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ORIGINAL RESEARCH

Institutional Nomogram for Estimating Risk of Metabolic Associated Fatty Liver Disease (MAFLD)

Tiansu Lv[1,2,*], Jie Tian[1,3,*], Yaohuan Sun[1,3], Yujuan Zhang[1,2], Fang Qi[1,2], Liulan Xiang[1,2], Yutian Cao[1,2], Wenhui Zhang[1,2], Jiaxuan Huai[1,2], Yinfeng Dong[4], Xiqiao Zhou[1,2]

[1]Department of Endocrinology, Jiangsu Province Hospital of Chinese Medicine, Affiliated Hospital of Nanjing University of Chinese Medicine, Nanjing, People's Republic of China; [2]The First Clinical Medical College of Nanjing University of Chinese Medicine, Nanjing, People's Republic of China; [3]School of Nursing, Nanjing University of Chinese Medicine, Nanjing, People's Republic of China; [4]Department of Pathology and Pathophysiology, School of Medicine, Nanjing University of Chinese Medicine, Nanjing, People's Republic of China

*These authors contributed equally to this work

Correspondence: Xiqiao Zhou; Yinfeng Dong, Email zhouxiqiao@njucm.edu.cn; dongyf@njucm.edu.cn

Background: Metabolic Associated Fatty Liver Disease (MAFLD) poses a significant threat to human health, as it can result in hepatic fibrosis and potentially progress to cirrhosis, in addition to causing a range of extrahepatic complications. The early detection of MAFLD is crucial, particularly during the initial stages when the condition may be amenable to reversal and the body composition could be vital importance.

Methods: Data from participants at the Jiangsu Province Hospital of Traditional Chinese Medicine, covering the period from January 1 to December 31, 2022, were collected and subsequently randomized into training and validation cohorts. Independent risk factors for MAFLD were identified using statistical methodologies in conjunction with clinical relevance, and these factors were ultimately utilized to develop the nomogram.

Results: In the training cohort, there were 356 cases of MAFLD out of a total of 513 patients, representing 71.2%, while in the validation cohort, 161 cases of MAFLD were identified out of 220 patients, accounting for 73.2%. In terms of statistical outcomes and clinical relevance, we identified a total of 12 closely related or significant variables. To enhance our understanding of the critical role of body composition parameters in predicting the incidence of MAFLD, we developed two distinct nomograms, one of which included body composition data. Notably, the nomogram that incorporated body composition demonstrated superior predictive performance, as evidenced by a well-fitted calibration curve and a C-index of 0.893 (with a range of 0.8625 to 0.9242). Furthermore, the decision curve analysis indicated that utilizing the nomogram that included body composition would yield greater benefits.

Conclusion: The nomogram serves as an effective tool for predicting MAFLD. Its utility in early risk identification of MAFLD is of significant importance, as it facilitates timely intervention and treatment for patients affected by this condition.

Keywords: Metabolic Associated Fatty Liver Disease, Body Composition, Nomogram

Background

Metabolic Associated Fatty Liver Disease (MAFLD) has garnered significant attention due to its strong correlation with pancreatic islet dysfunction and genetic predisposition. The global prevalence of MAFLD in the adult population is estimated to be between 13% and 31%,[1,2] with China experiencing rates of approximately 25% to 40%.[1,3] In 2020, an international panel of experts provided insights into the clinical implications of reclassifying non-alcoholic fatty liver disease (NAFLD) as MAFLD. They advocated for the adoption of the term MAFLD as a more suitable designation for liver conditions linked to metabolic dysfunction,[4,5] which further illustrates the growing recognition and significance that individuals attribute to the connection between disease and metabolism. Recent research has linked MAFLD to insulin resistance, inflammatory responses, the accumulation of fatty substances, and oxidative stress.[6,7] Furthermore, both

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environmental and genetic factors influence the interactions among various organs and tissues, including the pancreas, intestines, and adipose tissue, thereby exacerbating metabolic disorders in patients with MAFLD.[8] Currently, there is still no definitive pharmacological agent available that specifically targets the treatment of MAFLD.[9] Therefore, lifestyle modifications and weight reduction remain critical components of management. Consequently, early diagnosis of MAFLD is essential, as the condition can be reversed in its initial stages through appropriate lifestyle adjustments and weight loss.[5]

Essentially, liver steatosis is the primary pathological process underlying MAFLD. As the condition advances, liver tissue undergoes a repair process following fat degeneration and cells damage, which ultimately intensifies liver inflammation and results in the development of non-alcoholic steatohepatitis (NASH) or metabolic dysfunction associated steatohepatitis (MASH). Continued tissue damage and repeated repair efforts lead to the formation of fibrous structures that resemble pseudo-lobules within the liver, which may progress to liver fibrosis or even cirrhosis, thereby heightening the risk of hepatocellular carcinoma.[10] Furthermore, MAFLD may influence physiological functions beyond hepatic activity, potentially leading to cardiovascular and cerebrovascular diseases, as well as a range of extrahepatic complications, thereby presenting considerable risks to human health.[11,12] From these prospective, the prediction of early risk for MAFLD is of significant importance with considerable challenges. However, liver biopsy, recognized as the gold standard for assessment, is an invasive and potentially traumatic procedure. Although non-invasive methods such as Fibroscan and Fibrotouch are available, their accuracy is subject to variation depending on the diagnostic criteria employed and the individual differences among patients.[13,14] Furthermore, MAFLD is associated with metabolic factors, socio-economic status, geographical regions, and body composition.[15,16] This is especially relevant for non-obese individuals with MAFLD, with particular attention to body composition, which is frequently neglected.[17]

Among the various models available, a nomogram provides a personalized, evidence-based, and highly accurate risk assessment. This tool is user-friendly and facilitates informed decision-making in management. Consequently, our objective was to create a nomogram for the risk assessment of early-stage MAFLD. In our approach, we incorporated patients' fundamental information, clinical history, laboratory findings, metabolic factors, and body composition. Acknowledging the significance of body composition in the screening process for MAFLD, we devised two distinct nomograms based on this criterion. Given the diverse prevalence and heterogeneity of MAFLD across different regions, it is important to note that our model, which is primarily derived from data collected in East China, may offer enhanced predictive capabilities for MAFLD within this specific geographic area.[16,18]

Methods

Participants and Flow

Data were retrospectively collected from patients aged 18 years and older who visited the outpatient endocrinology departments at Jiangsu Province Hospital of Traditional Chinese Medicine between January 1, 2022, and December 31, 2022. This study received approval from the Institutional Ethics Committee of Jiangsu Province Hospital of Traditional Chinese Medicine and was conducted with the informed consent of all participants. The participants were randomly assigned into a training cohort and a validation cohort using R software, with a distribution ratio of 7:3 for development and validation purposes, respectively. The whole details are reported (Figure 1).

Diagnosis of MAFLD

The diagnosis of MAFLD is based on hepatic steatosis and satisfied requires the fulfillment of any one of obesity/overweight, diabetes, or metabolic dysfunction. According to the definition of MAFLD,[4] metabolic dysfunction must be fulfilled at least two of the following items: 1. waist circumference (>102 cm for male and >88 cm for female); 2. hypertension (arterial blood pressure ≥130/85 mmHg or receiving antihypertensive therapy); 3. hyperlipidemia (triglycerides (TG) ≥1.70 mmol/L or receiving lipid-lowering therapy); 4. serum high-density cholesterol (HDL-C) levels are reduced (<1.0 mmol/L for male and <1.3 mmol/L for female); 5. pre-diabetes, and 6. serum hypersensitivity C-reactive protein (hs-CRP) levels >2 mg/L.

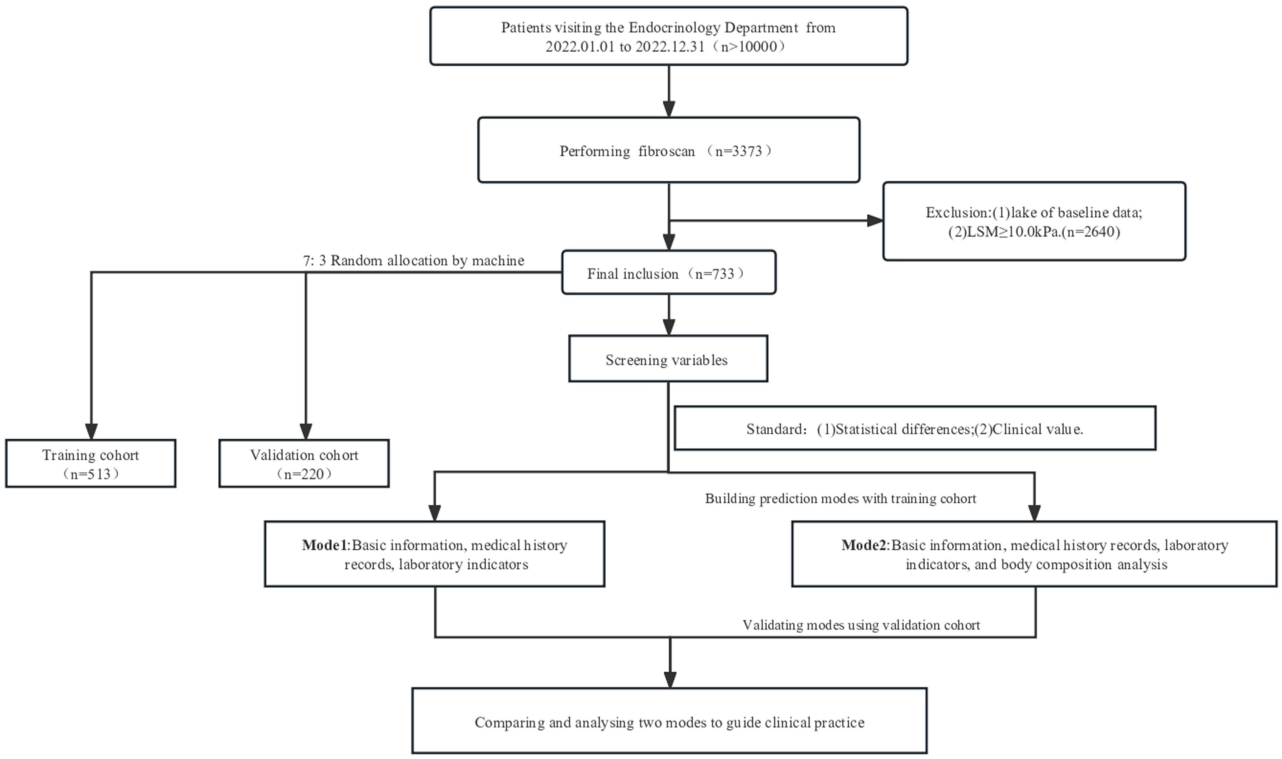

Figure 1 Diagram for data abstraction and partitioning into training and validation datasets.

Inclusion and Exclusion Criteria

The inclusion criteria consist of comprehensive baseline data, participants aged 18 years and older, and adherence to the diagnostic criteria for MAFLD. Given the nature of the outpatient population, we utilized Fibroscan parameters to assess the extent of liver steatosis as an alternative measure.[13] Specifically, we used controlled attenuation parameter (CAP) to determine the degree of liver steatosis, where the essence of steatosis was defined as CAP $\geq$ 244 dB/m.[14]

The exclusion criteria apply to patients exhibiting a predisposition to liver fibrosis, which was primarily assessed through liver stiffness measurement (LSM) via Fibroscan, where the tendency of liver fibrosis was set as LSM $\geq$ 10.0 KPa.[19] Therefore, for patients with LSM greater than or equal to 10, we exclude.

Clinical Variables

The clinical variables mainly contained the following items:[1] Basic information, including patient gender, age, height, weight, and place of residence;[2] Clinical history, including prediabetes, type 2 diabetes (T2DM), overweight, obesity, hypertension, Hashimoto's thyroiditis (HT), hypothyroidism, thyroid nodules, Grave's disease (GD), and helicobacter pylori infection (HP);[3] Laboratory examination, including white blood cells(WBC), red blood cells(RBC), platelets (Plt), hemoglobin (hB), C-reactive protein (CRP), glutamic-pyruvic transaminase (ALT), glutamic-oxaloacetic transaminase (AST), alkaline phosphatase (ALP), γ-glutamyltransferase (GGT), albumin (Abo), white bulb ratio (A/G), total bilirubin (Tbil), blood urea nitrogen(BUN), blood creatinine, cystatin c;[4] Metabolic factors, including fasting blood glucose (FBG), glycosylated hemoglobin (HbA1c), fasting insulin (INS), fasting C-peptide, uric acid (UA), cholesterol (TC), triglycerides (TG), high-density lipoprotein (HDL), low-density lipoprotein (LDL);[5] Body composition, mainly including body fat, body mass index (BMI), waist-to-hip ratio (WHR), visceral fat area (VFA), skeletal muscle index (SMI), etc. The details were seen in Table 1.

Statistical Analysis

In the course of model development, a total of 733 participants were randomly assigned to two distinct groups for the purposes of training and validation. This division aimed to enhance the balance between the robustness of the training

Table 1 Participant Characteristics

MAFLD (%)	No	207 (28.2)		
	Yes	526 (71.8)		
CAP (dB/m)	291.00 [249.00, 328.00]			
LSM (kPa)	5.50 [4.50, 6.90]			
Basic information			**Metabolism related indicators**	
Gender (%)	Female	426 (58.1)	FBG (mmol/L)	5.61 [5.08, 6.80]
	Male	307 (41.9)	UA (umol/L)	378.40 [308.00, 449.90]
Age (year)	40.00 [32.00, 50.00]		TC (mmol/L)	4.92 [4.30, 5.59]
Height (cm)	163.50 [159.00, 170.50]		TG (mmol/L)	1.63 [1.10, 2.35]
Weight (cm)	75.70 [65.90, 86.90]		HDL (mmol/L)	1.32 [1.13, 1.51]
Clinical history			LDL (mmol/L)	2.96 (0.78)
Hypertension (%)	No	581 (79.3)	HbA1c(%)	6.10 [5.70, 7.00]
	Yes	152 (20.7)	INS (ulU/mL)	9.19 [5.92, 14.76]
Prediabetes[a] (%)	No	570 (77.8)	C-Peptide (ng/mL)	2.27 [1.64, 3.01]
	Yes	163 (22.2)	**Body composition**	
T2DM (%)	No	403 (55.0)	BMI	27.90 [25.00, 31.20]
	Yes	330 (45.0)	TBW	35.10 [31.00, 41.80]
HT (%)	No	661 (90.2)	ICW	21.70 [19.10, 25.90]
	Yes	72 (9.8)	ECW	13.40 [11.80, 15.90]
Hypothyroidism (%)	No	694 (94.7)	Protein (kg)	9.40 [8.30, 11.20]
	Yes	39 (5.3)	Minerals (kg)	3.25 [2.88, 3.79]
Thyroid nodules (%)	No	612 (83.5)	BFM (kg)	26.60 [20.90, 33.00]
	Yes	121 (16.5)	SLM (kg)	45.00 [39.80, 53.70]
GO (%)	No	717 (97.8)	FFM (kg)	47.80 [42.10, 56.90]
	Yes	16 (2.2)	SMM (kg)	26.30 [22.90, 31.80]
HP (%)	No	698 (95.2)	PBF (%)	35.80 [29.80, 40.30]
	Yes	35 (4.8)	BMR (Calorie)	1403.00 [1279.00, 1599.00]
Overweight [b](%)	No	126 (17.2)	WHR	0.93 [0.89, 0.97]
	Yes	607 (82.8)	VFA (cm^2)	128.30 [96.20, 161.90]
Obesity[b] (%)	No	372 (50.8)	BCM (kg)	31.10 [27.30, 37.10]
	Yes	361 (49.2)	AC (cm)	33.30 [31.00, 35.90]
Metabolic dysfunction[c] (%)	No	187 (25.5)	AMC (cm)	28.10 [26.30, 29.90]
	Yes	546 (74.5)	BMC (kg)	2.66 [2.36, 3.10]
Laboratory examination			TBW/FFM	73.60 [73.40, 73.70]
CRP (mg/L)	0.57 [0.50, 1.36]		FFMI	18.00 [16.50, 19.70]
WBCs (10^9/L)	6.69 (1.78)		FMI	9.90 [7.70, 12.30]
RBCs (10^9/L)	4.90 (0.54)		Neck Circumference (cm)	37.60 [35.40, 39.90]
hB (g/L)	142.00 [132.00, 154.00]		Chest Circumference (cm)	98.90 [93.20, 105.10]
Pl t(10^9/L)	239.00 [201.00, 289.00]		Waist Circumference(cm)	94.20 [86.60, 103.70]
AST (U/L)	20.00 [16.00, 27.00]		Hip Circumference (cm)	101.20 [95.90, 106.90]
ALT (U/L)	24.00 [16.00, 41.00]		Right Arm Circumference(cm)	33.40 [31.10, 36.00]
ALP (U/L)	77.00 [64.00, 93.00]		Left Arm Circumference(cm)	33.30 [31.00, 35.90]
GGT (U/L)	34.00 [20.90, 53.90]		Right Thigh Circumference (cm)	54.80 [50.90, 58.80]
Abo (g/L)	46.80 (4.86)		Left Thigh Circumference(cm)	54.40 [50.60, 58.10]
A/G	2.00 [1.80, 2.20]		SMI	7.50 [6.80, 8.30]

(*Continued*)

Table 1 (Continued).

Tbil (umol/L)	11.66 (5.84)		
BUN (mmol/L)	5.17 (1.36)		
Creatinine (umol/L)	63.63 (14.25)		
Cystatin c (mg/L)	0.90 (0.17)		

Notes: a.Prediabetes refers to failure to meet the diagnostic criteria for diabetes but meets one of the following three conditions: glycosylated hemoglobin>6.0%, insulin resistance, and abnormal glucose tolerance test results; b.The overweight standard is BMI greater than or equal to 24, while the obesity standard is BMI greater than or equal to 28; c.Metabolic dysfunction can be found in the previous text in Definition of MAFLD. d.The continuous variable of normal distribution is median (SD), the continuous variable of non-normal distribution is median [IQR], and the categorical variable is percentage.

Abbreviations: CAP, controlled attenuation parameter; LSM, liver stiffness measurement; T2DM, type 2 diabetes; HT, Hashimoto's thyroiditis; GD, Graves disease; HP, helicobacter pylori infection; CRP, C-reactive protein; WBCs, white blood cells; RBCs, red blood cells; hB, hemoglobin; Plt, platelets; AST, glutamic-oxaloacetic transaminase; ALT, alanine aminotransferase; ALP, alkaline phosphatase; GGT, γ-glutamyltransferase; Abo, albumin; A/G, White bulb ratio; Tbil, total bilirubin; BUN, blood urea nitrogen; FBG, fasting blood glucose; UA, uric acid; TC, cholesterol; TG, triglycerides; HDL, high-density lipoprotein; LDL, low-density lipoprotein; HbA1c, glycosylated hemoglobin; INS, fasting insulin; BMI, body mass index; TBW, Total Body Water; ICW, Intracellular Water; ECW, Extracellular Water; BFM, Body Fat Mass; SLM, Soft Lean Mass; FFM, Fat Free Mass; SMM, Skeletal Muscle Mass; PBF, Percent Body Fat; BMR, Basal Metabolic Rate; WHR, Waist Hip Ratio; VFA, Visceral Fat Area; BCM, Body Cell Mass; AC, Arm Circumference; AMC, Arm Muscle Circumference; BMC, Bone Mineral Content; FFMI, Fat Free Mass Index; FMI, Fat Mass Index; SMI, Skeletal Muscle Index.

sample and the number of events present in the test sets. The training cohort was utilized for model development, while the validation cohort served to evaluate the model's performance. All patients included in the analysis presented in the article were selected based on comprehensive clinical data, ensuring that there were no missing values to address.

In relation to the baseline data, we initially ensured the integrity of the data throughout the screening process. The Kolmogorov–Smirnov test was employed to evaluate the normality of continuous variables. For data that did not conform to a normal distribution, the Mann–Whitney *U*-test was utilized, whereas normally distributed data were analyzed using the Student's *t*-test. Additionally, categorical data were presented as percentages and analyzed using the Chi-squared test.

Following the exclusion of variables incorporated in the models, we employed a combination of statistical methodologies alongside clinical significance to validate the variables within the model. Each variable deemed significant within the training cohort was evaluated through univariate logistic regression analysis to identify independent risk factors associated with MAFLD. All variables except for that exhibiting p value over 0.05 in univariate logistic regression analysis were further analyzed using stepwise multivariate logistic analysis. The least absolute shrinkage and selection operator (LASSO) binary logistic regression model is a widely recognized technique for regression analysis involving high-dimensional predictors. This methodology has been adapted and extensively utilized for the analysis of high-dimensional regression models. We further applied the LASSO regression model to identify the most pertinent clinical variables within the training cohort utilizing R software version 4.1.1 and the "glmnet" package. Additionally, we utilized R software version 4.1.1 and the "corrplot" package to conduct correlation analyses among partial variables. For continuous normally distributed data, Pearson correlation was employed; for non-normally distributed variables, Spearman's rho correlation was utilized. In the case of categorical variables, the Kendall tau correlation coefficient was applied. Ultimately, both the significant variables and their clinical relevance were considered in the development of the nomograms.

The nomogram was developed utilizing R software version 4.1.1 in conjunction with the "rms" package. Each regression coefficient from the multivariate logistic regression analysis was proportionally transformed to a scale ranging from 0 to 100. The variable exhibiting the highest absolute β coefficient was designated as 100%. Points were aggregated across the independent variables to calculate a total score, which was subsequently converted into predicted probabilities. The predictive performance of the nomogram was evaluated using the concordance index (C-index) and calibration techniques to mitigate the risk of overfitting.[20] Calibration plots were created to evaluate the performance characteristics of the nomogram, which facilitated the assessment of the alignment between actual outcomes and predicted outcomes for each nomogram. The x-axis denotes the predictions derived from the nomogram, while the y-axis indicates the actual occurrence of MAFLD. The 45-degree line serves as a benchmark for the performance of an ideal nomogram, signifying that the predicted outcomes align closely with the actual outcomes. A well-calibrated model will exhibit predictions that

are in proximity to this 45-degree line. Additionally, decision curve analysis was performed to assess the clinical utility of the nomograms by quantifying the net benefits across various threshold probabilities within the validation cohort.

In order to effectively predict MAFLD and to investigate the influence of body composition on these predictions, we developed two distinct models. Model 1 excluded body composition parameters, whereas Model 2 incorporated these parameters. The total score for each participant was derived from the nomograms. We employed receiver operating characteristic (ROC) curve analysis to determine the optimal cutoff values, which were established by maximizing the Youden index (ie, sensitivity + specificity - 1). Subsequently, we conducted a comparative analysis of the two models utilizing various metrics, including sensitivity, specificity, true positives, true negatives, false positives, false negatives, ROC curve area, C-index, Decision Curve Analysis (DCA), Net Reclassification Index (NRI), and Integrated Discrimination Improvement (IDI).

In all, $P < 0.05$ was considered to indicate statistical significance. All analyses were performed by R, version 4.1.1. and was conducted from January 1, to March 31, 2023.

Results

Clinicopathologic Characteristics

A total of over 3000 consecutive patients attending the endocrinology clinic were assessed for the presence of MAFLD, with 733 individuals subsequently enrolled in this study. Among these participants, 513 were allocated to the training cohort, while 220 were assigned to the validation cohort (refer to Supplemental Table 1). Our analysis revealed no statistically significant differences between the training and validation cohorts across all variables ($P \geq .05$), with the exception of platelet count. This indicates that the baseline characteristics of the training cohort and the validation cohort were both reasonable and comparable. The clinicopathologic characteristics of the patients are detailed in Table 1, where MAFLD was identified in 356 (71.2%) and 161 (73.2%) patients in the respective cohorts.

Feature Selection for MAFLD Prediction Building

We followed the principle of integrating statistical effects with clinical relevance in the selection of predictive model variables. We employed LASSO logistic regression in conjunction with both univariate and multivariate logistic regression to assess the statistical significance of the variables. Additionally, we took into account variables that, while not statistically significant, may possess potential guiding implications for practical clinical application.

The findings of the univariate logistic analysis are detailed in Table 2, where it was determined that 12 variables did not demonstrate statistical significance ($P>0.05$) and were therefore excluded from further analysis. Given that the univariate analysis did not account for interactions among variables, we opted to retain the remaining variables with P values less than or equal to 0.05 for the multivariate logistic analysis, as presented in Table 3. The results of the multivariate analysis, expressed as odds ratios(OR) (95% Confidence Interval), indicated that Age (1.041 [1.01–1.07]), Type 2 Diabetes Mellitus (T2DM) (2.872 [1.42–5.99]), Obesity (3.133 [1.24–8.08]), Metabolic Dysfunction (3.637 [1.94–6.92]), Hemoglobin (hB) (1.023 [1.01–1.05]), Total Cholesterol (TC) (1.747 [1.05–3.31]), Triglycerides (TG) (1.437 [1.06–2.05]), and High-Density Lipoprotein (HDL) (0.325 [0.10–0.91]) were found to be independently associated with MAFLD.

To address the constraints associated with variable screening through statistical analysis methods, we employed lasso regression for a comprehensive re-evaluation of the variables. In the context of texture features analyzed via LASSO logistic regression, the initial 69 features were refined to 19 potential predictors, determined by the minimum value of λ, based on a cohort of 513 patients in the training set (refer to Figure 2A and B). These 19 features were characterized by nonzero coefficients within the LASSO logistic regression model. Notably, the primary predictors of MAFLD identified included T2DM, HT, GO, Overweight, Obesity, Metabolic dysfunction, CRP, hB, ALT, ALP, FBG, TC, TG, HDL, HbA1c, PBF, AC, TBWFFM, and Right Arm.

Furthermore, drawing from the findings of prior literature research and their clinical relevance, specific variables were chosen for correlation analysis to enhance the characterization of our data, as detailed in Supplemental Table 2. Our analysis revealed that the majority of variables demonstrating statistical significance in the multivariate logistic regression also exhibited

Table 2 Univariate Logistic Regression Analysis of MAFLD in the Training Cohort

Univariate analysis					
	β	SE	P	OR	95% confidence interval
Age	−0.012	0.006	0.0501	0.988	(0.98,1.01)
Gender	0.357	0.170	0.0351	1.429	(1.03,2.00)
BMI	0.312	0.029	0.0000	1.366	(1.30,1.45)
Hypertension	0.628	0.225	0.0053	1.873	(1.23,2.30)
Prediabetes	0.284	0.205	0.1660	1.329	(0.90,2.00)
T2DM	0.363	0.167	0.0299	1.438	(1.04,2.01)
HT	−0.669	0.255	0.0086	0.512	(0.32,0.85)
Hypothyroidism	−0.129	0.357	0.7190	0.879	(0.45,1.83)
Thyroid nodules	−0.229	0.215	0.2860	0.796	(0.53,1.22)
GO	−0.147	0.546	0.7870	0.863	(0.31,2.77)
HP	−0.297	0.366	0.4170	0.743	(0.37,1.57)
Overweight	1.752	0.208	<2e-16	5.766	(3.85,8.70)
Obesity	2.352	0.220	<2e-16	10.504	(6.93,16.43)
Metabolic dysfunction	2.473	0.197	< 2e-16	11.858	(8.10,17.56)
CRP	0.174	0.054	0.0012	1.190	(1.08,1.34)
WBC	0.259	0.052	0.0010	1.296	(1.17,1.44)
RBC	0.906	0.170	0.0000	2.474	(1.78,3.47)
hB	0.030	0.005	0.0000	1.030	(1.02,1.04)
Plt	0.002	0.001	0.0636	1.002	(0.99,1.01)
AST	0.069	0.012	0.0000	1.072	(1.05,1.10)
ALT	0.044	0.006	0.0000	1.045	(1.03,1.06)
ALP	0.015	0.004	0.0001	1.015	(1.01,1.02)
GGT	0.004	0.002	0.0620	1.004	(1.01,1.02)
Abo	0.005	0.017	0.7840	1.005	(0.97,1.04)
A/G	−0.278	0.257	0.2786	0.757	(0.46,1.25)
TBil	0.001	0.014	0.9540	1.001	(0.97,1.03)
FBG	0.119	0.047	0.0107	1.126	(1.03,1.24)
UA	0.002	0.001	0.0064	1.002	(1.01,1.01)
Creatinine	0.014	0.006	0.0209	1.014	(1.01,1.03)
BUN	0.002	0.060	0.9685	1.002	(0.89,1.13)
Cystatin c	1.790	0.541	0.0009	5.989	(2.13,17.76)
TC	0.293	0.082	0.0004	1.341	(1.14,1.58)
TG	1.065	0.134	0.0000	2.899	(2.25,3.81)
HDL	−2.036	0.302	0.0000	0.131	(0.07,0.23)
LDL	0.473	0.111	0.0000	1.605	(1.30,2.00)
HbA1c	0.144	0.062	0.0205	1.155	(1.03,1.31)
INS	0.101	0.016	0.0000	1.106	(1.07,1.14)
C-Peptide	0.670	0.097	0.0000	1.954	(1.62,2.38)
Height	0.030	0.010	0.0039	1.030	(1.01,1.05)
Weight	0.079	0.008	<2e-16	1.083	(1.07,1.10)
TBW	0.097	0.014	0.0000	1.102	(1.07,1.13)
ICW	0.158	0.022	0.0000	1.171	(1.12,1.22)
ECW	0.248	0.036	0.0000	1.281	(1.20,1.38)
TBW/FFM	−0.092	0.291	0.7530	0.912	(0.52,1.62)
Protein	0.366	0.051	0.0000	1.442	(1.31,1.60)
Minerals	0.941	0.146	0.0000	2.561	(1.94,3.44)
BFM	0.126	0.013	< 2e-16	1.135	(1.11,1.17)
SLM	0.076	0.011	0.0000	1.079	(1.06,1.10)
FFM	0.071	0.010	0.0000	1.074	(1.05,1.10)

(*Continued*)

Table 2 (Continued).

Univariate analysis					
	β	SE	P	OR	95% confidence interval
SMM	0.121	0.017	0.0000	1.129	(1.10,1.17)
PBF	0.077	0.012	0.0000	1.080	(1.06,1.11)
BMR	0.003	0.000	0.0000	1.003	(1.00,1.01)
WHR	5.006	1.377	0.0003	149.27	(10.41,2312.90)
VFA	0.021	0.002	< 2e-16	1.022	(1.02,1.03)
BCM	0.110	0.015	0.0000	1.117	(1.09,1.15)
AC	0.412	0.037	<2e-16	1.510	(1.141,1.63)
AMC	0.466	0.044	<2e-16	1.593	(1.47,1.74)
BMC	1.095	0.176	0.0000	2.988	(2.14,4.27)
FFMI	0.416	0.047	< 2e-16	1.517	(1.39,1.67)
FMI	0.302	0.033	< 2e-16	1.352	(1.27,1.45)
Neck Circumference	0.368	0.035	<2e-16	1.445	(1.35,1.56)
Chest Circumference	0.156	0.014	<2e-16	1.169	(1.14,1.20)
Waist Circumference	0.118	0.011	<2e-16	1.125	(1.10,1.15)
Hip Circumference	0.160	0.015	<2e-16	1.174	(1.14,1.21)
Right Arm Circumference	0.408	0.036	<2e-16	1.503	(1.40,1.62)
Left Arm Circumference	0.412	0.037	<2e-16	1.510	(1.41,1.63)
Right Thigh Circumference	0.191	0.020	<2e-16	1.210	(1.17,1.26)
Left Thigh Circumference	0.201	0.021	<2e-16	1.223	(1.17,1.28)
SMI	0.767	0.091	< 2e-16	2.154	(1.81,2.59)

Table 3 Multivariate Logistic Regression Analysis of MAFLD in the Training Cohort

Multivariate analysis					
	β	SE	P	OR	95% confidence interval
Age	0.040	0.016	**0.0124**	1.041	(1.01,1.07)
Gender	−0.375	0.589	0.5244	0.687	(0.22,2.19)
BMI	−3.297	3.156	0.2963	0.037	(0.01,17.62)
Hypertension	−0.247	0.370	0.5056	0.781	(0.38,1.63)
Prediabetes	–	–	–	–	–
T2DM	1.055	0.366	**0.0040**	2.872	(1.42,5.99)
HT	−0.383	0.401	0.3398	0.682	(0.32,1.51)
Hypothyroidism	–	–	–	–	–
Thyroid nodules	–	–	–	–	–
GO	–	–	–	–	–
HP	–	–	–	–	–
Overweight	0.153	0.472	0.7460	1.165	(0.56,2.94)
Obesity	1.142	0.476	**0.0165**	3.133	(1.24,8.08)
Metabolic dysfunction	1.291	0.324	**0.0001**	3.637	(1.94,6.92)
CRP	0.080	0.058	0.1696	1.084	(0.98,1.23)
WBC	−0.023	0.081	0.7731	0.977	(0.83,1.15)
RBC	−0.063	0.324	0.8459	0.939	(0.50,1.77)
hB	0.023	0.010	**0.0230**	1.023	(1.01,1.05)
Plt	-	-	-	-	-
AST	−0.005	0.024	0.8481	0.995	(0.96,1.05)
ALT	0.025	0.013	**0.0546**	1.025	(9.99e-01,1.05e+00)
ALP	0.009	0.005	0.1035	1.009	(9.99e-01,1.02e+00)

(*Continued*)

Table 3 (Continued).

Multivariate analysis					
	β	SE	P	OR	95% confidence interval
GGT	-	-	-	-	-
Abo	-	-	-	-	-
A/G	-	-	-	-	-
TBil	-	-	-	-	-
FBG	0.050	0.105	0.6338	1.051	(0.86,1.30)
UA	0.001	0.001	0.6024	1.001	(9.98e-01,1.01e+00)
Creatinine	0.009	0.015	0.5437	1.009	(0.98,1.04)
BUN	-	-	-	-	-
Cystatin c	−0.677	0.984	0.4913	0.508	(0.07,4.52)
TC	0.558	0.283	**0.0484**	1.747	(1.05,3.31)
TG	0.362	0.170	**0.0330**	1.436	(1.06,2.05)
HDL	−1.123	0.547	**0.0400**	0.325	(0.10,0.91)
LDL	−0.461	0.339	0.1740	0.631	(0.30,1.18)
HbA1c	0.062	0.137	0.6501	1.064	(0.81,1.40)
INS	0.011	0.023	0.6279	1.011	(0.97,1.06)
C-Peptide	−0.197	0.180	0.2751	0.821	(0.58,1.17)
Height	−0.142	0.468	0.7612	0.867	(0.36,2.18)
Weight	3.228	7.801	0.6790	25.241	(5.95e-06,1.22e+08)
TBW	−1.279	5.646	0.8207	0.278	(4.33e-06,1.86e+04)
ICW	−1.249	3.799	0.7425	0.287	(1.64e-04 4.99e+02)
ECW	NA	NA	NA	NA	NA
TBW/FFM	-	-	-	-	-
Protein	2.726	4.408	0.5363	15.271	(2.69e-03,8.94e+04)
Minerals	4.896	5.787	0.3975	133.746	(1.57e-03,1.19e+07)
BFM	−3.319	7.824	0.6714	0.036	(7.15e-09,1.60e+05)
SLM	−3.742	4.166	0.3691	0.024	(7.15e-09,1.60e+05)
FFM	NA	NA	NA	NA	NA
SMM	1.828	3.532	0.6047	6.222	(6.17e-03,6.56e+03)
PBF	−0.051	0.164	0.7573	0.951	(0.69,1.32)
BMR	0.034	0.255	0.8952	1.034	(0.63,1.71)
WHR	−3.467	2.425	0.1528	0.031	(2.54e-04,3.49e+00)
VFA	0.018	0.028	0.5233	1.018	(0.96,1.08)
BCM	−0.583	3.337	0.8614	0.558	(8.01e-04,3.94e+02)
AC	0.710	1.477	0.6309	2.034	(0.11,37.65)
AMC	−0.679	1.196	0.5701	0.507	(0.05,5.21)
BMC	−7.136	6.891	0.3004	0.001	(9.68e-10,5.71e+02)
FFMI	1.559	2.834	0.5823	4.753	(1.84e-02,1.26e+03)
FMI	3.214	2.781	0.2478	24.888	(1.09e-01,6.10e+03)
Neck Circumference	−0.434	0.440	0.3244	0.648	(0.26,1.50)
Chest Circumference	0.389	0.399	0.3299	1.475	(0.67,3.26)
Waist Circumference	−0.034	0.175	0.8459	0.967	(0.68,1.35)
Hip Circumference	0.125	3.071	0.9676	1.133	(2.70e-03,4.71e+02)
Right Arm Circumference	0.009	0.441	0.9832	1.009	(0.50,2.85)
Left Arm Circumference	NA	NA	NA	NA	NA
Right Thigh Circumference	−0.025	0.945	0.9792	0.976	(0.16,6.25)
Left Thigh Circumference	−0.211	0.959	0.8260	0.810	(0.12,5.35)
SMI	2.582	1.441	**0.0731**	13.227	(9.91e-01,5.43e+02)

Notes: The variables independently associated with MAFLD are highlighted in bold.
Abbreviation: NA, Not Available.

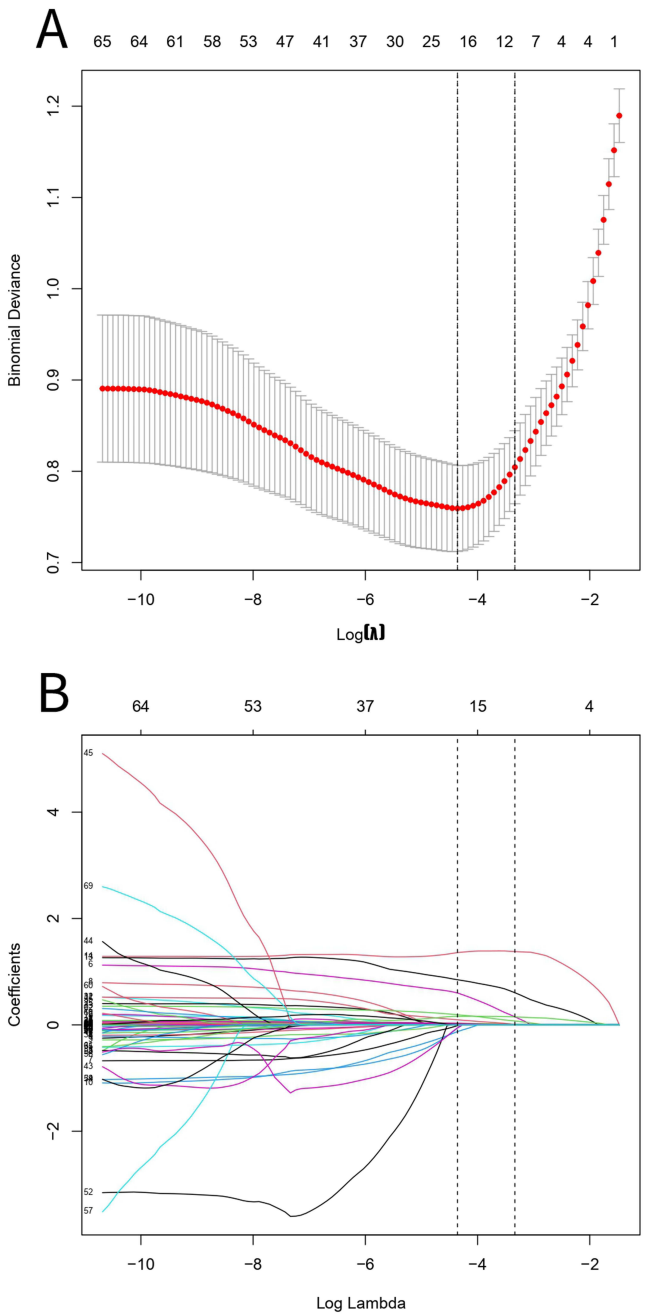

Figure 2 Texture feature selection using the least absolute shrinkage and selection operator (LASSO) binary logistic regression model. (**A**) Tuning parameter (λ) selection in the LASSO model used 10-fold cross-validation via minimum criteria. Binomial deviance was plotted versus log(λ). Dotted vertical lines were drawn at the optimal values by using the minimum criteria and the λ standard error of the minimum criteria (the 1-SE criteria). At this point, the minimum value of λ is 0.0128 while the value of the λ standard error of the minimum is 0.0356 according to 10-fold cross-validation. (**B**) LASSO coefficient profiles of the 69 texture features. A coefficient profile plot was produced against the log (λ) sequence. Vertical line(right) was drawn at the value selected using 10-fold cross-validation, where optimal λ resulted in 12 nonzero coefficients.

notable differences in the correlation analysis. Notably, metabolic dysfunction exhibited the strongest positive correlation with MAFLD, followed by BMI, whereas HDL displayed a significant negative correlation with MAFLD. Figure 3 illustrates the relationship between these variables and the risk of MAFLD, subsequently investigating the underlying risk factors.

Consequently, we integrated statistical differences and clinical significance to identify a total of 12 pertinent variables derived from the raw data, which include Age, T2DM, Metabolic Dysfunction, Hb, ALT, TC, TG, HDL, BMI, WHR, VAF, and SMI. It is important to highlight that, despite the strong association between obesity and MAFLD, we opted to utilize BMI as a variable rather than obesity itself, as BMI provides a quantifiable measure of

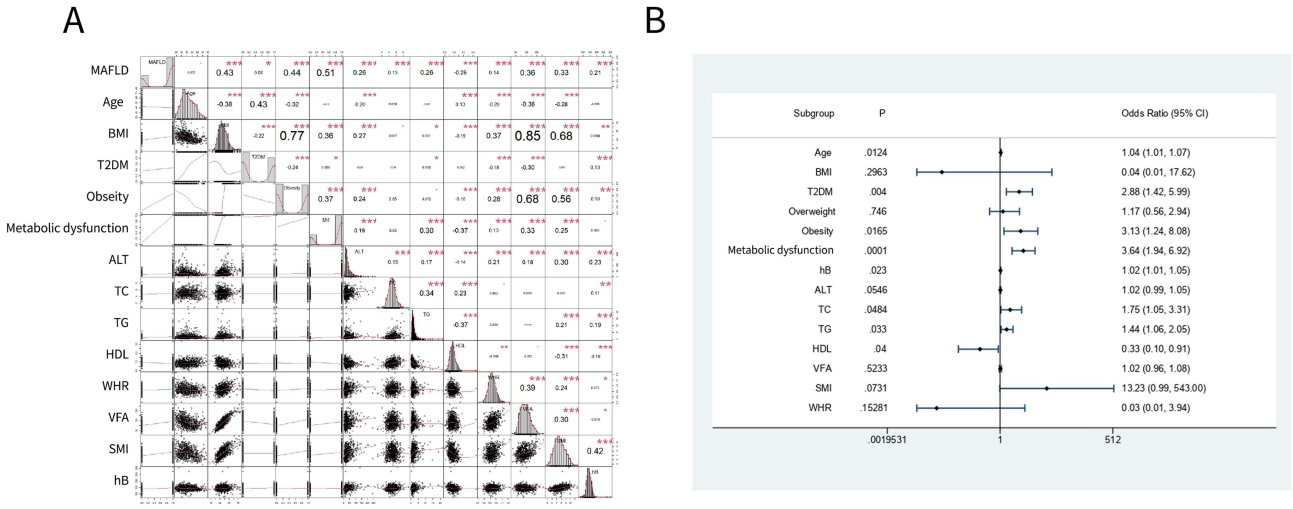

Figure 3 Correlation analysis and risk factor forest plot. (**A**) The correlation analysis of the selected variables, where the lower left corner shows the correlation curve, the diagonal represents the data distribution of the variables, and the upper right corner shows the correlation coefficient and statistical differences between variables (*p<0.05; **p<0.01; ***p<0.001). (**B**) The forest map of using Odds Ratio(95% CI) to represent the risk between selected variables and MAFLD, and the horizontal axis is the log form of Odds Ratio.

obesity to a certain degree. Furthermore, based on the findings from clinical significance and correlation analyses, we selected three innovative variables—WHR, VAF, and SMI—to assess the predictive value of body composition indicators in relation to MAFLD. To enhance our understanding of the critical role that body composition parameters play in the screening of MAFLD, we developed two distinct models. In Model 1, we excluded the relevant body composition parameters from the aforementioned 12 variables, specifically BMI, WHR, VAF, and SMI. Conversely, Model 2 incorporated all variables.

Nomogram for MAFLD Prediction

The selected variables were utilized to develop two distinct models for the prediction of MAFLD (Model 1 as illustrated in Figure 4A; Model 2 as depicted in Figure 5A). In comparison, the nomogram derived from Model 2 demonstrated a more favorable predictive capability. We focused on the interpretation of results using the nomogram based on Model 2. A case was presented involving a 50-year-old patient who was classified as obese with metabolic dysfunction, yet did not have diabetes. Recent laboratory results indicated a hemoglobin level of 120, ALP of 120, TC of 4, TG of 4, and HDL of 2.5. A body composition analysis revealed a BMI of 35, SMI of 10.5, VFA of 250, and a WHR of 1.1. Ultimately, utilizing the nomogram, we calculated the patient's total score to be approximately 562, which signifies a greater than 90% risk of developing fatty liver disease, thereby providing valuable insights for the screening of MAFLD in this patient.

The models underwent internal validation utilizing the bootstrap validation method. It was noteworthy that the nomogram for Model 2 exhibited superior accuracy in the training cohort for estimating the risk of MAFLD compared to Model 1, achieving a C-index of 0.893 (95% CI, 0.8625–0.9242) for Model 2, in contrast to 0.847 (95% CI, 0.8104–0.8838) for Model 1 (refer to Model 1 in Figure 4B and Model 2 in Figure 5B). In the validation cohort, Model 2 demonstrated superior predictive capability compared to Model 1, as evidenced by the ROC curve (refer to Model 1 in Figure 4C and Model 2 in Figure 5C). The nomogram for Model 2 exhibited a C-index of 0.893 (95% CI, 0.8416–0.9451) for estimating the risk of MAFLD, whereas Model 1 yielded a C-index of 0.858 (95% CI, 0.7990–0.9165) within the validation cohort.

While the calibration plots for both models illustrated a strong agreement regarding the presence of MAFLD between the risk estimations provided by the nomogram and the actual clinical confirmations from the outpatient services of the Endocrine Department (see Model 1 in Figure 4D and Model 2 in Figure 5D), it appeared that Model 2 exhibited less bias in its predictions, as indicated by a smaller Brier score (0.109 for Model 2 compared to 0.131 for Model 1). Additionally, both models displayed favorable calibration curves for risk estimation (see Model 1 in Figure 4E and Model 2 in Figure 5E).

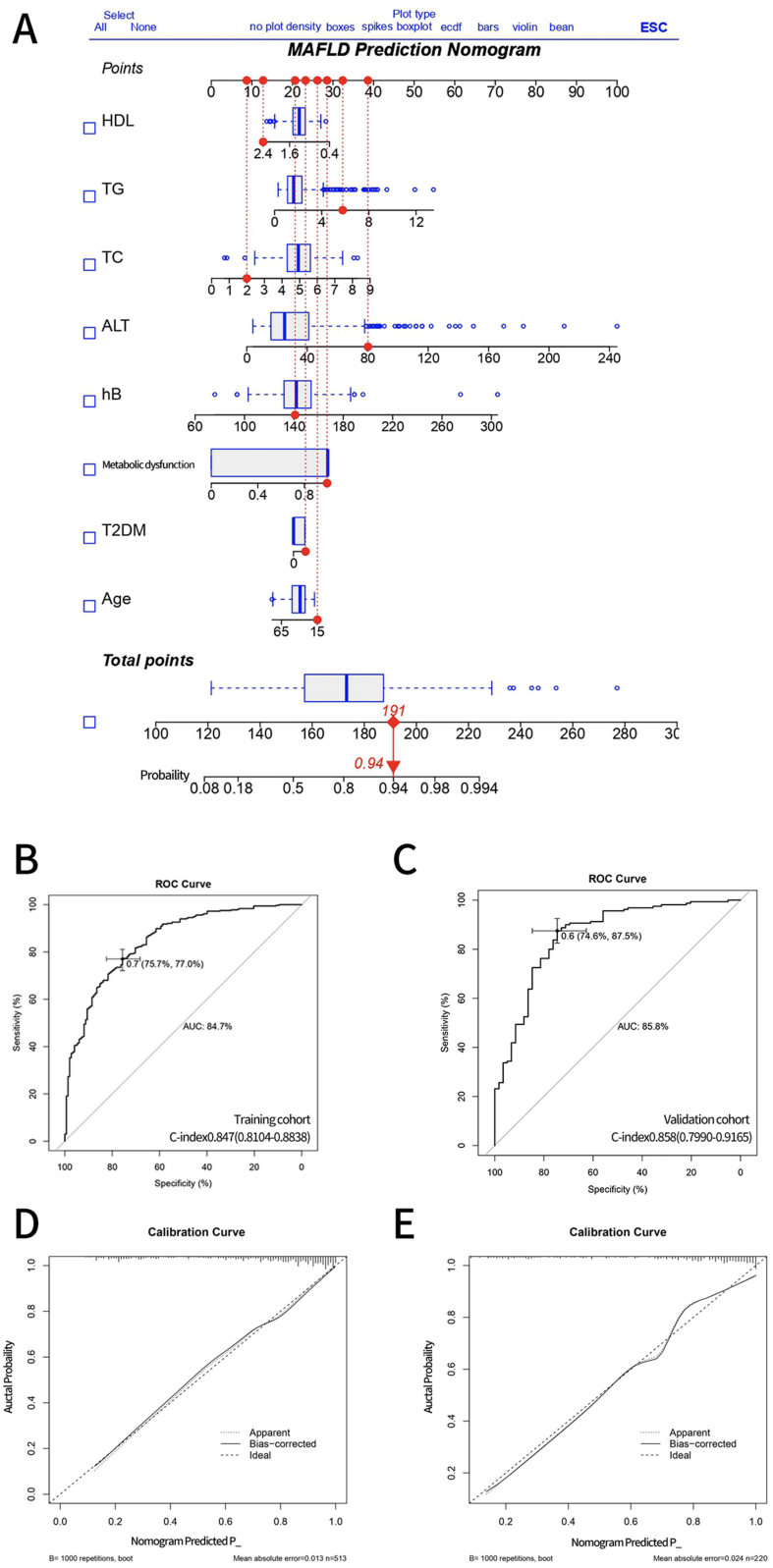

Figure 4 Nomogram for Preoperative Estimation of Metabolic Associated Fatty Liver Disease (MAFLD) Risk and Its Predictive Performance in model1. (**A**) Nomogram in model1 to estimate the risk of MAFLD presence. To use the nomogram, find the position of each variable on the corresponding axis, draw a line to the points axis for the number of points, add the points from all of the variables, and draw a line from the total points axis to determine the MAFLD probabilities at the lower line of the nomogram. (**B**) Validity of the predictive performance of the nomogram in model1 in estimating the risk of MAFLD presence in the training cohort (n = 513), where the C-index is 0.847. (**C**) Validity of the predictive performance of the nomogram in model1 in estimating the risk of MAFLD presence in the validation cohort (n = 220), where the C-index is 0.858; **D** and **E**. The calibration curves in training cohort and validation cohort respectively based on model1 show great fitness; C index, concordance index; and ROC, receiver operating characteristic.

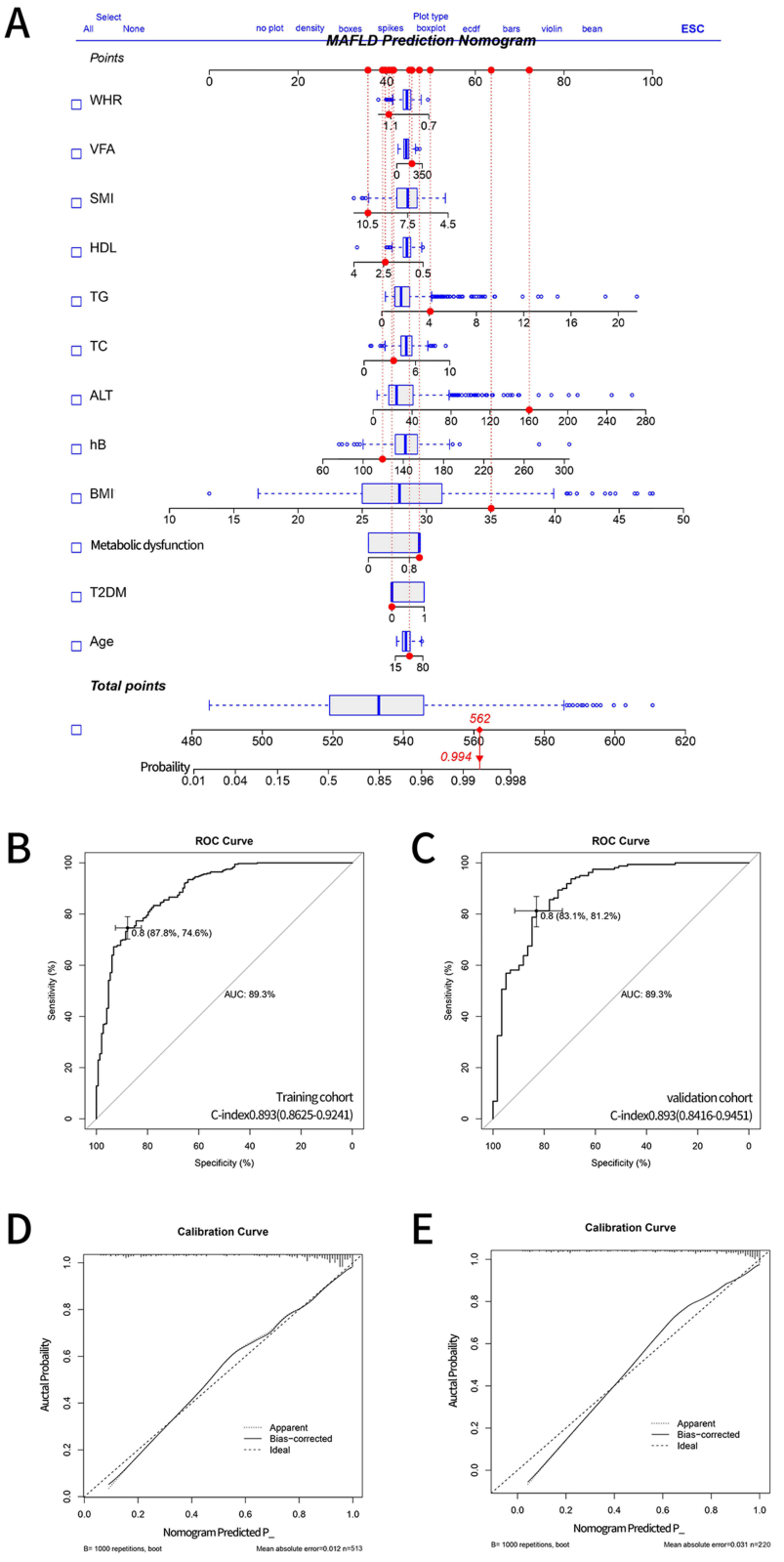

Figure 5 Nomogram for Preoperative Estimation of Metabolic Associated Fatty Liver Disease (MAFLD) Risk and Its Predictive Performance in model2. (**A**) Nomogram in model2 to estimate the risk of MAFLD presence. To use the nomogram, find the position of each variable on the corresponding axis, draw a line to the points axis for the number of points, add the points from all of the variables, and draw a line from the total points axis to determine the MAFLD probabilities at the lower line of the nomogram. (**B**) Validity of the predictive performance of the nomogram in model2 in estimating the risk of MAFLD presence in the training cohort (n = 513), where the C-index is 0.893. (**C**) Validity of the predictive performance of the nomogram in model2 in estimating the risk of MAFLD presence in the validation cohort (n = 220), where the C-index is 0.893; **D** and **E**. The calibration curves in training cohort and validation cohort respectively based on model2 show great fitness.

Abbreviations: C index, concordance index; and ROC, receiver operating characteristic.

Clinical Use and Comparison

The decision curve analysis (DCA) for Model 1 and Model 2 is illustrated in Figure 6. The DCA evaluates the net benefit, which is determined by subtracting the proportion of false positives from the proportion of true positives. The data were adjusted to account for the relative harm associated with forgoing treatment in comparison to the adverse effects of unnecessary treatment. Typically, the relative threshold probability represents the point at which the anticipated benefits of treatment are equivalent to the expected benefits of abstaining from treatment.[21] The DCA indicated that when the threshold probability falls between 5% and 80%, the nomogram derived from model 2 is preferred for predicting the risk of MAFLD, demonstrating greater advantages compared to both the treat-all-patients approach and the treat-none approach. It is important to note that within this specified range, the net benefit exhibited similarities with several overlapping instances.

Furthermore, we conducted a comparative analysis of the pertinent parameters of the nomograms derived from the two models, as presented in Table 4. Utilizing model 1 as a reference, we calculated the NRI and IDI for model 2 comparison to model 1, yielding values of 0.107 and 0.087, respectively. This indicates that the nomogram based on body composition enhances predictive performance by approximately 8.7% to 10.7% in comparison to the nomogram of model 1, with both results being statistically significant ($P < 0.05$).

Overall, nomogram developed based on model2 has high prediction efficiency and validation and estimate the presence of MAFLD in early diagnosis and intervention.

Discussions

MAFLD exerts a considerable adverse impact on the liver and metabolic functions of patients over time. Therefore, there is an imperative to enhance the detection and intervention strategies for MAFLD, as this will facilitate the timely administration of anti-fibrotic therapies and yield substantial clinical advantages for patients. We have developed two nomograms utilizing raw data to assist in predicting the risk of MAFLD. Upon comparison of the two models, it is

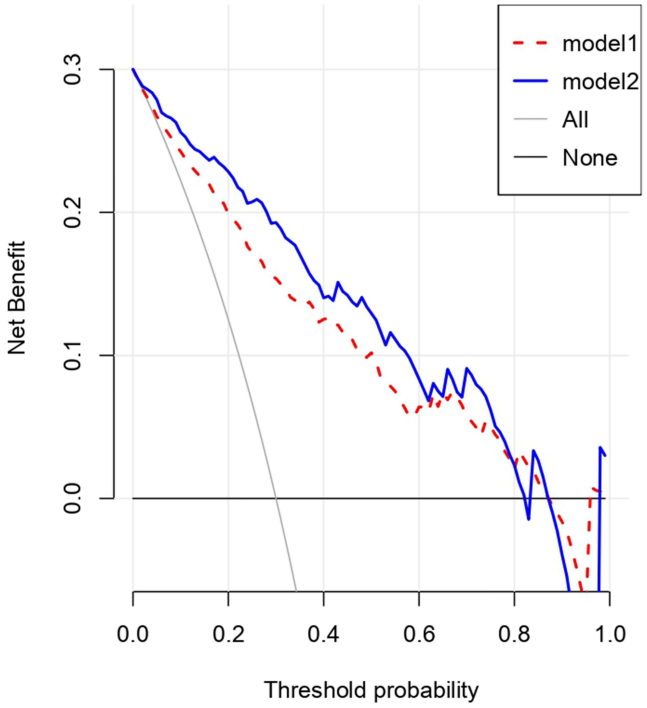

Figure 6 Decision curve analysis for the nomogram in model1 and the model2 with addition of body composition. The y-axis measures the net benefit. The red line represents the nomogram based on model1. The blue line represents the model2. The gray horizontal line represents the assumption that all patients have MAFLD. Thin last line represents the assumption that no patients have MAFLD. During the period of "Pt" ranging from about 0.05 to 0.80, the clinical predictive effect of model 2 is significantly higher than that of model 1, which means that patients choosing model 2 can achieve higher benefits compared to model 1 within this range; Pt, threshold probability.

Table 4 Comparison Between Nomograms Based on Two Models

Subgroup	Nomogram1-model1		Nomogram2-model2		P
	Training cohort	Validation cohort	Training cohort	Validation cohort	
True Positive Rate, TPR	66.30% (n=486)		65.35% (n=470)		-
False Positive Rate, FPR	12.96% (n=95)		9.55% (n=70)		-
True Negative Rate, TNR	15.28% (n=112)		18.69% (n=137)		-
False Negative Rate, FNR	5.45% (n=40)		6.41% (n=47)		-
Specificity	75.70%	74.60%	87.80%	83.1%%	-
Sensitivity	77.00%	84.50%	74.60%	81.20%	-
C-index (95% CI)	0.847 (0.8104,0.8838)	0.858 (0.799,0.9165)	0.893 (0.8625,0.9242)	0.893 (0.8416,0.9451)	-
R^2	0.435		0.547		-
Brier scaled	0.131		0.109		-
NRI	0.107 (model2 v model1)				**p<0.001**
IDI	0.087 (model2 v model1)				**p=0.018**

evident that the nomogram derived from model 2 demonstrates superior accuracy in predicting MAFLD, incorporating a total of 12 variables, namely Age, T2DM, Metabolic dysfunction, Hb, ALT, TC, TG, HDL, BMI, WHR, VAF and SMI.

The concept of MAFLD has gained increasing acceptance over the past three years; however, the development of predictive models for this condition remains relatively underdeveloped. Prior research efforts have sought to create pertinent MAFLD models utilizing clinical data. One study[22] mainly combines a certain serum marker and laboratory examination to establish a predictive model for MAFLD. Another study[23] established a predictive model for screening MAFLD through the NHANES database. Nevertheless, the two studies did not offer a detailed analysis of body composition parameters and prevalent metabolic factors. Given the considerable heterogeneity of MAFLD across various populations and regions, including instances of lean fatty liver, the development of a nomogram that integrates body composition with metabolic factors holds substantial significance. Although another study[24] comprehensively analyzed body composition-related parameters and established a model based on body composition to predict MAFLD in obese individuals, the relationship between metabolism and MAFLD is complex and cannot be easily delineated. We posit that the development of MAFLD is significantly influenced by metabolic factors, with notable variations in incidence rates and heterogeneity observed among individuals of differing socio-economic backgrounds and body compositions. Consequently, we have developed two nomograms for the screening of MAFLD, utilizing clinical data with a particular emphasis on body composition, to provide nuanced evidence for the early diagnosis of MAFLD. It is important to highlight that, in the initial stages of the condition, fat accumulation occurs without the progression to liver fibrosis. In such cases, lifestyle modifications and weight reduction are effective strategies for reversal. Therefore, our screening efforts are primarily concentrated on the early stages of MAFLD.

The nomogram for MAFLD indicates that factors such as age, the presence of diabetes, blood lipid levels, ALP levels, BMI, parameters associated with visceral fat, and waist circumference have been demonstrated to be associated with the development of MAFLD.[22–24] Our research also suggested that these factors were crucially important predictive factors for assessing the risk of MAFLD. In addition, we found that hemoglobin, and skeletal muscle index (SMI) were also valuable predictors of MALFD. While there have been no specific studies investigating the relationship between hemoglobin levels and MAFLD, our data analysis indicates a positive correlation between elevated hemoglobin levels and the presence of MAFLD. One plausible explanation for this association is that increased hemoglobin may signify a state of overnutrition. Given that East China is an economically developed region, many patients with MAFLD in this area present with hyperinsulinemia and obesity, necessitating a higher supply of oxygen in the bloodstream to accommodate the body's increased metabolic demands. Additionally, it is possible that elevated hemoglobin levels may also reflect an underlying inflammatory response:[25] In order to mitigate the detrimental effects associated with elevated levels of hemoglobin, liver macrophages may phagocytize red blood cells and adopt an anti-inflammatory

phenotype. This particular phenotype has the potential to reduce the progression of non-alcoholic fatty liver disease. Nevertheless, the relationship between these factors has not been definitively established, and socio-economic factors significantly influence the strength of this correlation. The Skeletal Muscle Index (SMI) is a widely utilized metric for evaluating muscle function, with a reduction in SMI frequently signifying the onset of sarcopenia. However, the correlation between muscle mass and the progression of MAFLD remains inadequately established. Several studies have indicated that a decline in muscle mass may contribute to the increased incidence of MAFLD, NAFLD, and even NASH.[26–28] In addition, decrease in muscle content and strength can also lead to an increase in mortality in NAFLD patients.[29] There exists a potential correlation between skeletal muscle mass and insulin function, as insulin exerts a nutritional influence on muscle tissue. Specifically, insulin facilitates the utilization of glucose within muscles and enhances the process of fat oxidation.[30] The majority of patients with MAFLD demonstrate insulin resistance or impaired pancreatic islet function, which leads to a reduction in SMI. Consequently, utilizing SMI for the risk stratification of muscle status holds considerable importance. In our research, we observed that SMI exhibited a certain, albeit weakly significant, difference in multivariate logistic regression after addressing potential biases associated with univariate logistic regression. Nevertheless, we opted to include SMI in the nomogram due to its notable clinical relevance in the context of MAFLD.

Recent advancements in the research of MAFLD and NASH have demonstrated that thyroid hormone receptor-β agonists possess the capability to lower LDL levels, triglycerides, and liver steatosis in clinical researches.[31,32] The thyroid hormone receptor-β agonists agents facilitate the reduction of fatty toxicity and enhancement of liver function by promoting fatty acid catabolism and stimulating mitochondrial biogenesis, ultimately leading to a decrease in hepatic fat accumulation.[33] Consequently, these compounds received marketing approval in 2024 for the treatment of metabolic-related steatohepatitis.[34] In light of this, we also undertook a statistical analysis of thyroid diseases while selecting variables, including HT, hypothyroidism, GD, and thyroid nodules. Although the variables associated with thyroid diseases were not represented in our final nomogram, our analysis revealed a marginal statistical difference between HT and MAFLD, with a p-value of less than 0.1 in univariate logistic regression. However, upon incorporating HT as a variable in multivariate logistic regression, no statistically significant difference was observed. Nonetheless, it is important to acknowledge that the occurrence of HT is somewhat correlated with MAFLD.[35] Our previous studies have also indicated an interactive relationship between the incidence of NAFLD and thyroid hormone levels.[36] Therefore, it is imperative to pursue further comprehensive research and discourse regarding thyroid disorders, particularly the relationship between HT and MAFLD.

Our research is subject to specific limitations. Firstly, it is important to highlight that our selection of diagnostic criteria for the disease is based on MAFLD, rather than the newly recommended metabolic dysfunction-associated steatotic liver disease (MASLD) as of 2023.[37] Consequently, there may be minor discrepancies in the prediction of MASLD. This is primarily due to the fact that when we developed our research and conducted the analysis in 2022, the nomenclature for MASLD had not yet been established, resulting in a temporal lag in our study. Nevertheless, in terms of the fundamental characteristics of fatty liver disease, MASLD and MAFLD share consistent disease transformations and pathological processes, thus providing certain reference value. In addition, the analysis is conducted using data from a single institution, which necessitates validation of the results across additional centers. However, this approach does provide insights into the disease characteristics of patients within this region, thereby prospective studies can be required to further establish the reliability of the nomogram. Thirdly, although the column chart demonstrates commendable predictive accuracy, there remain issues with false positives and negatives, indicating a need for further validation to enhance its performance. Lastly, given that the criteria are based on Fibroscan measurements, the accuracy of the nomogram must be improved through the incorporation of liver biopsy data.

Conclusion

In all, our study introduces a novel approach utilizing a nomogram to estimate the risk of MAFLD to inform clinical treatment strategies. Given the complexity of the MAFLD state, it is essential to consider various mechanisms, metabolic functions, and body composition in a comprehensive manner. Through multiple statistical tests and clinical value, twelve variables were selected to construct nomogram based on the combination of metabolic factors and body composition.

Therefore, we developed two models, differentiated by the inclusion of body composition parameters. Through comparative analysis of the concordance index and other relevant metrics, as well as clinical decision-making applications, we concluded that the nomogram incorporating body composition demonstrates a more promising predictive capability. This nomogram can serve as an initial screening tool for assessing MAFLD risk within the general population, facilitating the early identification of high-risk individuals. Such early detection will enable systematic and thorough clinical evaluations, ultimately providing significant clinical benefits to patients, and playing an excellent role in screening MAFLD patients at early stage where MAFLD can be potentially reversed.

Ethics Approval and Consent to Participate

The experimental protocol was established, according to the ethical guidelines of the Helsinki Declaration and was approved by the IRB of The Affiliated Hospital of Nanjing University of Traditional Chinese Medicine (number: ZX2021D1). All participants included in this study provided informed consent, and allowed clinical data to be statistically collected for further statistical and analytical purposes.

Author Contributions

Tiansu Lv and Jie Tian contributed equally to this work and should be considered co-first authors, Xiqiao Zhou and Yinfeng Dong should be regarded as co-corresponding authors and provided full guidance throughout the study. All authors contributed to data analysis, drafting or revising the article, have agreed on the journal to which the article will be submitted, gave final approval of the version to be published, and agree to be accountable for all aspects of the work.

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Disclosure

All authors agree that there were none reported.

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