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Qiqi Yang

Xijing Hospital, Air Force Medical University

Zhihui Lyu

Xijing Hospital, Air Force Medical University

Min Liu

Xijing Hospital, Air Force Medical University

Fanya Gao

Xijing Hospital, Air Force Medical University

yuan meng

Xijing Hospital, Air Force Medical University

yangfan gong

Xijing Hospital, Air Force Medical University

Xiaole He

Xijing Hospital, Air Force Medical University

Wei Ge

geweidr@fmmu.edu.cn

Xijing Hospital, Air Force Medical University

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Beyond BMI: Chinese Visceral Adiposity Index (CVAI) improves machine learning prediction of 9-year cardiometabolic multimorbidity in the CHARLS cohort

Yang Qiqi^{1#}, Lyu Zhihui^{1#}, Liu Min¹, Gao Fanya¹, Meng Yuan¹, Gong Yangfan², He Xiaole¹, Ge Wei^{1*}

¹ Department of General Practice, Xijing Hospital, Air Force Medical University, Xi'an 710032, China

[#] The two authors contributed equally to this article

Corresponding author: Wei Ge*, MD, Professor, Chief Physician, Director of the Department of General Practice, Xijing Hospital, Air Force Medical University. Email: geweidr@fmmu.edu.cn

Contributing authors: 741704938@qq.com, 825289986@qq.com

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Abstract

Background: Driven by rapid population aging and evolving lifestyle patterns across China, middle-aged and older individuals are at substantially elevated risk of cardiovascular disease (CVD) and diabetes mellitus (DM). The two disorders often co-occur and share metabolic risk determinants, collectively termed cardiometabolic multimorbidity (CMM). However, systematic predictive research targeting the composite endpoint of CMM remains relatively limited.

Methods: Based on data from the China Health and Retirement Longitudinal Study (CHARLS) spanning 2011 to 2020, three separate cohorts were established for DM (n=7,903), CVD (n=9,997), and CMM (n=9,490). Four machine learning algorithms, namely logistic regression, random forest, XGBoost, and LightGBM, were applied to develop 9-year risk prediction models. Model performance was evaluated using AUC, calibration curves, and Brier score, and decision curve analysis, with SHAP analysis applied for model interpretability.

Results: The 9-year cumulative incidence rates of DM, CVD and CMM were 11.8%, 22.7% and 28.9%, respectively. DM models achieved the best performance (AUC 0.703 - 0.715), with XGBoost reaching the highest AUC (0.715). CVD prediction proved the most challenging (AUC 0.604 - 0.630), with Logistic Regression performing best (0.630). CMM models showed intermediate performance (AUC 0.621 - 0.629), with XGBoost achieving the highest AUC (0.629). SHAP analysis revealed that glycemic and obesity-related indices were key predictors for DM; age and blood pressure parameters dominated CVD prediction; and the Chinese Visceral Adiposity Index (CVAI) together with depressive symptoms (CESD) emerged as the top predictors for CMM. Simplified scorecards retained most predictive performance for DM (AUC 0.681) and CMM (AUC 0.625) but failed for CVD (AUC 0.436).

Conclusions: DM was predicted with the highest accuracy using routine clinical data, while CVD prediction remained suboptimal, suggesting that novel biomarkers or imaging are needed. The composite CMM endpoint showed intermediate predictability, with CVAI and depressive symptoms as key predictors, underscoring the roles of visceral adiposity and mental health. Simplified scorecards offer practical tools for DM and CMM screening in primary care, but their failure for CVD highlights the inherent complexity of cardiovascular risk stratification.

Keywords: Cardiometabolic multimorbidity(CMM); Diabetes mellitus; Cardiovascular disease; Machine learning; CHARLS; Risk prediction

1.Introduction

Cardiovascular disease (CVD) is one of the leading causes of disability and mortality worldwide, posing a particularly serious threat to the middle-aged and elderly population in China [1, 2]. Meanwhile, the prevalence of diabetes mellitus (DM) is continuously increasing, and the two conditions frequently co-exist, forming cardiometabolic multimorbidity (CMM) [3, 4]. Against the backdrop of population ageing, CMM has become a major public health challenge globally, including in China [2, 5, 6].

Early identification of high-risk individuals and implementation of effective interventions are key strategies to reduce the incidence and disease burden of DM and CVD [7, 8]. However, traditional cardiovascular risk prediction tools, such as the Framingham Risk Score, are constructed using conventional statistical methods that typically assume linear associations between risk factors and outcomes and are limited in the number of variables, making it difficult to comprehensively capture non-linear and high-dimensional interactions among multidimensional factors [9–11]. Moreover, most previous prediction studies have focused on either DM or CVD as a single outcome, and systematic predictive research targeting the composite endpoint of CMM remains relatively limited.

Obesity, especially visceral adipose tissue accumulation, is a core driver of CMM. Although CT and MRI are the gold standards for quantifying visceral adipose tissue (VAT), their high cost and operational complexity limit their application in large-scale population screening [12, 13]. In recent years, the Chinese Visceral Adiposity Index (CVAI), a composite surrogate index calibrated for the Han Chinese population, integrates age, BMI, waist circumference, and lipid parameters, and has demonstrated good performance in identifying insulin resistance, metabolic syndrome, and cardiovascular event risk [14–16].

In recent years, machine learning (ML) methods have shown significant advantages in disease risk prediction by efficiently processing high-dimensional data and automatically capturing non-linear relationships among variables [11, 17]. Based on this, the present study utilized five waves of data from the China Health and Retirement Longitudinal Study (CHARLS) spanning 2011 to 2020 to develop 9-year risk prediction models for DM, CVD, and their composite endpoint CMM, respectively, and systematically compared the predictive performance, key risk factors, and clinical utility across the three sets of models. This study aims to provide scientific evidence for early risk screening and stratified management of cardiometabolic multimorbidity among middle-aged and older adults.

2. Methods

2.1 Study design and data source

This study utilized data from the China Health and Retirement Longitudinal Study, a nationally

representative longitudinal survey of the Chinese population aged 45 years and older. The CHARLS baseline survey was conducted in 2011 - 2012 across 28 provinces, 150 counties/districts, and 450 villages/urban communities, using a multistage probability-proportional-to-size sampling strategy with implicit stratification by region, urban/rural status, and gross domestic product per capita. A total of 10,257 households and 17,708 respondents were enrolled at baseline, with an overall response rate of 80.5% (94.2% in rural areas and 68.6% in urban areas) [18]. For this study, we used baseline data from wave 1 (2011 - 2012) and outcome data from waves 3 through 5 (2015, 2018, and 2020), providing a maximum follow-up duration of 9 years. The CHARLS study was approved by the Biomedical Ethics Review Committee of Peking University (IRB approval number: IRB00001052-11015). The data are publicly available at the CHARLS website (<https://charls.pku.edu.cn>) [18, 19].

2.2 Study population and inclusion/ exclusion criteria

We established three separate cohorts according to the outcome of interest: diabetes mellitus, cardiovascular disease, and cardiometabolic multimorbidity. The common inclusion criteria for all three cohorts were: (1) age ≥ 45 years at baseline; (2) complete data on core variables including BMI, and waist circumference; (3) clear outcome records during follow-up; and (4) missing rate for key variables $< 20\%$.

The exclusion criteria varied by cohort. For the DM cohort, we excluded participants with prevalent diabetes at baseline (defined as self-reported diabetes, fasting glucose ≥ 7.0 mmol/L, HbA1c $\geq 6.5\%$, or use of glucose-lowering medications). For the CVD cohort, we excluded participants with prevalent heart disease or stroke at baseline. For the CMM cohort, we excluded participants with either prevalent diabetes or prevalent CVD at baseline. Additionally, participants who were completely lost to follow-up or had extreme BMI values (< 15 or > 60 kg/m²) were excluded from all three cohorts. After applying these criteria, the final analytic samples comprised 7,903 participants for the DM cohort, 9,997 for the CVD cohort, and 9,490 for the CMM cohort.

The detailed participant selection process is illustrated in Figure 1.

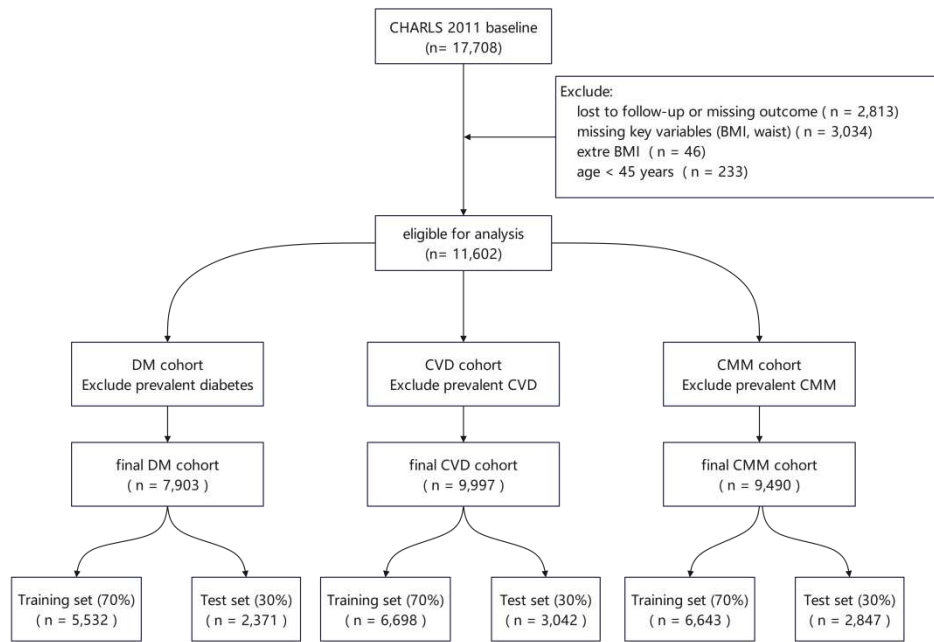


Figure 1. Study participant selection flowchart.

CHARLS, China Health and Retirement Longitudinal Study; DM, diabetes mellitus; CVD, cardiovascular disease; CMM, cardiometabolic multimorbidity (composite of DM or CVD). The final analytic cohorts were derived after applying cohort-specific exclusion criteria and randomly split into training and test sets at a 7:3 ratio using stratified sampling.

2.3 Outcome definitions

DM was defined as meeting any of the following criteria during follow-up: (1) fasting glucose ≥ 7.0 mmol/L; (2) glycated hemoglobin (HbA1c) $\geq 6.5\%$; (3) physician diagnosis of diabetes.

CVD was defined as a physician diagnosis of heart disease (including coronary heart disease, angina, heart failure, or other heart problems) or stroke during follow-up.

cardiometabolic multimorbidity (CMM) was defined as the first occurrence of either DM or CVD during the 9-year follow-up period.

2.4 Predictor variables

A total of 23 baseline variables were initially considered across four domains: sociodemographic factors, lifestyle factors, anthropometric and physiological measures, and metabolic/biochemical indicators. Additionally, several composite indices were calculated, including TyG index [20], CVAI [14], Lipid Accumulation Product (LAP), BRI [21], TyG-BMI, TyG-WC, Atherogenic

Index of Plasma (AIP), and Skeletal Muscle Index (SMI).

2.5 Data preprocessing

Missing values in continuous variables with a missing rate < 20% were handled using multiple imputation by chained equations (MICE) [22]. Categorical variables with missing rates < 30% were treated with "missing" as a separate category. The data were randomly split into training and test sets in a 7:3 ratio using stratified sampling to maintain consistent outcome proportions across both sets.

2.6 Feature selection

Feature selection was performed using a Random Forest-based SelectFromModel approach with a median importance threshold. This procedure was applied independently to the training sets of the three cohorts, retaining 16 features for each cohort.

The complete lists of selected features are provided in Supplementary Table S2.

2.7 Machine learning model development

Four supervised machine learning algorithms were employed for model construction: Logistic Regression (LR), Random Forest (RF) [23], XGBoost (XGB) [24], and LightGBM (LGB) [25]. All models were trained on the training sets and evaluated on the independent test sets. Hyperparameters for each model were optimized using 5-fold stratified cross-validation combined with grid search.

2.8 Model evaluation and performance metrics

Model performance was evaluated on the test sets using AUC (with 95% CI via bootstrap), sensitivity, specificity, Brier score, and calibration curves. SHAP analysis was applied to the best-performing models for interpretability, and simplified scorecards were developed based on the top 6 – 7 features for each cohort.

2.9 Model interpretability

To enhance model interpretability, we employed SHapley Additive exPlanations (SHAP) for the XGBoost models in the DM and CMM cohorts, and standardized regression coefficients for the logistic regression model in the CVD cohort. SHAP analysis generated beeswarm plots to illustrate feature importance rankings and direction of effects (positive or negative contributions to predicted risk). Dependence plots were also created to visualize nonlinear relationships between key features and predicted outcomes.

2.10 Statistical analysis

All statistical analyses were performed using Python 3.9 with scikit-learn (version 1.1.3), XGBoost (version 2.0.1), LightGBM (version 4.5.0), and SHAP (version 0.42.1) libraries. The significance level was set at $P < 0.05$ (two-sided) for all hypothesis tests.

3.Results

3.1 Baseline characteristics of the study population

The final analytic samples comprised 7,903 participants for the DM cohort (934 incident cases, 11.8%), 9,997 for the CVD cohort (2,265 incident cases, 22.7%), and 9,490 for the CMM cohort (2,745 incident cases, 28.9%). Across all three cohorts, individuals who developed the respective outcomes during follow-up exhibited a broadly similar pattern of adverse cardiometabolic profile at baseline: compared with non-cases, they had significantly higher BMI, waist circumference, fasting glucose, triglycerides, systolic and diastolic blood pressure, and lower HDL cholesterol (all $P < 0.001$). Likewise, all composite metabolic indices—including TyG index, CVAI, BRI, LAP, TyG-BMI, TyG-WC, and AIP—were significantly elevated in the incident case groups across all three cohorts (all $P < 0.001$). Hypertension was also consistently more prevalent among cases than non-cases across the three cohorts (DM: 50.9% vs. 37.6%; CVD: 49.1% vs. 33.2%; CMM: 46.3% vs. 31.6%; all $P < 0.001$).

Despite these shared features, each outcome exhibited distinct baseline characteristics. In the CVD cohort, participants with incident CVD were significantly older (60.00 ± 8.76 vs. 58.20 ± 9.24 years, $P < 0.001$) and had lower grip strength (standardized units: -0.08 ± 1.03 vs. 0.02 ± 0.99 , $P < 0.001$) compared with non-cases, suggesting a potential role of declining muscle function in cardiovascular risk. Notably, in the CMM cohort, individuals who developed CMM had significantly higher CESD depression scores at baseline (0.12 ± 1.03 vs. -0.05 ± 0.99 , $P < 0.001$) than those who did not, highlighting the contribution of psychological factors to cardiometabolic risk beyond conventional metabolic parameters.

After random splitting of each cohort into training and test sets at a 7:3 ratio using stratified sampling, no statistically significant differences were observed in age, sex, BMI, or other baseline characteristics, nor in outcome incidence, between the two sets (all $P > 0.05$), confirming successful randomization. Detailed baseline characteristics for all three cohorts, as well as comparisons between training and test sets, are presented in Table 1, Table 2, and Supplementary Table S1.

Table 1. Baseline characteristics of the three cohorts stratified by 9-year outcome

Variable	DM			CVD			CMM		
	No	Yes	P	No	Yes	P	No	Yes	P
	n=6969	n=934		n=7732	n=2265		n=6745	n=2745	
Age (years)	59.13 ± 9.24	58.87 ± 8.55	0.423	58.20 ± 9.24	60.00 ± 8.76	<0.001	58.19 ± 9.32	59.43 ± 8.82	<0.001
BMI (kg/m ²)	23.22 ± 3.68	24.97 ± 4.00	<0.001	23.19 ± 3.68	24.11 ± 4.02	<0.001	22.95 ± 3.56	24.12 ± 4.04	<0.001

Waist circumference (cm)	83.38 ± 12.14	88.18 ± 13.41	<0.001	83.34 ± 12.03	86.12 ± 13.15	<0.001	82.67 ± 11.83	85.97 ± 12.90	<0.001
Fasting glucose (mg/dL)	103.68 ± 19.96	113.95 ± 26.82	<0.001	108.39 ± 31.87	113.46 ± 43.40	<0.001	103.69 ± 19.71	107.52 ± 23.74	<0.001
Triglycerides (mmol/L)	1.39 ± 1.13	1.76 ± 1.29	<0.001	1.43 ± 1.19	1.54 ± 1.24	0.001	1.37 ± 1.13	1.54 ± 1.19	<0.001
HDL cholesterol (mmol/L)	1.35 ± 0.39	1.22 ± 0.37	<0.001	1.34 ± 0.40	1.30 ± 0.40	<0.001	1.36 ± 0.39	1.30 ± 0.39	<0.001
Systolic BP (mmHg)	129.29 ± 21.22	134.14 ± 20.82	<0.001	128.14 ± 20.44	134.03 ± 22.08	<0.001	127.63 ± 20.47	133.05 ± 21.62	<0.001
Diastolic BP (mmHg)	75.27 ± 12.15	77.95 ± 11.90	<0.001	74.91 ± 11.74	77.66 ± 12.46	<0.001	74.63 ± 11.73	77.48 ± 12.40	<0.001
Sex (male)	3294 (47.3)	405 (43.4)	0.025	3799 (49.2)	986 (43.5)	<0.001	3359 (49.9)	1229 (44.8)	<0.001
Education			0.784			0.081			0.024
- Illiterate	2021 (29.0)	272 (29.2)		2162 (28.0)	666 (29.4)		1891 (28.0)	797 (29.1)	
- Primary school	2923 (41.9)	377 (40.5)		3168 (41.0)	923 (40.8)		2782 (41.3)	1106 (40.3)	
- High school or above	1947 (27.9)	271 (29.1)		2307 (29.8)	636 (28.1)		1997 (29.6)	790 (28.8)	
Marital status (married)	6129 (87.9)	832 (89.1)	0.499	6842 (88.5)	1991 (87.9)	0.439	5953 (88.3)	2418 (88.1)	0.528
Urban residence	636 (14.9)	104 (18.3)	0.044	718 (15.3)	259 (19.0)	0.002	608 (14.9)	297 (17.9)	0.005
Smoking			0.001			<0.001			<0.001
- Never	4170 (60.0)	615 (66.0)		4630 (60.0)	1413 (62.7)		3981 (59.2)	1713 (62.7)	
- Former	577 (8.3)	74 (7.9)		557 (7.2)	200 (8.9)		477 (7.1)	228 (8.4)	
- Current	2199 (31.7)	243 (26.1)		2527 (32.8)	639 (28.4)		2266 (33.7)	789 (28.9)	
Drinking (yes)	2356 (33.8)	269 (28.8)	0.002	2713 (35.1)	696 (30.7)	<0.001	2415 (35.8)	860 (31.4)	<0.001
Adequate exercise (≥150 min/week)	181 (3.9)	36 (5.2)	0.136	150 (3.2)	71 (4.3)	0.034	130 (3.2)	74 (3.9)	0.235
Hypertension (yes)	2604 (37.6)	474 (50.9)	<0.001	2548 (33.2)	1112 (49.3)	<0.001	2117 (31.6)	1263 (46.3)	<0.001

Note: Percentages for urban residence and adequate exercise are calculated based on non-missing data; denominators may be smaller than the total cohort size.

Table 2. Baseline characteristics of the three cohorts stratified by 9-year outcome

Variable	DM			CVD			CMM		
	No	Yes	P	No	Yes	P	No	Yes	P
	n=6969	n=934		n=7732	n=2265		n=6745	n=2745	
TyG index	4.09 ±	4.40 ±	<0.001	4.14 ±	4.25 ±	<0.001	4.07 ±	4.22 ±	<0.001

	0.61	0.68		0.66	0.69		0.61	0.64	
CVAI	89.69 ±	109.76 ±	<0.001	89.09 ±	102.27 ±	<0.001	86.16 ±	100.40 ±	<0.001
	43.73	47.76		43.63	46.40		42.64	46.45	
BRI	4.04 ±	4.69 ±	<0.001	4.02 ±	4.40 ±	<0.001	3.93 ±	4.39 ±	<0.001
	1.47	1.64		1.45	1.62		1.42	1.60	
LAP	33.26 ±	50.66 ±	<0.001	34.35 ±	41.01 ±	<0.001	31.74 ±	40.43 ±	<0.001
	39.26	50.45		41.40	47.96		38.00	44.18	
TyG-BMI	95.56 ±	110.79 ±	<0.001	96.71 ±	103.44 ±	<0.001	94.20 ±	102.48 ±	<0.001
	23.68	27.71		24.82	27.09		23.10	25.84	
TyG-WC	342.62 ±	390.05 ±	<0.001	346.69 ±	368.08 ±	<0.001	338.34 ±	364.10 ±	<0.001
	80.09	92.90		84.12	92.01		78.49	86.70	
AIP	-0.04 ±	0.10 ±	<0.001	-0.03 ±	0.02 ±	<0.001	-0.05 ±	0.02 ±	<0.001
	0.33	0.34		0.34	0.34		0.33	0.33	
SMI (kg/m²)	6.71 ±	6.99 ±	<0.001	6.75 ±	6.80 ±	0.045	6.71 ±	6.83 ±	<0.001
	1.11	1.15		1.13	1.16		1.12	1.16	
Pulse pressure	54.02 ±	56.19 ±	<0.001	53.23 ±	56.38 ±	<0.001	53.00 ±	55.59 ±	<0.001
(mmHg)	14.77	15.13		14.16	16.07		14.16	15.59	

Abbreviations & formulas:

TyG index = $\ln(\text{fasting triglycerides [mg/dL]} \times \text{fasting glucose [mg/dL]} / 2)$

CVAI (Chinese Visceral Adiposity Index) = sex-specific formula using age, BMI, waist circumference, TG, and HDL

BRI (Body Roundness Index) = $364.2 - 365.5 \times \sqrt{(1 - (\text{waist} / 2\pi)^2 / (0.5 \times \text{height})^2)}$

LAP (Lipid Accumulation Product) = (waist - 65) × TG for men; (waist - 58) × TG for women

TyG-BMI = TyG index × BMI

TyG-WC = TyG index × waist circumference

AIP (Atherogenic Index of Plasma) = $\log_{10}(\text{TG} / \text{HDL})$

SMI (Skeletal Muscle Index) = appendicular skeletal muscle mass / height²

Pulse pressure = systolic BP - diastolic BP

Note: Data are presented as mean ± standard deviation. P-values were derived from t-test or Mann-Whitney U test.

The training and test sets were well balanced in terms of age, sex, BMI, and other baseline characteristics, as well as outcome incidence, with no statistically significant differences observed (all $P > 0.05$), indicating successful randomization.

3.2 Feature selection and model performance

3.2.1 Features selected by Random Forest-based SelectFromModel

Feature selection was performed using a Random Forest-based SelectFromModel with a median importance threshold. A total of 16 features were retained for each cohort. The complete lists of selected features are provided in Supplementary Table S2. Across all three cohorts, 13 features were consistently selected: BMI, fasting glucose, HDL cholesterol, LDL cholesterol, systolic blood pressure, diastolic blood pressure, grip strength, skeletal muscle index (SMI), body roundness index (BRI), lipid accumulation product (LAP), TyG-BMI, TyG-waist circumference (TyG-WC), and Chinese visceral adiposity index (CVAI). These commonly selected features span the domains of anthropometric measures, glycemic and lipid metabolism, blood pressure, muscle

function, and composite metabolic indices, highlighting the shared pathophysiological basis underlying diabetes, cardiovascular disease, and their composite endpoint.

3.2.2 Model performance comparison

The performance of the four machine learning models on the test sets is summarized in Table 3. Notably, the logistic regression for CMM showed poor calibration (H-L test $p<0.001$), suggesting that linear additive models may inadequately capture the complexity of CMM risk. Among the DM models, XGBoost achieved the highest AUC (0.715, 95% CI: 0.681 - 0.748), followed closely by logistic regression (0.709). For CVD, logistic regression performed best (AUC = 0.630, 95% CI: 0.607 - 0.652), while XGBoost showed the best performance for CMM (AUC = 0.629, 95% CI: 0.606 - 0.652). Overall, tree-based models (XGBoost and Random Forest) outperformed logistic regression in the DM and CMM cohorts, whereas logistic regression was comparable or superior in the CVD cohort.

Table 3. Performance comparison of machine learning models across the three cohorts												
	Diabetes (DM)				Cardiovascular disease (CVD)				Cardiometa-bolic multimor-bidity (CMM)			
	AUC (95% CI)	Sens	Spec	Brier	AUC (95% CI)	Sens	Spec	Brier	AUC (95% CI)	Sens	Spec	Brier
Logistic	0.709 (0.673–0.741)	0.696	0.645	0.215	0.630 (0.607–0.652)	0.734	0.466	0.239	0.623 (0.600–0.645)	0.543	0.647	0.238
Random Forest	0.706 (0.671–0.741)	0.721	0.592	0.188	0.623 (0.599–0.646)	0.800	0.385	0.170	0.624 (0.601–0.647)	0.708	0.461	0.197
XGBoost	0.715 (0.681–0.748)	0.600	0.724	0.204	0.618 (0.593–0.641)	0.700	0.490	0.239	0.629 (0.606–0.652)	0.544	0.642	0.235
LightGBM	0.703 (0.669–0.737)	0.596	0.714	0.203	0.604 (0.578–0.628)	0.710	0.453	0.238	0.621 (0.598–0.644)	0.561	0.627	0.234

Table note:

AUC: Area under the ROC curve; Sens: Sensitivity; Spec: Specificity.

Values in parentheses are 95% confidence intervals estimated by bootstrap (2000 resamples).

Bold values indicate the highest AUC within each cohort.

Brier scores lower values indicate better calibration. For CMM Logistic, calibration was suboptimal (Hosmer-Lemeshow $p<0.001$).

3.3 Feature Importance (SHAP Analysis)

3.3.1 Diabetes (DM) Model (XGBoost)

Figure 2a presents the SHAP beeswarm plot for the DM model. The top five features by SHAP importance were: fasting glucose, HbA1c, BMI, CESD depression score, and TyG-BMI. Fasting glucose showed the strongest contribution (mean SHAP = 0.279), followed by HbA1c (0.196) and BMI (0.150). Of note, CESD score ranked as the fourth most important predictor, suggesting that depressive symptoms may play a role in diabetes risk beyond traditional metabolic factors. The beeswarm plot reveals that higher values (red) of glucose, HbA1c, and BMI were associated with positive SHAP values (increased risk), while lower values (blue) showed protective effects. Composite metabolic indices including TyG-BMI, TyG-WC, LAP, and CVAI also demonstrated

substantial contributions to the prediction, reflecting the underlying insulin resistance and visceral adiposity pathways.

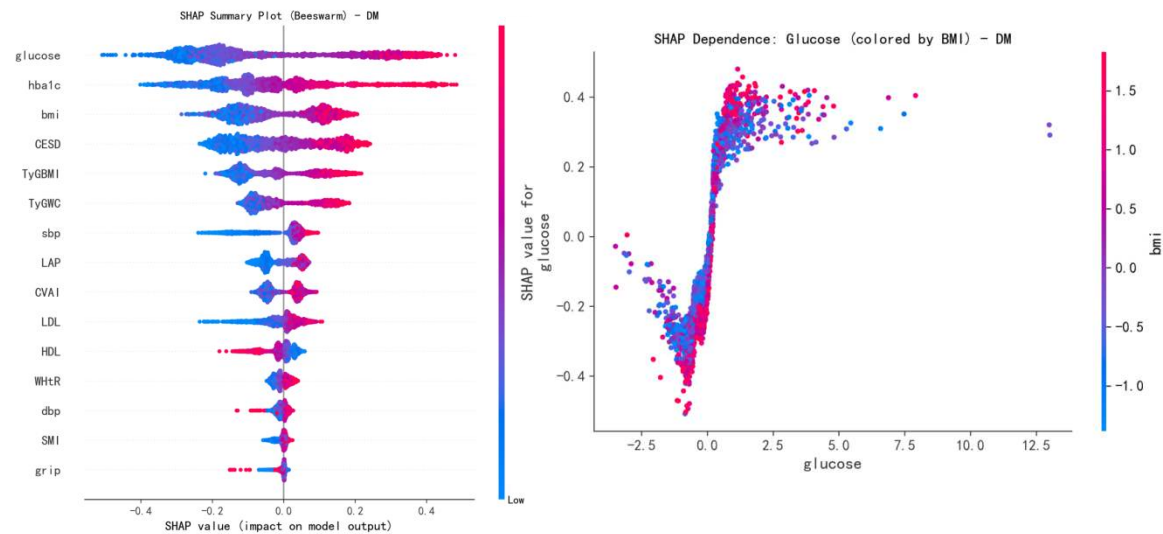


Figure 2a SHAP analysis for the diabetes (DM) model (XGBoost). Left panel: Beeswarm plot showing features ranked by mean absolute SHAP values (top 15 features). Color indicates feature value (red = high, blue = low). Right panel: Dependence plot for fasting glucose, illustrating the association between fasting glucose (standardized) and SHAP values, with color mapping for BMI. The vertical dashed line indicates the threshold of 6.1 mmol/L where SHAP values increase sharply.

3.3.2 Cardiovascular Disease (CVD) Model (Logistic Regression)

For the CVD cohort, standardized regression coefficients were used as the measure of feature importance (Figure 2b). The top five features were: CVAI (0.163), systolic blood pressure (0.127), pulse pressure (0.102), LDL cholesterol (0.086), and grip strength (- 0.073). Age and blood pressure parameters (SBP and pulse pressure) dominated the prediction, highlighting their central roles in CVD risk stratification. Notably, grip strength was the only feature with a negative coefficient, indicating that greater muscle strength serves as a protective factor against CVD. CVAI, a novel visceral adiposity index, emerged as the strongest predictor, surpassing traditional obesity metrics such as BMI, reinforcing the importance of central obesity in CVD development.

3.3.3 cardiometabolic multimorbidity (CMM) Model (XGBoost)

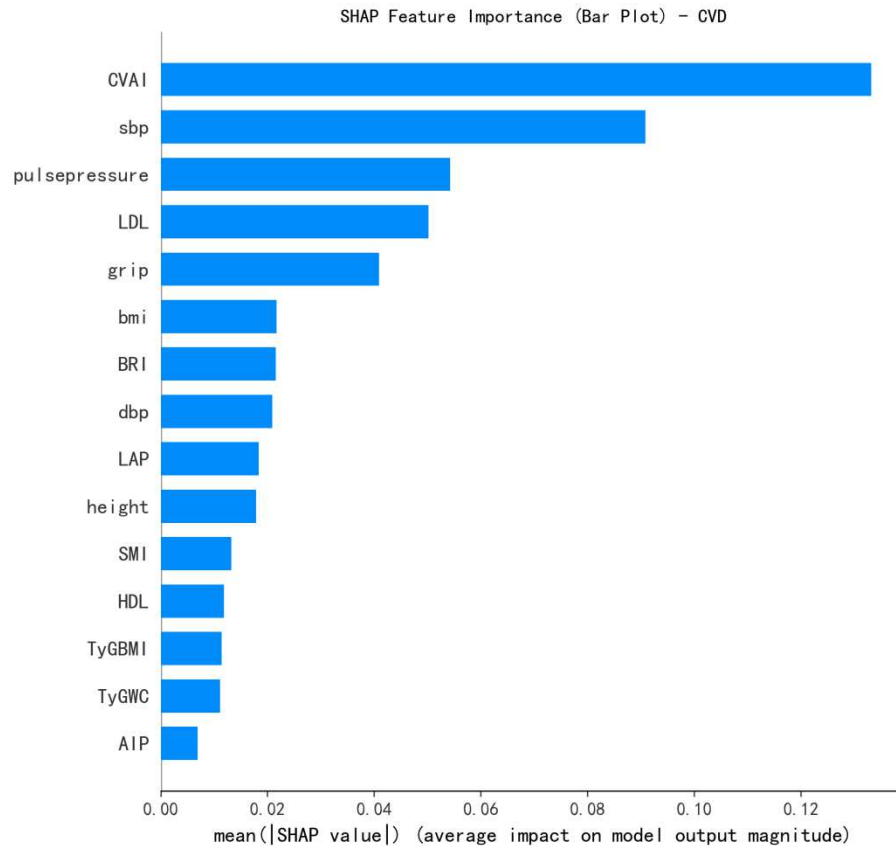


Figure 2b Standardized regression coefficients for the cardiovascular disease (CVD) model (logistic regression). Bar chart displaying the magnitude and direction of each feature's contribution to CVD risk. Positive coefficients indicate increased risk; negative coefficients indicate protective effects. Error bars represent 95% confidence intervals. CVAI: Chinese Visceral Adiposity Index; LAP: Lipid Accumulation Product.

Figure 2c displays the SHAP beeswarm plot for the CMM composite endpoint model, with the top five predictors ranked by mean absolute SHAP values: CVAI (0.228), CESD depression score (0.133), systolic blood pressure (0.075), HbA1c (0.061), and fasting glucose (0.061). Consistent with the feature importance ranking, higher values of CVAI, SBP, and CESD were positively associated with increased CMM risk, whereas lower values exerted protective effects. Importantly, CESD emerged as the second most important predictor, underscoring the substantial contribution of psychological health to cardiometabolic outcomes beyond traditional metabolic factors.

To further elucidate the interplay between visceral adiposity and depressive symptoms, we generated a SHAP interaction dependence plot (Figure 2d) with CVAI as the primary feature and CESD as the coloring variable. The plot reveals that for any given level of CVAI, individuals with higher CESD scores (yellow) consistently exhibit greater positive SHAP contributions of CVAI to CMM risk than those with lower CESD scores (purple). This synergistic pattern is most pronounced in the mid-to-high CVAI range (approximately 150 – 400), where the vertical spread of SHAP values by CESD level is widest. Conversely, when CVAI is below ~50, the SHAP values remain near or below zero regardless of CESD, suggesting that visceral adiposity may confer elevated CMM risk predominantly in the presence of coexisting psychological distress. These findings indicate a synergistic interaction between visceral adiposity and depressive symptoms,

wherein the adverse metabolic effects of central obesity are amplified by concomitant mental health burden. The prominence of both CVAI and CESD, together with their interaction, supports the emerging concept of a "psycho-metabolic" comorbidity axis and highlights the necessity of integrating mental health screening into routine cardiometabolic risk stratification for middle-aged and older adults.

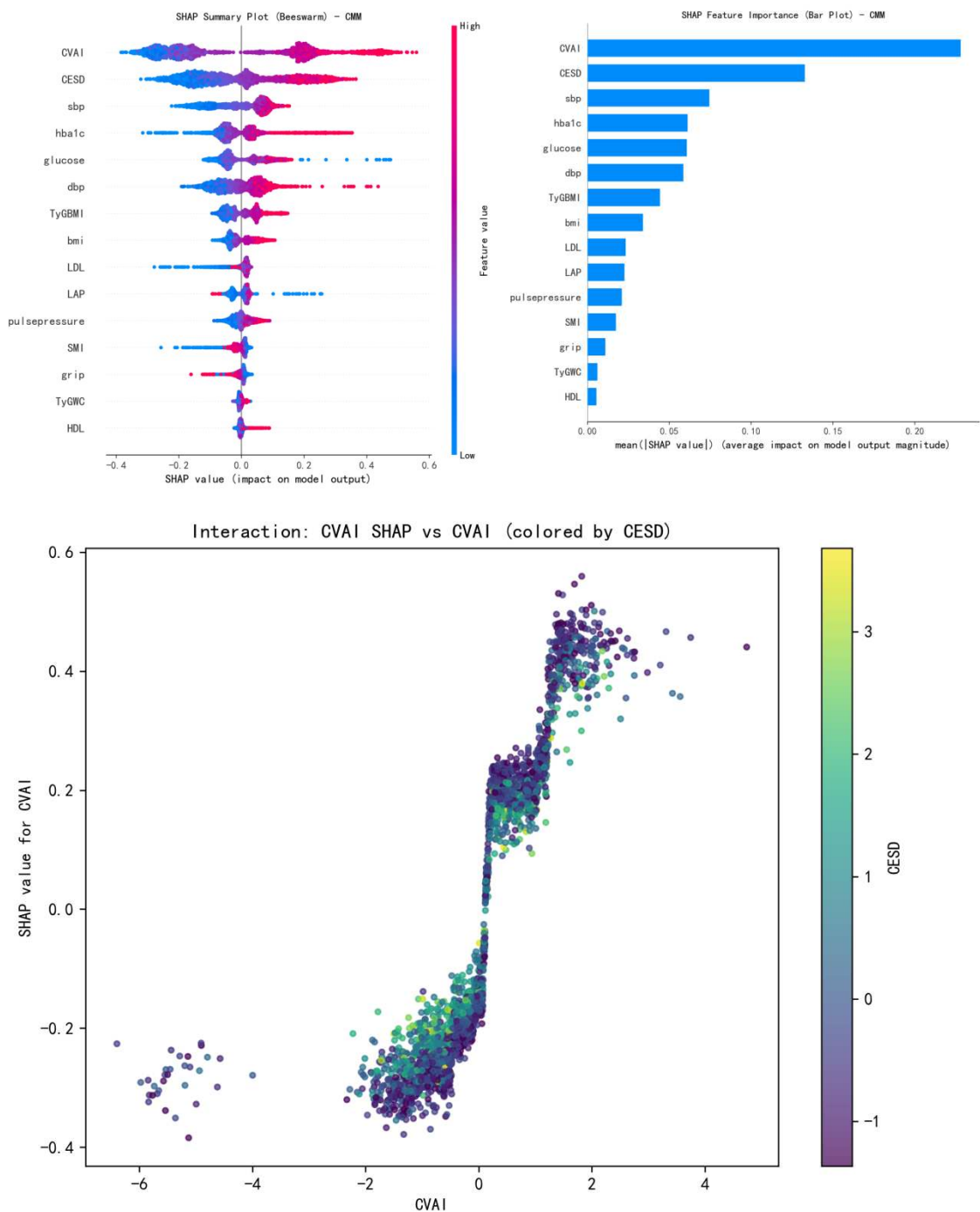


Figure 2c SHAP analysis for the Cardiometabolic multimorbidity (CMM) model (XGBoost). Beeswarm plot showing features ranked by mean absolute SHAP values (top 15 features). Color indicates feature value (red = high, blue = low). CVAI shows the strongest contribution to prediction, followed by CESD depression score and systolic blood pressure. CESD: Center for Epidemiologic Studies Depression Scale; CVAI: Chinese Visceral

Adiposity Index. SHAP interaction dependence plot between CVAI and CESD for the CMM model. The x-axis shows CVAI values, the y-axis shows the SHAP contributions of CVAI to predicted CMM risk, and the color gradient represents CESD scores (yellow: higher depressive symptoms). The plot reveals a synergistic interaction, wherein the risk contribution of CVAI is amplified in the presence of higher CESD scores, particularly in the mid-to-high CVAI range.

3.4 Simplified Risk Scorecards

To facilitate clinical application, we developed simplified risk scorecards based on the top features identified by SHAP analysis (DM and CMM) or standardized regression coefficients (CVD), with detailed point assignments provided in Supplementary Tables S3 – S5. The DM scorecard, constructed from six features (fasting glucose, HbA1c, BMI, LAP, SBP, and TyG-BMI), achieved a test set AUC of 0.681 (95% CI: 0.650 – 0.712), representing a modest reduction from the full XGBoost model (Δ AUC = - 0.034), and demonstrated good calibration across most of the score range (Figure 3a). For the CMM composite endpoint, the scorecard incorporated seven features (CVAI, CESD, SBP, HbA1c, fasting glucose, DBP, and age) using an equal-frequency binning approach combined with logistic regression coefficients, attaining a test set AUC of 0.625, nearly identical to the original logistic regression (0.623) and XGBoost (0.629) models (Δ AUC = - 0.004 vs. XGBoost). The CMM scorecard showed smooth risk progression from 0% to 48% across the total score range (206 – 481), with good calibration (Figure 3c). In striking contrast, the CVD scorecard—attempted with six features (CVAI, SBP, pulse pressure, LDL, grip strength, and BMI)—achieved a test set AUC of only 0.436, substantially lower than the original logistic regression model (0.630, Δ AUC = - 0.194), with poor discriminative ability and calibration (Figure 3b), indicating that cardiovascular risk prediction cannot be adequately captured by a simple linear scorecard.

In brief, the DM and CMM scorecards retained most of the predictive performance of their original models, supporting their potential utility as practical screening tools in primary care, whereas the CVD scorecard failed and is not recommended for clinical use. A summary comparison of scorecard performance across the three cohorts is presented in Table 4.

Figure 3a

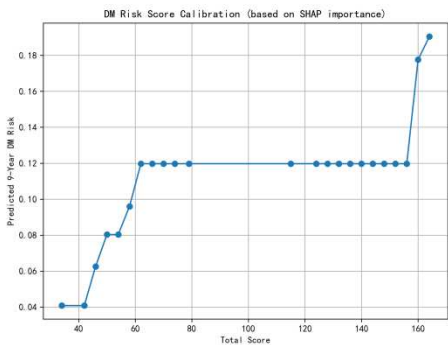


Figure 3c

Figure 3b

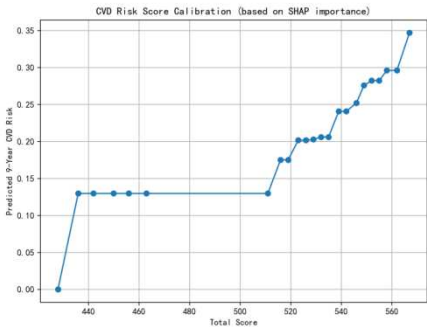
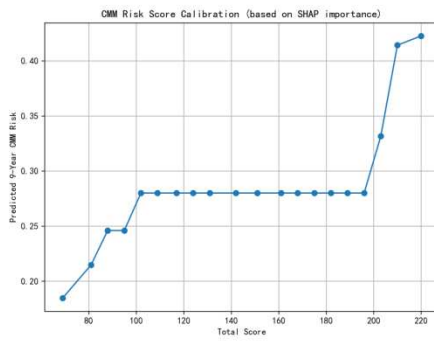


Figure 3a Calibration curve for DM simplified scorecard. The x-axis shows the total score (range:



34–164); the y-axis shows the predicted 9-year diabetes risk. The curve demonstrates good calibration across most of the score range.

Figure 3b Calibration curve for CVD simplified scorecard. The x-axis shows the total score (range: 440–570); the y-axis shows the predicted 9-year CVD risk. The curve shows limited discriminative ability and poor calibration, supporting the decision not to recommend this tool for clinical use.

Figure 3c Calibration curve for the Cardiometabolic multimorbidity (CMM) simplified scorecard. The x-axis shows the total score (range: 206–481); the y-axis shows the predicted 9-year CMM risk. The curve demonstrates good calibration and a smooth risk progression, supporting its potential utility in primary care.

Table 4. Performance comparison of simplified scorecards vs. original models in the three cohorts

Cohort	Original model	Original AUC	Scorecard AUC	Δ AUC
DM	XGBoost	0.715	0.681	- 0.034
CVD	Logistic	0.630	0.436	- 0.194
CMM	XGBoost	0.629	0.625	- 0.004

4. Discussion

In this nationally representative prospective cohort study, we leveraged four waves of data from CHARLS spanning 2011 to 2020 to systematically construct and validate comparative machine learning models for 9-year risk prediction of DM, CVD, and their composite endpoint CMM among Chinese middle-aged and older adults. The 9-year cumulative incidences were 11.8% for DM, 22.7% for CVD, and 28.9% for CMM, confirming the substantial disease burden in this population. Three principal findings emerged from our analyses. First, predictive performance varied substantially across outcomes: DM was the most predictable (AUC 0.703–0.715), followed by CMM (AUC 0.621–0.629), while CVD proved the most challenging (AUC 0.604–0.630). Second, feature importance analyses identified distinct yet overlapping risk factor profiles—glycemic and obesity-related indices dominated DM prediction, age and blood pressure parameters dominated CVD, whereas the Chinese Visceral Adiposity Index together with depressive symptoms (CESD) emerged as the top predictors for CMM. Third, simplified scorecards successfully retained most predictive performance for DM and CMM but failed for CVD, underscoring the inherent complexity of cardiovascular risk stratification.

The discriminative performance of our DM prediction model (AUC 0.703–0.715) is consistent

with previous machine learning-based risk prediction studies conducted in Chinese populations [26], though somewhat lower than the optimal AUC of 0.872 reported in the Henan Rural Cohort [27]. This discrepancy likely stems from differences in data sources, feature sets, and modeling strategies. Notably, our model achieved acceptable discrimination using a relatively parsimonious set of 16 routine clinical variables in a nationally representative cohort with 9-year follow-up, indicating that standard clinical and laboratory data are largely sufficient for community-based diabetes risk screening [20, 28]. Glycemic markers (fasting plasma glucose and HbA1c) and obesity-related indices (BMI and LAP) dominated the predictor rankings, aligning with established pathophysiological evidence [28–30]. More importantly, the SHAP dependence plot revealed a sharp increase in SHAP values when fasting glucose exceeded approximately 6.1 mmol/L, providing quantitative, data-driven support for the current diagnostic threshold and demonstrating the unique value of machine learning in uncovering clinically meaningful nonlinear relationships.

In marked contrast, cardiovascular disease prediction proved considerably more challenging, with AUCs ranging from only 0.604 to 0.630 across all four algorithms. Even the best-performing model—logistic regression (AUC = 0.630)—exhibited only modest discriminative ability. This modest performance is consistent with prior CHARLS-based studies [31], although Huang et al. reported a higher AUC of 0.818 using 61 predictors from the same database, highlighting that expanding the feature space with comprehensive lifestyle and psychosocial covariates can substantially improve CVD prediction [31]. Beyond variable selection, the inherent nature of CVD itself poses fundamental difficulties. Unlike diabetes, which arises from gradual, progressive metabolic decompensation and has well-defined objective diagnostic thresholds, CVD encompasses a heterogeneous cluster of conditions—atherosclerosis, thrombosis, chronic inflammation, and autonomic dysfunction—many of which are not fully captured by conventional risk markers [32]. Moreover, cardiovascular events such as myocardial infarction and stroke often present as episodic, abrupt occurrences, rendering their onset far less predictable than the insidious progression of hyperglycemia [33, 34]. The dominant predictors in our CVD model—age, systolic blood pressure, and pulse pressure—reinforce the critical role of classic risk factors [35], yet the overall modest AUC suggests that supplementary biomarkers (e.g., high-sensitivity troponin, NT-proBNP, inflammatory cytokines) or subclinical imaging markers (e.g., carotid intima-media thickness, coronary artery calcium score) are necessary to achieve clinically actionable performance [36, 37].

Prediction of the composite CMM endpoint carries distinct clinical implications compared with single-outcome models. The CMM models achieved intermediate discriminative performance (AUC 0.621–0.629), falling between those of DM and CVD—a finding consistent with the notion that composite endpoints tend to average out the predictive signals of their individual components [38]. Notably, CVAI emerged as the single most important predictor in the CMM model (mean SHAP = 0.228), surpassing conventional obesity metrics such as BMI. Developed and validated specifically for Chinese populations, CVAI integrates age, BMI, waist circumference, and lipid profiles into a sex-specific formula that more accurately quantifies visceral adipose dysfunction than general adiposity indices [14]. Visceral fat is a central mediator of insulin resistance, dyslipidaemia, and chronic low-grade inflammation, which constitute the primary pathogenic

mechanisms underpinning both DM and CVD [13, 39]. Accumulating evidence further indicates that CVAI independently predicts atherosclerotic cardiovascular disease risk and all-cause mortality in patients with type 2 diabetes, heart failure, and chronic kidney disease [40, 41]. Equally striking is the emergence of CESD-measured depressive symptoms as the second most influential predictor in the CMM model (SHAP = 0.133). This observation substantiates the well-documented “psycho-metabolic” axis, wherein psychological distress and metabolic dysfunction reciprocally reinforce each other through behavioural pathways (poor diet, sedentary lifestyle, treatment non-adherence) and core biological mechanisms—hypothalamic-pituitary-adrenal axis overactivation, persistent inflammatory activation, and autonomic nervous system imbalance [42–47]. The SHAP interaction plot (Figure 2d) further revealed a synergistic pattern: for any given level of CVAI, individuals with higher CESD scores exhibited greater positive SHAP contributions to CMM risk than those with lower CESD scores, particularly in the mid-to-high CVAI range. This interaction supports the concept that visceral adiposity may confer disproportionately elevated CMM risk in the presence of coexisting psychological distress, underscoring the necessity of integrating mental health screening into routine cardiometabolic risk stratification for middle-aged and older adults [45, 48].

From a translational perspective, the simplified risk scorecards developed in this study provide practical tools for primary care settings. The DM scorecard (AUC = 0.681) and CMM scorecard (AUC = 0.625) retained most of the predictive performance of their original machine learning models (Δ AUC = - 0.034 and - 0.004, respectively), indicating that these streamlined instruments can facilitate rapid risk stratification in community screening programs without sophisticated computational infrastructure [49]. In contrast, the CVD scorecard exhibited a substantial decline in discriminative ability (AUC = 0.436, Δ AUC = - 0.194), further demonstrating that cardiovascular risk prediction—owing to its multifactorial and nonlinear nature—resists simple linear simplification [11]. Several methodological strengths of this study warrant emphasis, including the use of a nationally representative cohort with up to 9 years of follow-up, rigorous hyperparameter optimization with cross-validation, and the systematic comparison of four machine learning algorithms across three clinically relevant outcomes. However, several limitations should be acknowledged. First, incident CVD events were ascertained primarily via self-reported physician diagnoses, which may introduce recall bias and underreporting, particularly for asymptomatic or undiagnosed cases. Although the validity of self-reported disease data in CHARLS has been verified in previous studies, the lack of objective clinical verification (e.g., electrocardiography, echocardiography, or medical record review) may result in outcome misclassification. Second, despite the comprehensive set of predictors included, several potentially critical determinants—including detailed dietary patterns, environmental exposures, genetic biomarkers, and medication adherence - were not available in the current dataset. Third, the models were developed and internally validated within a single cohort; external validation in independent populations is essential before clinical implementation. Future research should integrate multi-omics and imaging data to boost predictive discrimination for CVD, and prospective implementation trials are warranted to evaluate the real-world clinical utility and cost-effectiveness of these prediction tools across diverse healthcare settings.

5. Conclusion

In this CHARLS-based cohort study, DM was the most predictable outcome (AUC 0.703–0.715), CVD the most challenging (AUC 0.604–0.630), and the composite CMM endpoint showed intermediate performance (AUC 0.621–0.629), with CVAI and depressive symptoms (CESD) as its top predictors. Simplified scorecards offer practical screening tools for DM and CMM in primary care, but not for CVD. External validation and integration of multi-omics data are warranted to further enhance generalizability.

Abbreviations

AIP: Atherogenic Index of Plasma
BMI: body mass index
BRI: Body Roundness Index
CESD: Center for Epidemiologic Studies Depression Scale
CHARLS: China Health and Retirement Longitudinal Study
CMM: cardiometabolic multimorbidity
CT: computed tomography
CVAI: Chinese Visceral Adiposity Index
CVD: cardiovascular disease
DM: diabetes mellitus
HDL-C: high-density lipoprotein cholesterol
LAP: Lipid Accumulation Product
LGB: LightGBM
LR: Logistic Regression
MICE: multiple imputation by chained equations
ML: machine learning
MRI: magnetic resonance imaging
RF: Random Forest
SHAP: SHapley Additive exPlanations
SMI: Skeletal Muscle Index
TG: triglycerides
TyG-WC: TyG-waist circumference
VAI: visceral adiposity index
VAT: visceral adipose tissue
WC: waist circumference
XGB: XGBoost

Declarations

Ethics approval and consent to participate

The China Health and Retirement Longitudinal Study (CHARLS) was approved by the Biomedical Ethics Review Committee of Peking University (IRB approval number: IRB00001052-11015) and was conducted in accordance with the principles of the Declaration of Helsinki. All participants provided written informed consent prior to enrollment. The present study involved secondary analysis of de-identified publicly available data and did not require additional ethical approval.

Consent for publication

Not applicable. This study does not contain any individual person's data in any form (including individual details, images, or videos).

Availability of data and materials

The data that support the findings of this study are publicly available from the CHARLS website at <https://charls.pku.edu.cn>. All data used in this analysis are de-identified and accessible to researchers upon registration and approval by the CHARLS team.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Y.Q. and L.Z. contributed equally to this work. Y.Q. and L.Z. conceived and designed the study, performed data analysis, and drafted the manuscript. L.M., G.F., and M.Y. contributed to data acquisition and interpretation. G.Y. and H.X. participated in literature review and manuscript revision. W.G. supervised the entire study, provided critical intellectual input, and finalized the manuscript. All authors read and approved the final version of the manuscript.

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