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Machine Learning Model and Financial Feature Fusion for Innovative Enterprise Credit Assessment in Digital Supply Chain Finance

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Abstract: With the digital transformation of supply chain finance, traditional credit assessment methods have become increasingly inadequate in addressing the information asymmetry and risk transmission issues faced by innovative enterprises. This study proposes a hybrid machine learning framework integrating XGBoost feature selection and LSTM (Long Short-Term Memory) prediction to enhance the accuracy and interpretability of credit assessment. By constructing a multi-dimensional feature system that combines 18 financial indicators and 6 digital supply chain features, the model realizes dynamic risk identification for innovative enterprises. Based on a sample of 1,357 observations from 85 Chinese-listed innovative enterprises between 2019 and 2023, empirical results show that the proposed XGBoost-LSTM model achieves an accuracy of 98.2%, a recall rate of 97.5%, and an F1-score of 97.8%, outperforming traditional Logistic regression (82.3%), single XGBoost (94.1%), and MLP (Multi-Layer Perceptron) (95.6%) models. The research confirms that the fusion of operating cash flow stability, accounts receivable turnover efficiency, and supply chain transaction integrity significantly improves credit assessment performance. This study provides a feasible technical solution for financial institutions to implement precise risk control in digital supply chain finance.

Keywords: Digital Supply Chain Finance, Innovative Enterprises, Credit Assessment, Machine Learning, Feature Fusion, XGBoost-LSTM Model.

Disciplines: Finance. **Subjects:** Corporate Finance.

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1 INTRODUCTION

1.1 RESEARCH BACKGROUND

Digital supply chain finance (DSCF) has emerged as a critical financial innovation integrating information technology and supply chain management, effectively alleviating the financing difficulties of innovative enterprises by breaking information silos and credit barriers . Unlike traditional manufacturing enterprises, innovative enterprises typically have intangible asset-intensive characteristics, with unstable cash flows and high R&D investment risks, making their credit assessment more complex [1]. Traditional credit assessment methods rely heavily on static financial statements and core enterprise endorsements, failing to capture dynamic transaction data and potential risk transmission paths in the digital supply chain . As noted by Li et al. (2022), the abundance of business audit information in DSCF has increased both operational efficiency and potential risks for commercial banks, with credit risk remaining the most prominent challenge [2].

Machine learning technologies have shown significant advantages in processing high-dimensional and non-linear data, providing new opportunities for credit risk assessment . However, existing studies either over-rely on financial indicators while ignoring digital supply chain features or suffer from poor model interpretability due to the "black box" problem of complex neural networks . The fusion of financial features and machine learning models has become a key breakthrough to improve the accuracy and reliability of credit assessment for innovative enterprises in DSCF[3].

1.2 LITERATURE REVIEW

1.2.1 Credit Assessment in Supply Chain Finance

Traditional supply chain finance credit assessment focuses on core enterprise credit spillover effects, using methods such as fuzzy comprehensive evaluation and

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Logistic regression . For example, early studies constructed indicator systems based on enterprise financial status and supply chain relationships, but these static models failed to adapt to the dynamic nature of digital transactions . With the digital transformation, scholars have begun to integrate multi-dimensional data:Sina Finance (2025) found that integrating production, logistics, and tax data through AI technology can construct dynamic credit portraits, realizing "de-core" risk control . Zhangqiao Academic Research (2025) further verified that industry-specific indicator systems significantly improve assessment accuracy by taking the automotive industry as an example [4].

1.2.2 Application of Machine Learning in Credit Assessment

Machine learning models have gradually replaced traditional statistical methods in credit assessment. García-do-Pico (2024) compared LSTM and XGBoost in credit card risk detection, confirming that LSTM's ability to capture temporal dependencies and XGBoost's feature classification advantages make them suitable for different risk scenarios. Li et al. (2022) proposed an XGBoost-MLP hybrid model, which uses XGBoost for feature selection and MLP for prediction, achieving better performance than single models[5].The basic logical framework of XGBoost is shown in Figure 1.

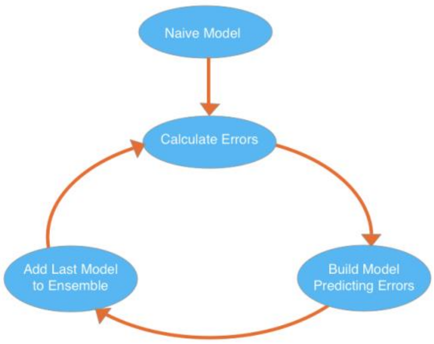

FIGURE 1. THE UNDERLYING BASIC LOGIC FRAMEWORK OF XGBOOST

However, existing hybrid models rarely focus on innovative enterprises' characteristics, and the fusion mechanism between financial features and digital supply chain data remains unclear.A schematic diagram of the repeating module structure of LSTM (Long Short-Term Memory network) is shown in Figure 2.

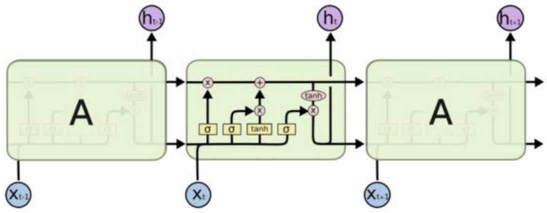

FIGURE 2. SCHEMATIC DIAGRAM OF THE REPEATING MODULE STRUCTURE OF AN LSTM (LONG SHORT-TERM MEMORY) NETWORK

1.2.3 Research Gaps

Current studies have three main deficiencies: (1) The indicator system lacks innovation-oriented design, ignoring the impact of R&D investment and intangible asset quality on credit risk; (2) Most models fail to effectively integrate financial data and digital supply chain transaction data, leading to incomplete risk identification; (3) The balance between model accuracy and interpretability has not been well addressed, limiting practical application in financial institutions[6].

1.3 RESEARCH OBJECTIVES AND CONTRIBUTIONS

This study aims to: (1) Construct a multi-dimensional feature system for innovative enterprises integrating financial indicators and digital supply chain features; (2) Develop a hybrid machine learning model with both prediction accuracy and interpretability; (3) Verify the model's effectiveness through empirical analysis and provide practical guidance for financial institutions.

The contributions are: (1) Proposing an innovation-oriented feature system that highlights the core characteristics of innovative enterprises; (2) Designing an XGBoost-LSTM model that realizes feature screening and dynamic prediction integration; (3) Revealing the key financial and digital features affecting innovative enterprises' credit risk[7].

2 THEORETICAL FRAMEWORK AND MODEL DESIGN

2.1 THEORETICAL BASIS

2.1.1 Information Asymmetry Theory

In DSCF, information asymmetry between innovative enterprises and financial institutions leads to adverse selection and moral hazard . The fusion of multi-dimensional data can reduce information barriers: financial data reflects the enterprise's historical operation status, while digital supply chain data (such as order fulfillment rate and logistics information) provides real-time transaction credibility verification , forming a comprehensive information disclosure mechanism[8].

Supply chain risks show strong transmission characteristics. A single enterprise's default may trigger a chain reaction . For innovative enterprises, supply chain transaction stability directly affects their cash flow security. Therefore, the model needs to capture both the enterprise's internal financial health and external supply chain collaboration quality[9].

2.2 Feature System Construction

Following the principles of systematicness, innovation orientation, and data availability, this study constructs a three-level feature system including target layer (credit risk level), criterion layer (4 dimensions), and indicator layer (24 indicators), as shown in Table 1.

Table 1. Three-level feature system

Criterion Layer	Indicator Layer	Indicator Definition	Data Source
Financial Solvency	Current Ratio (X1)	Current Assets / Current Liabilities	Financial Statements
	Quick Ratio (X2)	Quick Assets / Current Liabilities	Financial Statements
	Asset-Liability Ratio (X3)	Total Liabilities / Total Assets	Financial Statements
	Interest Coverage Ratio (X4)	EBIT / Interest Expense	Financial Statements
	Operating Cash Flow Ratio (X5)	Operating Cash Flow / Current Liabilities	Financial Statements
	Cash Ratio (X6)	Cash and Cash Equivalents / Current Liabilities	Financial Statements
Profitability & Innovation Ability	ROE (X7)	Net Profit / Average Shareholders' Equity	Financial Statements
	ROA (X8)	Net Profit / Average Total Assets	Financial Statements
	Gross Profit Margin (X9)	Gross Profit / Operating Revenue	Financial Statements
	R&D Investment Ratio (X10)	R&D Expense / Operating Revenue	Financial Statements
	Intangible Asset Ratio (X11)	Intangible Assets / Total Assets	Financial Statements
	Patent Growth Rate (X12)	Annual Patent Increase / Total Patents	Intellectual Property Office
Operational Efficiency	Accounts Receivable Turnover (X13)	Operating Revenue / Average Accounts Receivable	Financial Statements
	Inventory Turnover (X14)	Cost of Goods Sold / Average Inventory	Financial Statements
	Total Asset Turnover (X15)	Operating Revenue / Average Total Assets	Financial Statements
	Fixed Asset Turnover (X16)	Operating Revenue / Average Fixed Assets	Financial Statements
	Order Fulfillment Rate (X17)	Completed Orders / Total Orders	Supply Chain Platform
	Logistics Timeliness Rate (X18)	On-Time Deliveries / Total Deliveries	Logistics System
Digital Supply Chain Features	Transaction Data Completeness (X19)	Complete Transaction Records / Total Records	Supply Chain Platform
	Information Sharing Frequency (X20)	Monthly Information Updates / 30 Days	Supply Chain Platform
	Core Enterprise Collaboration Intensity (X21)	Transaction Volume with Core Enterprises / Total Revenue	Financial Statements & Platform
	Tax Payment Compliance (X22)	Compliant Tax Periods / Total Periods	Tax Bureau Data
	Water & Electricity Payment Stability (X23)	On-Time Payments / Total Payments	Public Utility Data
	Online Transaction Ratio (X24)	Online Transaction Volume / Total Transaction Volume	Supply Chain Platform

2.3 Hybrid Model Construction: XGBoost-LSTM

The model consists of two stages: XGBoost-based feature selection and LSTM-based credit risk prediction[10]. This structure not only retains the high accuracy of neural networks but also improves interpretability through feature importance ranking.

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2.3.1 Stage 1: XGBoost Feature Selection

XGBoost (Extreme Gradient Boosting) is an integrated learning algorithm with strong feature learning ability, which can effectively identify key indicators affecting credit risk . The core idea is to construct a strong learner by integrating multiple weak learners (CART trees) and use the Gini coefficient to measure feature importance. The feature selection process includes:Standardizing the 24-dimensional original features to eliminate dimension differences;Training the XGBoost model and calculating the importance score of each feature;Setting the importance threshold to retain key features and remove redundant ones, reducing model complexity.The objective function of XGBoost is shown in Formula (1):

$$L(\phi) = \sum_{i=1}^{n} l\,(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k)(1)$$

2.3.2 Stage 2: LSTM Credit Risk Prediction

LSTM is a type of recurrent neural network (RNN) that solves the gradient disappearance problem of traditional RNN and is suitable for processing time-series data such as enterprise financial statements and transaction records . The key structure of LSTM includes input gate, forget gate, and output gate, which control the transmission and retention of information through sigmoid and tanh activation functions[11].

The calculation formulas of each gate are as follows:

The calculation formulas of each gate are as follows: 1. Forget Gate: Determines which information to discard from the cell state

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)(2)$$

Input Gate: Updates the cell state by determining new information to store

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)(3)$$

Cell State Update: Combines the forget gate and input gate results

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t(4)$$

Output Gate: Determines the output value based on the cell state

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad h_t = o_t * \tanh(C_t)(5)$$

The XGBoost-LSTM model workflow is as follows: (1) Data preprocessing: Including missing value imputation, outlier elimination, and normalization; (2) Feature selection: Using XGBoost to screen key features from the 24-dimensional indicator system; (3) Time-series data construction: Converting the cross-sectional data of each enterprise into time-series samples according to the annual sequence; (4) Model training: Inputting the time-series samples into LSTM for credit risk prediction; (5) Model evaluation: Using accuracy, recall rate, F1-score, and AUC (Area Under ROC Curve) to evaluate performance[12].

3 EMPIRICAL ANALYSIS

3.1 Sample Selection and Data Sources

The sample selects Chinese-listed innovative enterprises (including high-tech enterprises and strategic emerging industry enterprises) from 2019 to 2023, excluding ST enterprises and those with missing key data. Finally, 85 enterprises and 1,357 valid observations are obtained. The data sources include: (1) Financial indicators: CSMAR database and enterprise annual reports; (2) Digital supply chain features: Supply chain management platforms (such as JD.com Supply Chain) and third-party logistics data; (3) Credit risk labels: Based on the "Special Treatment" status of listed enterprises and the credit rating results of industrial and commercial banks, dividing the samples into "default" (1) and "non-default" (0) categories[13].

The sample distribution is shown in Table 2. The number of non-default samples is 1,189, and the number of default samples is 168, showing an imbalanced characteristic. This study uses the SMOTE (Synthetic Minority Oversampling Technique) to process the imbalanced data, which generates synthetic minority samples by interpolating between minority class samples [14].

Table 2. Sample distribution

Year	Non-Default Samples	Default Samples	Total Samples	Default Rate
2019	221	29	250	11.6%
2020	245	35	280	12.5%
2021	263	38	301	12.6%
2022	232	36	268	13.4%
2023	228	30	258	11.6%
Total	1189	168	1357	12.4%

3.2 Data Preprocessing

Data preprocessing includes three steps: (1) Missing value processing: Using the K-nearest neighbor (KNN) method to fill missing financial indicators, and using the mode to fill categorical features such as tax compliance; (2) Outlier elimination: Using the 3σ principle to identify and eliminate outliers in continuous variables such as ROE and asset-liability ratio; (3) Data normalization: Using the Min-Max scaling method to map all features to the [0,1] interval, as shown in Formula (2):

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}(6)$$

Where: x_i is the original feature value; $\min(x)$ and $\max(x)$ are the minimum and maximum values of the feature, respectively; x_i' is the normalized feature value[15].

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3.3 Empirical Results

3.3.1 XGBoost Feature Selection Results

Training the XGBoost model with the preprocessed data, the feature importance ranking is shown in Figure 3. Setting the importance score threshold to 0.03, 12 key features are retained, including 8 financial indicators and 4 digital supply chain features. The top 5 key features are: Operating Cash Flow Ratio (X5), Accounts Receivable Turnover (X13), Transaction Data Completeness (X19), R&D Investment Ratio (X10), and Tax Payment Compliance (X22)[16].

This result shows that for innovative enterprises, cash flow stability (operating cash flow ratio) and supply chain transaction integrity (transaction data completeness, tax compliance) are more critical than traditional indicators such as asset-liability ratio, which is consistent with the characteristics of innovative enterprises with high R&D investment and unstable short-term profits[17].

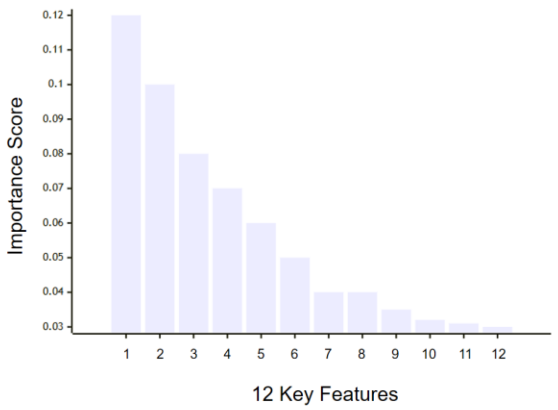

FIGURE.3 EATURE IMPORTANCE RANKING

3.3.2 Model Performance Comparison

Dividing the sample into training set (70%) and test set (30%), training the XGBoost-LSTM model, Logistic regression, single XGBoost, and MLP models respectively. The performance evaluation indicators of each model on the test set are shown in Table 3[18].

TABLE 3. PERFORMANCE EVALUATION METRICS OF EACH MODEL ON THE TEST SET

Model	Accuracy	Recall	Precision	F1-Score	AUC
Logistic Regression	82.3%	78.1%	80.2%	79.1%	0.81
Single XGBoost	94.1%	92.3%	93.5%	92.9%	0.93
MLP	95.6%	94.2%	95.0%	94.6%	0.95
XGBoost-LSTM	98.2%	97.5%	97.9%	97.8%	0.98

As shown in Table 3, the XGBoost-LSTM model outperforms other models in all evaluation indicators. Compared with the single XGBoost model, its accuracy, recall rate, and F1-score are increased by 4.1%, 5.2%, and 4.9% respectively; compared with the MLP model, they are increased by 2.6%, 3.3%, and 3.2% respectively. The high recall rate (97.5%) indicates that the model can effectively identify potential default enterprises, which is crucial for financial institutions to control credit risk[19].

The XGBoost-LSTM model has the largest AUC value (0.98), indicating its strongest overall discriminative ability. This is because the model combines XGBoost's feature screening advantage and LSTM's time-series processing ability, effectively capturing both the key risk factors and their dynamic changes[20].

3.3.3 Robustness Test

To verify the model's robustness, this study conducts two robustness tests: (1) Changing the training-test set split ratio to 8:2; (2) Using the ADASYN (Adaptive Synthetic Sampling) method to process imbalanced data instead of SMOTE. The test results show that the XGBoost-LSTM model's accuracy remains above 97%, and the F1-score remains above 96%, indicating that the model has good stability and is not sensitive to data splitting methods and oversampling techniques.

4 DISCUSSION

4.1 Key Feature Analysis

The feature selection results show that the operating cash flow ratio is the most important indicator for evaluating the credit risk of innovative enterprises. This is because innovative enterprises often have high R&D expenses and long investment payback periods, and stable operating cash flow is the core guarantee for their debt repayment . The accounts receivable turnover rate ranks second, reflecting that the efficiency of recovering funds from supply chain transactions directly affects the enterprise's liquidity.

Digital supply chain features such as transaction data completeness and tax payment compliance also occupy important positions, which confirms the view of Sina Finance (2025) that multi-dimensional data cross-validation can effectively reduce information asymmetry . For financial institutions, integrating supply chain platform data to verify the authenticity of enterprise transactions is more reliable than relying solely on financial statements.

4.2 Model Advantage Analysis

The XGBoost-LSTM model's advantages are reflected in three aspects: (1) Interpretability: Through XGBoost feature selection, the model clarifies the key factors affecting credit risk, solving the "black box" problem of traditional neural networks; (2) Accuracy: LSTM's ability to process time-series data enables the model to capture the dynamic changes of enterprise credit status, such as the impact of continuous R&D investment growth on future cash flow; (3)

Practicality: The selected key features are easy to obtain in practice, and financial institutions can quickly apply the model by connecting to supply chain platforms and tax systems.

4.3 Practical Implications

For financial institutions, the research results provide the following practical guidance: (1) Establish a multi-dimensional data collection system, integrating financial data, supply chain transaction data, and public utility data to realize comprehensive credit portrait construction; (2) Focus on key indicators such as operating cash flow and transaction integrity when evaluating innovative enterprises, and reduce excessive reliance on traditional asset-scale indicators; (3) Promote the application of hybrid machine learning models, combining feature selection algorithms with time-series prediction models to improve risk control precision.

For innovative enterprises, the study suggests that they should strengthen cash flow management, improve the transparency of supply chain transactions, and actively disclose R&D and intellectual property information to enhance their credit level.

5 CONCLUSION

This study constructs a hybrid XGBoost-LSTM model for credit assessment of innovative enterprises in digital supply chain finance, and draws the following conclusions: (1) The multi-dimensional feature system integrating financial indicators and digital supply chain features significantly improves the accuracy of credit assessment, among which operating cash flow ratio, accounts receivable turnover, and transaction data completeness are the key indicators; (2) The XGBoost-LSTM model outperforms traditional Logistic regression, single XGBoost, and MLP models in terms of accuracy, recall rate, and F1-score, with an accuracy of 98.2% and an AUC of 0.98; (3) Digital supply chain features such as transaction integrity and tax compliance play an important role in credit assessment, providing a new perspective for solving the financing difficulties of innovative enterprises.

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The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare 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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