Lipids in Health and Disease

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Association of triglyceride-glucose index and diabesity: evidence from a national longitudinal study

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Abstract

Background Diabesity, a co-occurrence of diabetes and obesity, is a growing public health concern globally. The triglyceride-glucose (TyG) index, a surrogate marker of insulin resistance, has been associated with various metabolic disorders. This study aimed to investigate the association between TyG index and new-onset diabesity in a national longitudinal study.

Methods We utilized data from the China Health and Retirement Longitudinal Study (CHARLS). Baseline data from the first wave (2011) and follow-up data from the third wave (2015) were analyzed. A Competing risks model based on Fine and Gray's subdistribution hazard approach was employed to examine the association between the TyG index and developing of three mutually exclusive outcomes: remaining free of diabetes and obesity, diabetes alone, and new-onset diabesity (co-occurrence of diabetes and obesity).

Results A total of 6,976 participants were included in the analysis. During a mean follow-up period of 4.0 years, a total of 557 diabetes and 155 diabesity were recorded, respectively. After adjusting for socio-demographic information, lifestyle and comorbidities, compared with participants in the lowest quartile of TyG, the corresponding adjusted subdistribution hazard ratios (HRs) with 95% confidence intervals (95% CIs) for participants in the second, third, and fourth quartiles were 2.112 (95% CI: 1.047–4.259; *P*-value = 0.037), 2.911 (95% CI: 1.481–5.722, *P*-value = 0.002), and 4.305 (95% CI: 2.220–8.346, *P*-value < 0.001). The association between TyG and diabetes alone was equally significant when diabesity treated as the competing risk. Sensitivity analyses proved the robustness of results.

Conclusion This national longitudinal study in China provides evidence that a higher TyG index is associated with an increased risk of developing diabesity.

Keywords Triglyceride-glucose index, Diabesity, Obesity, Diabetes

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Introduction

Diabesity, the co-occurrence of diabetes and obesity, has emerged as a major public health concern worldwide [1]. The prevalence of diabesity has been steadily increasing, driven by the global epidemics of type 2 diabetes and obesity [2]. Individuals with diabesity often experience a more severe disease course, higher risk of complications, and poorer health outcomes compared to those with either diabetes or obesity alone [3]. Therefore, understanding the risk factors and early identification of individuals at high risk of developing diabesity is crucial for implementing targeted prevention and intervention strategies.

The triglyceride-glucose (TyG) index, calculated as the product of fasting triglycerides and glucose levels, has emerged as a simple and cost-effective surrogate marker of insulin resistance [4]. Numerous studies have demonstrated the association between the TyG index and various metabolic disorders, including type 2 diabetes [5], non-alcoholic fatty liver disease, and cardiovascular diseases [6, 7]. Despite these findings, the potential effects of TyG on diabesity have yet to be fully elucidated. This knowledge gap has hindered our ability to accurately estimate the disease burden of diabesity attributable to TyG exposure.

This study aimed to examine the relationship between TyG index and risk of new-onset diabesity, as well as diabetes alone, using a Competing risks model in a national longitudinal study.

Methods

This study followed Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines [8] (Table S1).

Study population

This study utilized data from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative survey of middle-aged and older adults in China [9]. The baseline data were collected in 2011 (wave 1), and the follow-up data were obtained in 2015 (wave 3). All respondents signed an informed consent form and obtained ethics approval from the Biomedical Ethics Review Committee of Peking University (IRB00001052-11014; IRB00001052-11015). For the current analysis, we included participants who were free of diabetes and obesity at baseline (wave 1) and had complete data on the key variables of interest. Figure 1 depicts the participant screening process for this analysis.

Assessment of TyG index

After completing the questionnaires and physical examinations, 8 ml fasting blood samples were collected by trained nurses from the participants at the township hospitals or the local centers for disease prevention and control. The blood samples were collected after an overnight fast of at least 8 h, and were separated into plasma and buffy coat, immediately frozen, stored at a local hospital at -20℃ and stored at -70℃ until laboratory assaying at Capital Medical University. The following biomarkers were tested: triglyceride, total cholesterol, low-density lipoprotein cholesterol, high-density lipoprotein-cholesterol, glycosylated hemoglobin, uric acid, creatinine, blood urea nitrogen, fasting blood glucose, cystatin C, and C-reactive protein.

The TyG index was calculated as the natural logarithm of the product of fasting triglycerides (in mg/dL) and fasting blood glucose (in mg/dL), as follows: TyG index = ln (fasting triglycerides × fasting glucose) [10].

Ascertainment of incident diabesity events

The primary outcome of interest was the development of new-onset diabesity, defined as the co-occurrence of new-onset diabetes and obesity during the follow-up period. Diabetes was diagnosed based on self-reported physician diagnosis, use of antidiabetic medications, or a fasting plasma glucose level ≥ 126 mg/dL [11]. Obesity was defined as a body mass index (BMI) ≥ 28 kg/m^2 [12]. We also examined the development of new-onset diabetes alone as a secondary outcome.

Covariates

The covariates were selected based on prior knowledge and literature [13–18]. At baseline, trained interviewers collected information on sociodemographic status, lifestyle factors, and health status using a structured questionnaire. Sociodemographic status included age (< 60 years, ≥ 60 years), gender (male, female), education (primary school and below, high school or above), marriage (married, other); lifestyle factors included smoking (former, current), drinking (former, current), and sleep duration (< 7 h, ≥ 7 h); health status included lung disease (self-reported history of lung disease), heart disease (self-reported disease history), kidney disease (self-reported disease history), hypertension (defined as systolic blood pressure ≥ 140 mmHg and diastolic blood pressure ≥ 90 mmHg or self-reported history of hypertension), and depressive symptom (assessed by Center for Epidemiologic Studies Depression Scale) [19].

Statistical analysis

Table S2 lists the missing proportions for each covariate. We used the random forest method to imputed missing values [20]. Missing data were imputed using the missForest method, which is based on random forest and has been shown to perform well in handling missing values in epidemiological studies [20]. This non-parametric method can capture non-linear relationships and

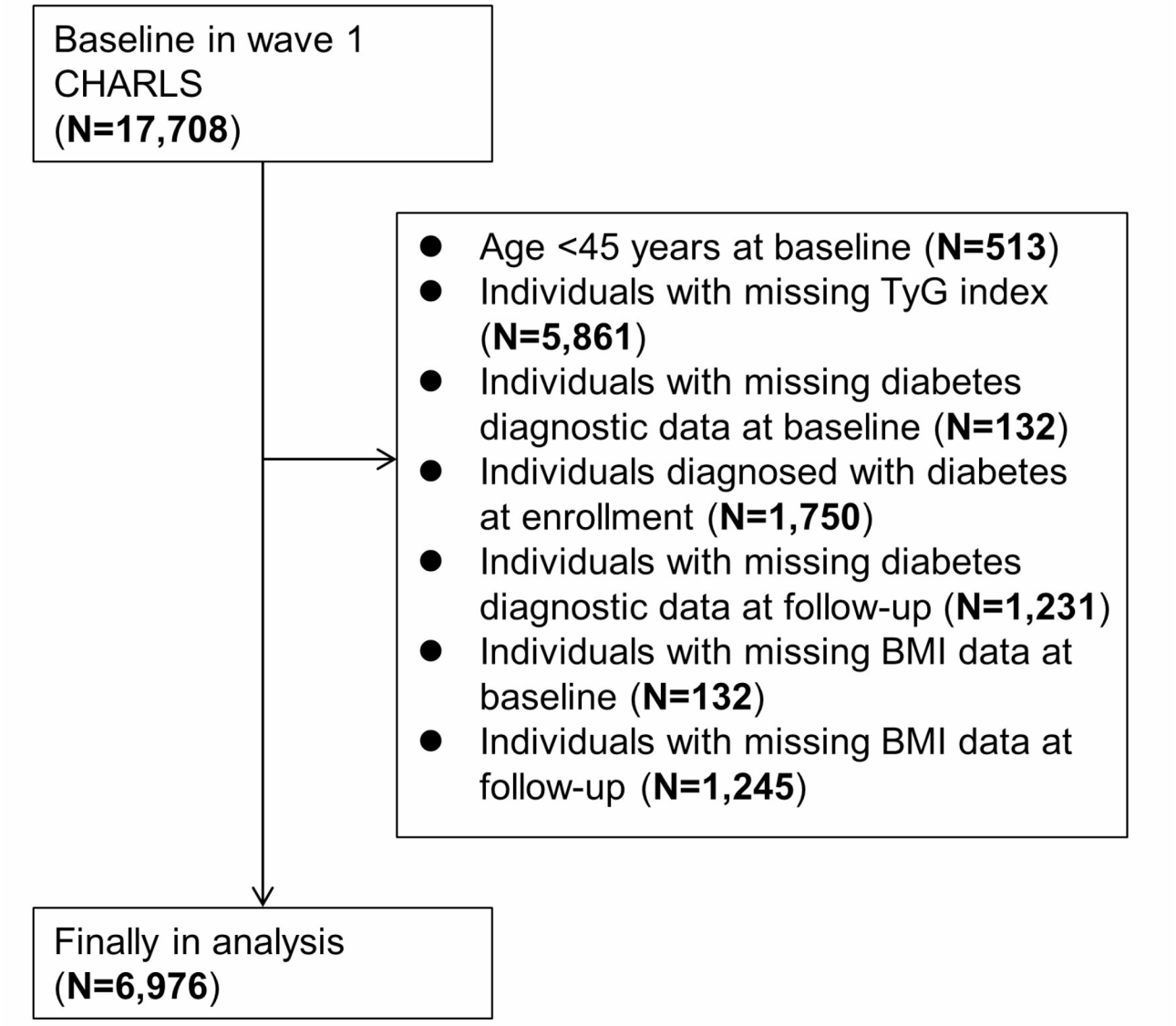

Fig. 1 Participants screening flowchart. CHARLS = China Health and Retirement Longitudinal Study; TyG = triglyceride-glucose; BMI = body mass index

complex interactions between variables, making it particularly suitable for mixed-type data (continuous and categorical). The imputation process was conducted using the 'missForest' package in *R*, with the default settings of 100 trees per forest and a maximum iteration of 10. To assess the robustness of our findings, we conducted two sensitivity analyses: one using the original dataset with missing values and another using complete-case analysis (including only participants with no missing data).

Baseline characteristics of the study participants were summarized using median and interquartile for continuous variables and frequencies and percentages for categorical variables. Differences in baseline characteristics between participants were assessed using Kruskal-Wallis rank sum test for continuous variables and chi-square tests for categorical variables.

A Competing risks model based on Fine and Gray's subdistribution hazard approach was employed to examine the association between the TyG index (categorized into quartiles) and the development of new-onset diabesity and new-onset diabetes alone, with participants remaining free of diabetes and obesity as the reference group. The subdistribution hazard ratios (HRs) and 95% confidence intervals (95% CIs) were calculated, adjusting for the aforementioned covariates. To test the proportional hazards assumption, we included time-varying coefficients in our competing risks model by incorporating interactions between covariates and follow-up time. This approach allowed us to assess whether the effect of predictors varied over the follow-up period.

To address the potential reverse causality, we have conducted additional sensitivity analyses, we excluded

participants with insulin resistance at baseline (defined as TyG index ≥ 8.93, the highest quartile).

All statistical analyses were performed using *R* software (version 4.2.0, R Foundation for Statistical Computing, Vienna, Austria). The two-tailed *P*-value < 0.05 was considered statistically significant.

Results

Baseline characteristics

The baseline characteristics table (Table 1) provides key demographic and clinical information for a total of 6,976 participants. The median (interquartile range [IQR]) age of the study population was 58 (52, 65) years, and 46.2% were male. The median (IQR) TyG index was 8.53 (8.19, 8.93).

When examining the characteristics based on the TyG quartile, it was found that the distribution of this group varied significantly across different subgroups (*P* value < 0.05). Specifically, a higher proportion of participants classified as "≥ 8.93" were female (59.5%) compared to other subgroups. Moreover, rural residency was more prevalent in the "≥ 8.93" subgroup (64.1%), while urban residency was higher in the "≥ 8.93" subgroup (35.9%). These findings suggest potential associations between TyG values, demographic characteristics, and clinical outcomes in the study population.

Association between TyG and incident diabesity events

During the mean follow-up period of 4.0 years, 557 participants developed new-onset diabetes, and 155 participants developed new-onset diabesity. Figure 2 illustrates the percentage of TyG quartiles with normal, diabetic, and diabesity.

The proportional hazards assumption was tested by including time-varying coefficients in the model. The results showed no significant time-varying effects for the TyG index quartiles (all $P > 0.05$), indicating that the proportional hazards assumption was not violated. In the Competing risks model, compared to participants in the lowest quartile of TyG index, the adjusted sub-distribution HRs on new-onset diabesity were 2.112 (95% CI: 1.047–4.259, *P*-value = 0.037) for the second quartile, 2.911 (95% CI: 1.481–5.722, *P*-value = 0.002) for the third quartile, and 4.305 (95% CI: 2.220–8.346, *P*-value < 0.001) for the fourth quartile, after adjusting for potential confounders (Table 2). Similar results were obtained from both sensitivity analyses using the original dataset (Table S3) and complete-case analysis (Table S4), suggesting that our findings were robust to different analytical approaches. In addition, we excluded participants with insulin resistance at baseline (defined as TyG index ≥ 8.93, the highest quartile), and similar results were obtained (Table S5).

The association between the TyG index and new-onset diabetes alone was also statistically significant when treating diabesity as the competing risk. In the fully adjusted model, the sub-distribution HRs for second, third, and fourth quartile were 1.351 (95% CI: 1.011–1.806, *P*-value = 0.042), 1.495 (95% CI: 1.122–1.993, *P*-value = 0.006), and 1.677 (95% CI: 1.259–2.234, *P*-value < 0.001), compared to the lowest quartile (Table 2). Similar results were obtained from the sensitivity analysis (Table S3-S5).

Discussion

Principal findings

In this large, nationally representative longitudinal study of middle-aged and older adults in China, we found that a higher TyG index, a surrogate marker of insulin resistance, was significantly associated with an increased risk of developing new-onset diabesity during the 4-year follow-up period. Specifically, compared to participants in the lowest quartile of the TyG index, those in the highest quartile had more than a 4-fold increased risk of developing new-onset diabesity, after adjusting for potential confounders. Interestingly, the TyG index was also associated with an increased risk of new-onset diabetes alone, even when treating diabesity as the competing risk.

To address the potential reverse causality between TyG index and diabesity, we conducted sensitivity analyses, and excluded participants with insulin resistance at baseline (defined as TyG index ≥ 8.93, the highest quartile) to minimize the possibility that pre-existing metabolic disorders might influence the observed associations. The results from sensitivity analyses were consistent with our main findings, suggesting that reverse causality is unlikely to fully explain the observed associations between TyG index and diabesity. However, we acknowledge that the relatively short follow-up period (4 years) may not completely rule out the possibility of reverse causality, and longer-term studies are needed to further validate these findings.

To assess the generalizability of our findings and potential misclassification bias, we compared our observed incidence rates with national data. In our study, the 5-year cumulative incidence of diabetes was 8.0% (557/6,976), corresponding to an annual incidence rate of approximately 1.6%. This is comparable to the reported annual incidence of diabetes (1.3–1.9%) in recent large-scale Chinese cohort studies [23, 24]. Similarly, our observed 5-year cumulative incidence of diabesity (2.2%, 155/6,976) aligns with previous reports from urban Chinese populations [25]. These comparisons suggest that our cohort's incidence rates are representative of the general Chinese population, minimizing concerns about selection bias or systematic misclassification of diabetes and obesity diagnoses.

Table 1 Patient demographics and baseline characteristics

Characteristic	TyG quartile [1]					*P*-value
	Overall (*N* = 6,976)	< 8.19 (*N* = 1,760)	8.19–8.53 (*N* = 1,716)	8.53–8.93 (*N* = 1,761)	≥ 8.93 (*N* = 1,739)	
Age, years	58 (52, 65)	58 (51, 65)	58 (52, 65)	58 (52, 65)	58 (52, 64)	0.097[3]
TyG index	8.53 (8.19, 8.93)	7.97 (7.80, 8.09)	8.37 (8.28, 8.45)	8.72 (8.62, 8.82)	9.24 (9.07, 9.53)	< 0.001[3]
Age group[4]						0.042[2]
< 60 years	3,924 (56.3%)	966 (54.9%)	950 (55.4%)	979 (55.6%)	1,029 (59.2%)	
≥ 60 years	3,052 (43.8%)	794 (45.1%)	766 (44.6%)	782 (44.4%)	710 (40.8%)	
Gender						< 0.001[2]
Male	3,222 (46.2%)	961 (54.6%)	810 (47.2%)	747 (42.4%)	704 (40.5%)	
Female	3,754 (53.8%)	799 (45.4%)	906 (52.8%)	1,014 (57.6%)	1,035 (59.5%)	
Marriage						0.518[2]
Married	6,206 (89.0%)	1,563 (88.8%)	1,543 (89.9%)	1,557 (88.4%)	1,543 (88.7%)	
Other	770 (11.0%)	197 (11.2%)	173 (10.1%)	204 (11.6%)	196 (11.3%)	
Residence						< 0.001[2]
Rural	4,736 (67.9%)	1,252 (71.1%)	1,198 (69.8%)	1,172 (66.6%)	1,114 (64.1%)	
Urban	2,240 (32.1%)	508 (28.9%)	518 (30.2%)	589 (33.4%)	625 (35.9%)	
Education						0.486[2]
Primary and below	4,911 (70.4%)	1,248 (70.9%)	1,185 (69.1%)	1,256 (71.3%)	1,222 (70.3%)	
Secondary and above	2,065 (29.6%)	512 (29.1%)	531 (30.9%)	505 (28.7%)	517 (29.7%)	
Former drinking						< 0.001[2]
None	4,284 (61.4%)	999 (56.8%)	1,037 (60.4%)	1,136 (64.5%)	1,112 (63.9%)	
Yes	2,692 (38.6%)	761 (43.2%)	679 (39.6%)	625 (35.5%)	627 (36.1%)	
Current drinking						< 0.001[2]
None	4,663 (66.8%)	1,079 (61.3%)	1,142 (66.6%)	1,237 (70.2%)	1,205 (69.3%)	
Yes	2,313 (33.2%)	681 (38.7%)	574 (33.4%)	524 (29.8%)	534 (30.7%)	
Former smoking						< 0.001[2]
None	4,275 (61.3%)	988 (56.1%)	1,052 (61.3%)	1,113 (63.2%)	1,122 (64.5%)	
Yes	2,701 (38.7%)	772 (43.9%)	664 (38.7%)	648 (36.8%)	617 (35.5%)	
Current smoking						< 0.001[2]
None	4,820 (69.1%)	1,132 (64.3%)	1,174 (68.4%)	1,249 (70.9%)	1,265 (72.7%)	
Yes	2,156 (30.9%)	628 (35.7%)	542 (31.6%)	512 (29.1%)	474 (27.3%)	
Sleep duration						0.106[2]
< 7 h	3,661 (52.5%)	898 (51.0%)	930 (54.2%)	946 (53.7%)	887 (51.0%)	
≥ 7 h	3,315 (47.5%)	862 (49.0%)	786 (45.8%)	815 (46.3%)	852 (49.0%)	
Lung disease						0.411[2]
None	6,311 (90.5%)	1,583 (89.9%)	1,553 (90.5%)	1,585 (90.0%)	1,590 (91.4%)	
Yes	665 (9.5%)	177 (10.1%)	163 (9.5%)	176 (10.0%)	149 (8.6%)	
Heart disease						< 0.001[2]
None	6,190 (88.7%)	1,606 (91.3%)	1,556 (90.7%)	1,539 (87.4%)	1,489 (85.6%)	
Yes	786 (11.3%)	154 (8.8%)	160 (9.3%)	222 (12.6%)	250 (14.4%)	
Kidney disease						0.547[2]
None	6,582 (94.4%)	1,658 (94.2%)	1,609 (93.8%)	1,666 (94.6%)	1,649 (94.8%)	
Yes	394 (5.6%)	102 (5.8%)	107 (6.2%)	95 (5.4%)	90 (5.2%)	
Hypertension						< 0.001[2]
None	4,012 (57.5%)	1,166 (66.3%)	1,047 (61.0%)	968 (55.0%)	831 (47.8%)	
Yes	2,964 (42.5%)	594 (33.8%)	669 (39.0%)	793 (45.0%)	908 (52.2%)	
Body mass index						< 0.001[2]
< 28 kg/m^2	6,128 (87.8%)	1,652 (93.9%)	1,551 (90.4%)	1,519 (86.3%)	1,406 (80.9%)	
≥ 28 kg/m^2	848 (12.2%)	108 (6.1%)	165 (9.6%)	242 (13.7%)	333 (19.1%)	
CESD[5]						0.354[2]
Normal	4,430 (63.5%)	1,134 (64.4%)	1,092 (63.6%)	1,088 (61.8%)	1,116 (64.2%)	
Depressive symptom	2,546 (36.5%)	626 (35.6%)	624 (36.4%)	673 (38.2%)	623 (35.8%)	
Serum urea, mg/dL	15.1 (12.6, 18.2)	15.8 (12.9, 18.9)	15.1 (12.7, 18.4)	14.7 (12.4, 17.7)	14.9 (12.4, 17.6)	< 0.001[3]

Table 1 (continued)

Characteristic	TyG quartile [1]					*P*-value
	Overall (*N* = 6,976)	< 8.19 (*N* = 1,760)	8.19–8.53 (*N* = 1,716)	8.53–8.93 (*N* = 1,761)	≥ 8.93 (*N* = 1,739)	
Blood glucose, mg/dL	101 (94, 108)	95 (88, 102)	99 (93, 105)	101 (95, 108)	107 (100, 115)	< 0.001[3]
Serum creatinine, mg/dL	0.76 (0.64, 0.87)	0.75 (0.64, 0.86)	0.75 (0.63, 0.87)	0.76 (0.64, 0.88)	0.76 (0.67, 0.89)	< 0.001[3]
Total cholesterol, mg/dL	189 (167, 213)	176 (156, 199)	187 (165, 209)	194 (171, 216)	201 (177, 229)	< 0.001[3]
Triglyceride, mg/dL	102 (73, 147)	60 (51, 68)	86 (79, 96)	120 (108, 135)	196 (165, 255)	< 0.001[3]
High density lipoprotein, mg/dL	50 (41, 61)	59 (51, 68)	53 (46, 63)	48 (41, 57)	40 (34, 48)	< 0.001[3]
Low density lipoprotein, mg/dL	114 (94, 136)	106 (88, 126)	116 (96, 136)	121 (101, 143)	114 (90, 141)	< 0.001[3]
C-reactive protein, mg/L	0.95 (0.52, 1.99)	0.82 (0.45, 1.77)	0.85 (0.48, 1.85)	0.96 (0.54, 1.98)	1.16 (0.66, 2.28)	< 0.001[3]
Hemoglobin A1c, %	5.10 (4.90, 5.30)	5.00 (4.80, 5.30)	5.10 (4.80, 5.30)	5.10 (4.90, 5.40)	5.18 (4.90, 5.40)	< 0.001[3]
Serum uric acid, mg/dL	4.25 (3.55, 5.10)	4.07 (3.44, 4.87)	4.13 (3.45, 4.98)	4.24 (3.56, 5.09)	4.60 (3.80, 5.46)	< 0.001[3]
Cystatin C, mg/L	0.97 (0.88, 1.09)	0.98 (0.89, 1.10)	0.98 (0.89, 1.10)	0.98 (0.90, 1.10)	0.93 (0.84, 1.05)	< 0.001[3]

[1] Data were presented as n (%) or median (interquartile range). [2] Pearson's Chi-squared test. [3] Kruskal-Wallis rank sum test. [4] Age was dichotomized at 60 years (< 60 years vs. ≥60 years) based on the traditional definition of elderly population in China and to maintain consistency with previous studies in Chinese populations [21, 22]. [5] Assessed by Center for Epidemiologic Studies Depression Scale, and scores ≥ 10 were deemed as depressive symptoms

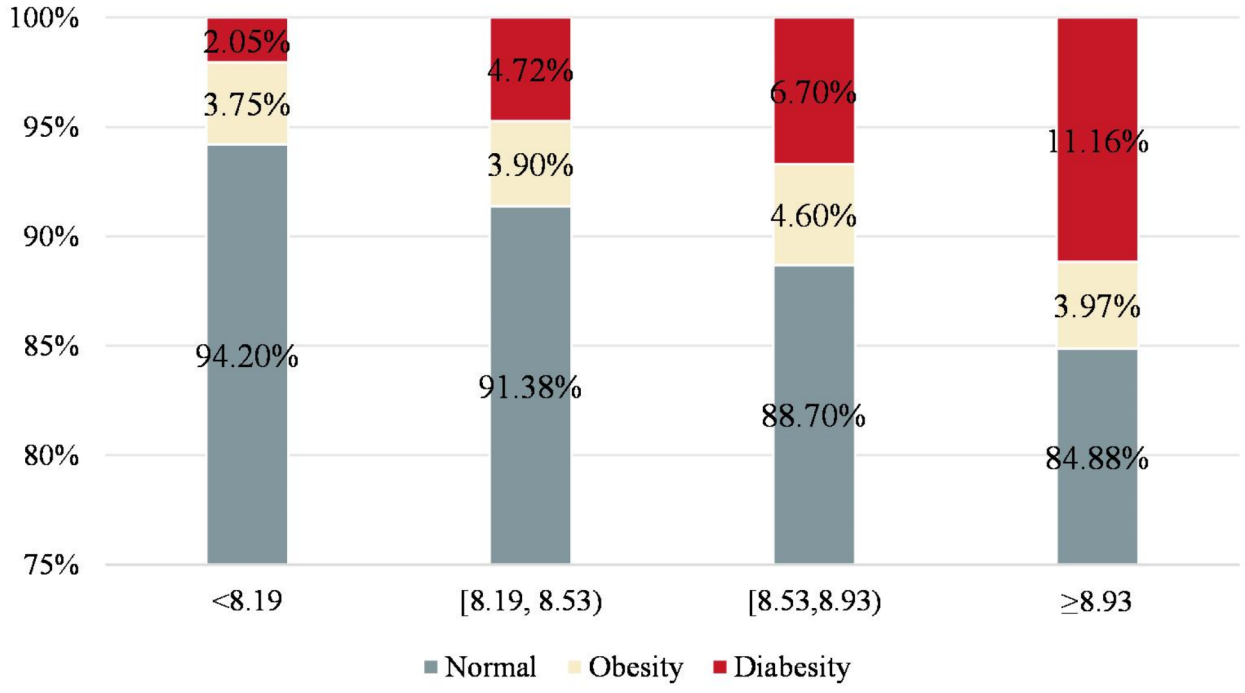

Fig. 2 Percentage of TyG quartiles with normal, diabetic, and diabesity

Comparison with previous studies

Previous longitudinal studies have primarily focused on the association between the TyG index and the incidence of type 2 diabetes or cardiovascular diseases [6, 7]. To the best of our knowledge, this is the first study to investigate the role of the TyG index in the development of diabesity using a Competing risks model, which allows for the examination of the distinct associations with new-onset diabetes alone and new-onset diabesity.

Several cross-sectional studies have reported a positive association between the TyG index and the presence of metabolic syndrome, which shares common features with diabesity. For instance, Simental-Mendía et al. found that the TyG index was significantly associated with insulin resistance and metabolic syndrome in a Mexican population [26]. Similarly, Lee et al. [27] demonstrated that the TyG index was independently associated with the presence of metabolic syndrome in Korean adults.

Regarding diabetes, our results align with longitudinal studies that have shown the predictive value of the TyG index for incident diabetes. A study by Zhang et al. [28] in a Chinese population found that the TyG index was a

Table 2 Risk of incident diabesity/diabetes according to TyG quartile

Characteristic	Univariable			Multivariable [2]	
	Event/Total	HR (95% CI)	*P*-value	HR (95% CI)	*P*-value
Diabesity as an outcome of interest					
TyG quartile					
< 8.19	11/1,760	1 [Reference]		1 [Reference]	
8.19–8.53	28/1,716	2.523 (95% CI: 1.257–5.064)	0.009	2.112 (95% CI: 1.047–4.259)	0.037
8.53–8.93	44/1,761	3.743 (95% CI: 1.937–7.232)	< 0.001	2.911 (95% CI: 1.481–5.722)	0.002
≥ 8.93	72/1,739	6.286 (95% CI: 3.341–11.826)	< 0.001	4.305 (95% CI: 2.220–8.346)	< 0.001
Diabetes as an outcome of interest					
TyG quartile					
< 8.19	91/1,760	1 [Reference]		1 [Reference]	
8.19–8.53	120/1,716	1.304 (95% CI: 0.998, 1.704)	0.051	1.264 (95% CI: 0.967,1.651)	0.086
8.53–8.93	155/1,761	1.600 (95% CI: 1.241, 2.061)	< 0.001	1.495 (95% CI: 1.160,1.927)	0.002
≥ 8.93	191/1,739	2.046 (95% CI: 1.600, 2.616)	< 0.001	1.926 (95% CI: 1.502,2.469)	< 0.001

[1] HR = Hazard ratio, 95% CI = 95% Confidence interval, TyG = Triglyceride-glucose. [2] Adjusted for age group, gender, marry, residence, education, current smoking, former smoking, current drinking, former drinking, sleep duration, lung disease, heart disease, kidney disease, hypertension, and depressive symptom

better predictor of incident type 2 diabetes compared to traditional glycemic markers. Our findings extend this association to the broader concept of diabesity. With respect to obesity, Zheng et al. [29] reported that the TyG index was associated with an increased risk of incident non-alcoholic fatty liver disease, a condition closely linked to obesity. Our study builds upon these findings by demonstrating the TyG index's association with the combined outcome of diabetes and obesity.

However, it's important to note that most previous studies have not specifically addressed diabesity as a combined outcome. A study by Ramírez-Vélez et al. came close to our approach by examining the association between the TyG index and cardiometabolic risk factors clustering, including both glycemic and obesity measures, but it was cross-sectional in nature [30].

Our longitudinal design and focus on diabesity as a specific outcome provide a unique contribution to literature. By using a Competing risks model, we were able to distinguish between the development of diabetes alone and diabesity, offering a more nuanced understanding of the TyG index's predictive capabilities.

Potential mechanism

The observed association between the TyG index and the development of diabesity may be attributed to the underlying mechanism of insulin resistance. The TyG index has been shown to be a reliable surrogate marker of insulin resistance, which is a key pathophysiological feature shared by both diabetes and obesity. Insulin resistance can lead to hyperglycemia, dyslipidemia, and increased visceral adiposity, ultimately contributing to the development of both diabetes and obesity, and their co-occurrence, i.e., diabesity [1].

Furthermore, insulin resistance has been linked to various inflammatory and metabolic pathways that can promote the progression from a state of insulin resistance to the development of overt diabetes and obesity [31, 32]. The synergistic effects of these pathways may explain the stronger association observed between the TyG index and the development of diabesity, compared to diabetes alone.

Implications for clinical practice

The findings of our study have several important implications for clinical practice, particularly in the context of diabesity prevention and management. From clinical, the TyG index emerges as a valuable tool for early identification of individuals at high risk of developing diabesity. Given its simplicity and cost-effectiveness, the TyG index could be easily incorporated into routine health screenings, allowing clinicians to stratify patients according to their risk of developing this complex metabolic condition [7]. Additionally, by identifying high-risk individuals early, healthcare providers can implement targeted interventions to prevent or delay the onset of diabesity. These interventions may include more intensive lifestyle modifications, such as structured diet and exercise programs, which have been shown to be effective in preventing both diabetes and obesity [33, 34]. At a healthcare system level, the TyG index could guide resource allocation by identifying populations at highest risk of diabesity, allowing for more efficient targeting of preventive programs and interventions [35].

Strengths and limitations

The strengths of this study include a prospective nature of our study allows for the assessment of temporal relationships between the TyG index and the development of diabesity, providing stronger evidence for causality compared to cross-sectional studies. Our use of competing risks models allowed us to distinguish between the development of diabetes alone and diabesity, providing a

more nuanced understanding of the TyG index's predictive capabilities.

However, several limitations should be acknowledged. First, we did not collect mortality data during the follow-up period, which prevented us from considering all-cause mortality as a competing risk in our analysis. This limitation may affect the accuracy of our risk estimates, as death could prevent the occurrence of diabesity. Second, the diagnosis of diabetes was based on self-reported physician diagnosis, use of antidiabetic medications, or a single fasting plasma glucose measurement, which may have led to some misclassification. Third, the assessment of obesity was limited to BMI measurements, and we lacked more comprehensive measures of body composition or fat distribution such as waist circumference, waist-to-hip ratio, or body fat percentage. Fourth, these additional measurements could have provided more accurate assessment of obesity status. despite our comprehensive adjustment for confounders, there may be residual confounding from unmeasured factors or measurement error in the assessed variables [36]. Fifth, we did not have repeated measurements of the TyG index over time, which could have provided information on how changes in the TyG index relate to diabesity risk. Sixth, although we used the missForest method, which has been validated in previous epidemiological studies, and conducted sensitivity analyses using raw data that showed consistent results, we cannot completely rule out the potential impact of missing data patterns on our findings. However, the consistency between analyses using imputed and raw data suggests that our conclusions are robust to the chosen analytical approach. Finally, lack of data on dietary patterns and physical activity. More detailed information on these lifestyle factors could have provided additional insights into the relationship between the TyG index and diabesity. Another important limitation is the lack of quantitative data on smoking and drinking behaviors. Our analysis was limited to categorical classifications (former/current smokers/drinkers) without detailed information on pack-years of smoking or alcohol consumption quantities. This simplified categorization may have masked potential dose-response relationships between these lifestyle factors and diabesity risk. More detailed quantification of smoking and drinking behaviors could provide better insights into their roles as potential confounders or effect modifiers in the relationship between TyG index and diabesity.

Future directions

While our study provides valuable insights into the association between the TyG index and diabesity, several areas warrant further investigation: (1) Future research should focus on elucidating the underlying biological mechanisms linking the TyG index to the development of diabesity. This could involve investigating the role of insulin resistance, inflammation, and oxidative stress in this relationship. (2) Ethnic and geographic variations: Given that our study was conducted in a Chinese population, future research should explore the applicability of the TyG index in predicting diabesity across different ethnic groups and geographic regions. (3) Integration with other biomarkers: Research should explore the potential of combining the TyG index with other biomarkers or risk scores to improve the prediction accuracy for diabesity. (4) Pediatric populations: Given the rising prevalence of childhood obesity and type 2 diabetes [34], studies exploring the utility of the TyG index in pediatric populations are needed. (5) Lifestyle intervention studies: Future research should explore how changes in lifestyle factors affect the TyG index and subsequent diabesity risk, potentially identifying key modifiable factors for prevention.

Conclusion

This large, nationally representative longitudinal study in China provides evidence that a higher TyG index is associated with an increased risk of developing new-onset diabesity. This information can guide targeted screening, early intervention, and the implementation of lifestyle modifications or pharmacological therapies to prevent the development of this detrimental metabolic condition. Further research is needed to explore the underlying mechanisms linking the TyG index to the pathogenesis of diabesity and to investigate the potential utility of the TyG index in guiding personalized prevention and management strategies.

Supplementary Information

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Supplementary Material 1

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Author contributions

Fan Zhang: Conceptualization, Data curation, Formal analysis, Methodology, Writing-original draft. Yan Bai: Conceptualization, Writing-review & editing. Yan Sun: Data curation. Rong Wu: Supervision, Conceptualization. Hua Yang: Funding acquisition, Supervision, Writing-review & editing. All authors read and approved the final manuscript. All authors contributed to this article.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics statement
The studies involving human participants were reviewed and approved by the Biomedical Ethical Review Committee of Peking University (IRB00001052-11015). The participants provided their written informed consent to participate in this study. The privacy rights of participants were observed.

Competing interests
The authors declare no competing interests.

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