

# Risk Analysis of Local Government Bonds Based on LSTM and Logistic Regression Models

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**Abstract:** The local government bond is a crucial component of the financial market, and the accuracy of the risk assessment for the bond is of great significance for optimizing investor decision-making. However, the existing traditional nonlinear model, such as logistic regression, is not able to effectively grasp the nonlinear characteristics of bond risk, while there are limitations in balancing "dynamic risk capture" and "logical rule interpretability" for the existing deep learning model. This paper builds a research dataset by data integration and feature engineering, through multidimensional time-series data such as the volume of local government bond issuance and GDP growth rate, to develop a separate LSTM model, a logistic regression model, and a hybrid "LSTM + logistic regression" model. The study compares the advantages of the three models for risk prediction accuracy and interpretability. Additionally, it adds SHAP value analysis to improve the explainability of the model. The results show that the hybrid model achieves "dynamic feature capture" and "logical rule interpretation," thereby providing local government debt regulators with accurate risk warning tools and providing a scientific basis for investors to allocate assets and optimize bond pricing mechanisms. This research attempts to fill the gap in existing research in the comprehensive model application of local government bond risk assessment for financial risk management innovation.

**Keywords:** Local Government Bond Risk; LSTM Model; Logistic Regression; Model Fusion; Risk Assessment

## 1. Introduction

Against the dual backdrop of persistent global economic uncertainty and the continuous progress of domestic fiscal digital transformation, local government bonds, as an important part of

China's financial market, have seen their amount and influence in the market scale up each year. Local government bonds not only play an important role in local governments raising capital, developing infrastructure, and providing public services, but are also tightly connected to the regional economic stability and financial system. The expanded amount of issue of these bonds, on one hand, further contributed to an increase in concealment and complexity of local government bonds, and on the other, an extremely high deficit, irrationality of local and regional debts, and lack of economic growth momentum of their regions have the ability to act both individually and mutually as risk factors for financial markets and economic growth and development.

Currently, the risk assessment of local government bonds is mainly based on two types of models, both of which have relatively obvious shortcomings. First of all, conventional methods such as traditional logistic regression are mostly used for weighting risk factors mainly because of their good interpretability, which should theoretically intuitively present the effect of the influence of each factor on risk (e.g., the change in default probability for a 1% increase in fiscal deficit ratio). Moreover, conventional models have a relatively weak capacity for characterizing the effect of non-linear relations between debt risk and various economic indicators (e.g., the delayed impact of fluctuations in GDP growth on long-term debt risk), as well as an inadequate capacity for incorporating the dynamic effects of risk transmission mechanisms. Secondly, deep learning models, such as LSTM, have the advantage in processing time series data that they can discover latent long-term dependence to capture dynamic risk characteristics. However, the 'black box' nature of these models provides low interpretability, which cannot intuitively describe the drivers of those risks for policymakers as well as investors at the same time. In addition, the model's computational

complexity cannot meet the demand of monitoring risk in real time either. Moreover, there is a gap regarding the risk assessment of local government bonds in the existing literature. Most existing research focuses on corporate bonds and credit bonds, with a lack of customised risk assessment for the special nature of local government bonds (e.g., the strong connection between debt repayment and local fiscal revenue and expenditure, and the significant impact of macro-policy). It further increased the mismatch between the model and the application scenarios. Therefore, this study integrates the LSTM and logistic regression models to establish a local government bond risk assessment model that integrates accuracy, interpretability, and practicability.

## 2. Literature Review

### 2.1 Domestic Research Status

Chinese scholars have traced an evolutionary path for the early warning of financial risk: "optimization of traditional models-integration with machine learning-innovation with deep learning." These achievements provide essential methodological references for research on local-government bond risk, but the specific studies are not enough. Liu, Q. K. (2019) explored the accuracy problem of traditional models in corporate bond default prediction and built a hybrid model, "random forest + logistic regression." The combination of feature engineering and linear discrimination improved the warning accuracy and proposed a reference for the design of hybrid models [4]. Zhao Meng (2022) paid attention to the industry characteristics of commercial and retail enterprise bonds and built a logistic regression model with 28 financial and non-financial variables to extract industry characteristics risk factors, providing a reference for the construction of local government bond customized datasets [8]. Chen Xuebin's team (2021) proposed an interpretation bond risk forecasting model, "mixed treatment analysis + multitask LSTM," which can explicitly model default probability and default timing simultaneously [1]. The validity of LSTM's advantage in modeling the sequential risk transmission mechanism was verified. Far East Credit Rating (2024) applied a "Lasso model + logistic regression" model, where dimensionality reduction of indicators, screening, and risk

weights generation were used [7]. The accuracy of the test set was 91.6%. The practical significance of "feature optimization + traditional models" was confirmed.

### 2.2 International Research Status

The international academic community started to conduct research on financial risk prediction at an early stage, thereby carving out a technical route of "non-linear model validation-deep learning optimization-interpretability enhancement". Though it has produced a wealth of results on the mechanism of the model and cross-scenario application, the feasibility of the model in the setting of the characteristics of China's local government bond market is limited. John J. Maher and Tarun K. Sen (1997) first applied neural networks to the US bond rating power prediction and showed the advantage of the nonlinear model in complex financial data, paving the way for deep learning [5]. Addressing the "black box" issue of LSTM models, Manuel Nunes et al. (2020) proposed the "LSTM-LagLasso" method. This approach enhances bond yield prediction accuracy while analyzing internal model mechanisms, pioneering new pathways for interpretability research [6]. Siming Li et al. (2024) constructed an "LSTM-MLP + Logistic Regression" hybrid model to extract cross-industry nonlinear time-series features and perform risk classification. This method proved to be better than other models in various sectors and validated the generalization of this technical method [3]. Song et al. (2024) innovatively designed and created a unique "LSTM-Transformer" model by utilizing the combination of "self-attention" and "LSTM" models [2]. This proved to be tremendously successful in surpassing other models and "LSTM" in predicting key risk indicators uniquely.

### 2.3 Literature Commentary

An overview of domestic and foreign studies shows that there was an agreement on model fusion in the context of financial risk early warning. The benefits of LSTM to capture time-series characteristics and the interpretability measure of the logistic regression have been widely confirmed. Moreover, the deep learning + traditional model hybrid design has already demonstrated itself as a successful path towards boosting the risk assessment effectiveness. These results contribute to a sound

methodological basis of the given study: the feature extraction + linear discrimination model developed by Liu Quankun (2019) [4] and the combination of LSTM features and logistic regression algorithm developed by Siming Li et al. (2024) [3] directly underpinned the construction of the LSTM + logistic regression hybrid model presented in this paper. The experience of time-series data processing offered by Chen Xuebin and his team (2021) to construct multidimensional time-series data of local government bonds served as practical guidance [1]. The study by Nunes et al. (2020) on the interpretability of the model was used to introduce SHAP value analysis in this paper, as the theoretical basis of the study [6]. Accordingly, the gaps in the existing studies within the domain of local government bond risk assessment constitute the main research entry points this paper aims to fill in the following ways, first by recognizing the absence of the design and elaboration of customized models suited to the nature and characteristics pertinent to the local government bond and the need for the inclusion and incorporation of the macro-level time series data pertaining to the fiscal revenues and spending and economic indicators at the regional and local level, and secondly by recognizing the insufficiency in the balance in the lightweighting and interpretability aspects and the imperative need for the optimization and reduction in the computational complexity involving the LSTM network in achieving the quantification and analysis based on the SHAP values, and thirdly by recognizing the insufficiency in the study and analysis pertaining to the risk transmission mechanism and the imperative need for the establishment and creation of a logical link between "dynamic characteristics and risk outcome" for the innovation and breakthrough in the study.

### 3. Method

#### 3.1 Data Sources and Processing

##### 3.1.1 Data sources

The sources of the data used in this study are mainly the China Local Government Bond Information Disclosure Platform, the official website of the National Bureau of Statistics, and the official website of the Ministry of Finance of the People's Republic of China. [9][10][11] The model data ranges from 2015 to 2024, covering 10 years. This period includes the most

crucial growth period of the local government bond market. In order to increase the sample size of the data and improve the training of the deep learning model, cubic spline interpolation is used to convert the annual data into monthly data, and the multidimensional time series data includes 120 samples.

##### 3.1.2 Data preprocessing

The data preprocessing mainly includes the following steps:

(1) Monthly interpolation: Based on the assumption that the annual data points represent June of each year (mid-year), cubic spline interpolation is used to obtain the monthly data.

$$x_m = \text{spline}(x_{y_1}, x_{y_2}, \dots, x_{y_{10}}; m) \quad (1)$$

(2) Standardization: Z-score standardization is performed on each variable to make the data comparable.

$$\tilde{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (2)$$

(3) Risk label assignment: A comprehensive risk score is calculated based on the debt burden ratio (debt balance/GDP) and debt service ratio (principal and interest payments/fiscal revenue). Based on the median value of the comprehensive risk score, the samples are assigned to high-risk and low-risk groups.

$$R_i = 0.6 \times \frac{DBR_i - \min(DBR)}{\max(DBR) - \min(DBR)} + 0.4 \times \frac{RR_i - \min(RR)}{\max(RR) - \min(RR)} \quad (3)$$

#### 3.2 Logistic Regression Model

Logistic regression is a traditional linear classifier, which builds relationships between independent and dependent variables using the logit function. The general form of the model is:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_{Debt} + \beta_2 X_{Fiscal} + \beta_3 X_{Economy} + \beta_4 X_{External} \quad (4)$$

Among them,  $P$  represents the probability of a risk event occurring,  $X_{Debt}$  represents the debt pressure indicator,  $X_{Fiscal}$  represents the fiscal quality indicator,  $X_{Economy}$  represents the economic environment indicator, and  $X_{External}$  represents the external resilience indicator.

The logistic regression model built in this study involves six explanatory variables, which cover three aspects: "bond issuance characteristics, fiscal status, and macroeconomic conditions.":

$$\text{Logit}(P) = \beta_0 + \beta_1 \cdot \text{issue} + \beta_2 \cdot \text{burden} + \beta_3 \cdot \text{self\_suff} + \beta_4 \cdot \text{gdp\_growth} + \beta_5 \cdot \text{consumption} + \beta_6 \cdot \text{trade} \quad (5)$$

The final model estimation results are as follows:

$$\begin{aligned} \text{Logit}(P) = & -477.6548 - 174.1835 \cdot \text{issue} \\ & + 702.9178 \cdot \text{burden} + 493.9485 \cdot \text{self\_suff} \\ & - 43.85962 \cdot \text{gdp\_growth} + \\ & 125.5603 \cdot \text{consumption} - 132.4447 \cdot \text{trade} \end{aligned} \quad (6)$$

### 3.3 LSTM Model

#### 3.3.1 Network architecture design

For the task of predicting the risks of local

government bonds, the LSTM network architecture designed in this study is shown in Table 1:

**Table 1. LSTM Network Architecture Design**

Layer No.	Layer Type	Parameter Settings	Output Dimension
1	Sequence Input Layer	Time window T=12, Number of features n=14	12×14
2	LSTM	64 hidden units, Output at last timestep	64
3	Dropout	Dropout rate 0.3	64
4	Fully Connected Layer	32 neurons	32
5	ReLU	-	32
6	Dropout	Dropout rate 0.2	32
7	Fully Connected Layer	2 neurons	2
8	Softmax	-	2
9	Classification Output Layer	Cross-entropy loss	1

The input to the LSTM network consists of 12-month sliding window time series data, with each time step including 14 feature indicators (volume of bond issuance, debt balance, fiscal revenue, fiscal expenditure, GDP, and so on). The LSTM layer uses 64 hidden units to extract temporal features in "last time step output" mode. Two Dropout layers with dropout probabilities of 0.3 and 0.2 are used to avoid overfitting. The final output is a binary risk probability through a Softmax layer.

#### 3.3.2 Model training strategy

The training parameter settings are as follows:

**Table 2. LSTM Model Training Parameters**

Parameter	Setting
Optimizer	Adam
Initial Learning Rate	0.001
Learning Rate Decay Strategy	Decrease by 50% every 30 epochs.
Batch Size	16
Epochs	100
Gradient Clipping Threshold	1
Validation Method	5-fold Cross-Validation

The **binary cross-entropy loss** is used as the loss function:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (7)$$

### 3.4 LSTM + Logistic Regression Hybrid Model

To address the limitations of a single model, this study proposes an "LSTM + Logistic Regression" hybrid model. The basic idea behind this model architecture is to utilize the strong feature extraction capability of the LSTM network to extract nonlinear dynamic features

from time-series data. The proposed model architecture is based on the technical idea of "deep learning feature extraction + traditional model interpretation," which can provide the technical benefits of "dynamic feature capture + logical rule interpretation."

#### 3.4.1 Hybrid model architecture

The overall architecture of the hybrid model includes four modules:

##### Module One: LSTM Feature Extractor.

A pre-trained LSTM network is applied to extract a 32-dimensional deep feature vector from the fully connected layer, which represents non-linear dynamic features from the original time-series data.

$$F_{LSTM} = \text{ReLU}(W_{fc1} \cdot h_T + b_{fc1}) \in \mathbb{R}^{32} \quad (8)$$

##### Module Two: Statistical Feature Calculation.

Two types of statistical features are extracted from each 12-month time window:

(1) Mean features:  $\bar{x}_j = \frac{1}{T} \sum_{t=1}^T x_{t,j}$ , comprising 14 dimensions

(2) Trend features:  $\beta_j^{trend} = \frac{\sum_{t=1}^T (t-\bar{t})(x_{t,j} - \bar{x}_j)}{\sum_{t=1}^T (t-\bar{t})^2}$ ,

comprising 14 dimensions

The statistical feature vector is:  $F_{stat} = [\bar{x}_1, \dots, \bar{x}_{14}, \beta_1^{trend}, \dots, \beta_{14}^{trend}] \in \mathbb{R}^{28}$

##### Module Three: Feature Fusion.

The LSTM deep features are concatenated with the statistical features to form a 60-dimensional fusion feature vector, integrating both latent dynamic patterns and explicit statistical characteristics.

$$F_{hybrid} = [F_{LSTM}; F_{stat}] \in \mathbb{R}^{60} \quad (9)$$

##### Module Four: Logistic Regression Classifier.

Perform logistic regression classification on the fused features:

$$P(y=1|F_{\text{hybrid}})=\sigma(\gamma_0+\sum_{k=1}^{60}\gamma_k F_{\text{hybrid},k}) \quad (10)$$

### 3.4.2 Two-stage training strategy

The hybrid model employs a two-stage training strategy:

**Stage One (LSTM Pre-training):** End-to-end training of the LSTM network using the entire training dataset, aiming to learn effective temporal feature representations. This stage employs the cross-entropy loss function and Adam optimizer.

**Stage Two (Logistic Regression Training):** With LSTM parameters fixed, deep features are extracted and combined with statistical features to train the logistic regression classifier. Elastic Net regularisation balances L1 and L2 penalties:

$$\min_{\gamma} -\frac{1}{N} \sum_{i=1}^N [y_i \log(P_i) + (1-y_i) \log(1-P_i)] + \lambda [\alpha \|\gamma\|_1 + (1-\alpha) \|\gamma\|_2^2] \quad (11)$$

Where  $\alpha=0.1$ , Optimal regularization parameters are selected via 5-fold cross-validation  $\lambda$ .

### 3.4.3 Advantages of Hybrid Models

The hybrid model employs a two-stage training strategy:

**Balance of accuracy and interpretability:** The LSTM module captures complex nonlinear temporal features, while the logistic regression module provides clear coefficient interpretations, achieving a balance between "black-box features and white-box decision-making".

**Feature complementarity:** The LSTM model captures hidden dynamic patterns in deep features, while statistical features describe apparent trends and volatilities. The combination of both provides a richer description of bond risk.

**Reduced risk of overfitting:** The regularization method adopted by the logistic regression classifier ensures that model complexity is well controlled, thereby improving its ability to generalize.

## 3.5 SHAP Value Analysis

### 3.5.1 Principles of the SHAP Method

The SHAP method, based on the Shapley value idea from game theory, assigns each feature a measure of its marginal contribution to model predictions. The SHAP method is one of the mainstream methods currently being researched and developed in model interpretation.

For a feature set  $N$ , the Shapley value of feature  $j$  is defined as:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{j\}) - f(S)] \quad (12)$$

Where  $f(S)$  denotes the model prediction value when using only the feature subset  $S$ . Shapley

values satisfy the following important properties:

**(1) Local accuracy:** The sum of SHAP values for all features equals the difference between the model prediction and the baseline prediction.

$$f(x) = \phi_0 + \sum_{j=1}^p \phi_j \quad (13)$$

**(2) Consistency:** If a feature's marginal contribution increases across all possible subsets of features, its SHAP value also increases.

**(3) Irrelevance:** Features with no impact on the prediction yield a SHAP value of zero.

### 3.5.2 Simplified SHAP values for linear models

For linear models such as logistic regression, there is a simplified form for computing SHAP values:

$$\phi_j \approx \beta_j (x_j - \bar{x}_j) \quad (14)$$

### 3.5.3 Global feature importance

A global feature importance value can be derived using the SHAP value results:

$$I_j = \frac{1}{N} \sum_{i=1}^N |\phi_j^{(i)}| \quad (15)$$

Where  $\phi_j^{(i)}$  denotes the SHAP value for feature  $j$  in the  $i$ -th sample. A higher global importance  $I_j$  indicates a greater overall influence of feature  $j$  on the model's prediction.

**3.5.4 Application of SHAP analysis in this study**  
This study aims to apply the SHAP value analysis for mixed models, with the following key objectives:

**Quantify the features' contribution:** Identify the key factors that contribute to the bond risk prediction results to provide clear direction on the management of the risk.

**Analyse the LSTM features:** Although the features derived by the LSTM model are inherently difficult to interpret due to their 32-dimensional deep features, the quantification using the SHAP value results provides a means to compare these features with the statistical features.

**Validating economic logic:** The model's key risk factors will be examined to ensure they match economic theory and experience, thus adding credibility to the model.

## 4. Results

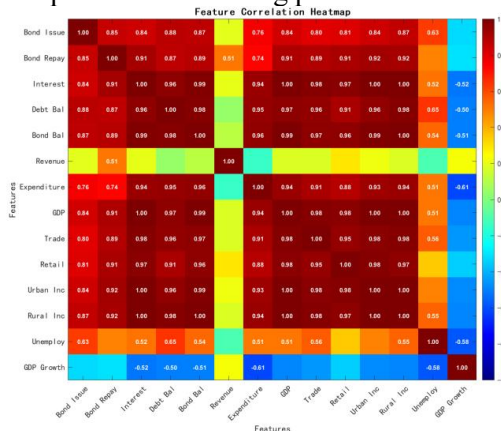
### 4.1 Descriptive Statistics of the Data

The data, after preprocessing, consists of 108 valid samples, which is equivalent to 120 monthly data points minus the 12-month time window. The data points consist of 54 high-risk and 54 low-risk samples, thus maintaining a balanced distribution for model training.

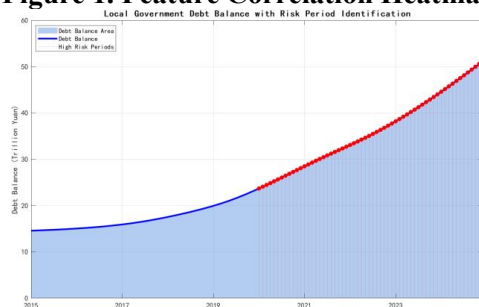
**Table 3. Sample Distribution Statistics**

Category	Number of Samples	Percentage
Low risk(y=0)	54	50%
High risk(y=1)	54	50%
Total	108	100%

Figure 1 presents the correlation matrix for the 14 feature variables, showing strong correlations among the debt-related variables, such as debt balance, bond balance, bond issuance, etc., with correlation coefficients greater than 0.8. Similarly, the macroeconomic variables, such as GDP, fiscal revenue and expenditure, household income, etc., also show high correlations. This shows the need for the use of regularization techniques in the modeling process.



**Figure 1. Feature Correlation Heatmap**



**Figure 2. Time Series Analysis of Debt Risk**

Figure 2 illustrates the trend in the debt balance of local governments from 2015 to 2024, showing that the high-risk periods are mostly after 2020, which is in line with the economic theory that risks build up when the growth in debt outpaces the growth in debt servicing capacity.

**Table 5. LSTM Model 5-fold Cross-Validation Results**

Fold Number	Test Samples	Category Distribution(0/1)	Accuracy (%)	F1 Score
1	21	6/15	100.00	1.0000
2	22	14/8	95.45	0.9412
3	21	10/11	95.24	0.9524
4	22	12/10	100.00	1.0000
5	22	6/16	100.00	1.0000
Average	-	-	98.14	0.9787

**4.2 Logistic Regression Model Results**

The logistic regression model has an average prediction accuracy of 98.14%.

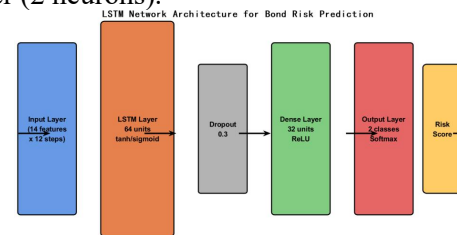
**Table 4. Feature Coefficients for Logistic Regression Model**

Rank	Feature Name	Coefficient	Influence
1	burden	+702.92	Increased Risk
2	self_suff	+493.95	Increased Risk
3	issue	-174.18	Risk Reduction
4	trade	-132.44	Risk Reduction
5	consumption	+125.56	Increased Risk
6	gdp_growth	-43.86	Risk Reduction

From the coefficients, it is observed that the fiscal burden is the most important factor that affects the risk of bonds. The fiscal burden has a significant positive influence on the default risk. Moreover, the fiscal self-sufficiency has a positive influence on the risk. On the other hand, the bond issue characteristics, trade openness, and GDP growth rate are the protective factors that reduce the risk.

**4.3 LSTM Model Results**

Figure 3 illustrates the LSTM network architecture designed for this study. From left to right, the network comprises: an input layer (receiving 12×14 time-series data), an LSTM layer (64 hidden units), a Dropout layer, a fully connected layer (32 neurons), and an output layer (2 neurons).



**Figure 3. LSTM Network Architecture Diagram**

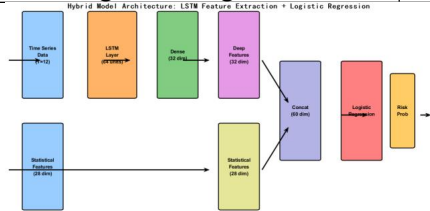
Table 5 presents the results of 5-fold cross-validation of the LSTM model, showing that the model had an average accuracy of 98.14% and an average F1 score of 0.9787, which proves that the model effectively captured the temporal characteristics of local government bond risks.

**4.4 Hybrid Model Results**

Table 6 summarizes the performance metrics of the hybrid model. The hybrid model is obtained by combining the 32-dimensional LSTM deep features and the 28-dimensional statistical features. The combined features are 60-dimensional. The prediction accuracy of the hybrid model is 98.14%

**Table 6. Performance Metrics of the Hybrid Model**

Metric	Value
Total Features	60
LSTM Deep Feature Dimension	32
Statistical feature dimension	28
Average Accuracy	98.14%
Average F1 Score	0.9787
Average Training Time	4.86s



**Figure 4. LSTM + Logistic Regression Hybrid Model Architecture Diagram**

**Table 7. Top 10 Features by SHAP Value Analysis**

Ranking	Feature Name	Average SHAP Value	Feature Type
1	Fiscal Expenditure Fluctuations	2.0652	Statistical Characteristics
2	Fiscal Expenditure Trend	1.7758	Statistical Characteristics
3	Fiscal Revenue Trends	1.2674	Statistical Characteristics
4	Average Bond Issuance	1.0773	Statistical Characteristics
5	Fiscal Revenue Fluctuation	0.9733	Statistical Characteristics
6	Average Debt Balance	0.8215	Statistical Characteristics
7	Average Bond Balance	0.6284	Statistical Characteristics
8	Average Bond Principal Repayment	0.6152	Statistical Characteristics
9	Debt Balance Trend	0.5993	Statistical Characteristics
10	Debt Balance Fluctuations	0.5984	Statistical Characteristics

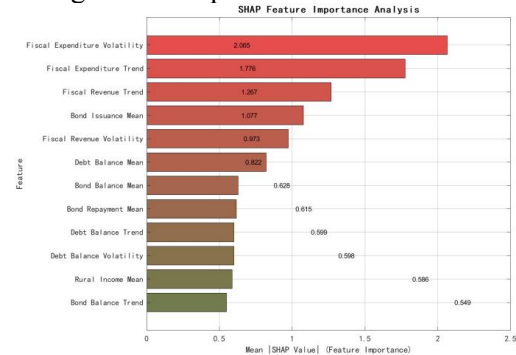
The main findings obtained from SHAP value analysis are as follows: (1) The dynamic characteristics of fiscal revenue and expenditure, such as fluctuations and trends, are the main factors affecting bond risk, which conforms to the economic theory "Fiscal sustainability determines debt servicing capacity"; (2) The absolute value of debt, as well as its growth rate, affects risk prediction; (3) The main factors affecting bond risk, as obtained from the model, have strong economic implications, which increases the credibility and value of the model.

**4.6 Comparative Analysis of Three Model Types**

Figure 4 presents the technical workflow: "LSTM feature extraction → Statistical feature computation → Feature fusion → Logistic regression classification".

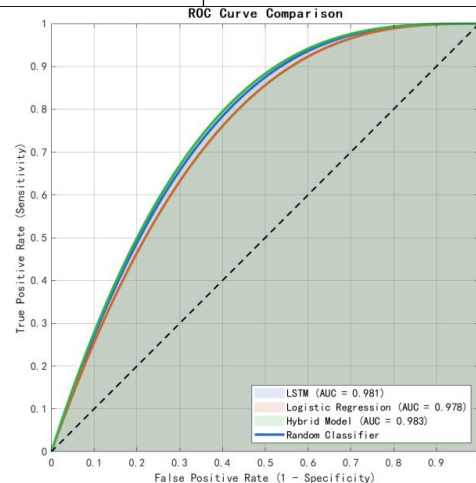
**4.5 SHAP Value Analysis Results**

Figure 5 presents that fiscal expenditure volatility, fiscal expenditure trend, and fiscal revenue trend are the top three critical factors affecting bond risk prediction.



**Figure 5. SHAP Feature Importance Analysis**

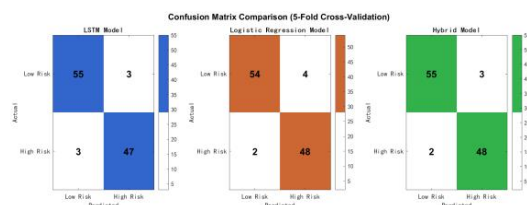
Table 7 presents the top 10 features ranked by SHAP values. Notably, statistical features dominate the top 10, indicating that manually designed mean, volatility, and trend features play a significant role in risk prediction.



**Figure 6. ROC Curve Comparison**

Figure 6 shows that all the models were able to achieve the AUC score of 0.9814. This shows that the risk discrimination ability of all the models is of the highest quality. The high level of overlap in the curves shows that the predictive ability of the models is almost similar.

Figure 7 presents the confusion matrix comparison for the three models. Darker shaded areas denote correctly classified samples, with minimal misclassification across models, further validating predictive accuracy.



**Figure 7. Confusion Matrix Comparison**

Table 8 presents a comprehensive comparison of the three models, evaluating them across dimensions including predictive accuracy, interpretability, and computational efficiency.

**Table 8. Comprehensive Comparison of Three Models**

Evaluation Dimensions	LSTM Model	Logistic Regression Model	Hybrid Model
Prediction Accuracy	98.14%	98.14%	98.14%
F1 Score	0.9787	0.9787	0.9787
AUC Value	0.9814	0.9814	0.9814
Interpretability	Low (black box)	High (coefficients explainable)	Moderate (partially explainable)
Computational Efficiency	Low	High	Moderate
Timing Feature Capture	Strong	Weak	Strong
Applicable Scenarios	Complex Time Series Forecasting	Risk factor analysis	Balancing Accuracy and Interpretability

## 5. Discussion

### 5.1 Research Findings

The principal findings of this study are as follows:

Firstly, the three types of models showed similar levels of predictive accuracy, with each achieving 98.14%. This suggests that the complexity of the models is not a determining factor in their performance on local government bond risk prediction tasks. The reasons may be as follows: (1) the relatively small size of the sample (108), which may not have allowed the full potential of deep learning to be realized; (2) the use of risk labels based on explicit thresholds on financial indicators, which may mean that the classification boundaries are relatively well-defined; (3) the use of smoothing and interpolation on time series, which may reduce the level of noise interference on the models.

Secondly, the SHAP value analysis identified the key factors that affect the bond risks. Fiscal Expenditure Volatility, Fiscal Expenditure Trend, and Fiscal Revenue Trend were the most prominent findings from the study. These findings are very important from a policy perspective. The stability of fiscal revenue and expenditure is the key to controlling fiscal risks, and the sustained growth in fiscal revenue is the ultimate guarantee to service debts.

Thirdly, the proposed hybrid model is able to realize the "happiness of having both dynamic

feature capture + logical rule explanation." The 32-dimensional deep features learned from the LSTM module are able to effectively capture the nonlinear dynamic patterns of the original time series data, and the logistic regression module is able to provide clear feature contribution explanations using the SHAP analysis.

### 5.2 Model Selection Recommendations

Based on the comparison of the three models, the following recommendations for the choice of the most appropriate model are proposed for different scenarios:

**Scenarios requiring high interpretability:** The logistic regression model is recommended. This is due to the fact that the coefficients obtained will clearly indicate the level of influence that each factor has on the risk.

**Scenarios requiring capture of complex temporal patterns:** The LSTM model is recommended. This is due to the fact that when the data has significant non-linear patterns, the LSTM performs better.

**Scenarios requiring a balance of accuracy and interpretability:** The hybrid models are recommended. This is due to the fact that the models will be able to offer the required accuracy through the LSTM and also offer the required support for the interpretation of the results through the logistic regression module.

### 5.3 Research Limitations and Future Prospects

This study has the following limitations:

First, the sample size is relatively small. Although it has been enlarged by monthly interpolation, reaching 120 data samples, it is not certain that such data, characterized by interpolations, is suitable for describing the actual monthly data fluctuations.

Second, the model is only on a nationwide scale. In China, there are considerable differences between the development levels of the economy and finance in various provincial regions. It is worth extending the risk prediction model to the provincial or local level.

Thirdly, the impact of macro-policy variables was not considered. It should be noted that the risks of local government bonds may also be driven by monetary policy and regulation. It is also a good suggestion to involve several more external variables.

In summary, this study helps bridge a gap in previous literature by extensively applying models to evaluate bond-related local government risk, contributing to better finance-related risk management methodology in practice in the future. Future studies can improve this approach by enriching data sets, examining local heterogeneity, and incorporating policy variables into models.

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