

Prediction of Insulin Resistance in Non-Diabetic Population Using LightGBM and Cohort Validation of Its Clinical Value:: A Cross-Sectional and Retrospective Cohort Study

Ting Peng, Rujia Miao, Hao Xiong, Yanhui Lin, Duzhen Fan, Jiayi Ren, Jiangang Wang, Yuan Li, Chen Jianwen

Submitted to: JMIR Medical Informatics
on: February 06, 2025

Disclaimer: © The authors. All rights reserved. This is a privileged document currently under peer-review/community review. Authors have provided JMIR Publications with an exclusive license to publish this preprint on its website for review purposes only. While the final peer-reviewed paper may be licensed under a CC BY license on publication, at this stage authors and publisher expressly prohibit redistribution of this draft paper other than for review purposes.

Table of Contents

Original Manuscript.....	5
Supplementary Files.....	32
Figures	33
Figure 1.....	34
Figure 2.....	35
Figure 3.....	36
Figure 4.....	37
Figure 5.....	38
Multimedia Appendixes	39
Multimedia Appendix 1.....	40
Multimedia Appendix 2.....	40
TOC/Feature image for homepages	41
TOC/Feature image for homepage 0.....	42

Prediction of Insulin Resistance in Non-Diabetic Population Using LightGBM and Cohort Validation of Its Clinical Value:: A Cross-Sectional and Retrospective Cohort Study

Ting Peng^{1*} MD; Rujia Miao^{1*} MD; Hao Xiong² PhB; Yanhui Lin¹; Duzhen Fan² PhB; Jiayi Ren² PhB; Jiangang Wang¹ Prof Dr Med; Yuan Li^{2*} PhD; Chen Jianwen^{2*} Prof Dr

¹ Third Xiangya Hospital Changsha CN

² Hunan University of Technology and Business Changsha CN

*these authors contributed equally

Corresponding Author:

Chen Jianwen Prof Dr

Hunan University of Technology and Business
No.569 Yuelu District
Changsha
CN

Abstract

Background: Insulin resistance (IR) is central to diabetes pathogenesis and a risk factor for chronic diseases.

Objective: This study aims to develop and validate a machine learning (ML) prediction model for IR in a non-diabetic population, using low-cost diagnostic indicators and questionnaire surveys.

Methods: This retrospective study analyzed data from individuals who underwent physical exams and completed surveys at the Health Management Center of Xiangya Third Hospital, Central South University, from January 2018 to August 2022. Insulin sensitivity was assessed using the HOMA-IR method. A total of 17,287 non-diabetic participants aged 18 and above were included for model training with 90 features. Five ML algorithms—Random Forest (RF), LightGBM, XGBoost, GBDT, and CatBoost—were used. Model optimization included resampling, feature selection, and hyperparameter tuning. Performance was evaluated using F1 score, accuracy, sensitivity, specificity, area under the curve (AUC), and Kappa value. SHAP analysis was applied to assess feature importance. A retrospective cohort followed for five years was used for time-to-event analysis with Kaplan-Meier survival curves to validate the model's ability to predict diabetes incidence.

Results: Data from 16,411 non-diabetic individuals were analyzed. The dataset was split 80% for training and 20% for testing. The final model included 34 lifestyle-related questionnaire features and 17 biochemical markers. The LightGBM model showed the best IR prediction performance with an accuracy of 0.7542, sensitivity of 0.6639, specificity of 0.7642, F1 score of 0.6748, Kappa value of 0.3741, and AUC of 0.8456. In the cohort, the high-risk IR group exhibited a significantly higher 5-year cumulative incidence of diabetes.

Conclusions: The LightGBM model effectively predicts IR status in non-diabetic individuals and identifies those at high risk of progressing to diabetes, supporting its clinical utility.

(JMIR Preprints 06/02/2025:72238)

DOI: <https://doi.org/10.2196/preprints.72238>

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

Please make my preprint PDF available to anyone at any time (recommended).

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

✓ **No, I do not wish to publish my submitted manuscript as a preprint.**

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain visible to the public.

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <https://www.jmir.org/preprint/72238>

No. Please do not make my accepted manuscript PDF available to anyone. I understand that if I later pay to participate in <https://www.jmir.org/preprint/72238>



Original Manuscript

Prediction of Insulin Resistance in Non-Diabetic Population Using LightGBM and Cohort Validation of Its Clinical Value:: A Cross-Sectional and Retrospective Cohort Study

Peng Ting^{1*}, Miao Rujia^{1*}, Xiong Hao², Lin Yanhui¹, Fan Duzhen², Ren Jiayi², Wang Jiangang¹, Li Yuan^{2*}, Chen Jianwen^{2*}

1. Health Management Center, The Third Xiangya Hospital, Central South University, Changsha, Hunan, China
2. Hunan University Of Technology and Business, Changsha, Hunan, China

*. These authors contributed equally to this work.

Correspondence author: Chen Jianwen, Prof.and Li Yuan, Dr.

Street address: No.569 Yuelu District, Changsha, Hunan, China, 410205.

Tel: +86-731-8861-8573;

Fax: +86-731-8861-8573;

Email address: Chen Jianwen : chenjianwen0731@163.com

ORCID: 0009-0009-1658-3910

Abstract

Background □ Insulin resistance (IR), a precursor to type 2 diabetes and a major risk factor for various chronic diseases, is becoming increasingly prevalent in China due to population aging and unhealthy lifestyles. Current methods like the gold standard hyperinsulinemic-euglycemic clamp has

limitations in practical application. The development of more convenient and efficient methods to predict and manage IR in non-diabetic populations will have prevention and control value.

Objective: This study aims to develop and validate a machine learning (ML) prediction model for IR in a non-diabetic population, using low-cost diagnostic indicators and questionnaire surveys.

Methods: A cross-sectional study was conducted for model development, and a retrospective cohort study was used for validation. Data from 17,287 adults with normal fasting blood glucose (FBG) who underwent physical exams and completed surveys at the Health Management Center of Xiangya Third Hospital, Central South University, from January 2018 to August 2022, were analyzed. IR was assessed using the HOMA-IR method. The dataset was split into 80% training and 20% testing. Five ML algorithms—Random Forest (RF), LightGBM, XGBoost, GBDT, and CatBoost—were employed. Model optimization included resampling, feature selection, and hyperparameter tuning. Performance was evaluated using F1 score, accuracy, sensitivity, specificity, AUC, and Kappa value. SHAP analysis was used to assess feature importance. For clinical implication investigation, a different retrospective cohort of 20,369 non-diabetic participants (from the Xiangya Third Hospital database between January 2017 and January 2019) was used for time-to-event analysis with Kaplan-Meier survival curves.

Results: Data from 16,411 non-diabetic individuals were analyzed, we randomly selected 13128 participants for the training group, and 3283 participants for the validation group. The final model included 34 lifestyle-related questionnaire features and 17 biochemical markers. In the validation group, their AUC were all >0.90 . In the test group, all AUC were also >0.80 . The LightGBM model showed the best IR prediction performance with an accuracy of 0.7542, sensitivity of 0.6639, specificity of 0.7642, F1 score of 0.6748, Kappa value of 0.3741, and AUC of 0.8456. Top ten features (BMI, FBG, HDL-C, TG, Cr, ALT, Sex, TBIL, Age, A/G). In the validation queue all participants were separated into the high-risk IR group and the low-risk IR group according to the LightGBM algorithm. Out of 5,101 high-risk IR participants, 235 (4.6%) developed diabetes, while

137 (0.9%) of 15,268 low-risk IR participants did. This resulted in a hazard ratio (HR) of 5.1, indicating a significantly higher risk for the high-risk IR group.

Conclusion: By leveraging low-cost laboratory indicators and questionnaire data, the LightGBM model effectively predicts IR status in non-diabetic individuals, aiding in large-scale IR screening and diabetes prevention, and might potentially become an efficient and practical tool for insulin sensitivity assessment in these settings.

Key Words Insulin resistance (IR), machine learning (ML), Light Gradient Boosting Machine (LightGBM).

Introduction

Insulin resistance (IR) refers to the reduced sensitivity or responsiveness of target organs such as the liver, skeletal muscles, or adipose tissue to insulin. In order to maintain normal blood glucose levels, the body compensates by secreting increased amounts of insulin [1]. As a condition that can exist prior to the onset of type 2 diabetes, IR is not only one of the key mechanisms underlying the development of diabetes but also a major risk factor for various diseases[2]. According to the International Diabetes Federation, it is estimated that by 2045, there will be 783.2 million people affected globally, with the vast majority having type 2 diabetes [3]. Furthermore, IR is even more common. Data from the National Health and Nutrition Examination Survey in the United States show that approximately 40% of adults aged 18-44 years have IR [4]. A study in China revealed that the standardized prevalence of IR in adults aged ≥ 25 years is 29.22%[5]. By scientifically assessing and managing IR, it is theoretically possible to effectively control the onset of diabetes. The first step is to identify IR. The high insulin clamp with normal blood glucose levels is considered the gold standard for assessing insulin sensitivity[6]. However, in practice, this method is time-consuming, expensive, and difficult to apply widely. The Homeostasis Model Assessment of Insulin Resistance ($\text{HOMA-IR} = \text{fasting glucose (mmol/L)} \times \text{fasting insulin (}\mu\text{U/ml)} / 22.5$) is regarded as an acceptable

method for evaluating IR[7]. However, fasting insulin, one of its components, is not a routine test, making it difficult to obtain in community and grassroots settings. Based on laboratory indicators and lifestyle characteristics that are correlated with the occurrence of IR and are easily accessible, it is crucial to explore more convenient ways to predict the prior probability of IR in individuals. This approach could guide more precise IR screening and has the potential for prevention and control within the large population of China.

Machine learning (ML), with its data-driven methods, has already shown good predictive value in health issues such as arteriosclerosis[8], fatty liver[9], diabetes[10], and hypertension(HBP)[11] . Obesity, dyslipidemia, lack of exercise, and sedentary lifestyles are considered risk factors for metabolic homeostasis [12]. By applying daily habits, basic information, and simple blood tests as features, we can build machine learning models in health check-up populations that are representative of the general population. The model of the ensemble learning algorithms based on decision trees, such as Random Forest (RF), LightGBM, XGBoost, GBDT, and CatBoost, using multiple decision trees for predictions. They are capable of capturing complex non-linear relationships, handling high-dimensional data, performing automatic feature selection, and mitigating the risk of overfitting through various mechanisms. Additionally, these models offer strong scalability and are suitable for large-scale datasets, with most models having built-in overfitting prevention capabilities. These models can effectively predict IR and identify key predictive factors that are crucial for individual intervention. Additionally, a retrospective cohort study can be used to determine the accuracy and practical value of these model results in distinguishing the onset of diabetes.

Methods

Study Population and Data Sources

The data used in this study were sourced from the electronic medical records of the Health

Management Center at Xiangya Third Hospital, Central South University. The dataset includes participants who underwent physical examinations and questionnaire surveys at the Health Management Center between Jan. 2018 and Aug. 2022. A total of 17,287 adults with normal fasting blood glucose were included, while individuals with fasting blood glucose (FBG) ≥ 6.1 mmol/L or those with a history of abnormal glucose tolerance/diabetes were excluded.

The subsequent retrospective cohort consisted of individuals who completed their first health check-up at the Health Management Center of Xiangya Third Hospital between Jan. 2017 and Jan. 2019. These participants were followed for 5 years, with those diagnosed with diabetes at external hospitals or those who had completed ≥ 2 times FBG tests at the hospital during the follow-up period being included. Participants were required to be over 18 years old and have FBG ≤ 6.1 mmol/L at the time of their first check-up. They also had to complete baseline assessments and surveys. Exclusion criteria included a history of abnormal glucose tolerance, diabetes, or gestational diabetes, as well as a history of tumors, pregnancy, or autoimmune diseases; and those who had used glucocorticoids or other relevant medications within the past month.

Using an IR prediction model, individuals in the cohort were classified as low-risk or high-risk based on their baseline data. Changes in FBG were then monitored. A FBG ≥ 7 mmol/L within 5 years or a diagnosis of diabetes at an external hospital was considered a positive result. A negative result was defined as maintaining normal FBG levels without a diabetes diagnosis at an external hospital over the 5-year follow-up period. Furthermore, by matching the ID card numbers, we excluded the participants who repeatedly appeared in the training set and the test set. Ensure this cohort was the different from the dataset used for model development.

Ethical considerations

This study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Xiangya Third Hospital, Central South University (approval no. 22206). All

participants provided informed consent.

Characteristics and Definitions

The dataset includes a total of 102 features, which encompass physical examination measurements such as age, height, weight, body mass index (BMI), waist circumference (WC), systolic blood pressure (SBP), and diastolic blood pressure (DBP). Blood test indicators include FBG, liver function markers (alanine aminotransferase(ALT), aspartate aminotransferase (AST), total bilirubin(TBIL), direct bilirubin(DBIL), serum albumin(ALB), serum globulin (GLO), albumin/globulin ratio(A/G), total protein(total(TP), bile acids(TBA), kidney function markers (serum creatinine(Sr), blood urea nitrogen (BUN), uric acid (UA), and lipid profile markers (total cholesterol (TC), triglycerides(TG), high-density lipoprotein cholesterol(HDL-C), low-density lipoprotein cholesterol (LDL-C). Additionally, information from questionnaires was collected, including past disease diagnoses, lifestyle factors (dietary preferences, smoking status, alcohol consumption, exercise habits, work status), psychological status, sleep patterns, and health literacy related to basic medical knowledge.

Insulin sensitivity was assessed using the Homeostasis Model Assessment of Insulin Resistance ($\text{HOMA-IR} = \text{fasting glucose (mmol/L)} \times \text{fasting insulin } (\mu\text{U/ml}) / 22.5$). A cut-off value of 2.69 was used, with a value ≥ 2.69 considered indicative of IR status[5].

Data Processing and Statistical Analysis

We excluded features with more than 30% missing data. For features with less than 30% missing data, continuous variables were imputed using the mean, while categorical variables were imputed using the mode. Ultimately, 90 features and 16,411 samples were retained. The entire dataset was randomly split into a training set (80%, 13,128 samples) and a test set (20%, 3,283 samples), with 2,782 samples categorized as IR.

For statistical analysis, continuous data that conform to a normal distribution were reported as means $\pm$ standard deviation(SD), otherwise, were reported as quartiles. Chi-square tests were conducted on categorical variables to assess the significant association between categorical features and the dependent variable. $P \leq .05$ was considered statistically significant.

Feature Engineering

Resampling

In this study, three resampling techniques—random undersampling, SMOTE oversampling, and SMOTE-Tomek combined sampling—were experimentally compared during the dataset preprocessing phase. It was found that random undersampling performed best in improving the prediction accuracy for the minority class. Therefore, random undersampling was applied to the training set, where a portion of the majority class samples were randomly removed to reduce the majority class sample size. This approach helped mitigate model bias toward the majority class and improved overall classification performance.

Feature Processing and Algorithm Selection

To enhance model accuracy and efficiency, reduce computational costs, and avoid overfitting, feature selection was conducted. Prior to feature selection, pearson correlation analysis was conducted for continuous features, while Kendall correlation analysis was used for discrete features. By examining the correlation matrix of the features, pairs of highly correlated features (with correlation coefficients greater than 0.6) were identified, and perform dimensionality reduction on these highly relevant features. Five machine learning algorithms—Random Forest (RF), Light Gradient Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost), Gradient Boosting Machine (GBDT), and CatBoost—were used to construct predictive models on the training dataset. The model demonstrating the best performance across various evaluation metrics was selected from the baseline models (CatBoost was chosen based on experimental results). The CatBoost model was then trained, and the importance scores for each feature were determined. Features were added to the

model in descending order of importance until the AUC score stabilized at its highest value with a specific number of features. At this point, no further features were added, and the model was constructed using the selected features.

Parameter Optimization and Model Evaluation

In addition to addressing class imbalance through resampling techniques, the model parameters were adjusted to assign different weights to each class, thereby balancing the class distribution. For the RF, GBDT, and CatBoost models, the parameter `class_weight = "balanced"` was set, while for the LightGBM and XGBoost models, `scale_pos_weight = "ratio of majority and minority class"` was used. Bayesian Optimization (BO) was employed for parameter tuning. BO is a global optimization algorithm based on Bayesian inference, which iteratively updates the posterior distribution of the parameters to identify the optimal configuration and optimize the objective function. To evaluate the optimization effects and improve the model's generalization ability, 10-fold cross-validation was performed. The experiments were repeated 10 times, and metrics such as AUROC were averaged to assess model performance. Additionally, model performance was evaluated using the F1 score, accuracy, sensitivity, and specificity, while the receiver operating characteristic (ROC) curve and the area under the curve (AUC) were used to assess the model's discriminatory ability. The Kappa value was also computed to evaluate the predictive capability of the model (**Figure 1**).

This research utilized several Python libraries and frameworks for data processing, feature engineering, model building, and hyperparameter tuning. The main tools used in the study are as follows: Python version: 3.6.4, NumPy version: 1.18.5, Pandas version: 1.1.5, SciPy version: 1.5.2, scikit-learn version: 0.24.2, LightGBM version: 4.3.0, XGBoost version: 1.5.2, CatBoost version: 1.1.1, bayes_opt version: 1.4.0.

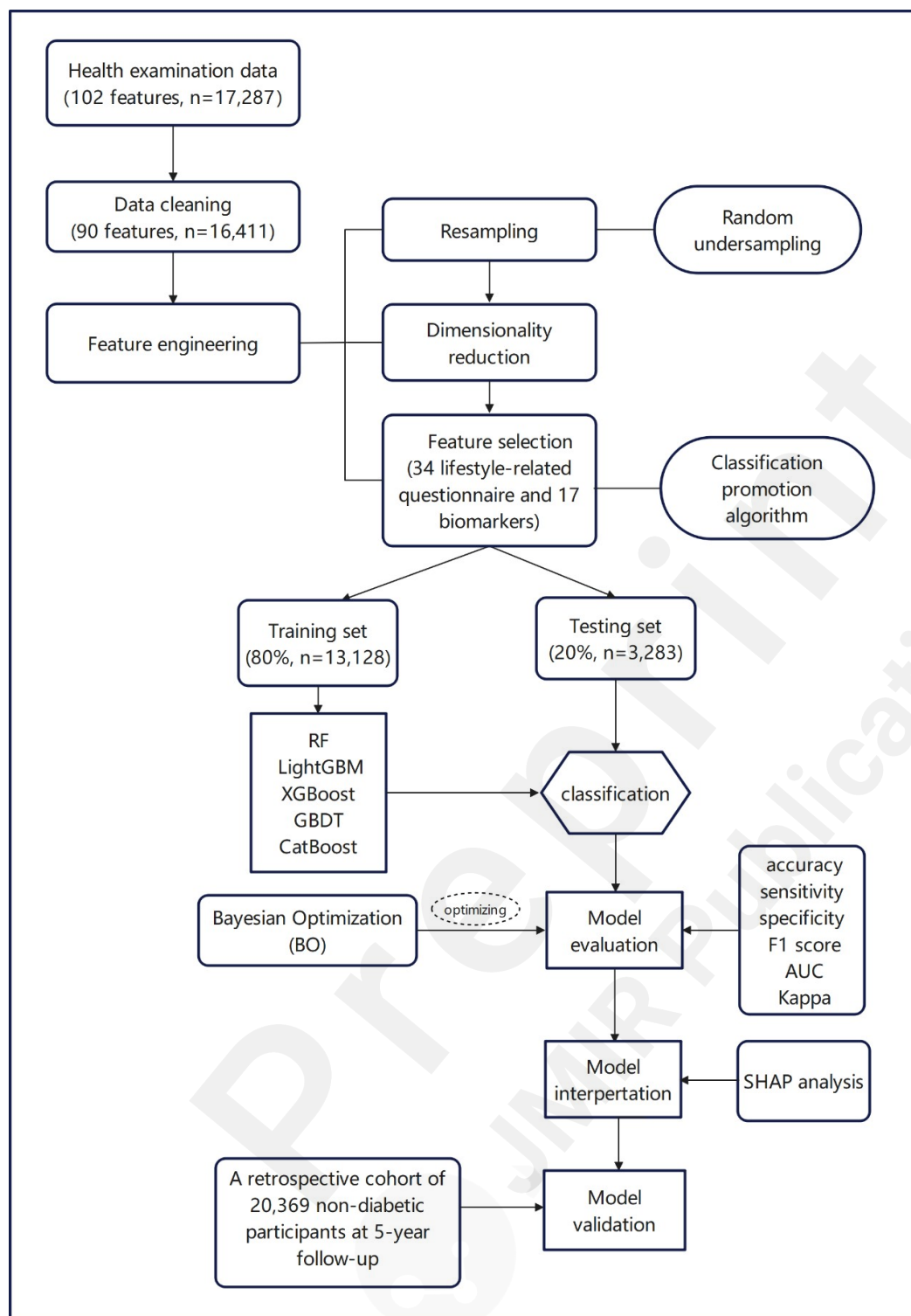


Figure1. Flow diagram of the study. The flow diagram of the study shows the entire research process, from data collection, preprocessing, model training and testing to final model evaluation and validation.

Feature Importance Ranking

Shapley Additive Explanations (SHAP) values are a method used to interpret machine learning model predictions. SHAP assigns a value to each feature, quantifying its contribution to the model's

output. Positive SHAP values indicate that the feature has a beneficial impact on the prediction, while negative SHAP values suggest a detrimental effect. The absolute magnitude of a SHAP value reflects the extent of the feature's influence on the model's decision. In this study, we utilized SHAP (version 0.45.0) for explainable machine learning to enhance interpretability.

Retrospective Cohort Validation of Model Application

Retrospective cohort data from a non-diabetic population were used as input to the aforementioned algorithms. The model outputs predicted the IR values for each participant, where a value of 1 was classified as high-risk IR and 0 as low-risk IR. Kaplan-Meier survival curves were employed to conduct time-to-event analysis, comparing the 5-year diabetes incidence between the high-risk and low-risk IR groups. This approach further validated the model's ability to accurately distinguish the onset of diabetes based on predicted IR levels.

Results

Characteristics of the Study Population

A total of 16,411 non-diabetic individuals who underwent health screenings were included in this study, with an average age of 42.74 ± 11.36 years. The sample comprised 8,205 males and 8,206 females. Overall, 17% of participants were diagnosed with IR, with a higher prevalence observed in males compared to females. In the IR group, levels of weight, WC, BMI, SBP, UA, ALT, AST, TG, and TC were significantly elevated compared to the non-IR group. Conversely, the average HDL-C level was significantly lower in the IR group ($P < .05$). Additionally, lifestyle factors such as diet, physical activity and health literacy exhibited significant differences between the two groups (Table 1, Table 2).

Table 1. Continuous characteristics of participants

Feature	All (n=16411),	IR $\square$ HOMA-IR $\square$ 2.69 $\square$ (n=13629), mean(SD)	Non-IR $\square$ HOMA-IR $\geq$ 2.5 $\square$ (n=2782), mean(SD)	Pvalue
---------	-------------------	--	---	--------

	mean(SD)			
Age(years)	42.74(11.36)	42.84(11.37)	42.23(11.30)	.01
Height(cm)	163.50(8.00)	163.14(7.93)	165.29(8.21)	<.001
Weight(Kg)	63.80(11.70)	62.21(11.10)	71.48(11.59)	<.001
WC(cm)	81.30(10.40)	79.82(9.81)	88.53(9.67)	<.001
BMI(kg/m ²)	23.85(3.37)	23.30(3.07)	26.54(3.48)	<.001
SBP(mmHg)	120.39(14.83)	119.49(14.7)	124.75(14.62)	<.001
DBP(mmHg)	73.80(10.80)	73.08(10.71)	77.02(11.04)	<.001
BUN(mmol/L)	4.72(1.22)	4.71(1.23)	4.79(1.19)	<.001
Sr(umol/L)	70.31(18.15)	69.99(18.52)	71.85(16.12)	<.001
UA(umol/L)	339.53(92.01)	331.13(89.53)	380.70(92.91)	<.001
TBA(umol/L)	4.22(4.80)	4.18(4.82)	4.44(4.69)	.01
ALT(u/L)	26.46(25.62)	23.30(24.73)	36.09(27.21)	<.001
AST(u/L)	24.89(18.88)	24.50(20.07)	26.83(11.17)	<.001
ALB(g/L)	46.62(2.91)	46.63(2.91)	46.60(2.93)	.56
GLO(g/L)	27.09(3.68)	26.93(3.65)	27.88(3.71)	<.001
A/G	1.73(0.24)	1.74(0.24)	1.70(0.25)	<.001
TP(g/L)	73.72(4.22)	73.56(4.19)	74.47(4.30)	<.001
DBIL(umol/L)	3.78(1.34)	3.83(1.35)	3.54(1.26)	<.001
TBIL(umol/L)	13.02(5.06)	13.21(5.11)	12.05(4.70)	<.001
FBG(mmol/L)	5.24(0.42)	5.20(0.42)	5.45(0.40)	<.001
TG(mmol/L)	1.70(1.53)	1.55(1.36)	2.44(2.01)	<.001
TC (mmol/L)	5.01(0.94)	4.98(0.93)	5.16(1.00)	<.001
HDL-C(mmol/L)	1.33(0.30)	1.36(0.29)	1.17±(0.24)	<.001
LDL-C(mmol/L)	2.89(0.79)	2.88(0.78)	2.93(0.84)	.003

It lists the continuous characteristics of the participants, including age, height, weight, waist circumference, BMI, blood pressure, and blood biochemical indicators, and compares the means and standard deviations between the IR and non-IR groups, along with the corresponding P-values to evaluate the association of each characteristic with insulin resistance. WC, waist circumference; BMI, body mass index; SBP, systolic blood pressure; DBP, diastolic blood pressure; BUN, blood urea nitrogen; Sr, serum creatinine; UA, uric acid; TBA, total bile acids; ALT, alanine aminotransferase; AST, aspartate aminotransferase; ALB, serum albumin; GLO, serum globulin, A/G, albumin/globulin ratio; TP, Total protein; DBIL, direct bilirubin; TBIL, total bilirubin; FBG, fasting blood glucose; TG, triglycerides; TC, total cholesterol; HDL-C, high-density lipoprotein cholesterol; LDL-C, low-density lipoprotein cholesterol.

Table 2. Questionnaire characteristics of participant

Type	Feature	Chivalue	P-value	Feature	Chivalue	Pvalue
Diet	Dietary preference	137.86	<.001	Dietary taste	125.78	<.001
	Daily meat intake	123.43	<.001	Fat meat consumption	88.97	<.001
	Fruit consumption	29.81	<.001	Animal organ consumption	25.31	<.001
	Coffee consumption	21.22	<.001	Staple food structure	33.95	<.001
	Nighttime snacking	54.97	<.001	Binge eating	73.63	<.001
	Social dining	90.56	<.001	Daily vegetable intake	23.77	<.001
	Legume and soy product consumption	13.40	.01	Milk consumption	13.20	.01
	Fish or seafood consumption	7.24	.124	Egg consumption	1.83	.61
	Sugary drink consumption	106.32	<.001	-	-	-
	Physical exercise	56.60	<.001	Exercise type	122.97	<.001
Exercise	Weekly exercise frequency	59.24	<.001	Years of consistent exercise	60.50	<.001
	Exercise duration per session	54.73	<.001	-	-	-
	Alcohol consumption	29.25	<.001	Smoking habits	42.55	<.001
Lifestyle	Alcohol frequency per week	25.38	<.001	Cigarettes per day	38.48	<.001
	Years of alcohol use	36.00	<.001	Years of smoking	56.12	<.001
	Alcohol quantity per session	57.59	<.001	Exposure to Harmful Substances	47.16	<.001
	Type of alcohol	13.95	.03	Sedentary time outside work	36.27	<.001
	Time since quitting drinking	6.65	.16	Regular meals	9.12	.03
	Work physical demands	95.25	<.001	Sleep quality	1.01	.60
	Workdays per week	3.85	.28	Reasons for sleep disturbance	22.03	.04
	Working hours per week	3.36	.500	Sleep duration	3.52	.32
	-	-	-	Main symptoms of sleep disturbance	15.448	.22
	Depression	0.10	.95	Anxious	0.18	.91
psychology	Difficulty concentrating	8.45	.04	Anxiety and restlessness	0.56	.76
	Increased anxiety	1.57	.46	Rrritable	0.76	.68
	Burnout	1.89	.39	Impatience	2.07	.36
	Depressed	3.19	.36	-	-	-
	Normal WC	25.37	<.001	History of hypertension	127.39	<.001
Health literacy	Active medical knowledge acquisition	22.63	<.001	Family history medicine	791.80	<.001
	Self-Monitoring of blood pressure and heart rate	20.81	<.001	Observe urination and defecation	13.10	.001
	Normal BP	7.82	.005	Bask	13.10	.004
	Normal BMI	6.71	.01	Seat belt usage	7.09	0.03
	Normal FBG	1.71	.19	Carrying emergency medication	3.35	.19
	Normal T	1.02	.31	Health check-up interval	12.46	.03
	Normal HR	1.07	.30	Personal history disease	1.25	.26
	Normal TG	0.72	.39	FHxDM	4.00	.046
	Normal TC	2.66	.10	Sex	151.26	<.001
	Normal Salt intake	78.68	<.001	-	-	-

It presents the questionnaire characteristics of the participants, including dietary habits, exercise, lifestyle,

psychological status, and health literacy, and assesses the association of each characteristic with insulin resistance using the chi-square test, listing the chi-square values and P-values. WC, waist circumference; BP, blood pressure; BMI, body mass index; FBG, fasting blood glucose; T, temperature; HR, heart rate; TG, triglycerides; TC, total cholesterol.

Feature Engineering

In the training set, random undersampling was applied to the majority class. Among the "physiological features," four highly correlated features: "BMI", "height", "weight," and "WC" were subjected to dimensionality reduction, with "BMI" retained. Similarly, for the two highly correlated features "SBP" and "DBP," only "SBP" was retained.

Feature importance scores were computed for 55 lifestyle-related questionnaire features using the CatBoost algorithm. These features were ranked from high to low based on their importance scores and then sequentially input into the CatBoost model. After each addition, the model's AUC score on the test set was recorded. As shown in **Figure 2**, the AUC score dropped significantly after adding 35 features, leading to the exclusion of 21 non-contributory questionnaire features. The 34 retained features, which showed significant contributions, include: BMI, SBP, age, sex, family history medicine, exercise type, years of consistent exercise, exercise duration per session, weekly exercise frequency, dietary preferences, staple food structure, dietary taste, sleep duration, Reasons for sleep disturbance, exposure to harmful substances, work physical demands, sedentary duration outside of work, consumption frequency of fruits, milk, meat, coffee, legume and soy products, sugary drink and fatty meats, daily vegetable intake, health check-up interval, self-monitoring of blood pressure and heart rate, observe urination and defecation, carrying emergency medications, regular meals, seat belt usage, bask, and awareness of normal salt intake and HR.

Additionally, the addition of 17 biochemical markers—BUN, Cr, UA, TC, TG, HDL-C, LDL-C, FBG, ALT, AST, TBIL, DBIL, TSP, ALB, GLO, A/G ratio, and TBA

—further improved the model's accuracy, sensitivity, and specificity. Thus, the final feature selection for the model included the 34 lifestyle-related questionnaire features and 17 biochemical markers.

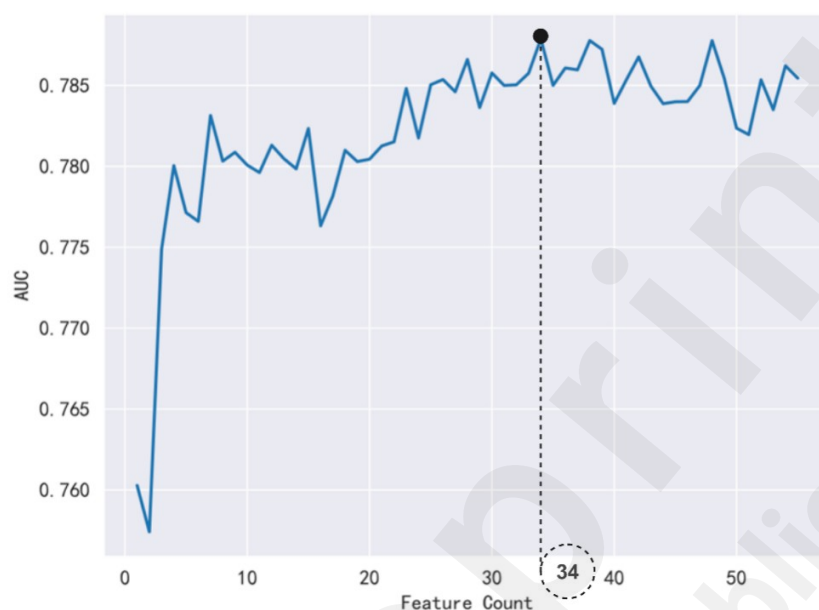


Figure2. The model's AUC score on the test set. It shows how the AUC score on the test set changes with the number of features included in the model. After adding 34 features, the AUC score drops significantly, indicating that these additional features no longer contribute to model performance improvement.

Model Performance Evaluation and Feature Importance Ranking

Based on the 51 selected features (34 questionnaire features and 17 biochemical markers), five machine learning algorithms were applied—RF, LightGBM, XGBoost, GBDT, and CatBoost—to build and evaluate models using both the training and testing datasets. The performance metrics of the five machine learning models are summarized in **Table 3**. The LightGBM model demonstrated the best performance across all metrics, including accuracy (0.7542), sensitivity (0.6639), specificity (0.7642), F1 score (0.6748), and Kappa (0.3741). Although the AUC (0.8456) of the LightGBM model was slightly lower than that of CatBoost, LightGBM was

determined to be the best model overall for predicting IR. The ROC curve for the best-performing LightGBM model is shown in **Figure 3**.

Table3. Performances of the five ML models using 51 selected features for participants

Model	Accuracy_train	Accuracy_test	Sensitivity	Specificity	F1_score	AUC_train	AUC_test	kappa
RF	0.8807	0.7344	0.6522	0.7516	0.6571	0.9552	0.8354	0.3451
LightGBM	0.8503	0.7542	0.6639	0.7642	0.6748	0.9285	0.8456	0.3741
M	0.9689	0.7460	0.6575	0.7556	0.6662	0.9966	0.8375	0.3588
XGBoost	0.9237	0.7505	0.6608	0.7598	0.6708	0.9799	0.8372	0.3668
CatBoost	0.8632	0.7493	0.6594	0.7576	0.6692	0.9445	0.8471	0.3637

RF: Random Forest

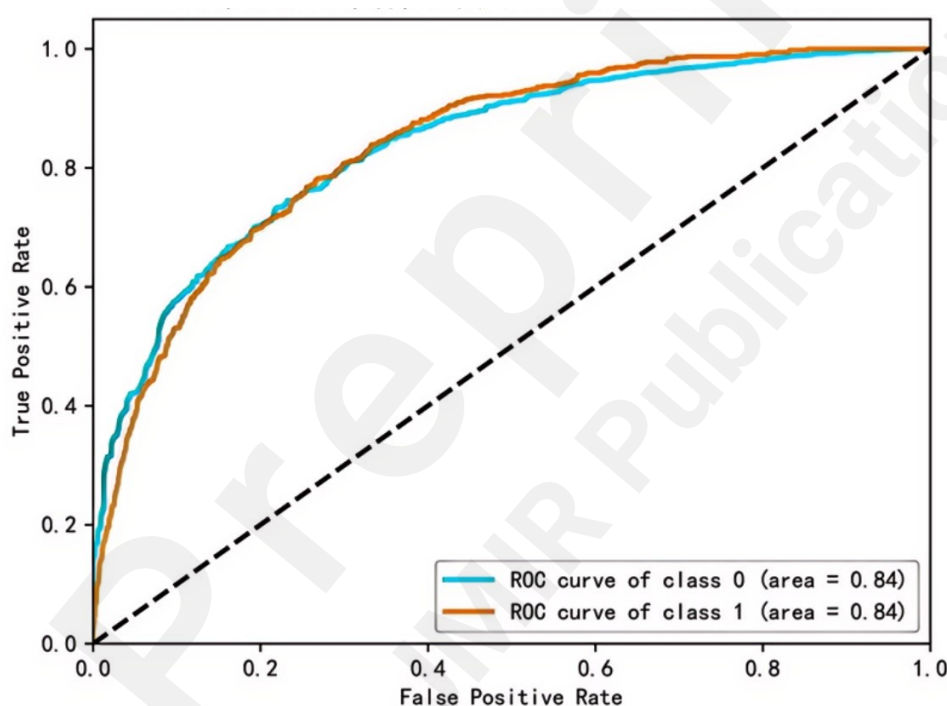


Figure3. Prediction of insulin resistance in patients with IR by LightGBM, ROC curve in test set. The area under the curve (AUC) is 0.8456, indicating that the model has good discriminant ability.

SHAP values were used to rank feature importance in the LightGBM model, as shown in **Figure 4A**. The top 10 features influencing IR were: BMI, FBG, HDL-C, TG, Cr, ALT, sex, TBIL, age, and A/G ratio. **Figure 4B** provides a visual representation of the SHAP values for the top 10 features, where BMI, FBG, TG, ALT, and sex were positively correlated with IR, while HDL-C, Cr, TBIL, age, and A/

G ratio were negatively correlated with IR.

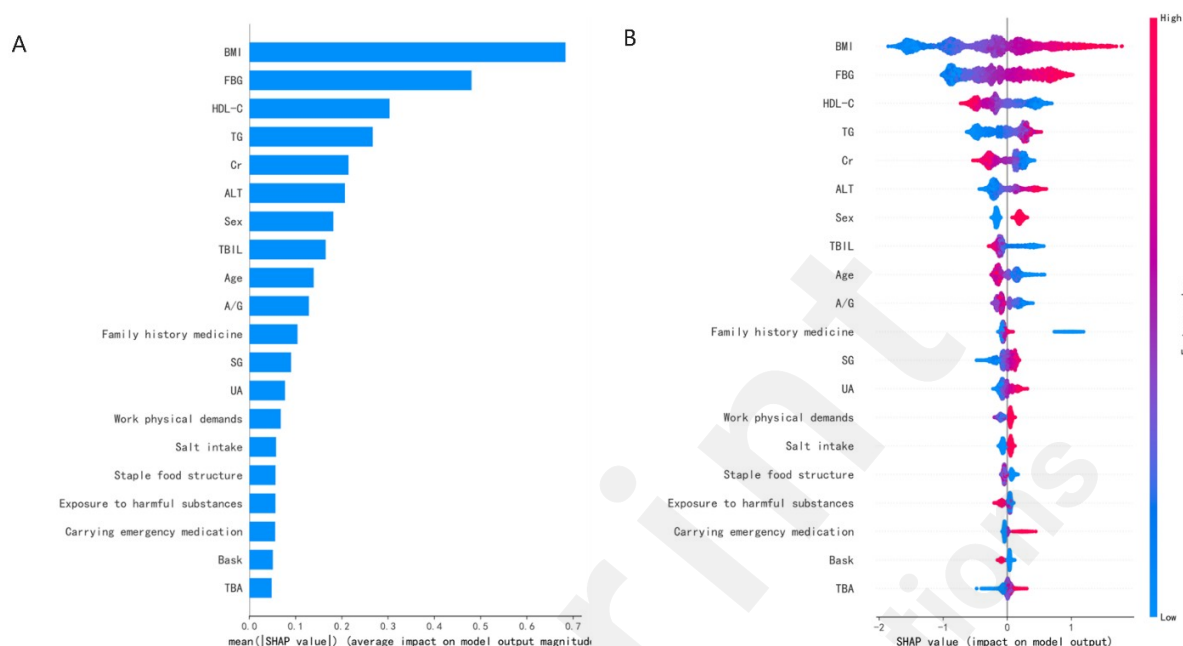


Figure4. Detailed features importance. A. Features importance by LightGBM. It shows the importance ranking of various features in the LightGBM model. The vertical coordinate (y-axis) shows the top 20 features. B. Explanation of each feature impact on the IR in the prediction model by the SHAP values in the LightGBM algorithm. The vertical coordinate (y-axis) shows the features in decreasing order of importance, while the horizontal coordinate (x-axis) displays the average absolute SHAP value of each feature. Red points indicate higher feature values, while blue points represent lower values. Positive SHAP values indicate a positive impact of the feature on the prediction, while negative values indicate a negative impact.

Retrospective Cohort for Validation and Clinical Significance Assessment

The retrospective cohort dataset was used to validate the differential occurrence of diabetes in populations stratified by the model. A total of 20,369 non-diabetic participants were continuously monitored (5,101 individuals classified as IR High Risk by LightGBM and 15,268 individuals classified as IR Low Risk), with the incidence of diabetes compared from baseline to five years. Out of 5,101 high-risk IR participants, 235 (4.6%) developed diabetes, while 137 (0.9%) of 15,268 low-risk IR participants did. This resulted in a hazard ratio (HR) of 5.1, indicating a significantly higher risk for the IR High Risk group compared to the IR Low Risk group. **Figure**

5A clearly illustrates the relationship between the cumulative incidence of diabetes in the high- and low-risk insulin resistance groups. The high-risk group exhibited a significantly higher cumulative incidence of diabetes compared to the low-risk group, particularly after the second year of follow-up, when the rate of increase accelerated. This suggests that individuals in the high-risk group have a higher likelihood of developing diabetes, and the cumulative effect of this risk becomes more pronounced over time.

The curve for the low-risk group starts at 1.00 (indicating that 100% of individuals were free of diabetes) and gradually declines over time, although the decrease is relatively small. In contrast, the high-risk group shows a much more rapid decline, especially after the second year, with a more noticeable downward trend (**Figure 5B**). The line chart depicting the diabetes incidence rates across different insulin resistance risk groups (**Figure 5C**) shows that the growth rate of incidence in the high-risk group is significantly higher than in the low-risk group. The incidence in the high-risk group rises sharply after the second year, reaching its peak by the fifth year. These findings suggest that individuals with high insulin resistance are more likely to develop diabetes within a shorter time frame.

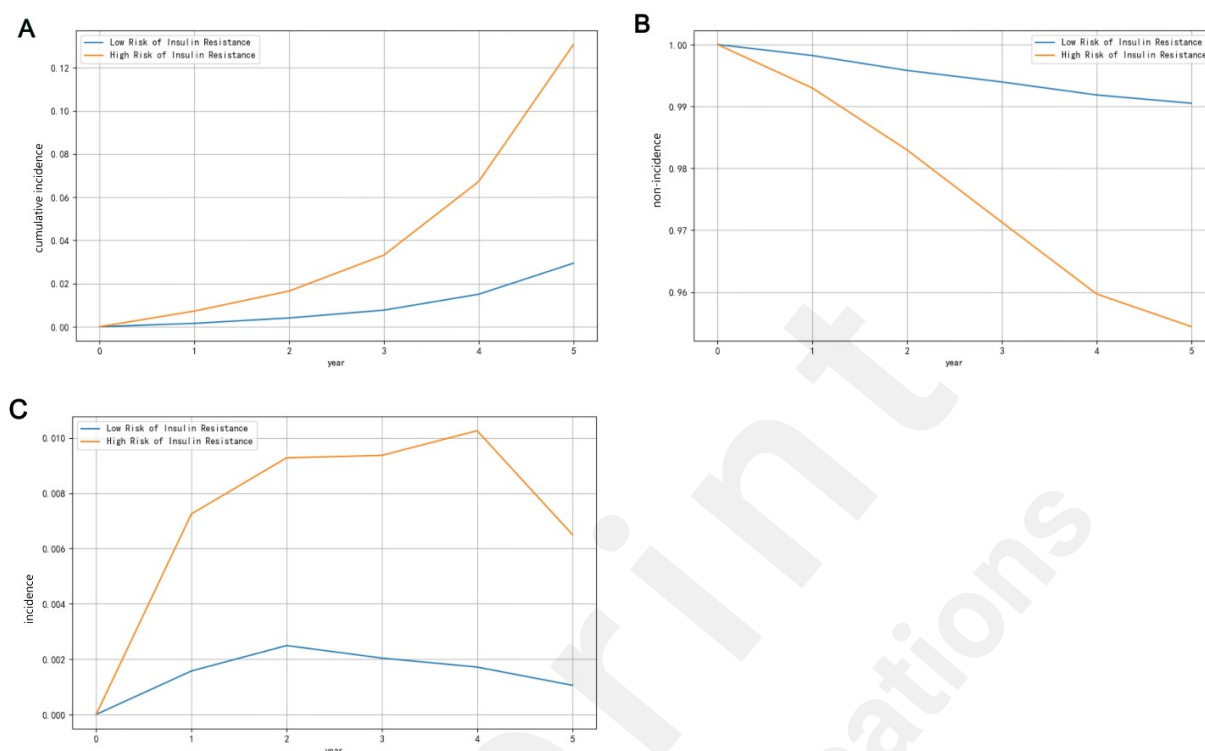


Figure5. Clinical implication (Incidence of diabetes) predicted by LightGBM algorithm from a retrospective cohort by the health management center. A. Kaplan-Meier curve of cumulative incidence of diabetes in different states of insulin resistance. The high-risk IR group has a significantly higher cumulative incidence of diabetes than the low-risk IR group. B. Kaplan-Meier curve of non-incidence of diabetes in different states of insulin resistance. The low-risk IR group has a significantly higher probability of not developing diabetes than the high-risk IR group. C. Incidence of diabetes in different states of insulin resistance. The incidence in the high-risk IR group is significantly higher than that in the low-risk IR group, with a sharp increase after the second year.

Discussion

Principal Findings

This study applied multiple machine learning methods using a health check-up database from southern China. Based on questionnaire data and easily accessible, low-cost laboratory measurements, a highly effective predictive model for IR was developed in a population with normal FBG. This ensures that the data required for model implementation is readily available, without the need for additional, expensive diagnostic procedures. This model holds significant value for precision screening of

IR and for targeting interventions aimed at managing individual risk factors associated with IR. Compared to other models, LightGBM demonstrated a clear overall advantage in terms of its parameters. LightGBM is a gradient boosting framework that employs decision tree-based learning algorithms. It offers several benefits, including faster training efficiency, lower memory usage, and higher accuracy. Additionally, it supports parallel learning and is capable of handling large-scale datasets [13].

Comparison to Prior Work

The previous studies have developed insulin resistance prediction models targeting different ethnic groups and populations, which proves that researchers recognize the necessity of conducting IR prediction. Tsai integrated the NHANES public database in the United States and the MAFOR database in Taiwan, China, and established the HOMA-IR machine learning (XGboost) prediction model for adults in the two regions. The AUC reached 0.87, the important feature spectrum revealed by SHAP analysis was similar to our results, confirming the determinative roles of factors such as BMI, FBG, TG, HDL-C and sex [14]. Prior to this, the team also developed an IR model using samples from 1,229 chronic kidney disease patients sourced from the NHANES database. The model included various nutritional and micronutrient indicators, and the overall evaluation metric showed that the XGBoost model achieved an AUC of 0.78[15]. Zhang developed a LightGBM model for IR in a cohort of nearly 10,000 adults aged 40 and above from certain communities in Hubei, China, with an ROC score of 0.794. The most significant features included FBG, BMI, WC, TG, and sex [16]. In a South Korean study involving 8,842 residents, in addition to measurement and laboratory indicators, high-cost, high-quality features such as genetic risk scores, food frequency questionnaires, and nutrients were included. The best-performing model, XGBoost, achieved an AUC of 0.86[17]. However, these

studies either use expensive features or fail to address multicollinearity issues between features. For example, physiological knowledge and typical data support a strong correlation between BMI and waist circumference[18], but these studies did not account for multicollinearity, which could lead to overfitting.

In our preliminary model, using only low-cost questionnaire features did not yield the expected results. However, when laboratory indicators of liver function and blood lipids were added, the performance improved significantly. Both feature importance rankings based on LightGBM and SHAP value calculations showed that BMI, FBG, HDL-C, and TG were among the top four most important features. In fact, a 2003 consensus from the American College of Clinical Endocrinology[19] formally defined IR syndrome as a multisystem disease centered around IR, with key elements including IR or hyperinsulinemia, with or without related cardiovascular-endocrine metabolic abnormalities. These elements include overweight BMI, abnormal glucose tolerance, HBP, elevated TG, and/or reduced HDL-C, based on the established epidemiological correlation between IR and these indicators [20, 21] □ From a pathophysiological perspective, IR and these metabolic indicators have an explainable causal relationship. For example, adipokines secreted by adipose tissue, such as adiponectin [22], TNF- α [23] can modulate insulin sensitivity through the insulin signaling pathway. Additionally, hydrolysis products of elevated triglycerides, such as free fatty acids, can induce insulin resistance by inhibiting insulin signal transduction and reducing the number of insulin receptors on target cells[24] □ Low HDL-C improves insulin resistance through reverse cholesterol transport and anti-inflammatory effects [25]. We also found that liver function indicators, such as ALT, bilirubin, and the A/G ratio, play a significant role in IR prediction, with fatty liver being closely linked to IR [26] □ These three abnormal indicators are common in

individuals with fatty liver disease [27]—which may indirectly reflect IR. Additionally, kidney function indicators showed correlations, which could be related to factors such as physical inactivity, chronic inflammation, oxidative stress, vitamin deficiencies, adipose factor imbalances, and changes in the gut microbiota in populations with kidney damage [28]. Finally, we applied the best LightGBM model results to baseline IR stratification in a retrospective cohort, further validating the significant impact of IR prediction on diabetes incidence. This aims to clarify the practical value of such models. By comparing the incidence of diabetes in low-risk and high-risk IR groups, we observed that individuals at high risk for IR were more likely to develop diabetes in a shorter period, confirming the model's value in assessing blood glucose metabolism.

Limitations and Future Directions

Despite the promising results in IR prediction, our study has several limitations. First, the geographical limitation of the sample. Our data came from a health check-up database from the Han Chinese population in Hunan Province in Central Southern China, which may impact the generalizability of the model to other regions or ethnic groups. Future studies could address this by incorporating data from different regions and ethnic populations to further validate the model's generalizability. We would try to develop these ML models into user-friendly web pages or applications that are accessible to the general public and primary care providers, getting more input information and feedback to optimize our models, which is virtually a significant advantage of ML. Second, we tested the clinical implications of this trained model with a retrospective cohort, and have not yet explored the predictive efficiency of the model in prospective research, and we plan to perform it in a follow-up study in the near future. Third, the diagnosis of diabetes in the cohort was based only on the

results of FBG, rather than OGTT or combined with postprandial blood glucose or glycated hemoglobin, Anyhow, we hope that we could do it in the further research in the near future. Finally, although five ML algorithms were employed in the present study, there may be other algorithms with better performance available currently or to be developed. It would be necessary for us to further iterate models with more promising algorithms to improve the predictive performance of the models in the future.

Conclusions

In conclusion, the ML models using the LightGBM algorithm, are efficient in predicting IR status in non-diabetic individuals, By leveraging low-cost laboratory indicators and questionnaire data, the model can accurately assess the current IR status in individuals with normal blood glucose levels, helping to identify those at high risk of progressing to diabetes within large-scale populations.

Acknowledgments

The authors thank all the staff, and participants of the Hunan University Of Technology and Business for their contributions to the research.

Funding statement

This work was supported in part by grant 2025JJ90208 from the Hunan Natural Science Foundation, grant 2023-CCA-ASCVD-018 from the Chinese Cardiovascular Association-ASCVD Fund and grant Z2023058 from the Project of State Key Clinical Department

Data availability

The datasets generated or analyzed during this study are not publicly available due privacy restrictions but are available from the corresponding author on reasonable request.

Conflict of Interest

All authors have nothing to disclose.

Authors' contributions

R.M. conceived the study, T.P. and R.M. wrote the initial draft. T.P. and R.M. contributed equally to this work and are considered co-first authors. J.C., and Y.L. reviewed, commented on and revised further drafts. J.C., and Y.L. are considered co-correspondence authors. Data analysis was conducted by Y.L. with the help of H.X., D.F. and J.R., J.W. and R.M. provided financial support. All authors had full access to the data in the study and were responsible for the decision to submit for publication.

Abbreviations

ALT alanine aminotransferase

ALB serum albumin

AST aspartate aminotransferase

A/G albumin/globulin ratio

AUC curve and the area under the curve

BMI body mass index

BUN blood urea nitrogen

BO bayesian optimization

DBP diastolic blood pressure

DBIL direct bilirubin

FBG fasting blood glucose

GBDT gradient boosting machine

GLO serum globulin

HBP hypertension

HDL-C high-density lipoprotein cholesterol

IR insulin resistance

LDL-C low-density lipoprotein cholesterol

LightGBM light gradient boosting machine

ML machine learning

RF random forest

ROC receiver operating characteristic

SBP systolic blood pressure

SD standard deviation

SHAP shapley additive explanations

Sr serum creatinine

TC total cholesterol

TG triglycerides

TP total proteintotal

TBIL total bilirubin,

TBA bile acids

UA uric acid

WC waist circumference

XGBoost extreme gradient boosting

Reference

1. Moller DE, Flier JS. Insulin resistance--mechanisms, syndromes, and implications. *N Engl J Med*. 1991 Sep 26;325(13):938-48. PMID: 1881419. doi: 10.1056/NEJM199109263251307.
2. Galicia-Garcia U, Benito-Vicente A, Jebari S, Larrea-Sebal A, Siddiqi H, Uribe KB, et al. Pathophysiology of Type 2 Diabetes Mellitus. *Int J Mol Sci*. 2020 Aug 30;21(17). PMID: 32872570. doi: 10.3390/ijms21176275.
3. Sun H, Saeedi P, Karuranga S, Pinkepank M, Ogurtsova K, Duncan BB, et al. IDF Diabetes Atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for

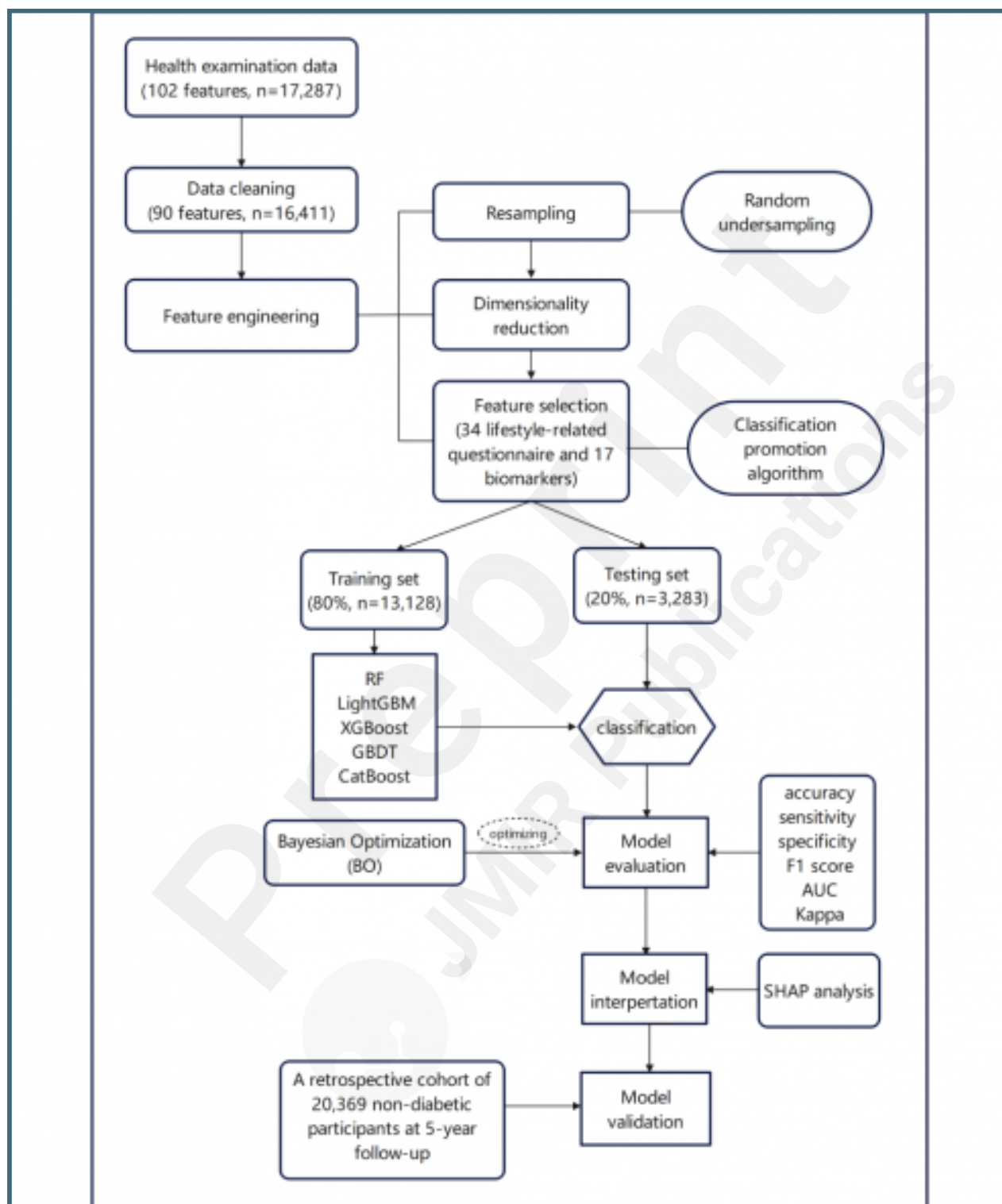
2045. Diabetes Res Clin Pract. 2022 Jan;183:109119. PMID: 34879977. doi: 10.1016/j.diabres.2021.109119.
4. Parcha V, Heindl B, Kalra R, Li P, Gower B, Arora G, et al. Insulin Resistance and Cardiometabolic Risk Profile Among Nondiabetic American Young Adults: Insights From NHANES. *J Clin Endocrinol Metab*. 2022 Jan 1;107(1):e25-e37. PMID: 34473288. doi: 10.1210/clinem/dgab645.
5. Xing XY, Yang WY, ZJ Y. The diagnostic significance of homeostasis model assessment of insulin resistance in metabolic syndrome a-mong subjects with different glucose tolerance. *Chin J Diabetes*. 2004 (03):31-5.
6. DeFronzo RA, Tobin JD, Andres R. Glucose clamp technique: a method for quantifying insulin secretion and resistance. *Am J Physiol*. 1979 Sep;237(3):E214-23. PMID: 382871. doi: 10.1152/ajpendo.1979.237.3.E214.
7. Bonora E, Targher G, Alberiche M, Bonadonna RC, Saggiani F, Zenere MB, et al. Homeostasis model assessment closely mirrors the glucose clamp technique in the assessment of insulin sensitivity: studies in subjects with various degrees of glucose tolerance and insulin sensitivity. *Diabetes Care*. 2000 Jan;23(1):57-63. PMID: 10857969. doi: 10.2337/diacare.23.1.57.
8. Miao R, Dong Q, Liu X, Chen Y, Wang J, Chen J. A cost-effective, machine learning-driven approach for screening arterial functional aging in a large-scale Chinese population. *Front Public Health*. 2024;12:1365479. PMID: 38572001. doi: 10.3389/fpubh.2024.1365479.
9. Ji W, Xue M, Zhang Y, Yao H, Wang Y. A Machine Learning Based Framework to Identify and Classify Non-alcoholic Fatty Liver Disease in a Large-Scale Population. *Front Public Health*. 2022;10:846118. PMID: 35444985. doi: 10.3389/fpubh.2022.846118.
10. Birk N, Matsuzaki M, Fung TT, Li Y, Batis C, Stampfer MJ, et al. Exploration of Machine Learning and Statistical Techniques in Development of a Low-Cost Screening Method Featuring the Global Diet Quality Score for Detecting Prediabetes in Rural India. *J Nutr*. 2021 Oct 23;151(12 Suppl 2):110S-8S. PMID: 34689190. doi: 10.1093/jn/nxab281.
11. Chen N, Fan F, Geng J, Yang Y, Gao Y, Jin H, et al. Evaluating the risk of hypertension in residents in primary care in Shanghai, China with machine learning algorithms. *Front Public Health*. 2022;10:984621. PMID: 36267989. doi: 10.3389/fpubh.2022.984621.
12. Yarbeygi H, Maleki M, Sathyapalan T, Jamialahmadi T, Sahebkar A. Pathophysiology of Physical Inactivity-Dependent Insulin Resistance: A Theoretical Mechanistic Review Emphasizing Clinical Evidence. *J Diabetes Res*. 2021;2021:7796727. PMID: 34660812. doi: 10.1155/2021/7796727.
13. Guolin Ke QM, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, Tie-Yan Liu., editor. LightGBM: A Highly Efficient Gradient Boosting Decision Tree. *Advances in Neural Information Processing Systems*; 2017.
14. Tsai SF, Yang CT, Liu WJ, Lee CL. Development and validation of an insulin resistance model for a population without diabetes mellitus and its clinical implication: a prospective cohort study. *EClinicalMedicine*. 2023 Apr;58:101934. PMID: 37090441. doi: 10.1016/j.eclim.2023.101934.
15. Lee CL, Liu WJ, Tsai SF. Development and Validation of an Insulin Resistance Model for a Population with Chronic Kidney Disease Using a Machine Learning Approach. *Nutrients*. 2022 Jul 9;14(14). PMID: 35889789. doi: 10.3390/nu14142832.
16. Zhang H, Zeng T, Zhang J, Zheng J, Min J, Peng M, et al. Development and validation of machine learning-augmented algorithm for insulin sensitivity assessment in the community and primary care settings: a population-based study in China. *Front Endocrinol (Lausanne)*. 2024;15:1292346. PMID: 38332892. doi: 10.3389/fendo.2024.1292346.
17. Park S, Kim C, Wu X. Development and Validation of an Insulin Resistance Predicting Model Using a Machine-Learning Approach in a Population-Based Cohort in Korea. *Diagnostics (Basel, Switzerland)*. 2022 Jan 16;12(1). PMID: 35054379. doi: 10.3390/diagnostics12010212.
18. Ngueta G, Laouan-Sidi EA, Lucas M. Does waist circumference uncorrelated with BMI add valuable information? *J Epidemiol Community Health*. 2014 Sep;68(9):849-55. PMID: 24915975. doi: 10.1136/jech-2014-204005.
19. Bloomgarden ZT. American Association of Clinical Endocrinologists (AACE) consensus conference on the insulin resistance syndrome: 25-26 August 2002, Washington, DC. *Diabetes Care*. 2003 Mar;26(3):933-9. PMID: 12610060. doi: 10.2337/diacare.26.3.933.
20. Pei D, Kuo SW, Wu DA, Lin TY, Hsieh MC, Lee CH, et al. The relationships between insulin resistance and components of metabolic syndrome in Taiwanese Asians. *Int J Clin Pract*. 2005 Dec;59(12):1408-16. PMID: 16351672. doi: 10.1111/j.1368-5031.2005.00661.x.
21. Lee S, Gungor N, Bacha F, Arslanian S. Insulin resistance: link to the components of the metabolic syndrome and biomarkers of endothelial dysfunction in youth. *Diabetes Care*. 2007 Aug;30(8):2091-7. PMID: 17475936. doi: 10.2337/dc07-0203.
22. Ceddia RB, Somwar R, Maida A, Fang X, Bikopoulos G, Sweeney G. Globular adiponectin

- increases GLUT4 translocation and glucose uptake but reduces glycogen synthesis in rat skeletal muscle cells. *Diabetologia*. 2005 Jan;48(1):132-9. PMID: 15619075. doi: 10.1007/s00125-004-1609-y.
23. Chuang CC, Bumrungpert A, Kennedy A, Overman A, West T, Dawson B, et al. Grape powder extract attenuates tumor necrosis factor alpha-mediated inflammation and insulin resistance in primary cultures of human adipocytes. *J Nutr Biochem*. 2011 Jan;22(1):89-94. PMID: 20382011. doi: 10.1016/j.jnutbio.2009.12.002.
24. Kovacs P, Stumvoll M. Fatty acids and insulin resistance in muscle and liver. *Best Pract Res Clin Endocrinol Metab*. 2005 Dec;19(4):625-35. PMID: 16311221. doi: 10.1016/j.beem.2005.07.003.
25. Drew BG, Rye KA, Duffy SJ, Barter P, Kingwell BA. The emerging role of HDL in glucose metabolism. *Nat Rev Endocrinol*. 2012 Jan 24;8(4):237-45. PMID: 22271188. doi: 10.1038/nrendo.2011.235.
26. Goto T, Onuma T, Takebe K, Kral JG. The influence of fatty liver on insulin clearance and insulin resistance in non-diabetic Japanese subjects. *Int J Obes Relat Metab Disord*. 1995 Dec;19(12):841-5. PMID: 8963349.
27. Marchesini G, Brizi M, Bianchi G, Tomassetti S, Bugianesi E, Lenzi M, et al. Nonalcoholic fatty liver disease: a feature of the metabolic syndrome. *Diabetes*. 2001 Aug;50(8):1844-50. PMID: 11473047. doi: 10.2337/diabetes.50.8.1844.
28. Spoto B, Pisano A, Zoccali C. Insulin resistance in chronic kidney disease: a systematic review. *Am J Physiol Renal Physiol*. 2016 Dec 1;311(6):F1087-F108. PMID: 27707707. doi: 10.1152/ajprenal.00340.2016.

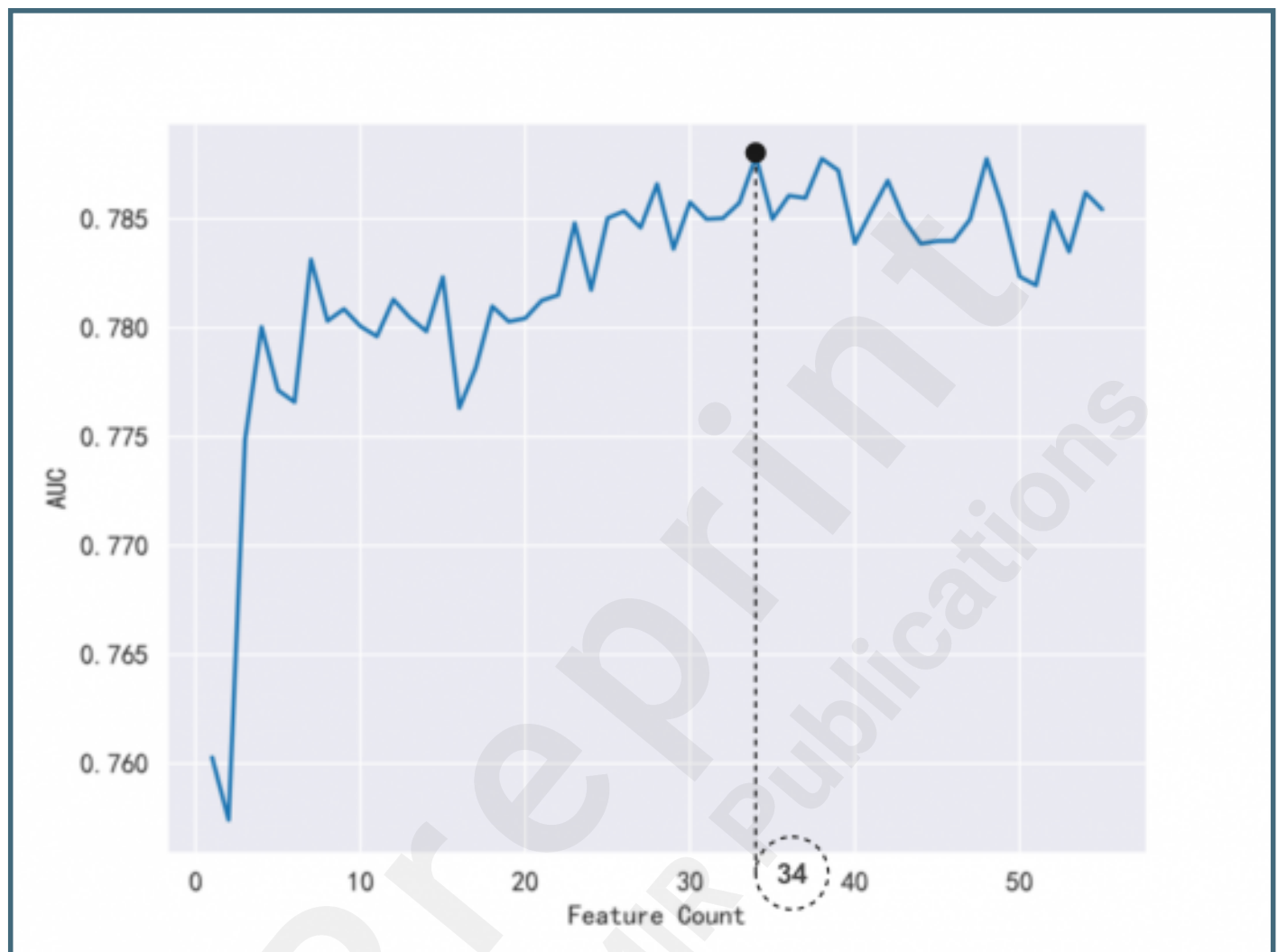
Supplementary Files

Figures

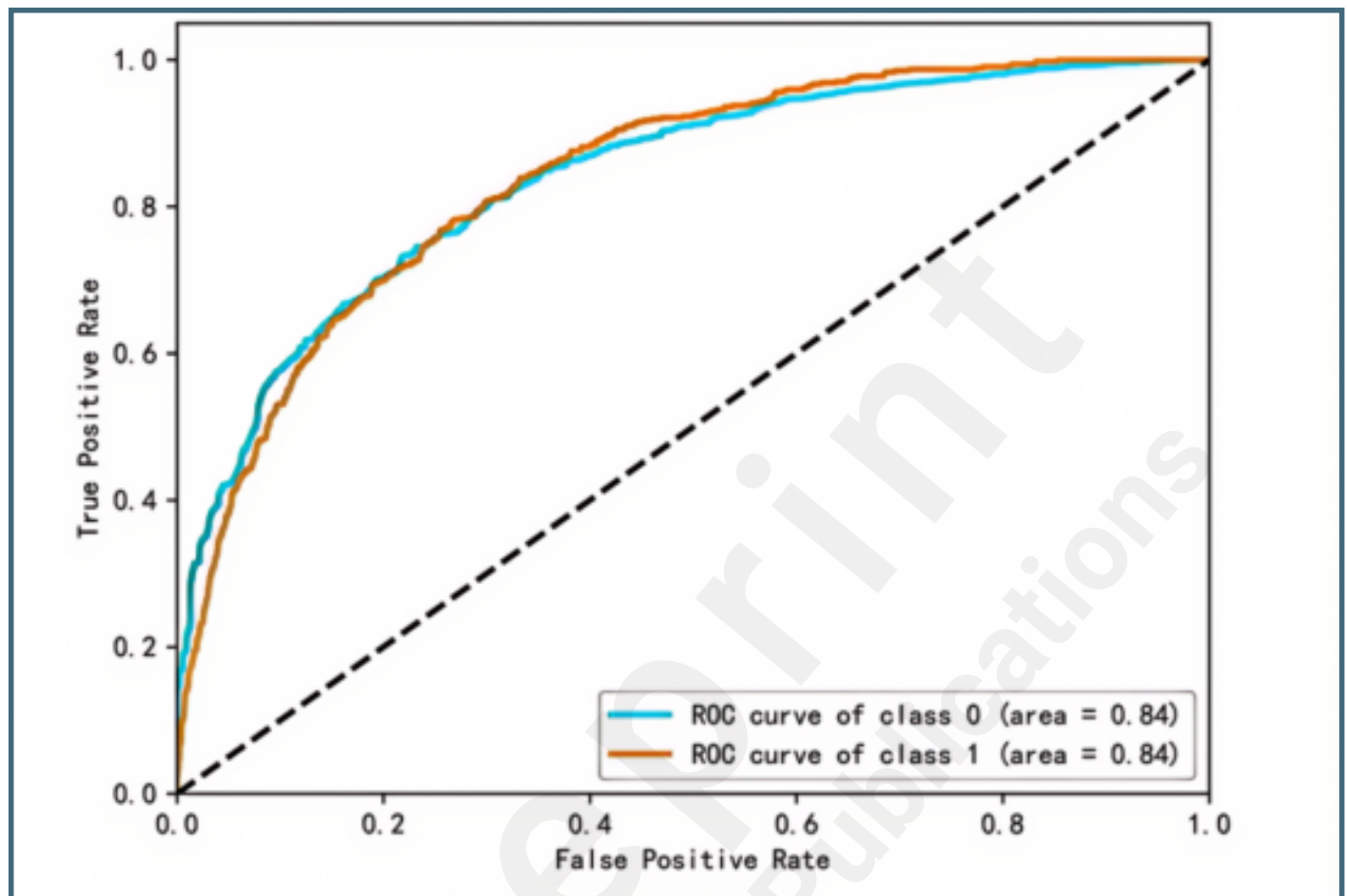
Flow diagram of the study. The flow diagram of the study shows the entire research process, from data collection, preprocessing, model training and testing to final model evaluation and validation.



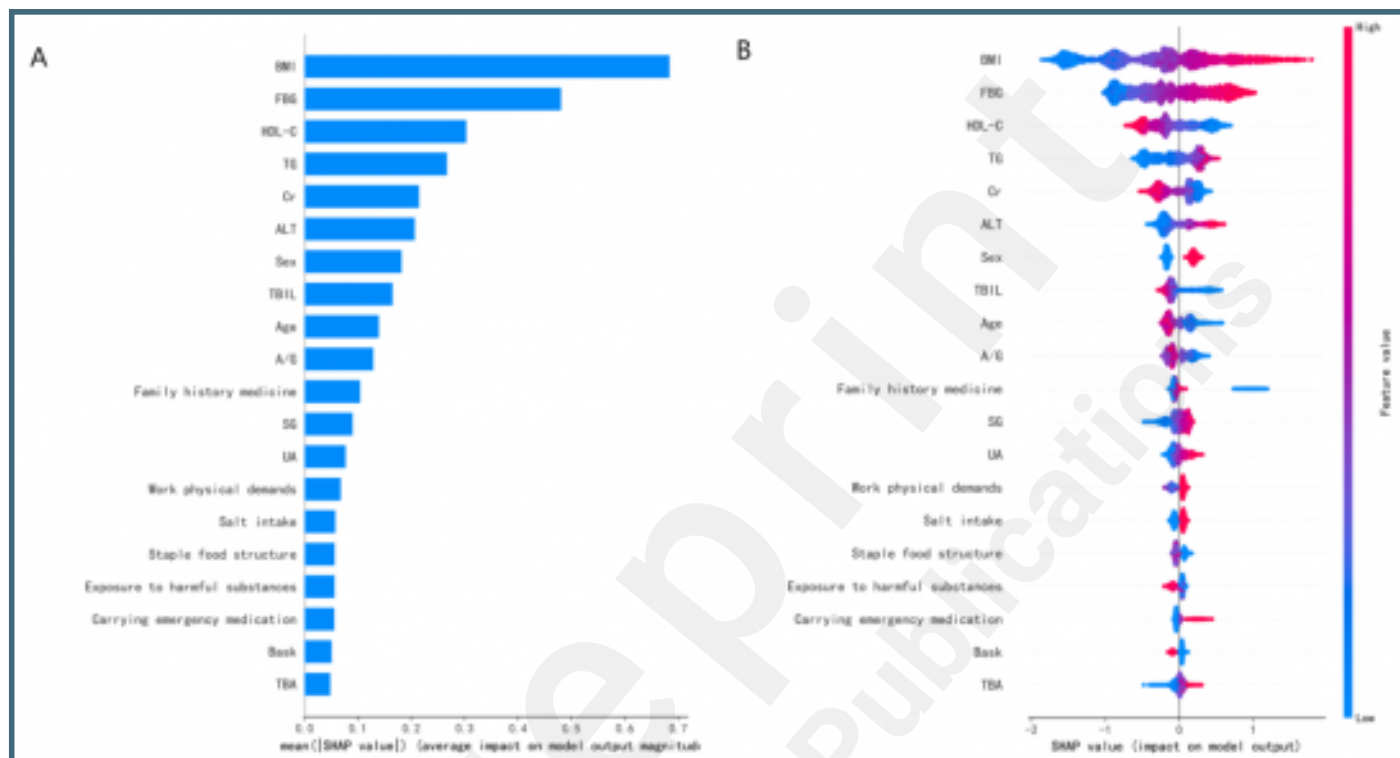
The model's AUC score on the test setIt shows how the AUC score on the test set changes with the number of features included in the model. After adding 34 features, the AUC score drops significantly, indicating that these additional features no longer contribute to model performance improvement.



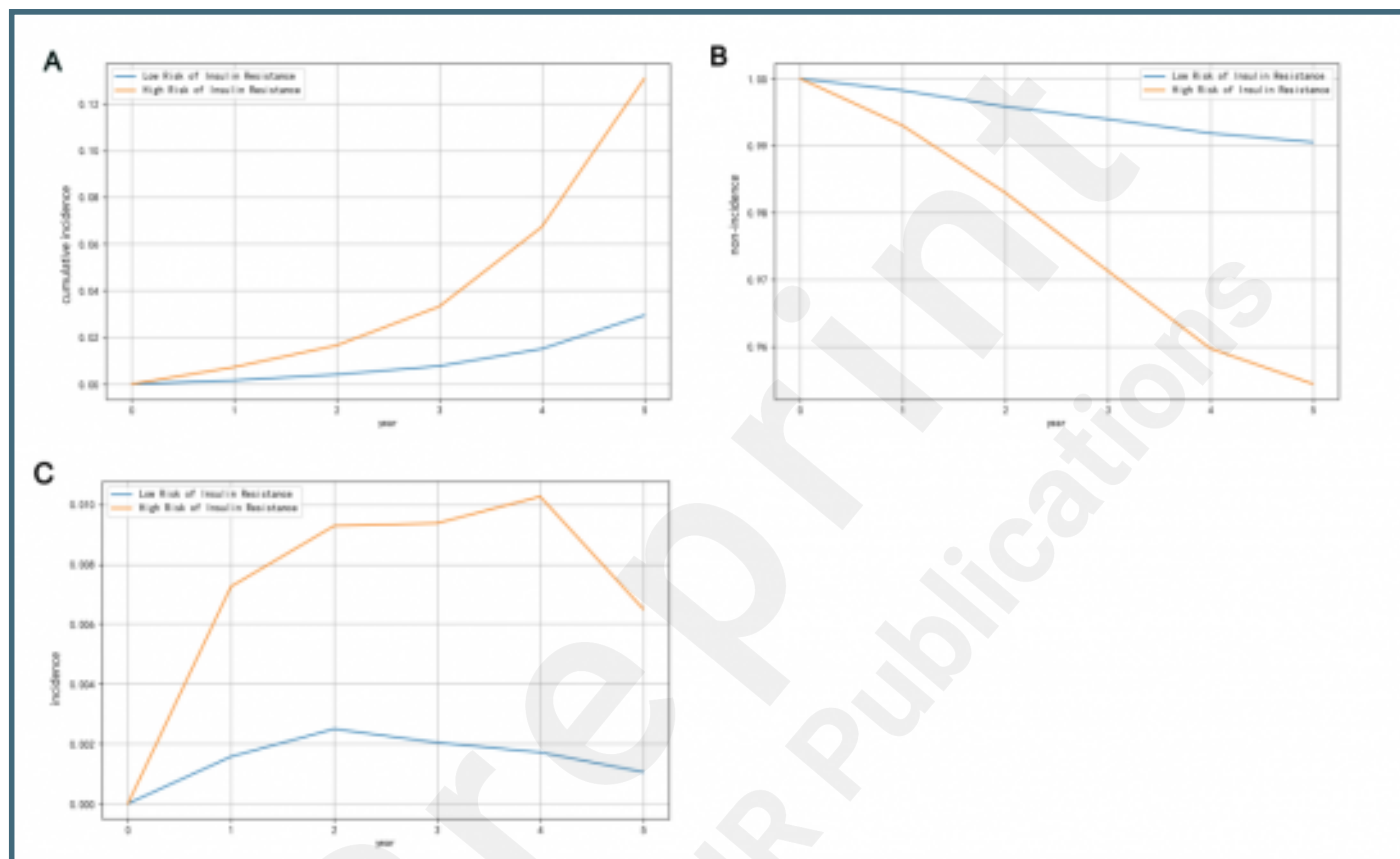
Prediction of insulin resistance in patients with IR by LightGBM, ROC curve in test set. The area under the curve (AUC) is 0.8456, indicating that the model has good discriminant ability.



Detailed features importance. A. Features importance by LightGBM. It shows the importance ranking of various features in the LightGBM model. The vertical coordinate (y-axis) shows the top 20 features. B. Explanation of each feature impact on the IR in the prediction model by the SHAP values in the LightGBM algorithm. The vertical coordinate (y-axis) shows the features in decreasing order of importance, while the horizontal coordinate (x-axis) displays the average absolute SHAP value of each feature. Red points indicate higher feature values, while blue points represent lower values. Positive SHAP values indicate a positive impact of the feature on the prediction, while negative values indicate a negative impact.



Clinical implication (Incidence of diabetes) predicted by LightGBM algorithm from a retrospective cohort by the health management center. A. Kaplan–Meier curve of cumulative incidence of diabetes in different states of insulin resistance. The high-risk IR group has a significantly higher cumulative incidence of diabetes than the low-risk IR group. B. Kaplan–Meier curve of non-incidence of diabetes in different states of insulin resistance. The low-risk IR group has a significantly higher probability of not developing diabetes than the high-risk IR group. C. Incidence of diabetes in different states of insulin resistance. The incidence in the high-risk IR group is significantly higher than that in the low-risk IR group, with a sharp increase after the second year.



Multimedia Appendixes

The questionnaires used in this study(Chinese-language).

URL: <http://asset.jmir.pub/assets/07b56f74802fdc7c933051c0478d22ec.doc>

The questionnaires used in this study(English).

URL: <http://asset.jmir.pub/assets/46f63c977165a3d93328b9c0c96e0900.docx>



TOC/Feature image for homepages

The image was generated by AI (1) the prompt : Insulin resistance (IR), machine learning (ML), Light Gradient Boosting Machine (LightGBM) (2) the date on April 24, 2025. (3) Ting Peng generated the image. (4) The image was generated by the Doubao app.

