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Predictive Performance of TyG, TyG-BMI, TyG-WC, METS-IR, and SPISE for incident MASLD in an Iranian prospective Cohort Study

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Abstract

Insulin resistance is a key contributor to metabolic dysfunction-associated steatotic liver disease (MASLD), yet comparative prospective data on surrogate metabolic indices are scarce. This study followed 1,277 adults aged 35–70 years without MASLD at baseline over five years to evaluate the predictive value of TyG, TyG-BMI, TyG-WC, METS-IR, and SPISE for incident MASLD. MASLD incidence was defined by a Fatty Liver Index ≥ 60 plus at least one cardiometabolic risk factor. Associations between metabolic indices and MASLD risk were assessed using multivariable Poisson regression with robust variance, and predictive performance was evaluated via ROC curves. Over follow-up, 195 participants (15.3%) developed MASLD. In adjusted models, the highest quartile of TyG-BMI (RR 18.57; 95% CI 8.08,42.69), METS-IR (RR 14.25; 6.57,30.87), and TyG-WC (RR 10.70; 5.49,20.85) showed the greatest risk. Each SD increase in TyG-BMI and METS-IR increased risk by 172% and 107%, respectively, while SPISE was inversely associated (RR 0.29; 0.23,0.36). TyG-BMI showed the highest discrimination (AUC 0.75). These findings indicate that composite metabolic indices, especially TyG-BMI and METS-IR, are robust predictors of incident MASLD and could be valuable for early risk stratification in clinical and population-level settings.

Introduction

Metabolic dysfunction associated steatotic liver disease (MASLD) was recently introduced as a replacement for nonalcoholic fatty liver disease (NAFLD). It is recognized as now a major contributor to the global burden of chronic liver disease and is strongly associated with metabolic dysregulation [1,2]. The diagnosis of MASLD requires evidence of hepatic steatosis in the presence of at least one cardiometabolic risk factor. It is commonly associated with a constellation of metabolic abnormalities, including obesity, type 2 diabetes mellitus, hypertension, and dyslipidemia [3]. MASLD may progress to metabolic dysfunction-associated steatohepatitis (MASH), a more severe form that significantly increases the risk of cirrhosis and hepatocellular carcinoma [4]. Currently, no specific pharmacological cure is available for MASLD. Management primarily focuses on lifestyle interventions, including dietary modification, structured physical activity, and weight reduction strategies [1,5]. The Fatty Liver Index (FLI) is a widely used non-invasive scoring system developed to estimate the probability of hepatic steatosis. It serves as a practical screening tool in epidemiological studies and clinical settings to identify individuals at risk of fatty liver disease, including NAFLD and MASLD [6,7].

Insulin resistance is a central mechanistic driver in the pathogenesis of MASLD [8]. It promotes hepatic steatosis through multiple pathways, including enhanced de novo lipogenesis mediated by upregulation of lipogenic enzymes and impaired suppression of adipose tissue lipolysis, which increases the flux of free fatty acids to the liver [9].The Triglyceride-Glucose (TyG) index and its derivatives, TyG-BMI and TyG-WC, have been proposed as reliable surrogate markers of insulin resistance, a key contributor to metabolic disorders. The TyG index, calculated using fasting triglyceride and glucose levels, is widely recognized as a simple and cost-effective proxy for insulin resistance [10,11]. TyG-BMI and TyG-WC incorporate anthropometric measures into the TyG formula, potentially enhancing its ability to capture metabolic risk. The metabolic score for insulin resistance (METS-IR) is a non-insulin-based index that incorporates fasting glucose, triglycerides, HDL cholesterol, and body mass index to estimate insulin resistance, offering a practical tool for large-scale epidemiological studies [12]. Similarly, the single-point insulin sensitivity estimator (SPISE), derived from HDL cholesterol, triglycerides, and BMI, provides a rapid and non-invasive estimate of insulin sensitivity. It has been validated in both pediatric and adult populations and has demonstrated utility in predicting future metabolic risk, including metabolic syndrome and cardiovascular disease [13–15].

Although insulin resistance indices have been increasingly investigated, important gaps remain. Most existing evidence is derived from cross-sectional studies, limiting evaluation of their predictive value for incident MASLD [16,17]. Direct longitudinal comparisons of TyG-derived indices (TyG-BMI and TyG-WC) with METS-IR and SPISE are limited, and it remains unclear which marker provides the best prediction of future MASLD across diverse metabolic profiles [18]. Furthermore, the generalizability of previous findings is limited, as most studies have focused on specific subgroups, such as non-obese individuals or patients with type 2 diabetes. A prospective, population-based cohort study from Iran could strengthen the global evidence base and help address these gaps [19].Accordingly, the present study aims to compare the predictive performance of TyG, TyG-BMI, TyG-WC, METS-IR, and SPISE for incidence MASLD in Iranian adults participating in the Hoveyzeh Cohort Study (HCS).

Results

A total of 1,277 participants free of MASLD at baseline were included in the final analysis. The mean age of the study population was 48.43 ± 9.07 years. During the 5-year reassessment, 195 individuals developed incidence of MASLD, corresponding to a cumulative incidence of 15.3%. (Table 1). Participants were categorized into four predefined age groups, with borderline differences observed between groups (p = 0.050). Although the proportion of males was slightly higher among individuals who developed MASLD (17.17% vs. 13.76%), this difference did not reach statistical significance (p = 0.093).

Adiposity related measures showed strong associations with incidence of MASLD. The incidence increased progressively across BMI categories, from 0% in underweight individuals to 39.0% among obese participants (p < 0.001). Similarly, participants with waist circumference >90 cm exhibited a markedly higher incidence compared to those with lower values (22.76% vs. 6.10%, p < 0.001).

Alcohol consumption was associated with a higher cumulative incidence of MASLD (35.29% vs. 15.0%, p = 0.021), although the absolute number of alcohol users was small. No statistically significant differences were observed across categories of smoking status, physical activity quartiles, socioeconomic status, systolic or diastolic blood pressure, lipid profile components (LDL, total cholesterol), diabetes, or hypertension.

Borderline associations were observed for HDL (p = 0.057), ALT levels (p = 0.065), diastolic blood pressure (p = 0.072), and triglycerides (p = 0.085), suggesting potential metabolic gradients warranting further multivariable evaluation.

As shown in Table 2, the incidence of MASLD increased significantly across quartiles of TyG (9.35% in Q1 to 18.18% in Q4, p = 0.008). A stronger dose–response pattern was observed for TyG-BMI, TyG-WC, and METS-IR, with markedly higher incidence in the highest quartiles compared with the lowest (all p < 0.001). In contrast, SPISE showed an inverse trend, with MASLD incidence decreasing progressively across increasing quartiles (p < 0.001). (Table 2)

In crude Poisson regression analyses, higher quartiles of all insulin resistance related indices were significantly associated with increased risk of MASLD, whereas SPISE showed a significant inverse association. (Table 3)

For the TyG index, participants in the highest quartile had a higher risk of MASLD compared with those in the lowest quartile (RR = 1.94, 95% CI: 1.25,3.02). This association remained statistically significant after adjustment for age and sex (RR = 2.01, 95% CI: 1.28,3.15) and after further adjustment for socioeconomic, lifestyle, clinical, and biochemical covariates (RR = 1.83, 95% CI: 1.14,2.95), indicating a modest but independent association.

Stronger associations were observed for indices incorporating adiposity measures. For TyG-BMI, the risk of MASLD increased markedly across quartiles, with participants in the highest quartile exhibiting more than an eighteen-fold higher risk compared with the lowest quartile in the fully adjusted model (RR = 18.57, 95% CI: 8.08,42.69). A similar dose response pattern was observed for TyG-WC, where the highest quartile was associated with a substantially increased risk (RR = 10.70, 95% CI: 5.49,20.85) in the fully adjusted model.

METS-IR also demonstrated a strong graded relationship with incidence of MASLD. Compared with the lowest quartile, the highest quartile was associated with a markedly elevated risk in the fully adjusted model (RR = 14.25, 95% CI: 6.57,30.87), with consistent estimates across all adjustment models.

In contrast, SPISE was inversely associated with MASLD risk. Participants in the highest quartile had a substantially lower risk compared with those in the lowest quartile (RR = 0.06, 95% CI: 0.02,0.14) after full adjustment, indicating a strong protective gradient consistent with higher insulin sensitivity.

In the fully adjusted model, each one standard deviation (SD) increases in insulin resistance–related indices were significantly associated with MASLD incidence. Specifically, the risk increased by 19% for the TyG index (RR=1.19, 95% CI: 1.05,1.36, P=0.007), 172% for TyG-BMI (RR=2.72, 95% CI: 2.32,3.19, P<0.001), 132% for TyG-WC (RR=2.32, 95% CI: 1.98,2.73, P<0.001), and 107% for METS-IR (RR=2.07, 95% CI: 1.78,2.40, P<0.001). In contrast, each one-SD increase in SPISE was associated with a significantly lower risk of MASLD (RR=0.29, 95% CI: 0.23,0.36, P<0.001).

Overall, the magnitude and direction of associations remained largely consistent across crude and adjusted models, suggesting robust relationships between insulin resistance–related indices and incidence of MASLD.

The predictive performance of metabolic indices for incidence of MASLD was evaluated using receiver operating characteristic (ROC) curve analysis (Figure 2).

Among the evaluated indices, TyG-BMI demonstrated the highest discriminative ability (AUC = 0.75, 95% CI :0.71, 0.78), followed closely by METS-IR (AUC = 0.74, 95% CI: 0.70,0.77) and TyG-WC (AUC = 0.71, 95% CI: 0.67,0.74). In contrast, the TyG index alone showed relatively poor predictive performance (AUC = 0.57, 95% CI: 0.52,0.61), indicating limited discrimination when not combined with anthropometric measures (Table 4).

Overall, indices incorporating adiposity measures (TyG-BMI and TyG-WC) or composite metabolic parameters (METS-IR) showed moderate predictive accuracy, whereas the TyG index alone demonstrated weak predictive capability.

These findings suggest that combining triglyceride glucose-based metrics with anthropometric parameters substantially improves risk discrimination for incidence of MASLD.

Discussion

In this prospective cohort study of adults free of MASLD at baseline, we observed a 5-year cumulative incidence of 15.3%. Higher levels of insulin resistance related indices were consistently associated with an increased risk of incidence of MASLD. While the TyG index alone showed a modest association, indices that combined metabolic and anthropometric measures—particularly TyG-BMI, TyG-WC, and METS-IR—showed stronger and more consistent relationships across quartiles. In contrast, SPISE was inversely associated with MASLD risk ROC analyses also showed that indices incorporating adiposity measures had better discriminative ability than TyG alone.

Our study confirms that insulin resistance-related indices are strong predictors of hepatic steatosis and MASLD. Previous cohort studies have reported clear dose response relationships between TyG-related indices and fatty liver risk. Longitudinal analyses indicate that persistently high TyG levels increase the risk of MASLD over time, even after adjusting for other factors. These findings support TyG as a simple marker of metabolic dysfunction and liver fat accumulation[20].

In line with earlier studies, composite indices such as TyG-BMI and TyG-WC performed better than TyG alone in identifying individuals at higher risk of fatty liver disease [21,22]. Incorporating adiposity measures likely enhances predictive performance, as excess body fat particularly central adiposity is closely linked to greater insulin resistance and increased hepatic fat accumulation. Comparative analyses of insulin resistance markers have similarly identified TyG-BMI as one of the strongest predictors of MASLD [23].

The positive association observed for TyG-WC is also supported by pooled evidence. A recent meta-analysis of over 38,000 participants reported a significant positive correlation between TyG-WC and NAFLD risk [24]. This suggests that indices combining lipid, glycemic, and central adiposity measures may better capture the underlying pathophysiology than single biomarkers.

Our findings on METS-IR are consistent with previous studies. Population-based studies have shown a clear dose response relationship between METS-IR and fatty liver disease. Higher METS-IR values are linked to significantly increased risk and demonstrate stronger predictive performance than simpler metabolic indices [25]. In contrast, the inverse association observed between SPISE and MASLD risk in the present study aligns with the conceptual framework of SPISE as a marker of insulin sensitivity rather than insulin resistance. Individuals with MASLD typically have lower insulin sensitivity and a worse metabolic profile compared with controls, supporting the biological plausibility of this inverse relationship [26].

The observed associations are biologically plausible. Insulin resistance increases the flow of free fatty acids to the liver and stimulates de novo lipogenesis, leading to triglyceride accumulation in hepatocytes [27,28]. Furthermore, visceral adiposity contributes to this pathophysiological cascade via enhanced release of free fatty acids and pro-inflammatory cytokines, thereby exacerbating both metabolic dysfunction and hepatic steatosis [29]. Surrogate indices such as TyG, TyG-BMI, TyG-WC, and METS-IR capture key metabolic disturbances, including dyslipidemia, impaired glucose metabolism, and adiposity. In contrast, SPISE reflects insulin sensitivity, consistent with its inverse association with MASLD risk[30,31].

This study has several strengths. The prospective cohort design allowed the assessment of incident MASLD and reduced the likelihood of reverse causation. The findings of this cohort study may be generalizable to populations with similar demographic and clinical characteristics. Evaluating multiple insulin resistance related indices within the same population enabled direct comparison of their associations and predictive performance. In addition, adjustment for a wide range of demographic, lifestyle, and clinical variables helped minimize confounding. However, several limitations should be considered. First, MASLD was defined using the Fatty Liver Index rather than imaging or histological methods, which may have resulted in misclassification. Second, MASLD status was assessed only at follow-up, and the exact timing of disease onset could not be determined. Finally, residual confounding such as genetic factors cannot be excluded despite multivariable adjustment.

Conclusion

In this prospective cohort study, insulin resistance-related indices especially TyG-BMI, TyG-WC, and METS-IR were independently associated with the 5-year incidence of MASLD, whereas SPISE showed a significant inverse relationship. These findings suggest that simple, routinely available metabolic indices could serve as practical tools for early risk stratification and identifying individuals at higher risk of MASLD in population-based settings. Further longitudinal studies in diverse populations are needed to confirm these results and refine clinically relevant cut-off values for risk prediction.

Methods

Study design and population

This prospective cohort study enrolled 10009 adults aged (35–70 years) at baseline (May 2016 and August 2018 until) from Hoveyzeh cohort study [32]. Due to logistical constraints, a subsample of approximately 30% of the original cohort (n = 3,019) was selected for a second-phase reassessment aimed at evaluating changes in lifestyle factors, anthropometry, and socioeconomic variables over time. The subsample was selected using systematic random sampling to ensure representativeness. All participants in this subsample underwent comprehensive clinical, anthropometric, and biochemical evaluations approximately five years after baseline. Participants with evidence of MASLD at baseline were excluded from the present analysis. Additional exclusions were made for those with missing data required to calculate insulin resistance–related indices or outcome variables. After these exclusions, 1,277 participants free of MASLD at baseline were included in the final analytic sample (Fig. 1).

Figure 1. flow chart of study

Outcome Assessment: metabolic dysfunction associated steatotic liver disease (MASLD)

The Fatty Liver Index (FLI) represents a well-validated, non-invasive algorithmic score designed to estimate the probability of hepatic steatosis. This biochemical prediction model employs routinely measured clinical parameters, including triglyceride levels, body mass index (BMI), γ-glutamyl transferase (GGT), and waist circumference to quantify steatosis risk. The FLI was originally developed and validated by Bedogni et al. [33], and is calculated using the following formula [34]:

$$FLI = \frac{(e[\,0.953\ \times\ ln\,(TG)\ +\ 0.139\ \times\ \ BMI\ +\ 0.718\ \times\ ln\,(GGT)\ +\ 0.053\ \times\ \ WC\ -\ 15.745\,)]}{(1\ +\ e[0.953\ \times\ \ ln\,(TG)\ +\ 0.139\ \times\ \ BMI\ +\ 0.718\ \times\ \ ln\,(GGT)\ +\ 0.053\ \times\ \ WC\ -\ 15.745\,])} \times\ 100$$

Incident hepatic steatosis was defined as an FLI value ≥ 60 at reassessment among participants with FLI < 60 at baseline.

The primary outcome was incident of MASLD, defined as hepatic steatosis (FLI ≥ 60) in the presence of at least one cardiometabolic risk factor, including overweight or obesity, characterized by a body mass index ≥ 25 kg/m² or elevated waist circumference (≥ 94 cm for men, ≥ 80 cm for women of Caucasian descent, with appropriate ethnic-specific adjustments applied where indicated); (2) dysglycemia, encompassing either type 2 diabetes or prediabetes, with the latter defined by impaired fasting glucose (100–125 mg/dL), abnormal glucose tolerance (2-hour post-load glucose 140–199 mg/dL), or elevated HbA1c levels (5.7%-6.4%); (3) hypertension, defined as blood pressure ≥ 130/85 mmHg or current use of antihypertensive pharmacotherapy; and

(4) atherogenic dyslipidemia, evidenced by elevated triglycerides (≥ 150 mg/dL), reduced HDL-cholesterol (< 40 mg/dL in men, < 50 mg/dL in women), or ongoing lipid-lowering treatment[34,35].

Exposure Assessment: metabolic indicators

Five metabolic indices were evaluated as predictors of incidence MASLD:

TyG index = ln (TG (mg/dL) × fasting glucose (mg/dL) / 2)[11,36]

TyG-BMI = TyG × BMI[37]

TyG-WC = TyG × waist circumference[37]

METS-IR = (ln ((2 × fasting glucose) + TG) × BMI) / ln (HDL-C)[38]

SPISE = 600 × HDL-C^0.185 / (TG^0.2 × BMI^1.338)

Covariates

Data were collected using standardized questionnaires, clinical examinations, and laboratory measurements at baseline and reassessment. Demographic variables included age (35–44, 45–54, 55–64, ≥ 65 years) and sex. Socioeconomic status was assessed using a household wealth index based on ownership of nine assets (washing machine, motorcycle, personal car, home ownership, computer, internet access, number of persons per room, vacuum cleaner, and freezer). Weighted scores were categorized into quintiles from poorest to reachest [39].

Lifestyle factors included physical activity, smoking status, and alcohol consumption. Physical activity was quantified using metabolic equivalent of task (MET) values and categorized into quartiles (from lowest activity in the first quartile to highest activity in the fourth) [40]. Smoking status was self-reported; individuals who had smoked at least 100 cigarettes during their lifetime were classified as smokers.

Anthropometric and clinical assessments included body mass index (BMI), calculated as weight (kg) divided by height squared (m²), waist circumference, and blood pressure. Laboratory measurements included fasting blood glucose, lipid profile (triglycerides, HDL, LDL, and total cholesterol), and liver enzymes. Elevated liver enzymes were defined as alanine aminotransferase > 30 U/L in men and > 20 U/L in women; aspartate aminotransferase > 30 U/L in men and > 20 U/L in women; and alkaline phosphatase ≥ 306 U/L. Type 2 diabetes was defined as a self-reported physician diagnosis, use of glucose-lowering medication, or fasting plasma glucose ≥ 126 mg/dL [41], Hypertension was defined as physician diagnosis, antihypertensive treatment, or measured systolic/diastolic blood pressure ≥ 140/90 mmHg [32].

Statistical Analysis

Baseline characteristics of the study population were summarized using descriptive statistics. The normality of continuous variables was assessed with the Shapiro–Wilk test. Continuous variables, including TyG, TyG-BMI, TyG-WC, METS-IR, and SPISE, were categorized into quartiles for descriptive analyses, while categorical variables were reported as counts and percentages. For the main analyses, metabolic indices were examined both as continuous variables and by quartiles to explore dose–response associations with incident MASLD. Differences across quartiles were tested using the chi-square test, when appropriate. MASLD was evaluated only at the 5-year follow-up, making the 5-year cumulative incidence the primary measure of disease occurrence. Associations between each metabolic index and MASLD were estimated using Poisson regression with robust (sandwich) variance estimators, which provide consistent risk ratio (RR) estimates for binary outcomes in cohort studies. As a supplementary analysis, we estimated the relative risk per 1-standard-deviation increase in each metabolic index, adjusting for relevant covariates, to allow standardized comparisons across variables with different units and to facilitate interpretation of effect sizes.

The predictive performance of the metabolic indices was assessed using receiver operating characteristic (ROC) curves. ROC curves were generated separately for TyG, TyG-BMI, TyG-WC, and METS-IR, and the area under the curve (AUC) with 95%

confidence intervals was calculated. Optimal cut-off values were determined using Youden's J statistic to balance sensitivity and specificity. All analyses were conducted in Stata version 14 and R version 4.4.3, and p-values < 0.05 were considered statistically significant.

Declarations

Ethics statement

The Ethics Research Committee at Ahvaz Jundishapur University of Medical Sciences approved this study, which was conducted in accordance with the Helsinki Declaration. The approval number is IR.AJUMS.REC.1404.361. All participants signed a written informed consent form.

Competing interest

The authors declare no conflict of interest.

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Author Contribution

BCh: conceptualization, project administration, formal analysis, methodology, and writing- review editing. ZR: conceptualization, formal analysis, methodology, writing-original draft, and writing- review editing. MSh: data curation, and writing-original draft. AHB: project administration, supervision, and writing- review editing. All authors read and approved the final manuscript.

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Data Availability

The datasets from the current study are included in the article.

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Tables

Table 1. Characteristics of participants at baseline phase (May 2016 and August 2018) until stratified by MASLD status at reassessment phase in southwest Iran.

characteristic	Overall(n=1277)	Incidence of MASLD	p-value
Sex			0.093
Female	712	98(13.76%)	
Male	565	97(17.17%)	
Age			0.050
35-44	513	84(16.37%)	
45-54	428	75(17.52%)	
55-64	256	26(10.16%)	
>=65	80	10(12.50%)	
BMI			<0.001
Underweight	33	0(0%)	
Normal	586	42(7.17%)	
Overweight	576	121(21.01%)	
Obese	82	32(39.02%)	
Waist circumference			<0.001
≤ 90	574	35(6.10%)	
> 90	703	160(22.76%)	
Wealth score			0.312
Poorest	269	38(14.13%)	
Poor	295	40(13.56%)	
Moderate	235	31(13.19%)	
Rich	238	45(18.91%)	
Richest	240	41(17.08%)	
Smoking			0.891
Yes	293	44(15.02%)	
No	984	151(15.35%)	
Use Alcohol			0.021
Yes	17	6(35.29%)	
No	1260	189(15%)	
Physical activity (MET)			0.375

characteristic	Overall(n=1277)	Incidence of MASLD	p-value
Q1	272	37(13.60%)	
Q2	291	41(14.09%)	
Q3	324	59(18.21%)	
Q4	390	58(14.87%)	
SPB			0.706
<130	1149	174(15.14%)	
≥130	128	21(16.41%)	
DPB			0.072
<85	1196	177(14.80%)	
≥85	81	18(22.22%)	
Triglycerides			0.085
Normal <150	972	139(14.30%)	
Abnormal ≥150	305	56(18.36%)	
HDL			0.057
Normal ≤40	1120	163(14.55%)	
Abnormal<40	157	32(20.38%)	
LDL			0.941
Normal <100	587	89(15.21%)	
Abnormal ≥100	690	106(15.36%)	
Total cholesterol			0.359
Normal <200	908	144(15.86%)	
Abnormal ≥200	369	51(13.82%)	
ALT			0.065
no	1,072	155(14.46%)	
yes	205	40(19.51%)	

characteristic	Overall(n=1277)	Incidence of MASLD	p-value
AST			0.966
no	1121	171(15.25%)	
yes	156	24(15.38%)	
ALK			0.125
no	1208	180(14.90%)	
yes	156	15(21.74%)	
Diabetes			0.432
no	1097	164(14.95%)	
yes	180	31(17.22%)	
Hypertension			0.626
no	1044	157(15.04%)	
yes	233	38(16.31%)	

P<0.05 significant for chi-square test

Table 2. Levels of TyG indices, METS-IR, and SPISE among participants in the baseline phase, stratified by MASLD status at reassessment phase in southwest Iran.

	Overall(n=1277) **(Mean ± SD)**	**No** MASL**D**	Incidence of MASLD	p-value
Tyg index	(8.61±0.52)			0.008
Q1	321	291(90.65%)	30(9.35%)	
Q2	318	265(83.33%)	53(16.67%)	
Q3	319	265(83.07%)	54(16.93%)	
Q4	319	261(81.82%)	58(18.18%)	
Tyg BMI	(215.45±30.25)			<0.001
Q1	320	314(98.13%)	6(1.88%)	
Q2	319	290(90.91%)	29(9.09%)	
Q3	319	259(81.19%)	60(18.81%)	
Q4	319	219(68.65%)	100(31.35%)	
Tyg WC	(780.88±84.48)			<0.001
Q1	320	310(96.88%)	10(3.13%)	
Q2	319	280(87.77%)	39(12.23%)	
Q3	319	261(81.82%)	58(18.18%)	
Q4	319	231(72.41%)	88(27.59%)	
METS_IR	(36.76±5.61)			<0.001
Q1	320	313(97.81%)	7(2.19%)	
Q2	319	286(89.66%)	33(10.34%)	
Q3	319	263(82.45%)	56(17.55%)	
Q4	319	220(68.97%)	99(31.03%)	
SPISE	(6.73±1.52)			<0.001
Q1	320	223(69.69%)	97(30.31%)	
Q2	319	255(79.94%)	64(20.06%)	
Q3	319	291(91.22%)	28(8.78%)	
Q4	319	313(98.12%)	6(1.88%)	

P<0.05 significant for chi-square test

Table 3. Risk ratios (RRs) and 95% confidence intervals for the association between insulin resistance–related indices and incidence of MASLD based on Poisson regression models.

	Model 1	P-value	Model 2	P-value	Model 3	P-value
Tyg index	1.42(1.10,1.82)	0.006	1.45(1.12,1.88)	0.004	1.40(1.05,1.89)	0.022
Q1	Ref		Ref		Ref	
Q2	1.78(1.13,2.79)	0.011	1.83(1.16,2.87)	0.008	1.84(1.17,2.88)	0.008
Q3	1.81(1.15,2.83)	0.009	1.82(1.16,2.86)	0.009	1.82(1.15,2.87)	0.010
Q4	1.94(1.25,3.02)	0.003	2.01(1.28,3.15)	0.002	1.83(1.14,2.95)	0.012
P-Trend		0.006		0.005		0.022
RR per 1-SD increase	1.20(1.07,1.34)	0.001	1.21(1.09,1.36)	<0.001	1.19(1.05,1.36)	0.007
Tyg BMI	1.02(1.02,1.03)	<0.001	1.03(1.02,1.03)	<0.001	1.03(1.02,1.04)	<0.001
Q1	Ref		Ref		Ref	
Q2	4.84(2.01,11.67)	<0.001	4.72(1.96,11.37)	0.001	4.68(1.94,11.31)	0.001
Q3	10.03(4.33,23.21)	<0.001	10.39(4.48,24.06)	<0.001	10.26(4.41,23.82)	<0.001
Q4	16.71(7.33,38.10)	<0.001	18.18(7.95,41.53)	<0.001	18.57(8.08,42.69)	<0.001
P-Trend		<0.001		<0.001		<0.001
RR per 1-SD increase	2.41(2.10,2.76)	<0.001	2.60(2.25,3.00)	<0.001	2.72(2.32,3.19)	<0.001
Tyg WC	1.00(1.00,1.01)	<0.001	1.00(1.0,1.01)	<0.001	1.01(1.00,1.01)	<0.001
Q1	Ref		Ref		Ref	
Q2	3.91(1.95,7.83)	<0.001	4.05(2.02,8.12)	<0.001	4.06(2.02,8.16)	<0.001
Q3	5.81(2.97,11.38)	<0.001	6.20(3.17,12.15)	<0.001	5.88(2.99,11.58)	<0.001
Q4	8.82(4.58,16.97)	<0.001	10.42(5.39,20.14)	<0.001	10.70(5.49,20.85)	<0.001
P-Trend		<0.001		<0.001		<0.001
RR per 1-SD increase	1.90(1.68,2.14)	<0.001	2.09(1.84,2.37)	<0.001	2.32(1.98,2.73)	<0.001
METS_IR	1.12(1.10,1.15)	<0.001	1.13(1.10,1.15)	<0.001	1.13(1.10,1.16)	<0.001
Q1	Ref		Ref		Ref	
Q2	4.72(2.09,10.69)	<0.001	4.70(2.08,10.64)	<0.001	4.64(2.04,10.51)	<0.001
Q3	8.02(3.65,17.60)	<0.001	8.15(3.71,17.91)	<0.001	8.11(3.68,17.86)	<0.001
Q4	14.18(6.59,30.53)	<0.001	14.13(6.56,30.45)	<0.001	14.25(6.57,30.87)	<0.001
P-Trend		<0.001		<0.001		<0.001
RR per 1-SD increase	1.97(1.67,2.33)	<0.001	1.99(1.69,2.34)	<0.001	2.07(1.78,2.40)	<0.001

SPISE	0.44(0.37,0.53)	<0.001	0.44(0.37,0.53)	<0.001	0.44(0.37,0.53)	<0.001
Q1	Ref		Ref		Ref	
Q2	0.66(0.48,0.90)	0.010	0.67(0.49,0.92)	0.014	0.65(0.47,0.89)	0.009
Q3	0.28(0.19,0.44)	<0.001	0.28(0.18,0.43)	<0.001	0.27(0.18,0.42)	<0.001
Q4	0.06(0.02,0.14)	<0.001	0.06(0.02,0.14)	<0.001	0.06(0.02,0.14)	<0.001
P-Trend		<0.001		<0.001		<0.001
RR per 1-SD increase	0.29(0.23,0.36)	<0.001	0.29(0.23,0.36)	<0.001	0.29(0.23,0.36)	<0.001

Model 1: crude; Model 2: adjusted for age and sex; Model 3: additionally adjusted for socioeconomic status, smoking, alcohol use, physical activity, liver enzymes, hypertension, and diabetes

P<0.05 significant for Poisson regression.

Table 4. Discriminatory ability of insulin resistance indices for predicting MASLD

	ROC area (95% CI)	**P-value**
Tyg BMI	0.75(0.71, 0.78)	Ref
METS_IR	0.74(0.70,0.77)	0.421
Tyg WC	0.71(0.67,0.74)	0.003
Tyg index	0.57(0.52,0.61)	<0.001

The areas under the ROC curves were compared using the DeLong test.

Figures

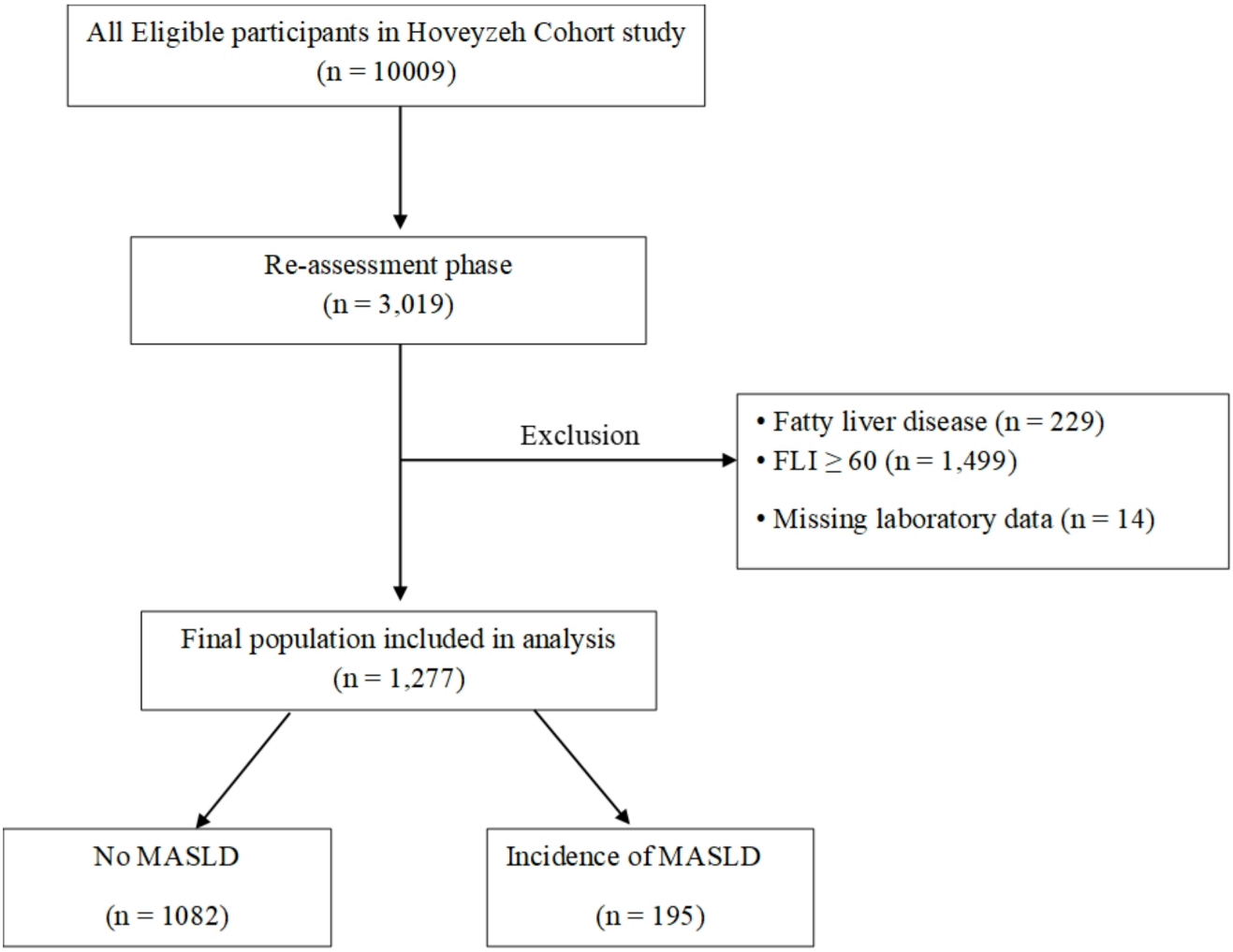


Figure 1

flowchart of study

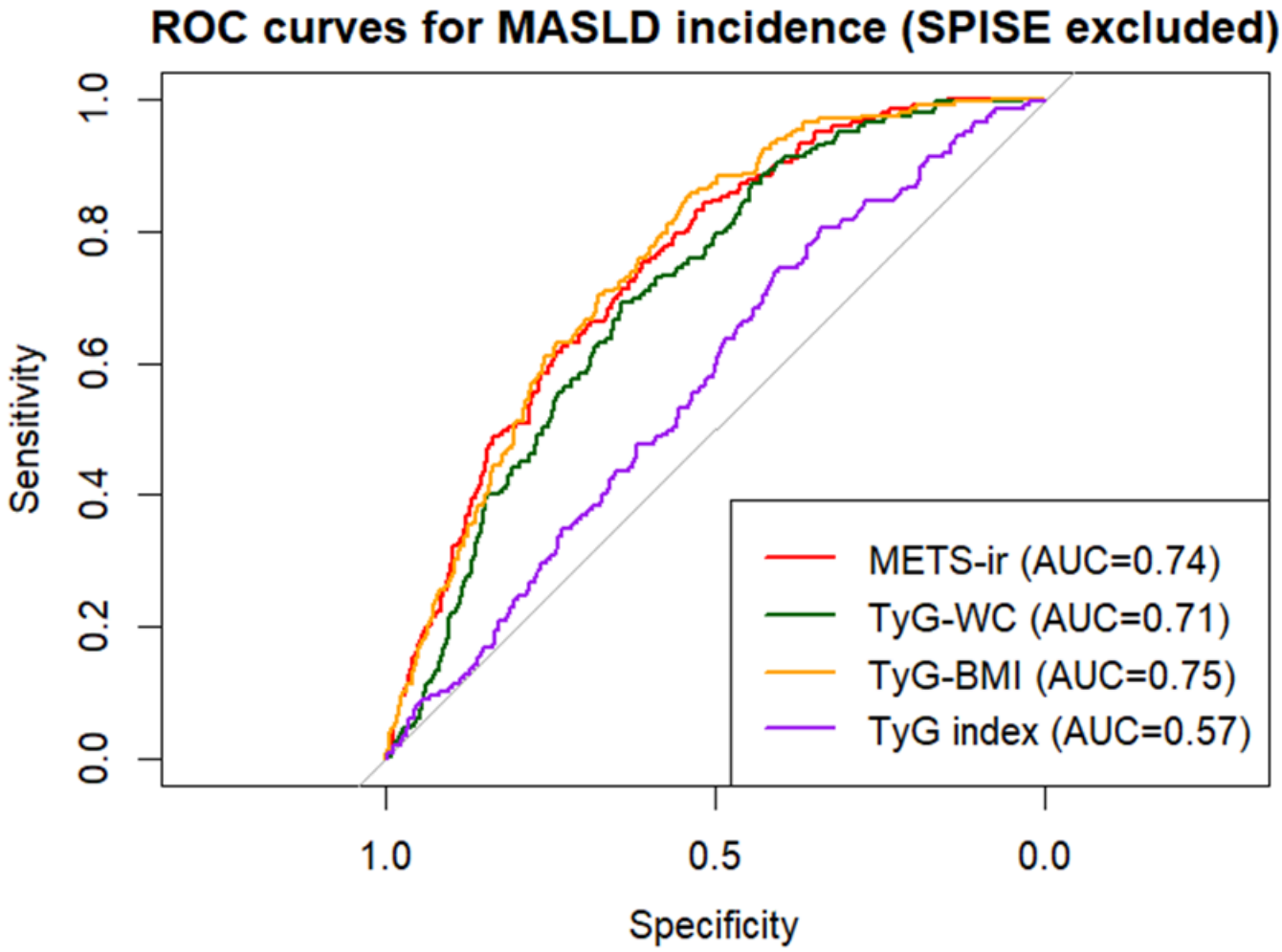


Figure 2

ROC curves for incidence of MASLD by metabolic indices.