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Triglyceride–glucose index: a potent predictor of metabolic risk factors and eating behavior patterns among obese individuals

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Abstract

Background The strong potential of triglyceride to glucose index (TyG) in prediction of metabolic abnormalities is well identified in numerous disease including diabetes, metabolic syndrome and kidney disorders. However, no study is available to assess its validity and association with metabolic phenotype among obese individuals. In the current study, we aimed to evaluate the TyG index, its validity and association with metabolic parameters among obese individuals.

Methods and materials : In the current cross-sectional study, 300 obese individuals were enrolled. Their demographic, anthropometric measurements were done and laboratory parameters including serum lipids, glycemic markers and insulin resistance were evaluated. Blood pressure was also measured with standard methods. The TyG index was calculated as the $\ln(\text{fasting triglyceride level [mg/dL]} \times \text{fasting glucose level [mg/dL]}/2)$. Eating pattern was measured with three factor eating behavior questionnaire (TFEQ). Receiver operator characteristic curve was used to assess the TyG validity.

Results Subjects at the higher TyG tertile had higher waist to hip ratio (WHR) and eating disorder compared with lowest tertiles. Also, those at the highest tertiles had significantly higher total cholesterol (TC), triglyceride (TG), and fasting blood sugar (FBS), and lower high density lipoprotein cholesterol (HDL). According to the ROC curve analysis for various metabolic parameters, TyG demonstrated the highest area under curve (AUC) value of 0.838 compared with other metabolic parameters in identification of metabolic syndrome.

Conclusion The current study provides valuable insights into the relationship between TyG index, metabolic parameters, and eating behaviors among obese individuals.

Keywords Obesity, Triglyceride to glucose index, TyG, Metabolic syndrome, Lipid profile

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Introduction

Obesity has burgeoned into a global health crisis of unprecedented proportions, transcending geographical, socioeconomic, and demographic boundaries. Obesity, is defined by the World Health Organization (WHO) as abnormal or excessive fat accumulation that presents a risk to health. Obesity has reached epidemic proportions, affecting individuals of all ages and backgrounds [1]. According to recent statistics, the prevalence of obesity has more than tripled worldwide since 1975 [1]. Worldwide adult obesity has more than doubled since 1990. In 2022, 2.5 billion adults aged over 18 years were overweight. Of these, 890 million adults were obese. In 2022, 43% of adults aged 18 years and over were overweight and 16% were obese [2, 3]. Alarming, the prevalence of obesity has continued to rise steadily, posing profound challenges to public health systems and necessitating urgent action to curb its escalating trajectory. This relentless surge in obesity rates underscores the urgent need for effective preventive strategies and targeted interventions to mitigate its far-reaching health consequences.

Obesity is intricately linked with a various metabolic abnormalities including insulin resistance, dyslipidemia, hypertension, and pro-inflammatory states [1, 4, 5]. This cluster of obesity-associated co-morbidities form a complex web of interrelated risk factors that substantially increase the burden of cardio-metabolic disorders such as type 2 diabetes mellitus, cardiovascular disease, and non-alcoholic fatty liver disease [6].

In the quest to combat the burgeoning epidemic of obesity-related morbidities, the exploration of novel diagnostic tools and indices holds immense promise. The Triglyceride-Glucose Index (TyG index) represents a paradigm shift in this regard, offering a holistic and integrated approach to assessing metabolic health in obese individuals [7]. Unlike conventional measures such as body mass index (BMI) or waist circumference, which provide limited insights into metabolic status, the TyG index encapsulates key components of metabolic dysregulation, including insulin resistance and dyslipidemia [8]. By leveraging the relationship between triglyceride levels and fasting glucose concentrations, the TyG index serves as a sensitive marker for identifying individuals at heightened risk of developing cardio-metabolic disorders [9–11].

TyG index was firstly introduced as a valid and reliable index for prediction of insulin resistance among apparently healthy individuals and could be used as an alternative to the standard insulin test [12]. Then, its simplicity, cost-effectiveness, and robust predictive value make it an invaluable tool in different other clinical situations like polycystic ovary syndrome (PCOS) [13], type two diabetes [10], acute coronary syndrome [10], cardiovascular disease [11, 14, 15], end-stage renal disorders [16],

metabolic syndrome [17], and in general apparently healthy individuals [5, 9, 18], enabling early detection of metabolic abnormalities. Although, among obese individuals its validation and role has limited investigations. As such, the exploration and validation of innovative indices like the TyG index hold significant implications for enhancing risk stratification, guiding therapeutic decision-making, and ultimately improving health outcomes in the burgeoning population of obese individuals. Therefore, we aimed to elucidate the significance of the TyG index and its predicting ability compared with other classic metabolic parameters and also, to identify its association with these biomarkers (e.g. anthropometric variables, serum lipids, blood pressure and glycemic markers) in obese individuals in a cross-sectional study.

Methods and materials

Participants

Participants were obese individuals based on established criteria of WHO as Body Mass Index (BMI) ≥ 30 kg/m². Participants were 164 male and 136 female subjects aged 18 to 65 years old. They were recruited from local health-care facilities and community centers for primary health care (PHC) in Riyadh, Saudi Arabia between March 2022 and November 2023. Recruitment procedure was through outreach initiatives, including informational sessions, flyers, and advertisements to raise awareness and garner interest among individuals grappling with obesity. Exclusion criteria included individuals with significant medical conditions that could affect weight (e.g., cancer, uncontrolled diabetes), pregnant or breastfeeding women, those with cardiovascular disorders, hypertension, kidney disorders, or taking any medication that could affect the study results; being on weight loss or other dietary programs for at least three months prior participation in the study. Potential participants were initially screened for eligibility criteria, including age, weight status, and absence of significant comorbidities that could confound the study outcomes. Comprehensive informed consent procedures were adhered to, ensuring that participants were fully apprised of the study objectives, procedures, and potential risks. The flowchart of study is provided in Fig. 1. The protocol of the current study has been approved by the ethics committee of King Khalid University through the reference number of CL/CO/B/5.

Sample size calculation

Sample size calculation was performed according to the formula of $\frac{Z^2 P (1-P)}{E^2}$, based on the previous study [5], where n=required sample size, Z=Z-score of 1.96 for 95% confidence level, P=estimated prevalence of obesity and E=desired margin of error or precision (5%).

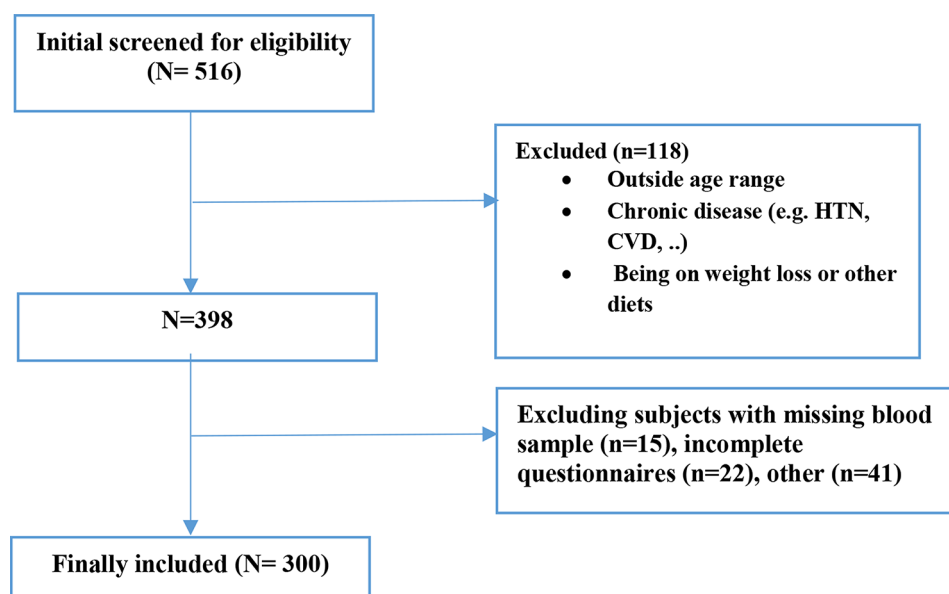


Fig. 1 The flowchart of participants' recruitment

Accordingly the estimated sample size along with possible drop-outs was 300.

Anthropometric measurements, physical activity and appetite assessment

Weight was measured using a calibrated scale while the participant is standing barefoot and wearing lightweight clothing. Height was measured using a wall-mounted height rod with the participant standing upright against a flat surface, with shoes removed. Waist circumference (WC) was measured at the midpoint between the lower margin of the last palpable rib and the top of the iliac crest using a flexible measuring tape and hip circumference (HC) at the widest part of the buttocks, with the measuring tape held parallel to the floor. The precision of measurement for weight, height and WC and HC were 0.1 kg, and 1 cm respectively. Waist to hip ratio (WHR) and BMI were calculated according to the above measurements. Physical activity was measured with the official Arabic short-version telephone format of IPAQ available at www.ipaq.ki.se [19], with seven items providing information on time spent for walking, in vigorous- and moderate-intensity physical activities and in sedentary activity during the previous seven days [19]. Appetite was measured with visual analogue scales (VASs), that are validated to assess feelings of hunger and satiety with 100 mm in the horizontal line with number 0 in the left side indicating a non-present/slightest, while the number 100 at the right side indicating a highest level of hunger or satiety [20]. "The VAS consisted of four questions including: "how hungry are you? How full are you? How strong is your desire to eat? And how much

food do you think you could eat?" with anchors between "not at all" to "extremely" [21].

Eating behaviors patterns

The three-factor eating questionnaire-R18 (TFEQ-R18) was used to analyze eating behavior patterns among participants. The TFEQ-R18 assesses three primary aspects of eating behavior: cognitive restraint, emotional eating, and uncontrolled eating. Cognitive restraint involves consciously limiting food intake to manage body weight, emotional eating relates to the inability to resist emotional triggers, and uncontrolled eating denotes consuming more than usual due to a perceived loss of control over intake and heightened feelings of hunger. Participants rate their responses to 18 questions on a 4-point scale (1–4), with higher scores indicating greater tendencies toward uncontrolled eating, cognitive restraint, or emotional eating [22, 23].

Biochemical assays and TyG calculation

Blood lipid profiles were determined following an overnight fast of at least 8 h. Venous blood samples were collected using standard aseptic techniques and processed promptly to obtain serum. Serum levels of total cholesterol (TC), triglycerides (TG), high-density lipoprotein cholesterol (HDL-C), and low-density lipoprotein cholesterol (LDL-C) were measured using commercially available enzymatic colorimetric assay kits. Fasting blood glucose levels were measured using enzymatic methods with glucose oxidase/peroxidase reagents. These assays were performed according to the manufacturer's instructions (e.g., Roche Diagnostics, Abbott Laboratories), ensuring adherence to standardized protocols and quality

control measures. Serum insulin levels were determined using a commercially available enzyme-linked immunosorbent assay (ELISA) kit (e.g., Mercodia Insulin ELISA Kit). Blood pressure measurements were obtained using a validated oscillometric automated blood pressure monitor (e.g., Omron Healthcare, Inc., Dabul Educational Trust). Participants were seated comfortably in a quiet environment with their arm supported at heart level. After a brief rest period of 5 min, blood pressure readings were recorded in duplicate, with the average value used for analysis. Systolic blood pressure (SBP) and diastolic blood pressure (DBP) were recorded in millimeters of mercury (mmHg), with appropriate cuff sizes selected based on arm circumference to ensure accurate measurements. The TyG index was calculated using fasting serum triglyceride (TG) levels and fasting plasma glucose (FPG) concentrations, as per the formula:

$$TyG = \ln \frac{\text{fasting TG (mg/dl)} \times FBS \left(\frac{\text{mg}}{\text{dl}} \right)}{2}$$

. Homeostatic model assessment of insulin resistance (HOMA-IR) was calculated as: $\text{HOMA-IR} = \frac{\text{Fasting insulin } \mu\text{IU/mL} \times \text{FBS (mmol/l)}}{22.5}$. HOMA-IR, first developed by Matthews et al. has been widely used for the estimation of insulin resistance with a high precision compared to the “gold” standard euglycemic clamp method [24, 25]. Metabolic syndrome (MetS) was defined as the International Diabetes Federation (IDF) criteria by having at least three of the following factors: (1) central obesity (2) elevated blood pressure (3) hyperglycemia; (4) increased triglycerides and (5) decreased high-density lipoprotein cholesterol [26].

Statistical assays

Statistical analyses were performed using the IBM SPSS Statistics software, version XX (IBM Corp., Armonk, NY, USA). Descriptive statistics were calculated for all variables of interest, including continuous variables (e.g., age, anthropometric measurements, blood lipids, blood pressure) and categorical variables (e.g., gender, sex). Continuous variables were expressed as means \pm standard deviations (SD) or as categorical variables were presented as frequencies and percentages. The TyG was categorized into tertiles according to study power of 80% and β of 0.2 [27]; accordingly, the categories of first tertile $TyG \leq 8.41$, second tertiles TyG between 8.41 and 8.91 and third tertile $TyG \geq 8.92$ cut-off points were applied.

To assess differences in continuous variables among multiple groups, one-way analysis of variance (ANOVA) was performed. Post-hoc pairwise comparisons using the Tukey test were conducted to identify significant differences between specific groups. The significance level was set at $p < 0.05$. General linear models (GLMs) were utilized to examine the association between dependent

variables (e.g., anthropometric measurements, blood lipids, blood pressure) and independent variables (TyG) with adjustments made for potential confounders such as age, gender, BMI and physical activity. Receiver operating characteristic (ROC) curve analysis was employed to evaluate the diagnostic accuracy of the TyG index in predicting metabolic risk factors. Area under the curve (AUC) values were calculated to quantify the discriminatory power of the TyG index, with higher AUC values indicating better predictive performance. Optimal cutoff points for the TyG index were determined based on Youden's index, maximizing the sum of sensitivity and specificity. Sensitivity, specificity were computed to assess the diagnostic accuracy of the TyG index.

Results

Table 1 represents the demographic characteristics of study participants across TyG tertiles. Totally, 164 male and 136 female subjects were participated in the current study and significantly higher proportions of male subjects were observed in highest versus lowest tertiles of TyG ($p < 0.001$). Notably, a significant difference in age distribution is evident, with participants in the first tertile exhibiting a younger mean age compared to those in the second and third tertiles ($P = 0.007$). Similarly, there is a significant disparity in height across tertiles, with individuals in the third tertile displaying a notably greater mean height than counterparts in the first and second tertiles ($P = 0.003$). Additionally, WHR exhibits a statistically significant discrepancy across TyG tertiles, indicating a trend towards higher WHR values in participants within the third tertile ($P = 0.015$). Conversely, variables such as education, weight, WC, body mass index (BMI), appetite, physical activity demonstrate no statistically significant variations across TyG tertiles. Table 2 presents the distribution of TFEQ subclasses and total scores across TyG tertiles. While no statistically significant differences are observed in TFE subclasses scores across TyG tertiles, there are notable trends worth considering. Participants in the first tertile demonstrate the lowest mean TFE cognitive score (14.21), indicative of reduced cognitive restraint over eating, compared to those in the second and third tertiles. Similarly, TFE emotional eating scores exhibit a non-significant trend towards higher values in the second and third tertiles, suggesting a potential association between TyG and emotional eating tendencies. Notably, the TFE total score, reflecting overall eating behavior, displays a statistically significant difference across TyG tertiles ($p = 0.045$). Participants in the second and third tertile exhibit the highest mean TFE total score (45.08 and 43.74 respectively), indicating a greater overall inclination towards disordered eating behaviors compared to individuals in the first and third tertiles.

Table 1 General demographic characteristics of study participants across TyG tertiles

Variable		N	Mean (SD)	P-Value *
Age (y)	1st	101	38.35 (9.11)	0.007
	2nd	96	41.90 (9.14)	
	3rd	103	41.86 (8.9)	
Gender (Male [%]) ^a	1st	101	45 (44.6)	<0.001
	2nd	96	44 (46.3)	
	3rd	103	75 (72.8)	
Education (≥ 12 years) ^a	1st	101	39 (38.6)	0.250
	2nd	96	45 (47.9)	
	3rd	103	38 (36.9)	
Weight (kg)	1st	101	92.40 (13.56)	0.791
	2nd	96	91.76 (14.31)	
	3rd	103	93.14 (14.64)	
Height (cm) ^a	1st	101	166.05 (10.16)	0.003
	2nd	96	166.54 (10.74)	
	3rd	103	170.49 (9.07)	
WC (cm)	1st	101	105.68 (9.33)	0.252
	2nd	96	107.44 (9.59)	
	3rd	103	107.74 (9.61)	
BMI (kg/m ²)	1st	101	33.43 (3.94)	0.089
	2nd	96	33.22 (5.30)	
	3rd	103	32.05 (5.07)	
WHR ^a	1st	101	0.91 (0.09)	0.015
	2nd	96	0.92 (0.07)	
	3rd	103	0.95 (0.06)	
Appetite	1st	101	33.67 (9.47)	0.99
	2nd	96	33.85 (8.31)	
	3rd	103	33.60 (8.63)	
PA (Met.min/week)	1st	101	2105.38 (3.5.12)	0.794
	2nd	96	2386.35 (388.52)	
	3rd	103	1915.87 (279.96)	

TyG, triglyceride to glucose index; WC, waist circumference; BMI, body mass index; WHR, waist to hip ratio; PA, physical activity. *, P-value obtained from one way analysis of variance. ^a indicates difference between third tertile with other tertiles according to Tukey's post hoc analysis

Table 2 TFEQ subclasses and total score across TyG tertiles

TFE subclasses		N	Mean (SD)	P-value
TFE cognitive score	1st	101	14.21 (2.93)	0.079
	2nd	96	15.82 (3.02)	
	3rd	103	15.14 (3.49)	
TFE uncontrolled score	1st	101	21.33 (5.04)	0.70
	2nd	96	22.39 (6.30)	
	3rd	103	21.67 (6.60)	
TFE emotional eating	1st	101	5.69 (1.87)	0.073
	2nd	96	6.87 (2.75)	
	3rd	103	6.92 (2.92)	
TFE total score ^a	1st	101	40.63 (5.62)	0.045
	2nd	96	45.08 (8.39)	
	3rd	103	43.74 (8.77)	

TyG, triglyceride to glucose index; TFEQ, three eating factor questionnaire. *, P-value obtained from one way analysis of variance. ^a indicates difference between second and third tertile with the first one according to Tukey's post hoc analysis

Table 3 Biochemical risk factors of study participants across TyG tertiles

Variables		N	Mean (SD)	P-Value *	P-Value **
TC (mg/dl) ^a	1st	101	179.12 (35.97)	<0.001	0.009
	2nd	96	192.26 (31.41)		
	3rd	103	203.60 (33.20)		
TG (mg/dl) ^a	1st	101	78.32 (19.19)	<0.001	<0.001
	2nd	96	129.09 (21.30)		
	3rd	103	241.75 (105.86)		
HDL (mg/dl) ^b	1st	101	45.99 (9.00)	<0.001	0.004
	2nd	96	44.23 (8.43)		
	3rd	103	39.66 (9.40)		
LDL (mg/dl)	1st	101	119.65 (34.22)	0.118	0.926
	2nd	96	122.18 (29.14)		
	3rd	103	128.35 (28.75)		
FBS (mg/dl) ^a	1st	101	87.42 (9.89)	<0.001	<0.001
	2nd	96	91.81 (12.80)		
	3rd	103	100.87 (29.29)		
Insulin (mIU/L)	1st	101	16.13 (12.57)	0.657	0.860
	2nd	96	15.63 (10.52)		
	3rd	103	17.85 (19.36)		
HOMA-IR	1st	101	3.5471	0.179	0.161
	2nd	96	3.6499		
	3rd	103	4.5537		
SBP (mmHg) ^b	1st	101	116.7624	<0.001	0.077
	2nd	96	124.1579		
	3rd	103	128.1068		
DBP (mmHg) ^b	1st	101	78.5248	<0.001	0.820
	2nd	96	82.0421		
	3rd	103	85.1359		

TyG, triglyceride to glucose index; TC, total cholesterol; TG, triglyceride; HDL, high density lipoprotein cholesterol; LDL, low density lipoprotein cholesterol; HOMA-IR, homeostatic model assessment of insulin resistance; SBP, systolic blood pressure; DBP, diastolic blood pressure. *, P-value obtained from one way analysis of variance; ** P value obtained from general linear model after adjustment for covariates of age, sex, BMI, PA. ^a indicates difference between all of tertiles with each other according to Tukey's post hoc analysis; ^b indicates difference between first and third tertiles according to Tukey's post hoc analysis

Table 3 outlines the biochemical risk factors observed among study participants across TyG tertiles. TC, TG, HDL, and FBS levels all demonstrate statistically significant variations across TyG tertiles ($p < 0.001$ for TC, TG, and FBS; $p = 0.004$ for HDL). Participants in the third tertile exhibit the highest mean values for TC, TG, and FBS, indicative of poorer lipid and glucose metabolism compared to those in the first and second tertiles. Conversely, HDL levels are notably lower in the third tertile. Interestingly, no statistically significant differences are observed across TyG tertiles for low-density lipoprotein cholesterol (LDL), insulin levels, or HOMA-IR. However, significant disparities in systolic blood pressure (SBP) and diastolic blood pressure (DBP) are evident across TyG tertiles ($p < 0.001$ for both).

Figure 2; Table 4 present the ROC curve and its characteristics for various metabolic parameters in prediction of metabolic syndrome. TyG demonstrates the highest

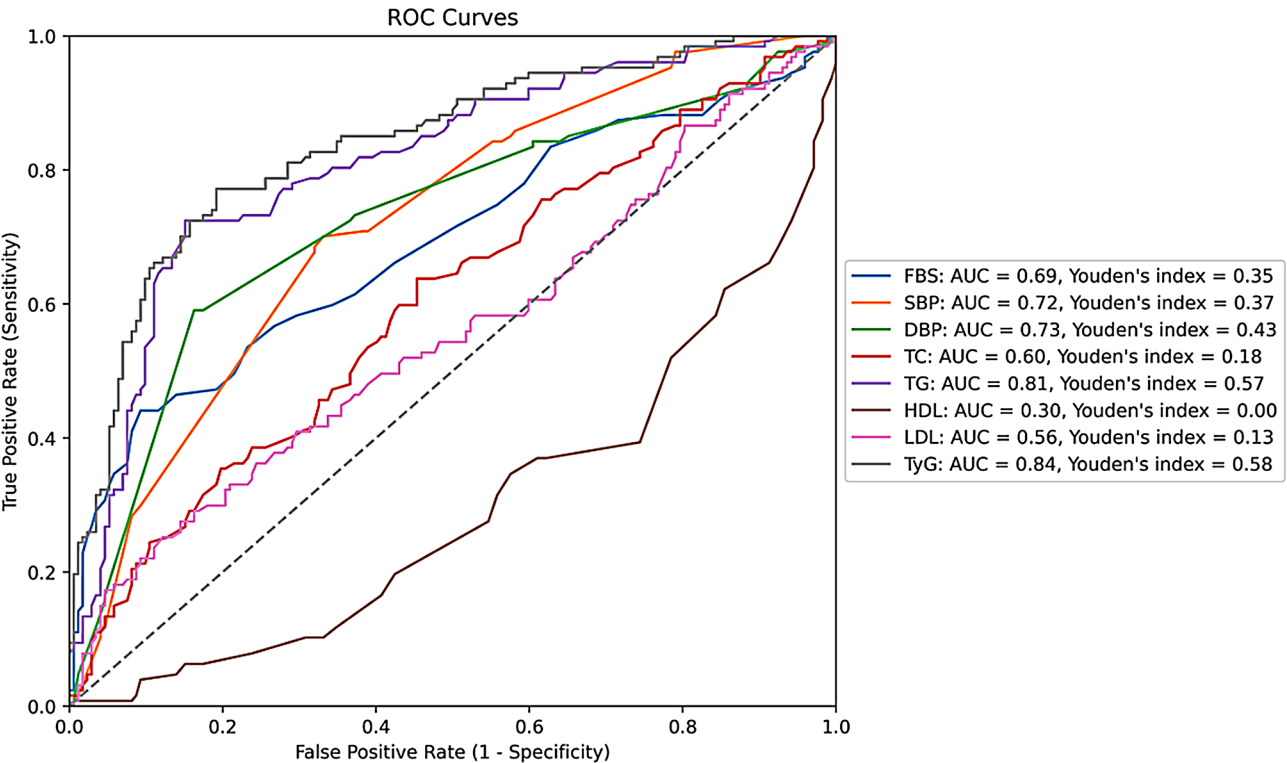


Fig. 2 Receiver operating characteristic curves for the detection of MetS using metabolic parameters. Abbreviations: AUC, area under curve; FBS, fasting blood sugar; SBP, systolic blood pressure; DBP, diastolic blood pressure; TG, triglycerides; TC, total cholesterol; HDL, high-density lipoprotein; LDL, low-density lipoprotein; TyG index, triglyceride-glucose index

Table 4 ROC curve characteristics for metabolic parameters

Area Under the Curve											
Variables	AUC	SE	P value	95% CI		Youden's index	Optimal cut-points	Sensitivity	Specificity	True positive rate	False positive rate
				Lower Bound	Upper Bound						
FBS (mg/dl)	0.691	0.032	<0.001	0.629	0.754	0.35	100	0.496	0.785	0.44	0.09
SBP (mmHg)	0.720	0.029	<0.001	0.663	0.788	0.37	127	0.44	0.91	0.70	0.33
DBP (mmHg)	0.732	0.031	<0.001	0.665	0.786	0.43	90	0.59	0.84	0.59	0.16
TG (mg/dl)	0.811	0.026	<0.001	0.761	0.861	0.57	151	0.717	0.849	0.72	0.15
TC (mg/dl)	0.604	0.033	0.002	0.539	0.668	0.18	188	0.598	0.570	0.64	0.45
HDL (mg/dl)	0.296	0.030	<0.001	0.237	0.356	0.00	68	0.370	0.378	0.01	0.01
LDL (mg/dl)	0.556	0.034	0.097	0.489	0.623	0.13	148.20	0.543	0.50	0.28	0.15
TyG	0.838	0.024	<0.001	0.792	0.884	0.58	8.76	0.773	0.797	0.77	0.19

TyG, triglyceride to glucose index; FBS, fasting blood sugar; SBP, systolic blood pressure; DBP, diastolic blood pressure; TG, Triglyceride; TC, total cholesterol, HDL, high density lipoprotein cholesterol; LDL, low density lipoprotein cholesterol; TyG, triglyceride-glucose index; AUC, area under the curve; SE, standard error; CI, confidence interval; ROC, receiver operating characteristic

area under curve (AUC) value of 0.838, indicating superior discriminatory power for identifying metabolic syndrome compared with other metabolic parameters. This is followed by TG with an AUC of 0.811. FBS also exhibits a moderate AUC of 0.691, while, TC and LDL demonstrate lower AUC values of 0.604 and 0.556, respectively, indicating limited discriminatory power. High-density lipoprotein cholesterol (HDL) exhibits the lowest AUC of 0.296, indicating poor predictive performance.

Additionally, sensitivity, specificity, and Youden's index values provide further insights into the performance of these parameters as diagnostic markers.

Discussion

The present study investigated the relationship between the TyG, metabolic parameters, and eating behaviors among study participants. Our findings revealed several

noteworthy associations that contribute to our understanding of metabolic health and eating behaviors.

Assessment the relationship between biochemical risk factors and TyG index provided valuable insights into the metabolic implications of TyG index. Significant differences were observed across TyG tertiles for TC, TG, HDL, and FBS, with individuals in higher TyG tertiles displaying adverse lipid and glucose profiles. However, no significant differences were noted for low-density lipoprotein cholesterol (LDL), insulin levels, or insulin resistance (HOMA-IR). Moreover, the overall TFEQ total score was significantly higher in individuals with higher TyG tertiles, indicating a greater inclination towards disordered eating behaviors.

The findings of our study align with existing literature highlighting the intricate relationship between glycemic status, metabolic parameters, and eating behaviors. Previous research has demonstrated the utility of the TyG as a marker of insulin resistance and metabolic syndrome, with elevated TyG values linked to an increased risk of cardiovascular disease and type 2 diabetes [9, 28]. Consistent with our results, studies have reported associations between higher TyG index values and adverse lipid profiles, including elevated triglycerides and reduced high-density lipoprotein cholesterol [12, 29]. Moreover, emerging evidence suggests a bidirectional relationship between glycemic dysregulation and eating behaviors, with disturbances in glucose metabolism influencing appetite regulation and food intake [30]. However, the mechanistic pathways underlying these associations remain incompletely understood and warrant further investigation.

Several mechanistic pathways may underlie the observed associations between TyG index, metabolic parameters, and eating behaviors. Insulin resistance, a hallmark of metabolic dysfunction, is implicated in dysregulated lipid metabolism and adipose tissue dysfunction, leading to elevated triglycerides and altered lipid profiles [31]. Additionally, chronic hyperglycemia and insulin resistance may disrupt hypothalamic signaling pathways involved in appetite regulation, promoting hyperphagia and weight gain [32]. Insulin resistance has great adverse effects; in obese individuals it leads to higher rate of weight gain and hyperinsulinaemia [33, 34], frailty risk among older adults [35, 36], cognitive impairment [37], polycystic ovary syndrome and related consequences [38, 39] and mitochondrial dysfunction [40]. The triglyceride–glucose (TyG) index, comprising fasting plasma glucose and triglycerides (TGs), is significantly associated with the hyperinsulinemia and podocytes damage as insulin-sensitive epithelial cells that finally leads to kidney disorders [34, 41]. It is suggested that up-regulation of secreted frizzled-related protein 4 (SFRP 4) in obese individuals is the main cause of prediabetes

and insulin resistance [42]. Furthermore, dysregulation of gut hormones such as ghrelin and leptin, which modulate hunger and satiety signals, may contribute to aberrant eating behaviors and metabolic disturbances [43]. Further elucidation of these mechanistic pathways is essential for informing targeted interventions aimed at improving metabolic health and mitigating the risk of metabolic diseases.

Similar to our findings, Yoon JS et al. [10], reported no association between TyG and insulin and a very weak association between TyG and LDL concentrations. Similarly, Zhang Y et al. [44] reported no association between TyG and LDL after propensity score matching among patients with acute coronary syndrome. In our study, LDL was higher in higher TyG tertiles but, this difference was not statistically significant. It is suggested that although LDL-C is a well-established mediator of atherosclerosis, despite substantial reduction in LDL-C, patients continue to have recurrent atherosclerotic cardiovascular events, therefore, hypertriglyceridemia is suggested as an important contributor of residual risk for cardio-metabolic events [45]. Also, we observed a higher glucose concentrations in highest versus lowest TyG tertiles, but, no significant difference was observed for serum insulin or HOMA-IR values toward TyG tertiles. Same as our results, Zhang Y et al. [44], reported a strong association between TyG and serum glucose while no association was observed with TyG and insulin concentrations in subjects with type 2 diabetes. In another study by While, in other study by Yang H et al. [13], TyG was in strong positive association with hyperlipidemia, hyperglycemia in patients with PCOS while in non-PCOS subjects no association between TyG and metabolic parameters were reported. This discrepancies in results is due to difference in subjects' characteristics, the disease of study and the study design.

Among anthropometric variables, TyG was positively associated with higher WHR values; no association was observed between TyG and BMI. Previous studies also reported similar results; for example, Yoon JS et al. [10], reported no association between TyG and BMI among overweight and obese children and adolescents ($r = -0.174$; $p = 0.076$). Similar finding was also reported in the study by Zhang Y et al. [44] and the study by Zho H et al. [11]. Several studies suggested that TyG-BMI index might be a simpler and clinically useful surrogate marker for obesity-related disorders [9, 46]. Although, further studies are needed to confirm this.

In our study, total TEFQ score was greater for higher tertiles of TyG. TEFQ is a self-report instrument to evaluate three dimensions of eating behavior: cognitive restraint in eating, susceptibility to periodic disinhibition of control over eating, and perceived hunger. Higher scores denotes disturbed eating behaviors. There

are no previous studies evaluating the direct association between eating behaviors and TyG and our study is the first one. However, previous studies reported the positive association between TyG and screen time [47] and a positive association between TyG-BMI and eating disorders that is an unpublished preprint by Xiao H et al. [48].

To our findings, ROC curve analysis revealed the diagnostic utility of various metabolic parameters in identifying metabolic abnormalities. Notably, the TyG index exhibited superior discriminatory power compared to other parameters. These findings highlight the potential of TyG as a robust indicator of metabolic health, with implications for risk stratification and early intervention in clinical practice. Our findings were in accordance of numerous previous studies that reported the potential ability of TyG in prediction of metabolic abnormalities. However, none of these studies were performed among obese individuals; Yang H et al. reported that TyG index indicated a good predictive ability of metabolic syndrome in women with PCOS [13]. In the study by Yoon JH et al. [10], TyG index was superior to other biomarkers in predicting T2DM in children and adolescents. Other studies also, revealed similar results in acute coronary syndrome [10], cardiovascular disease [11, 14, 15], end-stage renal disorders [16], metabolic syndrome [17], and in general apparently healthy individuals [5, 9, 18].

It is important to acknowledge several limitations of the study, including its cross-sectional design, which precludes causal relationships between the TyG index, metabolic risk factors, and eating behaviors. Also the self-reported nature of eating behaviors which were assessed using a questionnaire, are subject to recall bias and may not accurately reflect actual eating patterns. However, the questionnaires that were used for gathering dietary and eating behaviors had acceptable validity and reliability in the target population. Additionally, the study findings may not be representative of the general population, because we enrolled only obese individuals and this warrants caution in generalizing the findings. Future research should employ longitudinal designs and larger, more diverse samples to confirm these associations and explore potential underlying mechanisms.

According to our findings, the greater proportion of men in the higher TyG tertiles compared with lower tertiles were observed. This gender discrepancy aligns with previous research suggesting that men may be more likely to exhibit higher insulin resistance and associated metabolic abnormalities compared to women [49]. Some studies have shown that men, particularly those with abdominal obesity, are at a higher risk for developing insulin resistance, which could explain the higher representation of men in the higher TyG categories [50]. This observation is consistent with the well-documented relationship between gender and metabolic health, where

men tend to have higher levels of visceral fat, a key driver of insulin resistance [51]. While these trends were not the primary focus of our study, they highlight the importance of considering gender as a potential confounder when evaluating metabolic risk using the TyG index. Future research could explore these gender differences in greater detail to understand how sex-specific factors might influence insulin resistance and the predictive power of the TyG index.

In conclusion, our study, for the first time, provided valuable insights into the relationship between TyG index, metabolic parameters, and eating behaviors. The findings underscore the importance of glycemic status in metabolic health and highlight the potential of TyG as a diagnostic marker for identifying individuals at risk of metabolic abnormalities. These findings have implications for preventive and therapeutic interventions aimed at mitigating the burden of metabolic diseases.

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Author contributions

SOR, AJK and AHZ were involved in data collection and subjects' recruitment. MS, AAMAE, MS and MK were involved in hypothesis generation and statistics. AK was involved in data collection, data analysis and supervision of the project. LGK and AK were involved in statistical approaches and drafting the paper. RMM and SOR was also involved in data collection and revision of the paper. All of the authors contributed in writing the draft of manuscript and agreed to its submission.

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Data availability

The datasets of the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Written consent was obtained from all of the participants of the study. All methods in the current research were performed in accordance with the declaration of Helsinki's guidelines and regulations. The protocol of the current study has been approved by the ethics committee of King Khalid University through the reference number of CL/CO/B/5.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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