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Association between cardiac metabolic index and diabetic kidney disease: a cross-sectional study of NHANES 1999–2018

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Abstract

Background The Cardiac Metabolic Index (CMI) is a comprehensive metabolic indicator, but studies on its relationship with Diabetic Kidney Disease (DKD) are limited. We aim to explore the association between CMI and DKD.

Methods We obtained participant-related data from the National Health and Nutrition Examination Survey (NHANES), including complete information on DKD, CMI, and other covariates. We employed weighted multivariable logistic regression models, restricted cubic spline (RCS) regression analysis, subgroup analyses, and interaction tests to explore the relationship between CMI and DKD. Additionally, we utilized receiver operating characteristic (ROC) curves to compare the performance of CMI in identifying DKD relative to a body shape index (ABSI), body roundness index (BRI), visceral adiposity index (VAI), and lipid accumulation product (LAP) indices.

Results According to the logistic regression analysis, a positive correlation between CMI and DKD was observed among the 2371 participants included in the study (OR: 1.40, 95% CI: 1.19–1.66). RCS analysis indicated that this relationship is nonlinear. When CMI was converted from a continuous variable to quartiles, the prevalence of DKD in the highest quartile group showed a significant 84% increase compared to the lowest quartile group (OR: 1.84, 95% CI: 1.24–2.72). The area under the ROC curve of CMI for identifying DKD was 0.67, outperforming other indices. The results of subgroup analyses and interaction tests were stable.

Conclusion Elevated CMI is associated with an increased risk of DKD and can serve as a low-cost screening tool, allowing physicians to potentially identify high-risk diabetic patients early and implement timely interventions to slow the progression of DKD.

Keywords Cardiac metabolic index, Type 2 diabetes mellitus, Diabetic kidney disease, Cross-sectional study, Restricted cubic spline

Introduction

Diabetes is a global metabolic disease characterized by chronic hyperglycemia caused by spontaneous metabolic disorders [1, 2] and has become one of the top ten causes of death worldwide [3]. Diabetic kidney disease (DKD), as a serious complication of diabetes [4], plays a significant role in leading to end-stage kidney disease (ESKD) and related mortality. In the United States, over 40% of individuals (approximately 29 million people) with type 2 diabetes mellitus (T2DM) have DKD, resulting in substantial economic and healthcare losses [5]. Therefore,

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to intervene in the progression of DKD more timely, it is crucial to identify more effective novel biomarkers, which are essential for establishing effective treatment strategies promptly.

In the context of the high prevalence and mortality rates of diabetes worldwide, Wan H et al. proposed that obesity, particularly abdominal obesity, has long been considered a potential risk factor for diabetic complications [6]. Common anthropometric methods used in clinical practice, such as Body Mass Index (BMI) and Waist Circumference (WC), are commonly used to assess obesity and its associated risks, but these indicators have relative limitations. BMI cannot distinguish between types or distribution of fat and muscle mass to a certain extent, while WC cannot further predict visceral adipose tissue at the individual level [7]. To address these issues, a number of novel anthropometric indices have emerged in recent years, including Cardiac Metabolic Index (CMI), a body shape index (ABSI), body roundness index (BRI), visceral adiposity index (VAI), and lipid accumulation product (LAP). Additionally, there are triglyceride-glucose index (TyG) and metabolic syndrome insulin resistance index (Mets-IR), which focus more on insulin resistance and glucose metabolism abnormalities [8], while CMI, ABSI, BRI, VAI, and LAP are more focused on assessing obesity morphology and fat distribution [9]. Among these, CMI effectively combines anthropometric markers with metabolism. It is a novel metabolic index proposed in 2015 [10], defined as the ratio of waist-to-height ratio (WHtR) and triglycerides to high-density lipoprotein cholesterol (TG/HDL-C). WHtR is primarily used to measure the degree of obesity, while TG/HDL-C is used to assess lipid levels. Research has shown that CMI can effectively reflect the degree of obesity and lipid levels. A previous meta-analysis indicated that waist-to-hip ratio (WHR)/WHtR is associated with a higher likelihood of developing DKD in patients with T2DM [11]. A survey based on an Italian diabetes center showed that low HDL-C and high TG levels are independent risk factors for the occurrence of DKD within four years [12].

Previously, CMI has been used for the prediction and diagnosis of various diseases, such as metabolic-associated fatty liver [13], hypertension [14], and atherosclerosis [15], but there has been no research on the correlation between CMI and DKD. Its predictive potential lies in its ability to synthesize multiple risk factors into a single, easily interpretable metric. Therefore, this study aims to investigate the relationship between the novel anthropometric index CMI and DKD among adults in the United States using the National Health and Nutrition Examination Survey (NHANES) database. Additionally, we will compare CMI with ABSI, BRI, VAI, and LAP using ROC curves.

Materials and methods

Study population and participant selection

The NHANES, led by the Centers for Disease Control and Prevention (CDC), is a nationally representative survey designed to assess the health and nutritional status of adults and children in the United States. The survey includes demographic, dietary, examination, laboratory, and questionnaire data. Currently, data is collected and published every two years by the CDC's National Center for Health Statistics (NCHS). For this cross-sectional study, we used data obtained from NHANES as the basis for analysis, primarily focusing on data from 1999 to 2018, which includes 10 NHANES cycles. The NHANES study protocol has been approved by the NCHS Research Ethics Review Board, and written informed consent has been obtained from all participants.

The exclusion criteria for this study are as follows (Fig. 1): (1) individuals under the age of 20; (2) individuals missing data required for the calculation of CMI, ABSI, BRI, VAI, and LAP; (3) individuals missing estimated glomerular filtration rate (eGFR), urine albumin-to-creatinine ratio (UACR), and T2DM data; (4) individuals

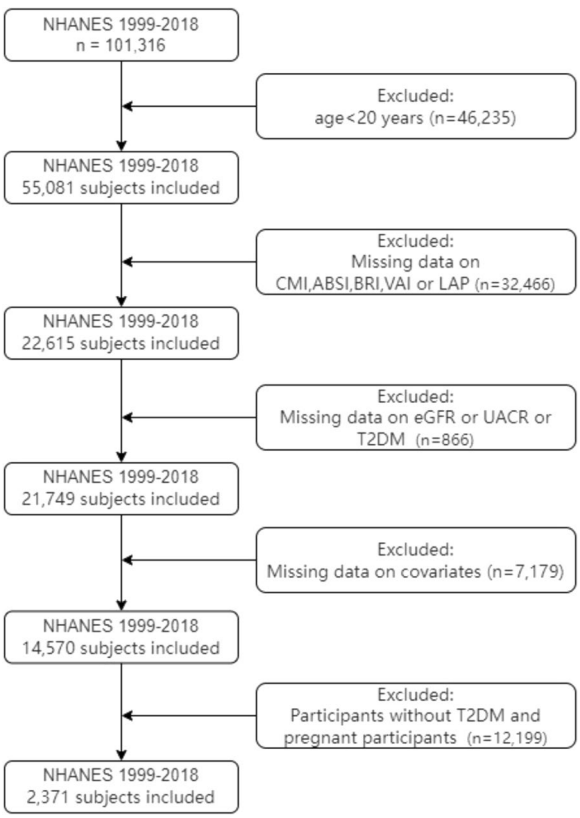

Fig. 1 Participant selection flowchart

with incomplete covariate data; (5) individuals with non-T2DM and those who are pregnant. Ultimately, a total of 2,371 individuals met the inclusion criteria for this study.

Exposure variables

In our study, CMI, ABSI, BRI, VAI, and LAP were used as exposure variables. They are derived from BMI, height, waist, WC, triglycerides (TG), and HDL-C based on different calculation methods. The specific calculation methods for the five novel anthropometric indices are detailed in Table 1.

Outcome variables

First, we diagnosed diabetes based on self-reported diabetes, the use of insulin or other diabetes medications, or a diagnosis based on fasting blood glucose (mmol/l) ≥ 7.0 or hemoglobin A1c (HbA1c)(%) ≥ 6.5. Subsequently, among patients with T2DM, DKD patients were identified based on the eGFR (< 60 mL/min/1.73 m^2) and/or UACR ≥ 30 mg/g [20].

Covariates

The covariates in this study include age (years), gender (male/female), race (non-Hispanic white/non-Hispanic black/Mexican American/other races), poverty income ratio (PIR), BMI (kg/m^2), smoking status, education level (less than high school/high school graduate/ general education development (GED) /above high school), marital status, physical activity, cardiovascular disease (CVD) (yes/no), hypertension (yes/no), and hyperlipidemia (yes/no). PIR is categorized into three groups: low (≤ 1.39), medium (> 1.39, ≤ 3.49), and high (> 3.49). BMI is categorized as < 25, 25–29.9, and ≥ 30 kg/m^2. Smoking status for each participant was obtained through household interviews, classifying them as current smokers, former smokers, or never smokers. Physical activity was converted to metabolic equivalent (MET) scores, with MET minutes/week ≥ 500 considered active and MET minutes/week < 500 considered inactive [21]. For CVD, it is defined as having been informed by a doctor or other health professional of having congestive heart failure (CHF), coronary heart disease (CHD), angina, heart attack, or stroke. Hypertension is defined as self-reported diagnosis of hypertension, use of antihypertensive medications, average systolic blood pressure (SBP) ≥ 140 mmHg, or average diastolic blood pressure (DBP) ≥ 90 mmHg [22]. Hyperlipidemia is defined [23] as male high-density lipoprotein ≤ 40 mg/dL, female ≤ 50 mg/dL, TG ≥ 150 mg/dL, total cholesterol ≥ 200 mg/dL, low-density lipoprotein ≥ 130 mg/dL or use of cholesterol-lowering medications.

Table 1 Specific calculation methods for the five novel anthropometric indices

Indices	Calculation Formula	References
CMI	CMI = WHtR×[TG(mmol/L)/HDL-C(mmol/L)]	[10]
ABSI	$ABSI = \frac{WC(m)}{BMI^{2/3} \times Height(m)^{1/2}}$	[16]
BRI	$BRI = 364.2 - 365.5 \times (1 - [WC(m)/2\pi]^2 / [0.5 \times height(m)]^2)^{1/2}$	[17]
VAI	For males: VAI = [WC(cm)/(39.68 + 1.88*BMI)]×[TG(mmol/L) /1.03]×[1.31/HDL-C(mmol/L)]	[18]
	For females: VAI = [WC(cm)/(36.58 + 1.89×BMI)]×[TG(mmol/L)/0.81]×[1.52/HDL-C(mmol/L)]	
LAP	For males: LAP = [WC(cm)-65]×TG(mmol/L)	[19]
	For females: LAP = [WC(cm)-58]×TG(mmol/L)	

CMI, Cardiac Metabolic Index; WHtR, Waist-to-Height Ratio; TG, triglycerides; HDL-C, High-Density Lipoprotein Cholesterol; ABSI, a body shape index; WC, Waist Circumference; BMI, body mass index; BRI, body roundness index; VAI, visceral adiposity index; LAP, lipid accumulation product

Statistical analysis

The characteristics of the participants are reported as mean ± standard deviation (SD) for continuous variables and as percentages for categorical variables. Participants were divided into two groups based on the presence of DKD. Weighted t-tests were used to assess differences in continuous variables between the two groups, while weighted chi-square tests were used to evaluate differences in categorical variables. Finally, through the Shapiro–Wilk normality test analysis, we found that the original data of the CMI, ABSI, BRI, VAI, and LAP indices exhibited a right-skewed distribution. Therefore, we performed a log2 transformation.

We conducted weighted multivariable logistic regression analyses to assess the association between the five novel anthropometric indices and the risk of DKD. Results are presented as odds ratios (OR) with 95% confidence intervals (CI). Logistic regression models were adjusted for covariates: the crude model was unadjusted, Model 1 adjusted for age, sex, and race, Model 2 further adjusted for PIR, physical activity, BMI, education level, and smoking status, and Model 3 additionally adjusted for CVD, hypertension, and hyperlipidemia based on Model 2. To explore potential nonlinear associations between the novel anthropometric indices and the prevalence of DKD, we further fitted restricted cubic splines (RCS) with three knots set at the 10th, 50th, and 90th percentiles, using the 50th percentile as the reference.

We used receiver operating characteristic (ROC) curves to compare the predictive value of the novel anthropometric indices in assessing the prevalence of DKD to determine the relatively best predictive indicator among the five indices. Additionally, we employed DeLong's test to compare the differences in the area under the curve (AUC) for the ROC curves of different

indices. Finally, based on CMI, stratified analyses and interaction tests were conducted for gender (male or female), age (<60 or ≥60 years), smoking status (non-smoker or smoker), cardiovascular disease (yes or no), hypertension (yes or no), and hyperlipidemia (yes or no). Statistical analyses were performed using R Studio (version 4.2.2) with the "survey," "survival," "survminer," "rms," "ggplot2," and "pROC" packages. The significance level was set at $p < 0.05$ (two-tailed).

Results

Baseline characteristics of participants

A total of 2371 participants were included in this study (mean [se] age of 57 [14] years), among which there were 820 participants with DKD (474 males [weighted proportion 55%] and 346 females [weighted proportion 45%]). Compared to non-DKD patients, those with DKD showed statistically significant differences in age, poverty level, education level, marital status, cardiovascular disease, hypertension, VAI, ABSI, CMI, and LAP (all $p < 0.05$). However, no significant differences were found between DKD patients and non-DKD patients regarding sex, race, BMI, smoking status, physical activity, hyperlipidemia, and BRI (Table 2).

Association between novel anthropometric indices and DKD

According to the logistic regression analysis, we observed a positive correlation between CMI (OR = 1.40, 95% CI: 1.19–1.66), BRI (OR = 1.34, 95% CI: 1.00–1.79), VAI (OR = 1.24, 95% CI: 1.09–1.41), and LAP (OR = 1.26, 95% CI: 1.11–1.44) with DKD. We further converted the five indices (CMI, ABSI, BRI, VAI, and LAP) from continuous variables to categorical variables (quartiles) for analysis. The results showed that the prevalence of DKD increased with higher levels of CMI, BRI, VAI, and LAP compared to the lowest quartile of these indices, with increases of 84% (OR: 1.84, 95% CI: 1.24–2.72), 54% (OR: 1.54, 95% CI: 1.03–2.29), 103% (OR: 2.03, 95% CI: 1.33–3.10), and 73% (OR: 1.73, 95% CI: 1.21–2.48), respectively (Table 3).

Assessment of nonlinear relationships

We used RCS to further explore the nonlinear associations between the novel anthropometric indices (considered as continuous variables) and DKD. The results showed that Log2-ABSI, Log2-BRI, Log2-LAP, and Log2-CMI had nonlinear relationships with the risk of DKD (All p for nonlinear < 0.05). Notably, the association between Log2-ABSI and DKD was not significant. Additionally, Log2-VAI exhibited a linear relationship with DKD risk (P for nonlinear = 0.09) (Fig. 2).

Comparison of predictive ability for disease

We conducted a comparative analysis of the predictive ability of the novel anthropometric indices for disease risk based on ROC curves. The results showed that CMI outperformed ABSI, BRI, VAI, and LAP in predicting the prevalence of DKD, with the highest AUC value in Model 3 (CMI: 0.670 vs. LAP: 0.668 vs. VAI: 0.666 vs. BRI: 0.660 vs. ABSI: 0.658) (Fig. 3). Similar results were also observed in other models. However, after the DeLong test, although the AUC value of CMI was numerically higher than that of the other indices, these differences did not reach statistical significance (all $p > 0.05$). CMI can be considered a comparable predictor for DKD risk assessment.

Subgroup analysis

CMI is considered the relatively optimal indicator for predicting the prevalence of DKD. Subgroup analyses stratified by sex, age, smoking status, hypertension, hyperlipidemia, and cardiovascular disease showed that the highest quartile of CMI was more strongly associated with the prevalence of DKD in males, individuals aged (< 60 years), patients with hyperlipidemia, patients with hypertension, and those without cardiovascular disease compared to the lowest quartile (Fig. 4). Additionally, no significant interactions were observed between CMI levels and the stratified variables, with all interaction p-values exceeding 0.05.

Discussion

This study is the first to explore the relationship between CMI and the prevalence of DKD based on NHANES, and it compares CMI with four other novel anthropometric indices: ABSI, BRI, VAI, and LAP. We found that CMI, BRI, VAI, and LAP were strongly correlated with the prevalence of DKD, whether analyzed as continuous or categorical variables, while ABSI was not significant. Additionally, we observed a nonlinear relationship between CMI, ABSI, BRI, and LAP and the risk of DKD. The results of the ROC curve indicate that CMI has the highest AUC value compared to other novel anthropometric indices. The results of the subgroup analysis were stable, and no interactions were found.

CMI is a novel marker derived from obesity and lipid profiles, calculated from variables such as TG/HDL-C and WHtR, combining lipid levels and visceral obesity [10] [24]. Previous reports have indicated that Miao et al. pointed out that CMI is independently associated with microalbuminuria, suggesting that this index can be used to assess the risk of microalbuminuria, especially in diabetic patients [25], which is consistent with our results. Additionally, considering the composition of CMI, some

Table 2 Basic characteristics of participants in the NHANES 1999–2018

Characteristic	Overall, N[1] = 2371 (100%)[2]	DKD, N[1] = 820 (31%)[2]	Non-DKD, N[1] = 1551 (69%)[2]	*P* Value[3]
Age (years)	57 (14)	62 (14)	56 (13)	**< 0.001**
Gender				> 0.9
Female	1031 (45%)	346 (45%)	685 (46%)	
Male	1340 (55%)	474 (55%)	866 (54%)	
Race				0.3
Non-Hispanic White	939 (65.4%)	333 (63%)	606 (67%)	
Non-Hispanic Black	524 (12.3%)	178 (12%)	346 (12%)	
Mexican American	461 (9.1%)	169 (11%)	292 (8.4%)	
Other Race	447 (13.2%)	140 (14%)	307 (12.6%)	
PIR				**< 0.001**
High (> 3.5)	670 (39%)	203 (33%)	467 (42%)	
Low (≤ 1.3)	717 (20%)	277 (23%)	440 (18%)	
Medium (> 1.3, ≤ 3.5)	984 (41%)	340 (44%)	644 (40%)	
BMI				0.14
Normal (< 25)	357 (13%)	135 (15%)	222 (12%)	
Obese (≥ 30)	1248 (58%)	437 (59%)	811 (57%)	
Overweight (≥ 25, < 30)	766 (29%)	248 (26%)	518 (31%)	
Smoking status				0.4
Current smoker	398 (17%)	143 (18%)	255 (16%)	
Former smoker	820 (34%)	304 (36%)	516 (33.5%)	
Never smoker	1153 (49%)	373 (46%)	780 (50.5%)	
Education attainment				**0.012**
Less Than 9th Grade	338 (7.1%)	135 (8.5%)	203 (6.4%)	
9-11th Grade	353 (11%)	133 (11.6%)	220 (10.7%)	
High School Grad/GED	598 (28%)	211 (31.4%)	387 (26.5%)	
Some College or AA degree	659 (30.6%)	213 (31.1%)	446 (30.4%)	
College Graduate or above	423 (23.3%)	128 (17.4%)	295 (26%)	
Marital status				**0.038**
Married/cohabiting	1505 (66.4%)	488 (62.8%)	1017 (68%)	
Never married	213 (8.7%)	59 (7.2%)	154 (9.4%)	
Widowed/divorced/separated	653 (24.9%)	273 (30%)	380 (22.6%)	
Physical activity				0.8
Active	750 (32%)	254 (31%)	496 (32%)	
Inactive	1621 (68%)	566 (69%)	1055 (68%)	
CVD	470 (18%)	233 (26.2%)	237 (14.7%)	**< 0.001**
Hypertension	1609 (66%)	649 (77.6%)	960 (61.1%)	**< 0.001**
Hyperlipidemia	2073 (89%)	742 (89.9%)	1331 (87.9%)	0.2
Log2-VAI	1.13 (1.14)	1.27 (1.19)	1.07 (1.11)	**0.002**
Log2-ABSI	−3.58 (0.08)	−3.56 (0.08)	−3.58 (0.07)	**< 0.001**
Log2-CMI	−2.22 (0.87)	−2.07 (0.91)	−2.29 (0.85)	**< 0.001**
Log2-BRI	2.68 (0.52)	2.73 (0.51)	2.66 (0.52)	**0.041**
Log2-LAP	6.16 (1.10)	6.29 (1.16)	6.09 (1.07)	**0.002**

[1] N not Missing (unweighted);[2]Mean ± SD for continuous; n (%) for categorical;[3]t-test adapted to complex survey samples; chi-squared test with Rao & Scott's second-order correction. CVD, cardiovascular disease; VAI, visceral adiposity index; ABSI, a body shape index; CMI, Cardiac Metabolic Index; BRI, body roundness index; LAP, lipid accumulation product

studies have shown that TG and HDL-C are significantly independently associated with DKD [26]. In a study of middle-aged and elderly Chinese subjects, it was found that TG levels were significantly elevated in the group with mildly reduced eGFR, while HDL-C levels were significantly decreased [27]. Of course, there are also studies

Table 3 Association between CMI, ABSI, BRI, VAI, LAP, and DKD

	Crude model OR (95% CI)	Model 1 OR (95% CI)	Model 2 OR (95% CI)	Model3 OR (95% CI)
Log2-CMI	1.34(1.16, 1.54)***	1.44(1.23, 1.69)***	1.44(1.24, 1.69)***	1.40(1.19, 1.66)***
Q1	Reference	Reference	Reference	Reference
Q2	1.12(0.78, 1.60)	1.09(0.75, 1.59)	1.06(0.73, 1.54)	1.06(0.72, 1.55)
Q3	1.27(0.87, 1.86)	1.34(0.90, 1.99)	1.35(0.90, 2.03)	1.32(0.86, 2.04)
Q4	1.72(1.24, 2.40)**	2.00(1.40, 2.86)***	1.98(1.39, 2.84)***	1.84(1.24, 2.72)**
Log2-ABSI	41.3(8.00, 214)***	6.91(1.13, 42.2)*	5.36(0.85, 33.9)	4.35(0.67, 28.1)
Q1	Reference	Reference	Reference	Reference
Q2	0.96(0.66, 1.38)	0.87(0.59, 1.27)	0.85(0.58, 1.24)	0.81(0.55, 1.19)
Q3	1.27(0.88, 1.85)	1.03(0.69, 1.53)	1.00(0.66, 1.53)	0.94(0.61, 1.46)
Q4	2.04(1.47, 2.85)***	1.48(1.02, 2.17)*	1.41(0.96, 2.08)	1.33(0.90, 1.98)
Log2-BRI	1.30(1.01, 1.69)*	1.50(1.11, 2.01)**	1.50(1.12, 1.99)**	1.34(1.00, 1.79)*
Q1	Reference	Reference	Reference	Reference
Q2	1.05(0.74, 1.49)	1.00(0.69, 1.46)	1.04(0.71, 1.54)	0.99(0.66, 1.49)
Q3	1.17(0.81, 1.69)	1.17(0.80, 1.71)	1.17(0.80, 1.70)	1.06(0.72, 1.57)
Q4	1.47(1.01, 2.14)*	1.77(1.19, 2.61)**	1.79(1.21, 2.63)**	1.54(1.03, 2.29)*
Log2-VAI	1.17(1.06, 1.29)**	1.27(1.13, 1.42)***	1.25(1.12, 1.40)***	1.24(1.09, 1.41)**
Q1	Reference	Reference	Reference	Reference
Q2	1.70(1.20, 2.42)**	1.73(1.20, 2.50)**	1.70(1.17, 2.46)**	1.67(1.13, 2.45)*
Q3	1.09(0.76, 1.56)	1.26(0.87, 1.82)	1.21(0.84, 1.76)	1.20(0.80, 1.81)
Q4	1.77(1.28, 2.46)***	2.20(1.52, 3.19)***	2.16(1.49, 3.13)***	2.03(1.33, 3.10)**
Log2-LAP	1.18(1.07, 1.31)**	1.30(1.16, 1.47)***	1.29(1.15, 1.45)***	1.26(1.11, 1.44)***
Q1	Reference	Reference	Reference	Reference
Q2	1.03(0.75, 1.40)	1.04(0.75, 1.43)	1.01(0.72, 1.40)	1.00(0.71, 1.41)
Q3	1.11(0.78, 1.58)	1.25(0.87, 1.81)	1.21(0.84, 1.76)	1.16(0.78, 1.74)
Q4	1.45(1.09, 1.93)*	1.91(1.40, 2.61)***	1.87(1.37, 2.55)***	1.73(1.21, 2.48)**

Crude model: unadjusted for any covariates. Model 1: adjusted for age, sex, and race. Model 2: adjusted for age, sex, race, poverty income ratio, physical activity, education level, and smoking status. Model 3: adjusted for age, sex, race, poverty income ratio, physical activity, education level, smoking status, cardiovascular disease, hypertension, and hyperlipidemia. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; $p < 0.05$ was considered statistically significant. CMI, Cardiac Metabolic Index; ABSI, a body shape index; BRI, body roundness index; VAI, visceral adiposity index; LAP, lipid accumulation product

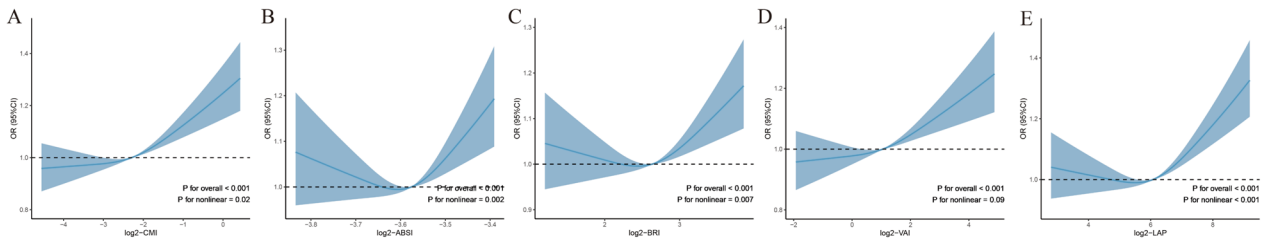

Fig. 2 Nonlinear relationships between CMI and other novel anthropometric indices with DKD. **A** Log2-CMI and DKD; **B** Log2-ABSI and DKD; **C** Log2-BRI and DKD; **D** Log2-VAI and DKD; **E** Log2-LAP and DKD. CMI, Cardiac Metabolic Index; ABSI, a body shape index; BRI, body roundness index; VAI, visceral adiposity index; LAP, lipid accumulation product

indicating that WHtR is closely related to kidney function [28, 29], with some researchers noting that for each unit increase in WHtR, the prevalence of CKD and albuminuria increases by 6 times and 6.19 times, respectively [30].

The association between CMI and DKD may be attributed to several factors, and the composition of CMI may explain its potential underlying mechanisms. First, WHtR is a simple and easily obtainable marker of general and abdominal obesity. Many adipokines and hormones produced by abdominal adipose tissue may lead to endocrine metabolic comorbidities [31], and abdominal obesity is associated with the production of inflammatory

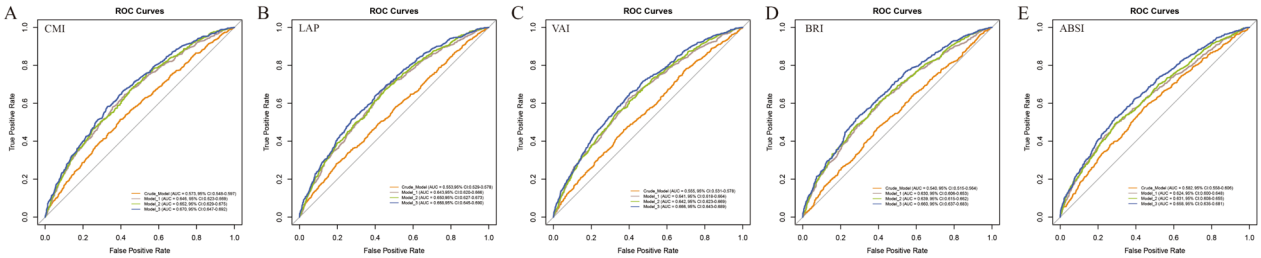

Fig. 3 ROC curves for predicting the incidence of DKD. CMI, Cardiac Metabolic Index; ABSI, a body shape index; BRI, body roundness index; VAI, visceral adiposity index; LAP, lipid accumulation product

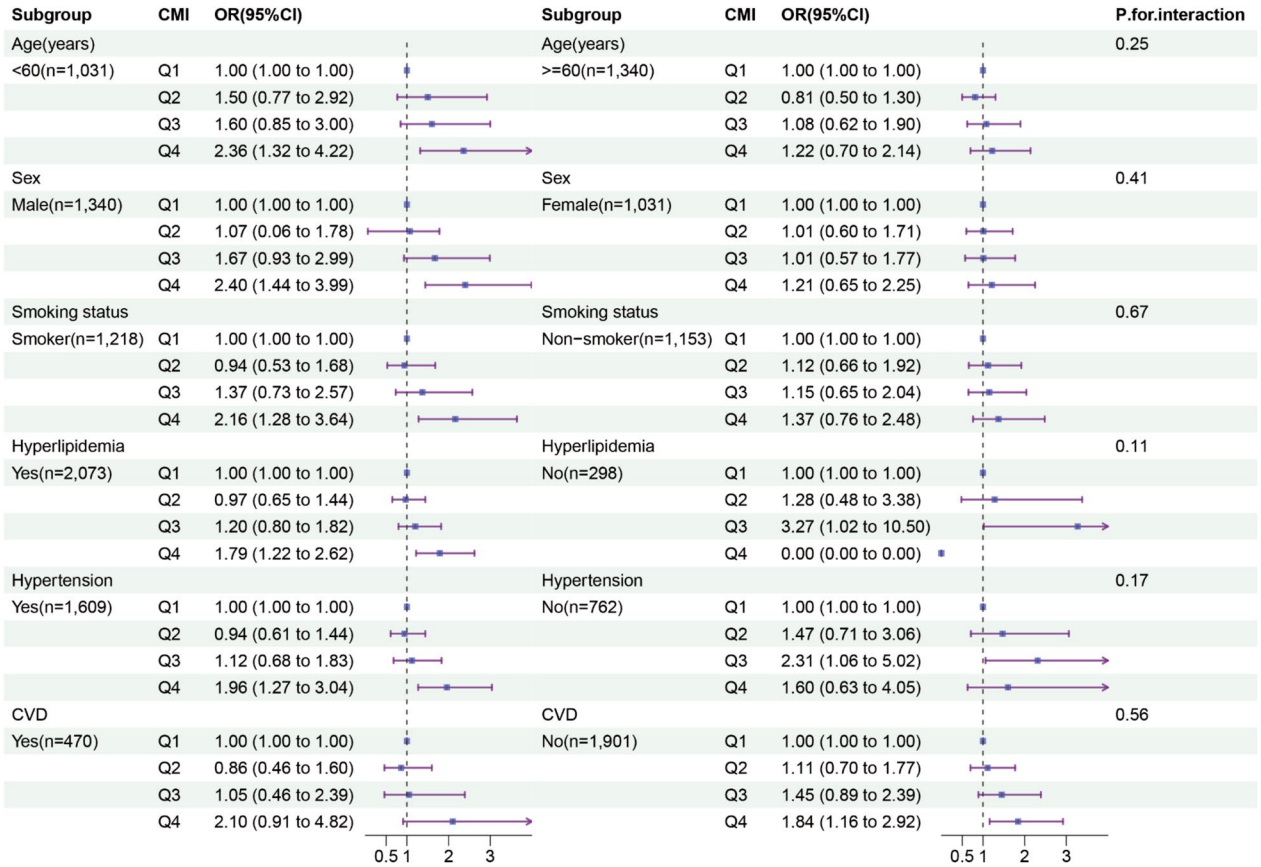

Fig. 4 Subgroup Analyses. The results of subgroup analysis were adjusted for all covariates except the effect modifier. CVD, cardiovascular disease

cytokines, such as TNF-α and IL-6, which may be related to kidney damage [32]. On the other hand, obesity-induced immunosuppression can lead to urinary tract infections, which in turn exacerbate renal dysfunction [33].The downregulation of lipoprotein lipase delays the metabolism of triglycerides by hydrolyzing very low-density lipoprotein and chylomicrons, leading to lipid accumulation in renal tissue [34]. Additionally, research has shown that lipoproteins rich in TG and apolipoprotein B can accelerate the progression of kidney disease [35], and impaired reverse cholesterol transport mediated by HDL-C further damages glomerulosclerosis and renal interstitium [36]. Second, abnormal lipid levels, such as high total cholesterol (TC) and high TG, may lead to tubular interstitial damage through the infiltration and deposition of fat in the renal tubule [37]. Furthermore, dyslipidemia can increase urinary albumin excretion and renal dysfunction by accelerating renal vascular atherosclerosis. Finally, CMI levels reflect the coexistence of multiple factors, and the complex interactions between

obesity and lipid levels may negatively impact endothelial cells, leading to impaired renal function [38–40].

This study has several notable strengths that enhance the reliability and significance of the findings. First, it is the first study to investigate the association between CMI levels and the prevalence of DKD, providing new insights for timely and effective intervention strategies for diabetic patients. Second, the use of NHANES data, which employs a rigorous multi-stage probability sampling design, ensures that the results are representative. Third, this study utilized ROC curves, further demonstrating that CMI can serve as the best predictive indicator for DKD compared to other novel anthropometric indices (ABSI, BRI, VAI, and LAP).

Our study has several limitations that should be acknowledged. First, due to the cross-sectional design, the relationship between CMI and DKD can only be interpreted as an association rather than a causal relationship. This means we cannot determine whether changes in CMI directly contribute to the development of DKD. Second, although we adjusted for most known confounding factors, residual confounders, such as medication use (e.g., lipid-lowering or antidiabetic drugs), may still influence the results. Third, the study population was derived from a U.S. database, which may limit the generalizability of our findings. Genetic backgrounds, lifestyle factors, and environmental exposures vary across populations, and these differences could affect the relationship between CMI and DKD. Therefore, further validation in diverse cohorts is necessary to confirm the universality of our results. Finally, long-term randomized controlled trials are needed to establish a causal link between CMI levels and DKD risk, which would provide stronger evidence for CMI as a potential screening tool for early DKD detection.

Conclusion

Our study indicates that high levels of CMI are positively correlated with the risk of DKD. This provides an important tool for assessing the occurrence of DKD in diabetic patients. This finding not only offers a basis for clinicians to identify high-risk patients early but also serves as a reference for the formulation of public health policies, emphasizing the importance of monitoring CMI in diabetic patients to enable timely interventions.

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Author contributions
ZL contributed to the conception and design of the study and data analysis. YZQ and LCY contributed to design of the study and wrote the first draft of the manuscript. LQZ contributed to the revision of the manuscript. All authors contributed to the article and approved the submitted version.

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Data availability
All data for this study are publicly available. This data can be found here: The National Health and Nutrition Examination Survey dataset at https://www.cdc.gov/nchs/nhanes/index.htm.

Declarations

Ethics approval and consent to participate
Not applicable. We used publicly available data that were obtained with ethical approval from their respective institutional review boards and informed consent from all participants. No administrative permissions were required for accessing the data.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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