

Clinical Value of Machine Learning Model Based on Non-Invasive Myocardial Work Parameters and Glycolipid Metabolism Indicators for the Early Diagnosis of Coronary Heart Disease

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Abstract: Objective This study aims to explore the clinical value of machine learning models constructed by combining non-invasive Myocardial Work (MW) parameters and clinical glycolipid metabolism indicators for the early diagnosis of coronary heart disease (CHD). **Methods** A total of 183 suspected CHD patients scheduled for coronary angiography (CAG) admitted to the Affiliated Hospital of Youjiang Medical University for Nationalities from October 2024 to June 2025 were enrolled in this study. Subjects were randomly divided into a training set (n=129) and a validation set (n=54) at a ratio of 7:3. General clinical data, laboratory test results and echocardiographic parameters of all enrolled subjects were collected. Univariate Logistic regression analysis, multicollinearity test and multivariate Logistic regression analysis were performed on the training set to screen independent predictive factors for CHD, based on which six distinct machine learning models were established. The optimal machine learning model was selected comprehensively according to the area under the receiver operating characteristic curve (AUC), accuracy (ACC), sensitivity, specificity, F1-score and Youden's index. Receiver operating characteristic (ROC) curves, calibration curves and clinical decision curves were adopted to evaluate the diagnostic performance and clinical benefit of the model. Finally, SHapley Additive exPlanations (SHAP) algorithm was applied to conduct interpretability analysis of the final model. **Results** Multivariate Logistic regression analysis revealed that Metabolic Syndrome (MetS) (OR=3.070, $P=0.004$), Triglyceride-Glucose Index (TyG index) (OR=24.710, $P<0.001$), High Density Lipoprotein Cholesterol (HDL) (OR=0.224, $P=0.012$), Global Constructive Work (GCW) (OR=0.999, $P=0.004$) and Global Wasted Work (GWW) (OR=1.005, $P=0.027$) were independent predictive factors for CHD. The Multilayer Perceptron (MLP) model achieved the optimal performance, with an AUC of 0.799, an ACC of 0.796, an F1-score of 0.820, a sensitivity of 0.833, a specificity of 0.750 and a Youden's index of 0.583 in the validation set. Calibration curve and clinical decision curve analyses demonstrated that the predicted probabilities of the MLP model were in good agreement with the observed actual probabilities, and the model yielded considerable clinical net benefit across a wide range of threshold probabilities. The SHAP algorithm was adopted to visualize variable importance within the MLP model. The results indicated that GCW exerted the greatest predictive contribution, followed by MetS and GWW with moderate contributions, HDL with moderate-to-low contribution, and the TyG index with the lowest contribution. **Conclusions** The MLP machine learning model constructed based on GCW, GWW, MetS, HDL and TyG index exhibits favorable diagnostic performance for the early identification of CHD, which can provide reference for clinical decision-making.

Keywords: Coronary Heart Disease; Non-Invasive Myocardial Work; Glycolipid Metabolism Indicators; Machine Learning.

1. Introduction

Statistical data indicate that cardiovascular disease (CVD) remains the leading cause of morbidity and mortality worldwide [1, 2], among which CHD stands out. CHD is frequently accompanied by concealed manifestations in its early stage, leading to delayed diagnosis [3]. Although CAG serves as the gold standard for CHD diagnosis, its invasiveness, radiation exposure and high cost restrict its application in early screening. A large number of patients with suspected CHD presenting with chest pain receive negative CAG results, which not only imposes financial burdens and psychological stress on patients, but also results in medical resource waste. Accordingly, it is critical to identify early CHD via non-invasive and convenient approaches prior to CAG. Existing studies have demonstrated that glycolipid metabolic disorders are vital risk factors for coronary atherosclerosis [4, 5]. MetS and the TyG index can reflect

abnormal metabolic status of the human body [6-11]. MW generates left ventricular pressure-strain loops by combining speckle-tracking strain with brachial cuff pressure, eliminating the limitation that conventional strain parameters are affected by afterload, and enabling early detection of myocardial dysfunction induced by myocardial ischemia [12-16]. Most current CHD prediction models only adopt biochemical indicators or imaging parameters alone, resulting in incomplete evaluation [17]. Furthermore, the majority of existing machine learning models suffer from severe "black-box" problems, which limits their clinical acceptance.

Given the above research background, this study aims to explore the clinical value of machine learning models constructed by integrating non-invasive myocardial work parameters and clinical glycolipid metabolism indicators for the early diagnosis of CHD, so as to improve the accuracy and specificity of early CHD diagnosis, provide clinicians with a more comprehensive non-invasive evaluation tool, and

reduce subsequent unnecessary invasive examinations.

2. Materials and Methods

2.1. Study Subjects

A total of 190 suspected CHD patients admitted to the Department of Cardiovascular Medicine, Affiliated Hospital of Youjiang Medical University for Nationalities from October 2024 to June 2025 who underwent CAG in our hospital were enrolled initially. Inclusion criteria: 1) Age ≥ 18 years old; 2) Complete echocardiography and full panel of laboratory tests performed within 3 days before CAG; 3) Complete medical records available; 4) Signed written informed consent obtained.

Exclusion criteria: 1) Severe organic heart diseases including congenital heart disease, severe valvular heart disease, cardiomyopathy, etc.; 2) Peripheral vascular diseases rendering brachial artery pressure unable to represent central arterial pressure; 3) Segmental wall motion abnormalities detected by echocardiography; 4) Prior administration of statin lipid-lowering agents; 5) Complicated with severe hepatic or renal insufficiency, malignant tumors or systemic disorders; 6) Previous history of PCI or coronary artery bypass grafting (CABG); 7) Poor quality of echocardiographic images.

Ultimately, 183 subjects were included and divided into the CHD group (96 cases) and non-CHD group (87 cases) according to CAG findings. This study was approved by the Hospital Ethics Committee (Approval No. YYFY-2024-248) and conducted in accordance with the Declaration of Helsinki.

2.2. Collection of Baseline Data

Collection of general information: General information included the subjects' age, gender, height, weight, smoking history, blood pressure, and medical histories (diabetes mellitus, smoking status, presence or absence of MetS).

Collection of laboratory indicators: FBG, HbA1c, TG, TC, HDL and LDL were recorded. After converting TG and FBG units from mmol/L to mg/dL, the TyG index was calculated using the following formula:

$$\text{TyG} = \ln[\text{TG (mg/dL)} \times \text{FBG (mg/dL)} / 2]$$

Collection and analysis of echocardiographic data: A GE Vivid E95 ultrasonic diagnostic system equipped with an M5S transducer was used at a frame rate of 70–80 fps. Conventional echocardiographic parameters were acquired, including left atrial diameter (LAD), left ventricular end-diastolic dimension (LVEDD) and left ventricular ejection fraction (LVEF). Dynamic images of apical two-chamber, three-chamber and four-chamber views were stored for offline analysis on the Echo-PA workstation to derive global longitudinal strain (GLS). Brachial artery blood pressure values were imported into the workstation to calculate myocardial work parameters: global work index (GWI), GCW, GWW and global work efficiency (GWE). Fifteen subjects were randomly selected to assess intra-observer and inter-observer measurement reproducibility, and intraclass correlation coefficient (ICC) was adopted to evaluate measurement consistency.

2.3. Statistical Methods

Statistical analyses were performed using SPSS 27.0 and R 4.3.1 software. Subjects were randomly split into a training set ($n=129$) and a validation set ($n=54$) at a ratio of 7:3 via simple random sampling. Ten-fold cross-validation was

applied for internal validation.

Measurement data conforming to normal distribution were expressed as mean $\pm$ standard deviation ($\bar{x} \pm s$), and intergroup comparisons were conducted using independent-samples *t* test. Non-normally distributed measurement data were presented as median (interquartile range). Categorical data were compared by Pearson chi-square test and Fisher's exact test. Univariate Logistic regression, multicollinearity test and multivariate Logistic regression analyses were carried out on the training set to screen independent predictive factors for CHD. A 97.5% confidence interval was adopted to strictly control estimation uncertainty, and $P < 0.05$ was defined as statistically significant. The intra-observer and inter-observer consistency of GLS and myocardial work parameters was evaluated by two-way random-effects ICC.

Six machine learning models were established based on the independent predictors of CHD, including Stochastic Gradient Descent (SGD), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), MLP, Logistic Regression (LR) and Decision Tree (DTree). Model performance was comprehensively assessed via multiple metrics: AUC, ACC, sensitivity, specificity, F1-score and Youden's index, based on which the optimal model was selected. The SHAP algorithm was used for model interpretability analysis. Multiple visualization graphs were plotted subsequently, including the Double-loop Analysis Chart of Feature Effects, the Bar Chart of Feature Importance Ranking, the SHAP Summary Plot, the Feature Interaction Dependency Plot, the Sample Prediction Path Diagram (Including Misclassified Cases), the SHAP Explanation for Instance, and the Feature Importance Heatmap.

3. Results

3.1. Analysis of General Clinical Data of Study Subjects

The results shown in Table 1 indicated that there were no statistically significant differences ($P > 0.05$) in age, systolic blood pressure, diastolic blood pressure, BMI, gender, hypertension, smoking status, MetS and diabetes mellitus between the training set and validation set, suggesting good comparability between the two groups.

3.2. Analysis of Serological Indicators of Study Subjects

The results presented in Table 2 demonstrated that there were no statistically significant differences ($P > 0.05$) in HbA1c, TC, TyG index, LDL, HDL and FBG between the training set and validation set, which indicated favorable comparability between the two groups.

3.3. Analysis of Echocardiographic Parameters of Study Subjects

The results in Table 3 showed that there were no statistically significant differences ($P > 0.05$) in LA, LVEDD, LVEF, GLS, GWI, GWW, GCW and GWE between the training set and validation set, which verified satisfactory comparability between the two groups.

3.4. Univariate Logistic Regression Analysis

Table 4 presents the results of univariate Logistic regression analysis for the training set. Seven potential influencing variables with statistically significant differences ($P < 0.05$) were screened out via univariate Logistic regression,

namely HDL, FBG, TyG index, MetS, GWI, GWW and GCW.

Table 1. Baseline Characteristics of General Clinical Data in the Training and Test Sets

general clinical	Training (n=129)	validation(n=54)	t/z/ χ^2	P value
Age (years)	55.00 (51.00, 59.00)	53.50 (48.50, 59.00)	-0.752	0.452
systolic blood pressure (mmHg)	136.51±16.49	131.63±18.12	-1.773	0.244
diastolic blood pressure (mmHg)	79.00(70.00,87.00)	79.00(70.00,85.00)	-0.623	0.533
BMI (kg/m ²)	24.31(21.94,27.63)	24.03(21.89,25.82)	-0.643	0.521
gender(%)			0.662	0.416
Female	49(38.00)	24(44.40)		
Male	80(62.00)	30(55.60)		
hypertension (%)			1.119	0.290
No	63(48.80)	31(57.40)		
Yes	66(51.20)	23(42.60)		
smoking status (%)			0.082	0.775
No	77(59.70)	31(57.40)		
Yes	52(40.30)	23(42.60)		
MetS (%)			0.026	0.873
No	70(54.30)	30(55.60)		
Yes	59(45.70)	24(44.40)		
diabetes mellitus (%)			0.465	0.495
No	119(92.20)	52(96.30)		
Yes	10(7.80)	2(3.70)		

Table 2. Baseline Characteristics of Serological Indicators in the Training and Test Sets

serological indicators	Training (n=129)	validation(n=54)	t/z	P value
HbA1c (%)	5.78(5.35,6.10)	5.78(5.57,6.10)	-0.923	0.353
TC (mmol/L)	4.47(3.57,5.35)	4.45(3.67,4.83)	-0.728	0.466
TyG index	8.90(8.68,9.02)	8.89(8.69,8.99)	-0.164	0.870
LDL (mmol/L)	2.29±0.82	2.28±0.77	-0.080	0.238
HDL (mmol/L)	1.19(0.96,1.40)	1.24(1.03,1.39)	-0.321	0.748
FBG (mmol/L)	5.45(4.98,5.86)	5.35(5.01,5.81)	-0.367	0.713

Table 3. Baseline Characteristics of Echocardiographic Parameters in the Training and Test Sets

Echocardiographic Parameters	Training (n=129)	validation(n=54)	t/z	P value
LA(mm)	29.70(27.70,32.90)	29.40(27.85,31.40)	-0.182	0.855
LVEDD(mm)	47.00(44.00,50.00)	48.00(45.00,50.25)	-1.212	0.225
LVEF(%)	64.00(59.50,69.00)	62.00(58.00,66.00)	-1.863	0.062
GLS(%)	17.00(16.00,19.00)	17.00(16.00,18.63)	-0.175	0.861
GWI(mmHg%)	1798.46±405.72	1693.32±392.09	-1.614	0.994
GWW(mmHg%)	174.00(127.25,246.50)	178.50(122.25,248.75)	-0.254	0.800
GCW(mmHg%)	2135.00(1903.25,2430.50)	2060.25(1813.38,2396.75)	-1.071	0.284
GWE(%)	92.00(89.00,94.00)	92.00(89.00,94.00)	-0.261	0.794

Table 4. Univariate Logistic Regression Analysis of Variables

Variables	OR	97.5%CI	P value
HDL	0.154	0.051~0.464	<0.001
FBG	2.292	1.273~4.128	0.002
TyG index	35.682	7.420~171.589	<0.001
MetS	2.827	1.415~5.645	0.001
GWI	0.999	0.998~1.000	0.001
GWW	1.005	1.001~1.009	0.002
GCW	0.999	0.998~1.000	0.001

Note: OR stands for odds ratio; CI stands for confidence interval.

3.5. Multicollinearity Test

Table 5. Test for Multicollinearity

Variables	VIF	Tolerance
HDL	1.132	0.883
TyG index	1.377	0.726
MetS	1.087	0.920
GWl	7.795	0.128
GWw	1.188	0.842
GCW	7.433	0.135
FBG	1.199	0.834

Table 6. Test for Multicollinearity

Variables	VIF	Tolerance
HDL	1.105	0.905
TyG index	1.355	0.738
MetS	1.056	0.947
GWw	1.083	0.923
GCW	1.115	0.597
FBG	1.199	0.834

Multicollinearity test was performed on the variables screened out by univariate Logistic regression analysis. Conventionally, a variance inflation factor (VIF) less than 5 indicates low collinearity between variables; a VIF ranging from 5 to 10 suggests potential collinearity; a VIF of 10 or higher represents severe multicollinearity. The results in Table 5 revealed that the VIF values of all variables were below 10, among which GCW and GWl had VIF values greater than 5, while the VIF values of the remaining variables

were all less than 5. The variable GWl with the highest VIF value was eliminated stepwise, and collinearity diagnosis was repeated on the residual variables to guarantee that the VIF values of all retained variables were less than 5 (Table 6).

3.6. Multivariate Logistic Regression Analysis

Table 7 demonstrated that HDL, TyG index, MetS, GWw and GCW were significant independent predictors for CHD onset. HDL (OR=0.224, 97.5%CI: 0.069–0.724, $P=0.012$), TyG index (OR=24.710, 97.5%CI: 5.108–119.526, $P<0.001$), MetS (OR=3.070, 97.5%CI: 1.440–6.545, $P=0.004$), GWw (OR=1.005, 97.5%CI: 1.001–1.009, $P=0.027$), GCW (OR=0.999, 97.5%CI: 0.998–1, $P=0.004$).

Table 7. Multivariate Logistic Regression Analysis of Variables

Variables	OR	97.5%CI	P value
HDL	0.224	0.069~0.724	0.012
TyG index	24.710	5.108~119.526	<0.001
MetS	3.070	1.440~6.545	0.004
GWw	1.005	1.001~1.009	0.027
GCW	0.999	0.998~1.000	0.004
FBG	1.819	0.940~3.518	0.076

Note: OR stands for odds ratio; CI stands for confidence interval.

3.7. Model Selection and Efficacy Comparison

Among the six machine learning algorithms compared via performance metrics, the MLP model exhibited optimal comprehensive performance (Table 8). In the training set, the MLP model yielded an AUC of 0.849, an ACC of 0.814, an F1-score of 0.824, a sensitivity of 0.848, a specificity of 0.778, and a Youden's index of 0.626. In the validation set, the corresponding values were an AUC of 0.799, an ACC of 0.796, an F1-score of 0.820, a sensitivity of 0.833, a specificity of 0.750, and a Youden's index of 0.583.

Table 8. Performance evaluation of 6 machine learning models

Model	ACC	AUC	F1-score	sensitivity	specificity	Youden's index
Training						
DTree	0.984	0.999	0.985	1.000	0.968	0.968
SVM	0.713	0.745	0.704	0.667	0.762	0.421
LR	0.736	0.733	0.776	0.894	0.571	0.465
SGD	0.721	0.720	0.760	0.864	0.571	0.363
KNN	0.736	0.738	0.773	0.879	0.587	0.466
MLP	0.814	0.849	0.824	0.848	0.778	0.626
validation						
DTree	0.759	0.778	0.772	0.733	0.792	0.525
SVM	0.667	0.649	0.690	0.667	0.667	0.333
LR	0.667	0.642	0.727	0.800	0.500	0.300
SGD	0.667	0.647	0.735	0.833	0.458	0.183
KNN	0.667	0.658	0.679	0.633	0.708	0.342
MLP	0.796	0.799	0.820	0.833	0.750	0.583

To further assess the predictive accuracy and clinical applicability of the MLP model, the ROC curve (Figure 1), calibration curve (Figure 2) and clinical decision curve (Figure 3) of the MLP model were plotted for the training set and validation set respectively. Figure 1 illustrated that the

MLP model achieved relatively high diagnostic sensitivity and specificity in both the training set (a) and validation set (b). The AUC value of the MLP model was approximately 0.849 in the training set and around 0.799 in the validation set.

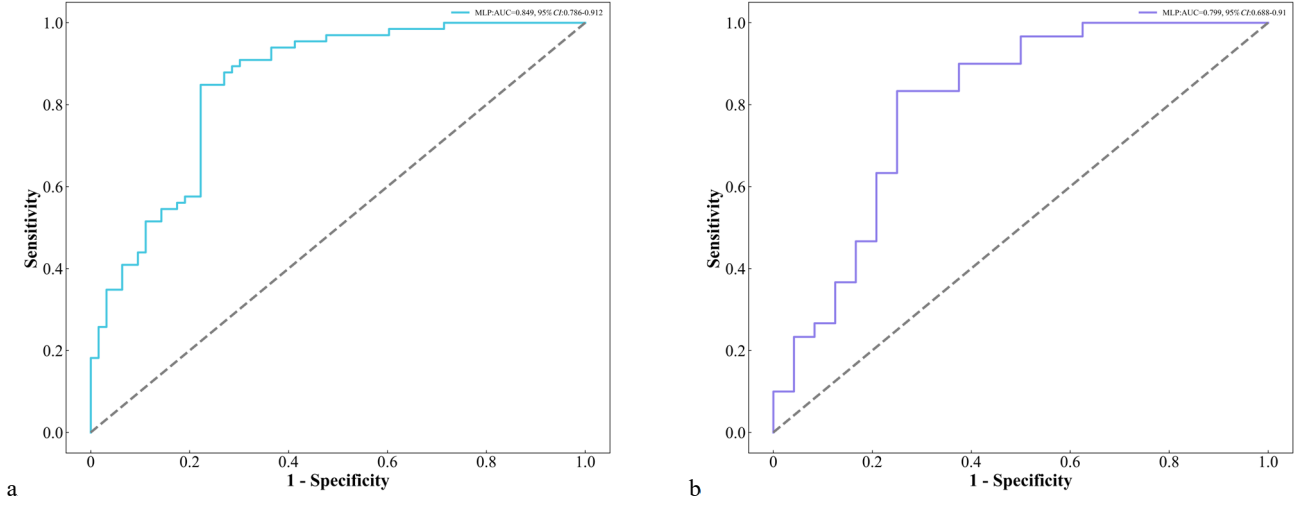


Figure 1. ROC Curves of MLP model
a: Training set; b: Validation set

The calibration curves of the MLP model in the training set and validation set (Figure 2) demonstrated that the predicted probabilities of the MLP model were in good agreement with the actual outcomes in the low and high probability intervals,

while a certain degree of risk underestimation was observed in the medium-to-high risk interval. Despite this limitation, the model still possessed favorable overall clinical application value.

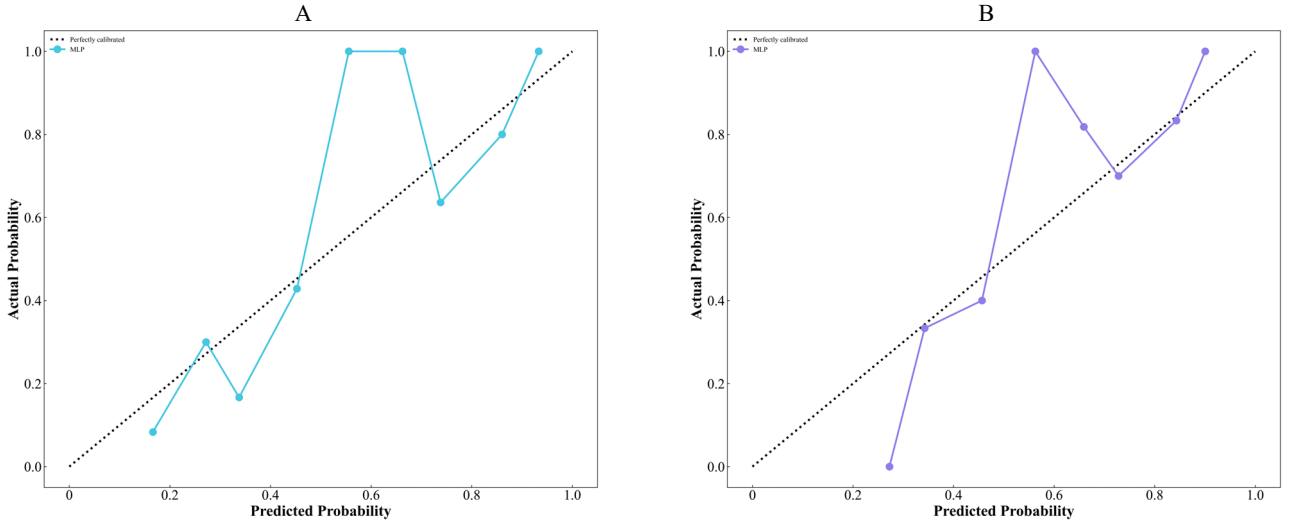


Figure 2. Calibration curves of MLP
a: Training set; b: Validation set

Decision curve analysis of the MLP model (Figure 3) revealed that within the threshold probability range of approximately 0-0.8 for both the training set and validation set, the net benefit of the model was significantly higher than the "treat all" and "treat none" strategies, indicating that the MLP model delivers favorable clinical benefits for auxiliary clinical decision-making.

3.8. Interpretability Analysis and Visualization of the Final Model

Figure 4 presents the dual-loop feature effect diagram. The

inner ring illustrates the distribution of feature importance. The area of each sector corresponds to the proportion of feature importance; a larger sector area with darker color indicates higher global importance of the feature for model prediction, serving as a key factor affecting model outputs. The inner ring structure shows that GCW contributes 26% to CHD outcomes, MetS accounts for 24.6%, GWW for 23.8%, HDL for 18.5%, and the TyG index for 7.1%.

The outer ring reflects the feature effect dependence relationship. Scatter points on the outer ring represent the correlation between feature values and model SHAP values.

The farther a scatter point lies from the ring center, the larger the corresponding SHAP value, meaning the feature value exerts a stronger impact on model prediction. As observed from the figure, the deep red scatter points corresponding to GCW are densely distributed and farthest from the center. For MetS and GWW, a considerable number of red and blue scatter points are visible with relatively high numerical

dispersion and moderate distances from the center. Scatter points for HDL are mainly light-colored with few red points; most samples cluster at medium-low levels, with limited high-value individuals and short distances to the center. The TyG index has the lightest, sparsest scatter points located closest to the center.

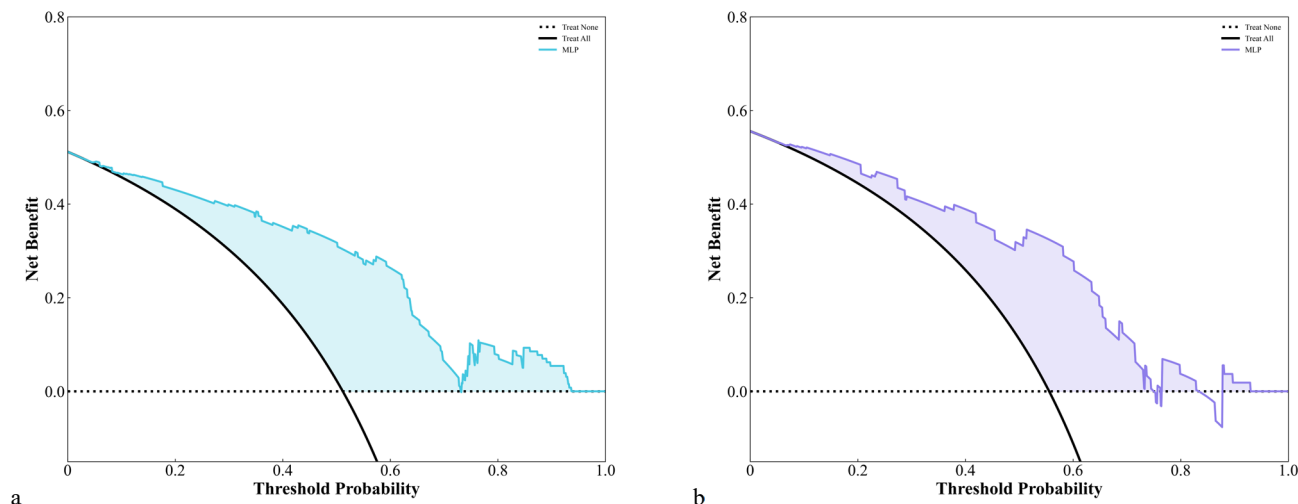


Figure 3. Decision curves analysis of MLP
a: Training set; b: Validation set

Figure 5, the feature importance ranking bar chart, intuitively demonstrates the contribution magnitudes of the above variables: GCW ranks highest, MetS and GWW

occupy the middle tier, HDL falls into the medium-low range, and the TyG index shows the lowest contribution.

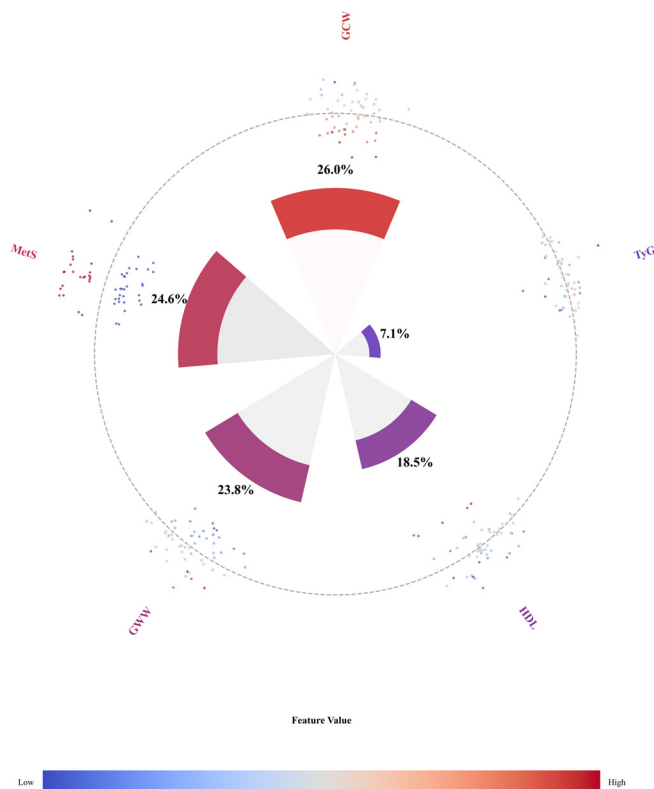


Figure 4. The Double-loop Analysis Chart of Feature Effects

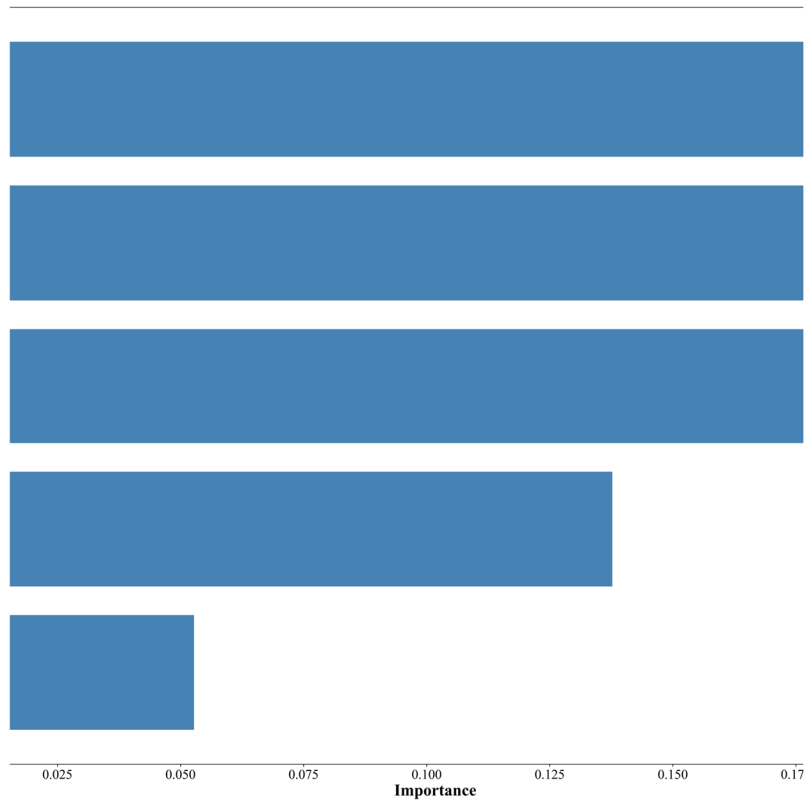


Figure 5. Bar Chart of Feature Importance Ranking

Figure 6 illustrates the correlation between the value of each variable and its corresponding SHAP value. Feature values are distinguished by color, and the horizontal axis represents SHAP values; a larger absolute SHAP value indicates a stronger influence of the variable on MLP model prediction. GCW presents a wide range of SHAP values: high GCW values (red dots) cluster in the negative SHAP region, while low GCW values (blue dots) gather in the positive

SHAP region, suggesting that higher GCW corresponds to a lower risk of CHD onset. High values of MetS and GWW are associated with positive SHAP values, making them risk factors for CHD. High HDL values concentrate in the negative SHAP interval, acting as a protective factor. The SHAP values of the TyG index are mainly distributed within -0.2 to $+0.2$, showing only a weak positive correlation and exerting the slightest impact on model prediction.

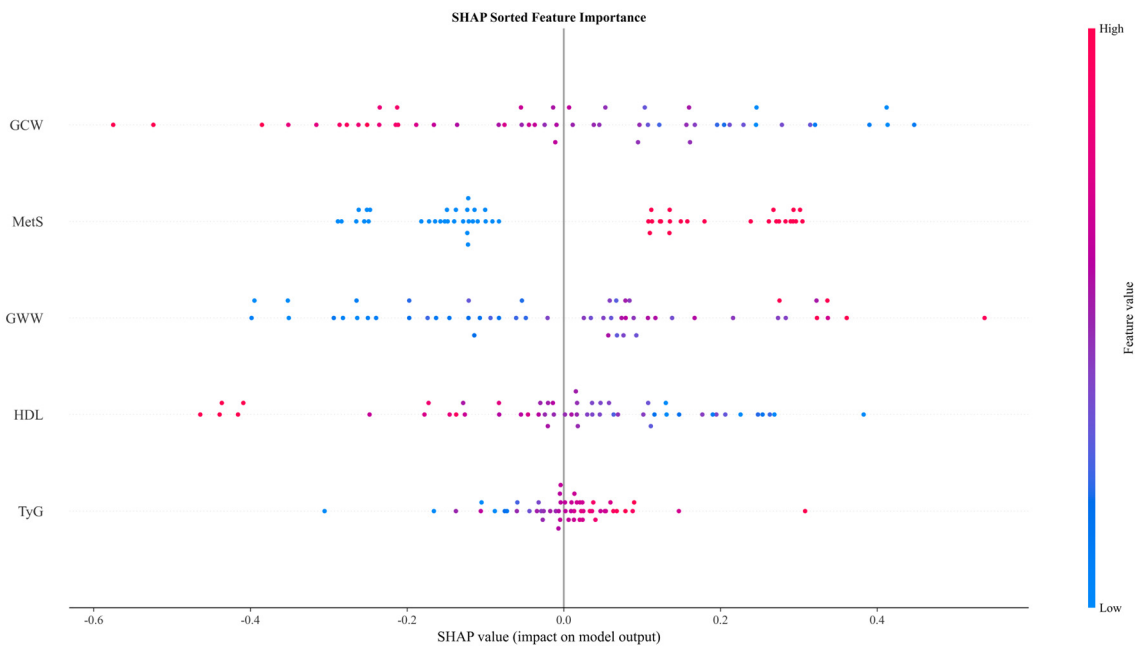


Figure 6. SHAP Summary Plot

To explore the interaction between variables, feature interaction plots (Figure 7) were drawn in this study. The

results revealed a significant non-linear interaction effect between GCW and MetS. SHAP values were mostly positive

when GCW was low, and turned negative after GCW rose above 2000. Within the high GCW range, the protective effect of GCW was attenuated in the MetS-positive subgroup,

whereas the protective function of GCW was prominent in the MetS-negative subgroup, indicating that MetS can significantly modulate the predictive effect of GCW on CHD.

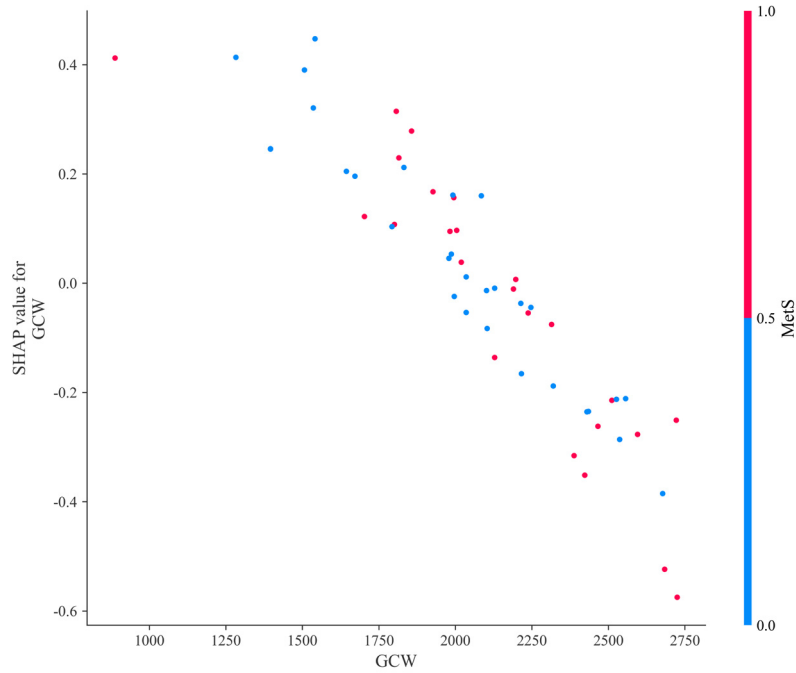


Figure 7. Feature Interaction Dependency Plot

Figure 8 is a sample prediction path diagram including misclassified cases. In this study, prediction path visualization was adopted to interpret the decision logic of the model. Each line corresponds to the changing path of predicted value for a single sample; red highlighted lines denote misclassified samples identified by the model, and the jitter amplitude of lines reflects the instability of feature contribution. From the

sample prediction path diagram with misclassification information, it can be observed that the prediction paths of overall samples (a) remain relatively stable. Nevertheless, substantial path fluctuations exist for a small number of samples (b), which suggests that the MLP model has decision blind spots when dealing with these misjudged samples.

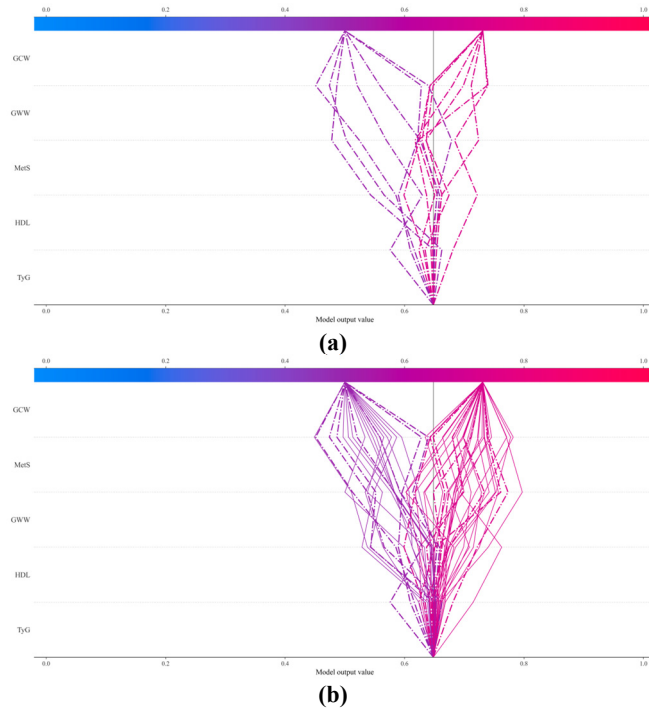


Figure 8. Sample Prediction Path Diagram (Including Misclassified Cases)
a: The whole sample; b: The minority sample

To evaluate the rationality and reliability of the model, prediction visualization was performed for a single specific

sample in this study. Figure 9 is a single-sample prediction explanation plot, which presents the actual value of each

indicator and its corresponding SHAP value. When GCW was 1541.5 mmHg%, the SHAP value reached +0.450, acting as the largest positive contributing factor that markedly elevated the model's predicted risk. In the absence of combined MetS, the SHAP value was -0.13, serving as a negative influencing factor for the model. At a GWW level of 260.5 mmHg%, the SHAP value was +0.07, exerting a mild positive effect. When

HDL was 1.32 mmol/L, the SHAP value was -0.02, and the TyG index of 8.949 corresponded to a SHAP value of +0.02; both variables exerted only trivial effects. Taken together, GCW provided the dominant positive driving effect on the predictive result of this sample, while MetS exerted an inhibitory negative effect, with all other features contributing minimally.

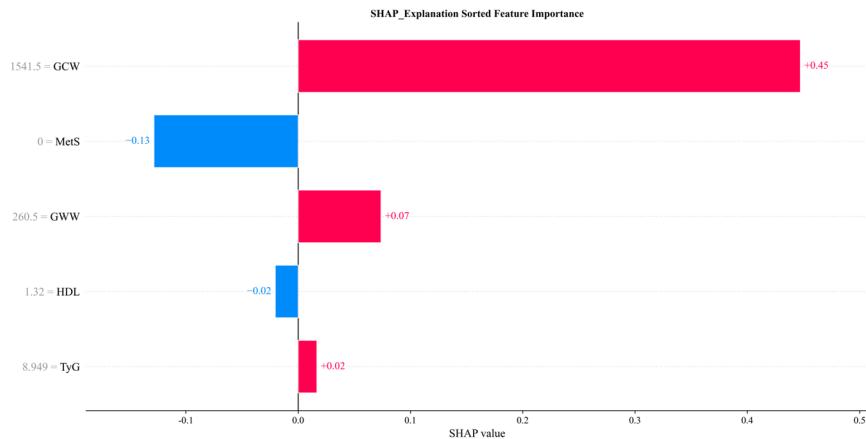


Figure 9. SHAP Explanation for Instance

Figure 10 is a feature importance heatmap. The contribution differences of each variable are visualized by SHAP values and color gradients (warm and cold tones). GCW, MetS and GWW are high-importance predictors: GCW is displayed as dark color blocks with an average SHAP value of 0.194; MetS (0.184) and GWW (0.177) appear as

moderately dark blocks with the second-highest SHAP values. HDL is shown as light blue blocks with a SHAP value of 0.138, representing moderate importance. In contrast, the TyG index corresponds to the lightest color blocks and has the lowest SHAP value of 0.053, indicating the weakest predictive impact on CHD outcomes.

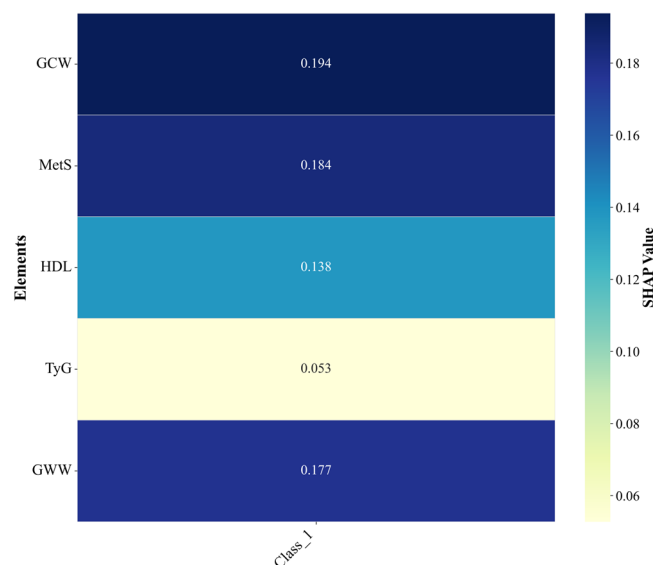


Figure 10. Feature Importance Heatmap

3.9. Inter-observer Consistency and Intra-observer Reproducibility Test of Non-invasive Myocardial Work Analysis

Table 9. Intra- and Inter-observer ICC of GLS and MW parameter measurements

group	ICC (95%CI)				
	GLS	GWI	GCW	GWW	GWE
intra-observer	0.877 (0.635~0.959)	0.945 (0.837~0.982)	0.965 (0.896~0.988)	0.928 (0.784~0.976)	0.876 (0.632~0.959)
inter-observer	0.910 (0.731~0.970)	0.899 (0.698~0.966)	0.947 (0.842~0.982)	0.919 (0.760~0.973)	0.796 (0.393~0.932)

ICC, the intraclass correlation coefficient, reflects the correlation degree among variables within the same dataset, ranging from 0 to 1. An ICC greater than 0.6 indicates strong consistency. The ICC values of two repeated measurements performed by a single operator are summarized in Table 9. The results demonstrated that the measurements of GLS and myocardial work (MW) parameters acquired by the two sonographers exhibited favorable intra-observer reproducibility and inter-observer consistency.

4. Discussion

The incidence of CHD is rising worldwide. Early clinical manifestations of CHD are insidious, making rapid identification challenging for clinicians. Conventional diagnostic models for CHD are limited by unsatisfactory predictive efficacy and poor interpretability. To date, few machine learning diagnostic models for CHD have been constructed by combining non-invasive myocardial work parameters with glycolipid metabolic indicators. In the present study, six machine learning models were established integrating non-invasive myocardial work parameters and glycolipid metabolic markers, among which the MLP model achieved favorable diagnostic performance for CHD. Within the MLP model, GCW contributed the most to prediction, followed by MetS and GWW; HDL exerted a moderate effect, while the TyG index had the lowest predictive weight.

This study analyzed the clinical predictive value of relevant echocardiographic parameters including LVEF, GLS and myocardial work (MW) parameters for CHD. The results demonstrated that GCW and GWW among MW parameters served as independent predictors of CHD, whereas LVEF and GLS were not independent predictive factors for CHD. GLS and LVPW are morphological markers secondary to myocardial ischemia, which are susceptible to confounding factors such as hypertension and cardiomyopathy; their predictive efficacy declines even after adjustment for confounders[18]. In contrast, the MW technique eliminates the interference of preload on conventional strain parameters and enables earlier detection of cardiac dysfunction and energy consumption caused by myocardial ischemia [19-21]. During coronary ischemia, subendocardial myocardium is injured first. Impaired ATP hydrolysis for energy supply damages myocardial contractile proteins and reduces effective myocardial work, accompanied by decreased GCW[22]. Coronary stenosis disrupts the timing of regional myocardial motion and raises wasted myocardial energy, leading to elevated GWW. This finding matches the result of our MLP model that GCW exerts the strongest predictive weight, followed by moderate contribution of GWW. No statistically significant differences were observed for GWI and GWE in the present study. This may be explained by the fact that early ischemia only involves a small number of myocardial segments together with the Frank-Starling compensatory effect, resulting in subtle variations of these two parameters[23]. In addition, the limited sample size may weaken the statistical power to detect their predictive performance. Accordingly, GCW and GWW have unique advantages in identifying early CHD without obvious regional wall motion abnormalities.

This study verified via univariate and multivariate Logistic regression that MetS, HDL-C and TyG index were independent predictors of CHD, consistent with previous studies. This indicates that the three indicators reflect

glycolipid metabolic disorders from distinct dimensions, and thus can evaluate the risks of atherosclerosis and early myocardial ischemia[24-26]. As a major risk factor for CHD, MetS ranked second only to GCW in feature contribution within the MLP model. MetS triggers endothelial injury, lipid deposition and chronic inflammation mediated by insulin resistance; multiple metabolic abnormalities jointly aggravate coronary atherosclerosis, enabling comprehensive assessment of systemic metabolic burden[27]. HDL-C serves as a cardiovascular protective factor, exerting vascular protective effects through reverse cholesterol transport, anti-inflammatory and anti-oxidative mechanisms[28, 29]. Reduced HDL-C accelerates lipid deposition in coronary arteries, with a moderate predictive weight between MetS and the TyG index in our model. As a convenient marker of insulin resistance, the TyG index was significantly correlated with CHD in Logistic regression analysis, and multiple meta-analyses have validated that elevated TyG index elevates the incidence risks of atherosclerosis and cardiovascular diseases[30]. Nevertheless, the TyG index exhibited the lowest predictive contribution in the interpretability analysis of the MLP model, which differed from its strong correlation observed in Logistic regression. This discrepancy stems from the fundamental differences between the two analytical approaches: Logistic regression focuses on statistically independent associations after adjusting for confounders, whereas machine learning prioritizes the actual marginal predictive benefit of each variable. Partial overlap exists in the biological pathways of the TyG index and MetS, leading to information redundancy. MetS covers most metabolic disorder information carried by the TyG index, thereby diminishing the weight of the TyG index in the machine learning model. Further research is required to dissect the pathological pathways linking MetS and the TyG index and clarify the independence of their biological effects.

CHD is a multifactorial disease resulting from the combined effects of metabolic disorders, hemodynamic changes and myocardial dysfunction. Most conventional predictive models established in previous studies only adopt a single type of predictor, such as serological indicators or imaging parameters alone. Moreover, traditional Cox proportional hazards regression and Logistic regression are restricted by linear assumptions, which tend to ignore complex associations among variables. As a feedforward neural network, the MLP model is capable of capturing non-linear interactions between features[31]. Feature interaction analysis in our study confirmed a prominent non-linear interaction between GCW and MetS. In patients complicated with MetS, metabolic disturbances attenuate the protective effect of favorable myocardial function. Although myocardial compensation can partially offset the risks induced by glycolipid metabolic disorders, such compensation cannot fully reverse adverse outcomes. This finding indirectly indicates that clinicians should comprehensively evaluate the dynamic changes of both myocardial function and metabolic status for early CHD identification, rather than making arbitrary judgments relying merely on a single indicator.

This study has several limitations. First, it is a single-center investigation with a limited sample size. Only internal validation was performed, while external multi-center validation was absent. Therefore, the generalization ability, stability and universality of the model remain to be further verified. Future multi-center prospective studies with

expanded clinical datasets will be carried out to improve model performance and enhance the reliability of the findings.

In conclusion, the interpretable MLP machine learning model constructed based on glycolipid metabolic markers and non-invasive myocardial work parameters serves as an effective tool for the early diagnosis of CHD, improving predictive efficacy and enabling more comprehensive and accurate risk evaluation. It can provide evidence for non-invasive preoperative risk stratification in patients with suspected coronary heart disease and help reduce unnecessary CAG.

Patents

Author Contributions: CL and JQW: Writing, reviewing, editing, and validation.

Institutional Review Board Statement: This study was conducted according to the guidelines of the Declaration of Helsinki.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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