001$), with 95% CIs excluding 1. Although WHtR and ABSI showed implausibly high ORs (838.891 and 2.22×10^{24} , respectively), their wide CIs and preserved AUCs indicated that extreme values did not compromise discriminative performance.

3. **Calibration:** this was acceptable for BMI, WC, WHtR and COI (HL test, $p>0.05$) but poor for VAI and ABSI ($p<0.05$).

These findings underscore WHtR and COI as optimal tools for CVDR prediction, whereas VAI and ABSI require further validation (table 3).

Predictive performance of combined-indicator models

The predictive performance of four models (model G–J) for CVDR was evaluated based on AUC, AIC, BIC and the HL test. Model G demonstrated the highest AUC (0.825, 95% CI 0.818 to 0.831), followed by models I (0.824, 0.818 to 0.831), H (0.822, 0.816 to 0.829) and J (0.821, 0.815 to 0.828). Lower AIC and BIC values further supported the superiority of model G (AIC=17401.34, BIC=17577.25). Notably, model G achieved comparable discriminative accuracy to the best single-indicator model (WHtR; AUC=0.826) but with fewer parameters (AIC=174010.34 vs . 17348.12), demonstrating superior parsimony. The HL test indicated adequate calibration

for models G ($\chi^2=14.961$, $p=0.06$) and I ($\chi^2=11.831$, $p=0.159$), whereas model J showed poor calibration ($\chi^2=20.898$, $p=0.007$). For model G, the borderline significance ($p=0.06$) marginally exceeded the conventional threshold ($\alpha=0.05$), suggesting minor deviations unlikely to compromise clinical utility. Notably, despite calibration issues in model J, its AUC remained comparable to others, suggesting that calibration anomalies minimally affected discriminative ability. Extreme OR values (eg, ABSI OR= 2.22×10^{24}) likely stem from collinearity or scaling artefacts; however, discriminative performance (AUC) remained robust, as AUC prioritises ranking over absolute risk estimation. Thus, the ranking based on AUC remains robust, and all models retain practical utility for CVDR prediction (table 4).

Comparison of all prediction models

The comprehensive analysis of 10 models for CVDR prediction highlights nuanced differences in performance. Among single-indicator models, model C retained the highest discriminative ability (AUC=0.826, 95% CI 0.819 to 0.832), marginally outperforming even the best combined model (model G, AUC=0.825, 95% CI 0.818 to 0.831). However, model G exhibited superior parsimony (AIC=174010.34, BIC=175770.25) compared with model C (AIC=173480.12, BIC=175240.03), suggesting that the

Table 4 Combined predictor model evaluation via logistic regression and ROC analysis

Mode	Predictors	AUC (95% CI)	AIC	BIC	Hosmer–Lemeshow test	
					χ^2	P value
G	COI+VAI + ABSI	0.825 (0.818 to 0.831)	17 401.34	17 577.25	14.961	0.06
H	COI+VAI	0.822 (0.816 to 0.829)	17 485.11	17 661.02	15.61	0.048
I	COI+ABSI	0.824 (0.818 to 0.831)	17 405.64	17 581.55	11.831	0.159
J	VAI+ABSI	0.821 (0.815 to 0.828)	17 535.13	17 703.05	20.898	0.007

Performance evaluation of combined-predictor logistic regression models for CVD risk prediction. Reports AUC, AIC, BIC and Hosmer–Lemeshow test results for models combining COI, VAI and/or ABSI. Model G (COI+VAI+ABSI) achieved the highest AUC (0.825) and good parsimony (low AIC/BIC), with adequate calibration.

ABSI, a body shape index; AIC, Akaike information criterion; AUC, area under the curve; BIC, Bayesian information criterion; COI, composite obesity index; CVD, cardiovascular disease ; VAI, visceral adiposity index.

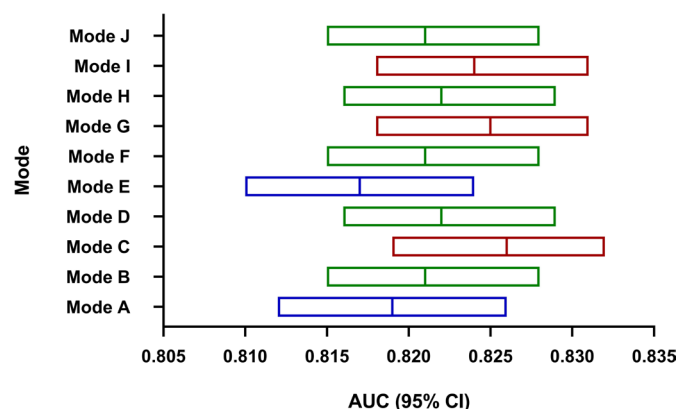


Figure 1 Forest plot illustrating the area under the curve (AUC) and 95% CI of 10 cardiovascular risk prediction models (models A–J). Model definitions are provided in [table 2](#). The highest value was observed in model C (WHtR-based).

combined model achieved comparable predictive power with fewer parameters. Notably, model I closely followed model G (AUC=0.824), further emphasising the added value of integrating composite obesity indices with ABSI.

Among combined models, model J showed the lowest performance (AUC=0.821), likely due to poor calibration (HL test, $p=0.007$) and instability from extreme ORs (eg, ABSI OR=2.22 $\times 10^{24}$). Despite these anomalies, the discriminative capacity (AUC>0.8 across all models) remained robust, underscoring the utility of multi-indicator approaches. Although single-indicator models like WHtR excel in AUC, their clinical applicability is limited by implausible effect sizes (eg, WHtR OR=838.891), whereas combined models balance interpretability and reliability. Thus, among the models tested, model G appeared to be the most balanced or preferable choice for CVDR prediction, integrating accuracy, parsimony and clinical feasibility ([table 3](#), [table 4](#), [figure 1](#)).

DISCUSSION

Principal findings and comparison with previous studies

This large community-based study provides a head-to-head comparison of novel visceral adiposity indices (ABSI and VAI) against traditional anthropometric measures for predicting CVDR in an urban Chinese population. Our key findings demonstrate that while both traditional and novel indices showed significant associations, the WHtR exhibited the highest discriminative power (AUC=0.826). The PCA-derived COI also performed strongly (AUC=0.822) and effectively addressed multicollinearity among traditional measures. The novel indices ABSI and VAI provided valuable additional stratification, with ABSI showing a clear risk gradient (38.5% detection rate in the high-risk group) and VAI contributing unique metabolic information in adjusted models. Combination models incorporating COI, ABSI and VAI achieved comparable predictive accuracy to WHtR alone but with enhanced parsimony.^{31–34}

Our results corroborate prior evidence and extend it to an urban Chinese population by demonstrating that ABSI and VAI capture distinct dimensions of cardiometabolic risk. ABSI, which quantifies visceral fat geometry, exhibited a pronounced risk gradient, with the high-risk group (ABSI ≥ 0.085) showing a 38.5% CVDR detection rate—approximately three times higher than the low-risk group (12.7%). This aligns with its proposed role in identifying individuals with normal BMI but high visceral adiposity, a subgroup often overlooked by conventional metrics.^{35–37} Similarly, VAI, integrating lipid profiles and insulin resistance markers, outperformed BMI alone (AUC=0.817 vs 0.819), underscoring its utility in reflecting metabolic dysregulation independent of body mass. These findings address critical gaps highlighted in the systematic review by Liu et al. (2025), which emphasise the need for region-specific adiposity indices in populations with unique fat distribution patterns, such as Eastern China. By validating ABSI and VAI in a Chinese cohort, this study helps address a key knowledge gap and provides evidence that may help reduce the over-reliance on BMI-centric paradigms in CVDR assessment.^{38–40}

Implications for public health and clinical practice

The high prevalence of CVD high-risk individuals (23.3%) in Nanjing underscores the urgency of refining screening tools. Our data suggest that WHtR (AUC=0.826) and the PCA-derived COI (AUC=0.822) outperform traditional metrics like BMI and WC, supporting their adoption in clinical workflows. The simplicity and strong predictive power of WHtR (OR=838.89, $p<0.001$; per 0.1-unit increase) make it particularly suitable for resource-limited settings, where rapid risk stratification is critical. Furthermore, the integration of ABSI and VAI into multi-indicator models (eg, model G: AUC=0.825) enhances discriminative accuracy without compromising parsimony (AIC=17 4010.34), offering a pragmatic solution for urban clinics burdened by high patient volumes.^{41–43} For rural areas, where metabolic testing infrastructure may be lacking, WHtR and ABSI could serve as cost-effective first-line tools to identify high-risk individuals requiring further biochemical evaluation.

Methodological challenges and interpretation of findings

The severe multicollinearity among traditional indices (VIF>40 for BMI and WC) highlights the limitations of using these metrics in isolation. Our PCA approach mitigated this issue, demonstrating that composite indices retain predictive validity while reducing redundancy—a methodological advancement aligned with recommendations in previous studies. However, the implausibly high ORs for WHtR and ABSI (eg, 2.22 $\times 10^{24}$) necessitate caution in interpreting effect sizes, likely reflecting collinearity or scaling artefacts rather than true biological associations. Conversely, in multivariable-adjusted models, VAI demonstrated a modest yet robust association with CVD risk (OR=1.026, 95% CI 1.011 to 1.042; $p=0.001$), suggesting its unique ability to capture

metabolic dysregulation independent of traditional adiposity measures.⁴⁴ However, this significance was not observed in univariate analysis (OR=0.999, $p=0.931$), indicating that VAI's predictive value is contingent on adjustment for covariates such as age and hypertension. This aligns with its design as a composite index integrating lipid profiles and anthropometrics, which may require contextual interpretation within multifactorial risk models, particularly in younger populations with subclinical dyslipidaemia.

An intriguing finding from our multivariate models was the modest positive association between higher physical activity levels and increased CVDR (OR≈1.12–1.13). This counterintuitive result may be attributed to potential misclassification or reverse causality. Misclassification could arise from the use of self-reported physical activity data in our study, where participants might overestimate their activity levels or inaccurately recall intensity and duration, leading to non-differential misclassification that biases effect estimates. Alternatively, reverse causality is plausible, whereby individuals with pre-existing subclinical conditions or higher perceived risk might have been advised to, or intentionally, increased their physical activity levels. Consequently, the observed association may not reflect a true causative increase in risk due to activity itself but the behaviour pattern of a subgroup already at high risk. Future studies employing objective measures of physical activity (eg, accelerometers) are needed to clarify this relationship.^{45 46}

Limitations and future research directions

Limitations

Although this study benefits from a large, well-characterised community-based sample, several limitations must be considered when interpreting the findings. First, the cross-sectional design precludes the establishment of causal inferences between the adiposity indices and CVD outcomes; it only identifies associations. Second, the reliance on self-reported data for lifestyle factors (eg, smoking, physical activity and diet) is susceptible to recall and social desirability bias, potentially leading to misclassification. Third, the generalisability of our findings may be limited to urban and peri-urban populations in Eastern China, as participants were recruited solely from Nanjing, and regional variations in diet, genetics and lifestyle could influence adiposity patterns and risk associations. Fourth, although PCA was employed to address multicollinearity, the extreme and implausible ORs observed for WHtR and ABSI (eg, 2.22×10^{24}) suggest potential model instability or overfitting, underscoring a challenge in the direct clinical interpretation of these particular results. Finally, while novel, ABSI and VAI are derived from formulas and thresholds primarily validated in Western populations; their optimal cut-off points for risk stratification in Chinese adults may require further refinement.

Future research directions

Prospective cohort studies are urgently needed to validate the temporal relationship between these indices and the actual incidence of hard CVD endpoints (eg, myocardial infarction and stroke), which would strengthen causal inference. Future work should also prioritise the use of objective measures (eg, accelerometers for physical activity and biomarkers for dietary intake) to minimise measurement bias from self-reporting. Research should expand to include more diverse geographical regions and ethnic groups within China to assess the external validity and potential need for region-specific adaptations of these indices. The extreme effect sizes observed necessitate external validation in independent cohorts to determine their reproducibility and explore alternative modelling strategies that yield more clinically interpretable parameter estimates. Finally, cost-effectiveness analyses are crucial next steps to evaluate the feasibility and impact of implementing WHtR-based screening, supplemented by novel indices for high-risk individuals, within the framework of China's primary healthcare system.

CONCLUSION

This study establishes WHtR and COIs as superior predictors of CVDR in Nanjing, while affirming the incremental value of ABSI and VAI in capturing visceral and metabolic risks. By addressing the limitations of traditional metrics and providing actionable screening strategies, our findings pave the way for tailored CVD prevention policies in China's urbanising regions. Public health initiatives should prioritise WHtR-based screenings in primary care, supplemented by ABSI/VAI assessments for high-risk subgroups, to mitigate the growing burden of cardiovascular morbidity.

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in topic analysis and discussions under the leadership and instruction of XH. All authors read and approved the final manuscript. XH and KL are co-corresponding authors and contributed equally to supervising the work. They are both responsible for all communications regarding the manuscript. XH is the guarantor. Deepseek software was used to conduct language and textual fluency checks on the manuscript.

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