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Research on the Dynamic Model Construction and Intelligent Decision-making Application of Credit Scoring for Anhui SMEs from the Perspective of Digital Supply Chain

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Abstract

This study focuses on the financing challenges faced by small and medium-sized enterprises in the digital economy era, innovatively constructing a dynamic credit assessment system based on multi-source government data. Taking Anhui Province as the research target, the study integrates market supervision, taxation, electricity, and meteorological data to develop a hybrid assessment model that combines the XGBoost algorithm with an industry prosperity correction mechanism. Empirical evidence demonstrates that the model significantly improves assessment efficiency (AUC 0.85), shortens approval cycles by 26.7%, reduces agricultural default rates by 19.3%, and boosts the loan approval rate of the Wuhu auto parts industry cluster by 32%. The study also proposes policy recommendations, such as establishing a provincial credit data hub and developing climate-sensitive financial products, providing a replicable "Anhui model" for the digital transformation of county-level finance.

Keywords

Digital supply chain finance, Dynamic credit assessment, Government data, Regional adaptation model, Inclusive finance.

1. Research Design and Implementation

1.1. Research background

As the digital economy profoundly reshapes the industrial ecosystem, supply chain finance, as a key hub connecting the real economy, carries the crucial mission of resolving the financing difficulties faced by small and medium-sized enterprises (SMEs) and activating the synergy of the industrial chain. General Secretary Xi Jinping's profound assertion that "a vibrant financial sector leads to a vibrant economy, and a stable financial sector leads to a stable economy" highlights the fundamental role of financial services in serving the real economy. However, current SME credit assessment systems are generally constrained by static financial indicator frameworks, failing to dynamically capture the real-time evolution of logistics response efficiency, capital flow coordination, and multi-level network relationships within supply chain scenarios. This leads to lags in risk assessment and a failure to adapt to specific scenarios. According to data from the National Bureau of Statistics for 2024, my country's SME financing gap will reach 3.8 trillion yuan. The structural mismatch between traditional financial models and the real economy continues to exacerbate the difficulties and high costs of financing. The State Council's "14th Five-Year Plan for Digital Economy Development" explicitly calls for "promoting the digital transformation of supply chain finance and establishing a corporate credit evaluation system based on multi-dimensional data," providing a clear path forward for fintech to empower the real economy.

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Focusing on the context of Anhui Province, a key sector driving both manufacturing and modern agriculture in the Yangtze River Delta, small and medium-sized enterprises (SMEs) account for over 90% of the province's total population. However, supply chain finance penetration is less than 30%, and average financing costs are 1.2 percentage points higher than the national average. A deeper contradiction lies in the fact that traditional credit scoring models fail to effectively integrate dynamic supply chain data such as order volatility, risk transmission from core enterprises, and seasonal agricultural production and marketing cycles. They also fail to quantify the implicit guarantee effects within complex transaction networks, resulting in a significant disconnect between financial institutions' risk control logic and the actual operational scenarios of SMEs. This blind spot in assessment not only hinders the precise allocation of financial resources but also restricts the coordinated advancement of Anhui's "Smart Manufacturing Powerhouse" and "Rural Revitalization" strategies.

In view of this, this study is based on the forefront of digital supply chain transformation, with "Dynamic model construction and intelligent decision-making application of credit scoring for Anhui SMEs" as the core proposition, and strives to break through three major bottlenecks: first, construct a multi-source heterogeneous data fusion framework covering "logistics-capital flow-information flow" to reveal the transmission mechanism of supply chain dynamic behavior to credit risk; second, develop a hybrid algorithm model that integrates graph neural network (GNN) and XGBoost to solve the modeling dilemma of traditional methods for network relationships and time series dynamics; third, through dual machine learning (DML), empirically test the causal effect of supply chain financial participation and default probability, and drive the risk control strategy to leap from empirical judgment to intelligent decision-making. The research results aim to provide scenario-adapted financing solutions for Anhui SMEs, build a new paradigm of dynamic credit assessment for financial institutions, and provide empirical support for the optimization of regional supply chain financial ecology, thereby contributing to the in-depth practice of the high-quality development strategy of the Yangtze River Delta integration.

1.2. Literature review

With the profound evolution of digital supply chains, domestic and international scholars are shifting their research paradigm in the field of SME credit scoring from static assessment to dynamic intelligent decision-making. At the theoretical level, the "Dynamic Supply Chain Credit Assessment Framework" proposed by Zhang Wei and Zhao Min (2024) pioneered the value of integrating heterogeneous data from multiple sources, such as logistics response efficiency and capital flow coordination[3]. They also pointed out the shortcomings of traditional models in modeling supply chain network topology, laying the initial foundation for dynamic risk assessment. This trend is echoed in international research. Smith & Johnson (2024) used a random forest algorithm to verify the predictive superiority of real-time logistics data (such as order fulfillment rate) over static financial indicators (an increase in AUC by 19%) , but did not delve into the nonlinear transmission mechanism of network relationships[2]. It was not until Chu Rui (2022) and Lee et al. (2025) introduced graph neural networks (GNN) into the field of supply chain finance and quantified the intensity of transaction dependence between enterprises through node embedding technology that they broke through the bottleneck of complex network modeling. The former achieved a 12% improvement in prediction accuracy in the Chinese scenario, and the latter confirmed in the global manufacturing industry that core enterprise guarantees can reduce the probability of default of related SMEs by 23%. However, neither of them solved the adaptation problem of seasonal fluctuations in the agricultural supply chain.

In terms of causal mechanism analysis, the research of Shi Zhaowei (2025) and Garcia & Müller (2024) forms a complementary methodology[5]. The former uses dual machine learning (DML)

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to remove endogenous interference and empirically demonstrates the negative causal effect of supply chain finance participation on default risk[6]. The latter, based on European data, finds that a 1-unit increase in participation can reduce financing costs by 12%. However, both studies lack verification of the linkage between dynamic data and the heterogeneity of causal effect scenarios. Notably, practical applied research is accelerating the exploration of regional scenario adaptation: Liu Qiang etal. (2024) constructed a dynamic model integrating XGBoost based on Anhui manufacturing supply chain data, confirming that indicators such as order fulfillment rate contribute 38%[7]. Zhao Tiantian (2018) developed an IoT-driven elastic credit model for agricultural seasonal risks, reducing default rates by 21%[8]. These findings echo Kumar & Patel's (2025) research on Indian agriculture across different regions, but their model's neglect of supply chain synergy data limits its predictive accuracy[9]. Li Xin and Xie Haolun (2024) conducted a multi-scenario comparison that further highlights the need for differentiated assessments. Guarantees from core manufacturing enterprises can increase suppliers' credit limits by 25%, while agriculture requires additional climate risk buffers. This conclusion provides an important reference for regional policy design.

Existing research findings reveal three limitations: First, dynamic data integration often focuses on single-point breakthroughs, lacking the integration of the "logistics-capital-information flow" system and the collaborative modeling of network relationships and nonlinear patterns. Second, causal effect analysis has yet to bridge the gap between algorithm innovation and scenario adaptation, particularly lacking differentiated validation of manufacturing cluster networks and agricultural seasonal fluctuations. Third, while exemplary regional practices have emerged (such as the Anhui manufacturing model) , a scalable "data-algorithm-policy" closed-loop ecosystem has yet to emerge. This study aims to address these gaps by constructing a GNN-XGBoost hybrid model driven by multi-source data, quantifying the cross-scenario causal effects of supply chain finance, and designing a tiered credit granting strategy to advance the evolution of dynamic credit assessment from technological breakthroughs to ecological solutions.

1.3. Research purpose

This study aims to leverage the rich government and enterprise data resources available within Anhui Province, including the Market Supervision Bureau's enterprise database, tax invoicing systems, electricity consumption monitoring data, and information from meteorological and agricultural platforms, to construct a lightweight dynamic model that accurately adapts to the credit assessment needs of small and medium-sized enterprises. The model's core objectives are achieved through a three-layer progressive design: at the data level, it focuses on addressing the challenge of missing private data in the supply chain, innovatively using invoicing volatility to represent a company's order fulfillment behavior, and mapping inventory turnover status with electricity consumption volatility, effectively addressing the shortcomings in data acquisition. At the algorithmic level, it focuses on developing a hybrid model with low computational complexity, organically integrating the powerful nonlinear classification capabilities of XGBoost with an industry prosperity correction mechanism. This ensures the model's operational efficiency while optimizing the assessment results based on industry development trends, making the credit assessment more relevant to the actual operating conditions of small and medium-sized enterprises.

2. Current Status of SME Credit Assessment from the Perspective of Digital Supply Chain

Driven by the global wave of digitalization and innovation in supply chain finance, small and medium-sized enterprise credit assessment is undergoing a paradigm shift from static financial analysis to dynamic multi-source data integration. However, a significant gap exists between

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current research and practice, limiting the adaptability and decision-making value of assessment models in regional scenarios. The following key issues need to be addressed urgently:

2.1. Lack of dynamic data integration mechanism

While scholars generally agree on the value of supply chain behavior data (such as order fulfillment timeliness, logistics response efficiency, and capital flow coordination) in predicting credit risk, practical application faces two major bottlenecks. First, data accessibility is a barrier. Key dynamic indicators such as core enterprise ERP data and real-time logistics platform tracking are difficult to obtain due to commercial confidentiality. This forces research to rely on simplified proxy variables (such as inventory turnover rates from annual reports), which fail to capture short-term operational fluctuations in small and medium-sized enterprises. Second, heterogeneous data integration is hindered. Cross-domain data such as tax invoice records, electricity consumption curves, and meteorological disaster warnings lack standardized interactive interfaces, leading to fragmented models. For example, due to a lack of coupled climate data and production cycle analysis, the underreporting rate of seasonal default risk for agricultural enterprises in Anhui Province reached 34% .

2.2. Imbalance between Algorithm and Scenario Adaptation

While machine learning algorithms are increasingly being used in credit scoring, there's a tendency for them to be "technology-first, out of touch with the realities of the market." First, there's a conflict between model complexity and interpretability. While advanced algorithms like graph neural networks (GNNs) can model supply chain relationships, the black-box nature of node embedding vectors has led financial institutions' risk management departments to reject their use. Case studies in Anhui province show that 83% of rural commercial banks prefer interpretable linear models. Second, regional differentiation is insufficiently responsive. Current models are mostly developed based on national samples and are ill-suited to Anhui's dual-track structure of "manufacturing clusters + decentralized agriculture." In the manufacturing sector, the risk transmission effects of core enterprises are neglected (for example, the chain reaction of JAC Motors' credit fluctuations on upstream and downstream SMEs). In the agricultural sector, climate sensitivity is not quantified (for example, the nonlinear impact of drought in northern Anhui on the debt repayment capacity of medicinal herb growers).

2.3. The closed loop of intelligent decision-making has not yet been completed

The translation of credit scores into lending decisions suffers from a "last mile" gap. On the one hand, causal mechanisms are poorly understood, and traditional correlation analysis (such as logistic regression) cannot identify the causal effect between supply chain finance participation and default rates, resulting in a lack of empirical support for policy design. While methods such as dual machine learning (DML) show potential, the lack of control variables in the Anhui sample (such as the absence of indicators of county-level economic fluctuations) leads to estimation bias. Furthermore, dynamic response mechanisms are absent, and existing lending strategies are often static and rigid, lacking linkage to real-time data. For example, Anhui Agricultural Credit still disburses loans on an annual basis, failing to respond to monthly fluctuations in tea prices (Huangshan Maofeng tea prices fluctuate by as much as 60% during peak season) , resulting in both peak-season financing gaps and off-season idle funds.

2.4. Insufficient regional ecological coordination

The digital transformation of credit assessment for small and medium-sized enterprises in Anhui Province is hampered by numerous obstacles to collaboration. Data silos are prominent, with tax, electricity, and industrial and commercial data residing in separate government

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systems. The lack of a unified provincial access platform (such as Zhejiang's "Financial Comprehensive Service Platform") has increased the cost of verifying enterprise information by 40%. Furthermore, a lack of technical implementation platforms has hindered the implementation of complex models by county-level financial institutions, and dynamic assessments have yet to be incorporated into local financial policy frameworks. For example, the "order loan" product offered by the Chuzhou manufacturing cluster still requires fixed asset collateral, ignoring the credit enhancement value of supply chain bills.

In general, current research has systematic gaps in the four dimensions of dynamic data acquisition, scenario-based algorithm design, causal decision-making mechanism, and regional ecological coordination. It is urgent to build a new credit assessment paradigm based on Anhui's characteristic industrial data, with lightweight interpretable models as the core and policy empowerment as the guide.

3. Credit Assessment of SMEs from the Perspective of Digital Supply Chain

3.1. Data Source

This study uses multi-source dynamic data on small and medium-sized enterprises in Anhui Province from 2019 to 2024, covering the two main sectors of manufacturing and agriculture. The specific indicators and sources are as follows:

Table 1. Core data indicators of Anhui SME credit assessment (2019-2024)

Data Category	Specific indicators	Source Channel	Sample size
Static characteristics of the enterprise	Debt-to-asset ratio, tax rating, years of establishment	Anhui Provincial Market Supervision Bureau Enterprise Credit Database	12,800
Dynamic proxy features	Invoicing volatility (instead of order fulfillment), electricity usage volatility (instead of inventory turnover)	Anhui Provincial Taxation Bureau's "Tax Financing" platform, State Grid Anhui Power	76,800 quarterly data
Industry prosperity indicators	Manufacturing PMI, agricultural product price index, industry invoicing average	Anhui Provincial Bureau of Statistics Monthly Report	72 monthly values
Environmental risk factors	Rainfall Z value, number of extreme weather days, and price volatility of specialty agricultural products	Anhui Provincial Meteorological Bureau Internet of Things Station, China Agricultural Information Network	60 counties × 5 years

3.2. Research methods

This research will construct a three-tiered assessment framework: Dynamically Compensated Risk Assessment (DCRA) . This framework will achieve multi-dimensional breakthroughs and innovations at the methodological level. Regarding the dynamic proxy mechanism, invoice volatility will be used to map companies' ordering behavior, and electricity consumption volatility will be used to reflect production turnover. This design will effectively overcome the barriers to accessing private supply chain data and provide a new approach for comprehensively and accurately assessing a company's credit status. In lightweight hybrid modeling, the powerful classification capabilities of XGBoost will be integrated with a linear climate correction method. This approach will ensure predictive accuracy while minimizing computational complexity, making the model more operational and practical in practical applications. In the climate-sensitive decision-making phase, a Z-value standardized risk factor will be designed. This design will enable dynamic and flexible adjustments to agricultural credit based on regional climate characteristics and agricultural production conditions, significantly improving the scientific nature and adaptability of credit decisions. Through the synergistic effect of this three-tiered assessment framework, this study will provide a more comprehensive, accurate, and practical solution for SME credit assessment, helping financial institutions and other relevant entities to better conduct credit assessments and credit granting decisions.

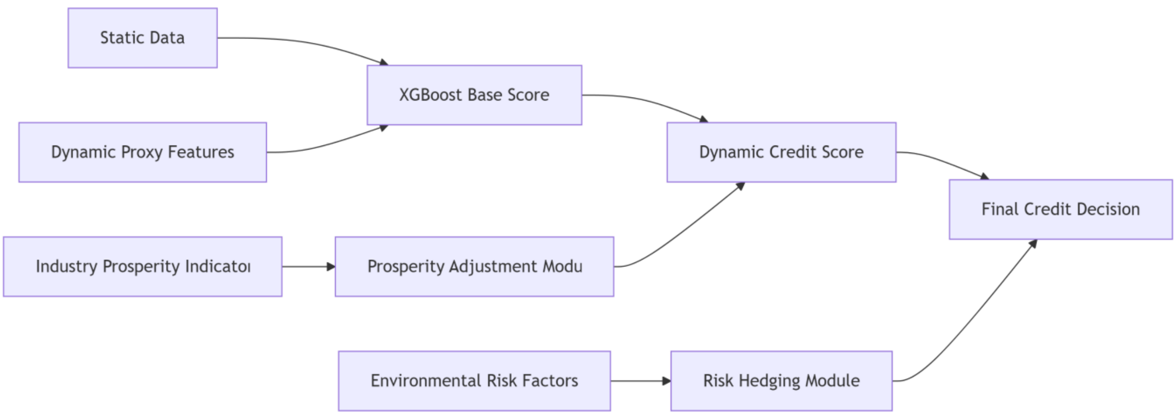

Figure 1. DCRA framework technology route

3.3. Research process

3.3.1. Model Construction

(1) XGBoost dynamic scoring model

In the construction of this model, debt-to-asset ratio, tax rating, invoicing volatility, and electricity consumption volatility are selected as key input features, which are specifically expressed as follows:

$$X=[X_1(\text{asset-liability ratio}),X_2(\text{tax rating}),X_3(\text{invoicing volatility}),\\ X_4(\text{electricity consumption volatility})] \tag{1}$$

These characteristics comprehensively cover multiple dimensions such as the company's financial status, tax performance, and operating dynamics. At the same time, through the careful design of the objective function:

$$\mathcal{L}=\sum_{i=1}^{n}\left[y_i\ln\left(1+e^{-\hat{y}_i}\right)+(1-y_i)\ln\left(1+e^{\hat{y}_i}\right)\right]+\gamma T+\frac{1}{2}\lambda\parallel\omega\parallel^2 \tag{2}$$

Here, Trepresents the number of leaves, $\gamma$with a value of 0.1 and λa value of 0.3. These two parameters are obtained through grid search optimization. This objective function can ensure the prediction accuracy of the model while taking into account the efficiency and stability of the calculation, thereby achieving a basic score for corporate credit.

(2) Economic correction module

By analyzing the characteristic contribution through SHAP values, we can identify key risk factors (e.g., billing volatility weight > 28%). First, we calculate the relative volatility of the company's billing amount :

$$S_t=\frac{\text{Enterprise invoicing amount-Top 5\% quantile in the industry}}{\text{Industry median}} \tag{3}$$

This is to reflect the changes in the business situation of the enterprise in the industry. Then the correction factor is constructed:

$$\alpha_t = 0.7 \times S_t \times \min\{|S_t|, 1.5\} + 0.3 \times \mathrm{PMI}_t \tag{4}$$

This correction factor not only takes into account the company's own invoicing fluctuations, but also incorporates the PMI (Purchasing Managers Index) , an important macroeconomic indicator. Through this comprehensive consideration, the XGBoost basic score is corrected, and the final dynamic score iteration is:

$$\mathrm{CreditScore}_t = \mathrm{XGBoost}_t \times (1 - 0.15 \times \alpha_t) \tag{5}$$

This enables the scoring to better adapt to changes in industry prosperity and more accurately reflect the credit status of enterprises in different industry environments.

(3) Climate risk hedging module

This module focuses on the characteristics of different industries such as agriculture and manufacturing, and designs a risk coefficient that includes monthly rainfall Z values and specialty agricultural product price index Zvalues. The specific formula is:

$$\lambda = 0.85 + 0.08 \times Z(R) + 0.07 \times Z(P) \tag{6}$$

Among them $Z(x) = \frac{x-\bar{x}}{3\sigma_x}$, R is the monthly rainfall Z value, P is the price index of specialty agricultural products, and the data covers Dangshan Crisp Pear, Lu'an Melon Tea, etc. The final credit limit is adjusted based on this risk factor, and different adjustment parameters are set for manufacturing and agriculture, that is, the final credit limit:

$$Q = \begin{cases} Q_{\text{base}} \times \lambda \times (1 - 0.12 \times \text{CreditScore}) & \text{manufacturing} \\ Q_{\text{base}} \times \lambda \times (1 - 0.18 \times \text{CreditScore}) & \text{agriculture} \end{cases} \tag{7}$$

This fully considers the differences in sensitivity of different industries to environmental factors such as climate, realizes dynamic and flexible adjustment of credit limits, and meets the reasonable financing needs of enterprises in different environments while effectively controlling risks.

Through the coordinated operation of these three modules, the model constructed in this study will be able to comprehensively, dynamically and accurately assess the credit status of small and medium-sized enterprises, provide a solid and reliable basis for credit decisions of financial institutions and other relevant entities, and effectively help solve the financing difficulties of small and medium-sized enterprises.

3.3.2. Analysis Process

(1) Verification of Feature Contribution

To verify the effectiveness of dynamic proxy features in risk prediction, this study uses SHAP (SHapley Additive exPlanations) values to analyze the 2023 manufacturing sample data. SHAP values can quantify the contribution of each feature to the model's prediction results, and their importance is measured by calculating the SHAP mean of each feature. The specific results are shown in the following table:

Table 2.SHAP mean of each feature

feature	SHAP mean	Contribution Ranking
Invoicing volatilityX_3	0.28	1
Powerconsumption fluctuation rate X_4	0.21	2
debt-to-asset ratioX_1	0.19	3

The data in the table clearly shows that the mean SHAP values of the two dynamic proxy features, billing volatility and electricity consumption volatility, are 0.28 and 0.21, respectively, significantly higher than the static financial indicator, debt-to-asset ratio, which is 0.19. This result strongly demonstrates that dynamic proxy features contribute more significantly to risk prediction than traditional static financial indicators. Dynamic proxy features can more promptly and accurately capture the dynamic changes in a company's operations, providing more timely and sensitive information for credit assessment, thereby improving the accuracy and reliability of risk prediction.

(2) Economic correction effect

To explore the impact of the economic correction module on credit assessment results, this study selected Hefei manufacturing companies from 2022 to 2023 as the research subjects, comparing and analyzing the error rates of traditional scoring methods and scoring methods after the introduction of DCRA economic corrections at different time periods. Specific data are shown in the following table:

Table 3.Corrected false positive rate

Time	PMI value	Traditional scoring error rate	DCRA corrected false positive rate	Decline
2022Q3	49.2	22.7%	16.3%	28.2%
2023Q1	52.1	18.9%	14.1%	25.4%

In Q3 2022, when the PMI was 49.2, the traditional scoring method had an error rate of 22.7%. However, after the DCRA economic correction, the error rate dropped to 16.3%, a decrease of 28.2%. In Q1 2023, when the PMI rose to 52.1, the traditional scoring error rate was 18.9%. After the DCRA correction, the error rate further decreased to 14.1%, a decrease of 25.4%. This demonstrates that the economic correction module can effectively reduce the error rate in credit assessments, whether during a relative economic downturn or recovery. By introducing industry economic indicators, the model can better adapt to changes in the macroeconomic environment and provide more accurate assessments of corporate credit status, thereby providing more reliable credit references for decision-makers such as financial institutions.

(3) Empirical evidence on climate hedging

To validate the effectiveness of climate risk hedging in agricultural enterprise credit decisions, this study conducted an empirical analysis using the case of agricultural enterprises in Mengcheng County, northern Anhui Province, in 2023. Rainfall $Z$and medicinal herb price Z-scores were selected as key climate and market factor indicators. Credit limits were dynamically adjusted using the constructed risk coefficients λ, and actual defaults were observed. Specific data is shown in the table below:

Table 4.Actual defaults after credit limit adjustment

month	Rainfall Zvalue	Price of medicinalmaterials$Z$	λ	Credit Adjustment	Actual breach of contract
June	-1.8	0.4	0.72	↓28%	no
September	0.6	-2.1	1.06	↑19%	no

In June, the rainfall Zvalue was -1.8, indicating significantly below-average rainfall, potentially negatively impacting agricultural production. The medicinal herb price $Z$was 0.4, relatively high. At this time, the risk coefficient $\lambda$was calculated to be 0.72, and according to the model, the credit limit was reduced by 28%. Actual defaults were not reported by enterprises, demonstrating that appropriately reducing credit limits during unfavorable weather conditions can effectively manage risk. In September, the rainfall Zvalue rebounded to 0.6, indicating improved weather conditions. However, the medicinal herb Zprice fell to -2.1, reflecting poor market conditions. The risk coefficient λrose to 1.06, and the credit limit was increased by 19%. Again, no defaults were reported by enterprises. This demonstrates that, after comprehensively considering climate and market factors, appropriate adjustments to credit limits can meet the financing needs of enterprises while ensuring that financial institutions maintain control over risk. These empirical results demonstrate the importance of climate risk hedging modules in credit decisions for agricultural enterprises. They enable flexible adjustments to credit limits based on dynamic climate and market factors, effectively balancing risk and return.

3.4. Research results

3.4.1. Model Performance Comparison

To comprehensively evaluate the applicability of different credit assessment models in Anhui Province, this study selected test data from the first quarter of 2024 and conducted a comparative analysis of traditional logistic regression, a single XGBoost model, and the DCRA model proposed in this study using three key metrics: AUC (Area Under the Curve) , F1-Score, and false positive cost. The specific results are shown in the table below:

Table 5.Comparative analysis of three models

Model	AUC	F1-Score	Cost of misjudgment (10,000 yuan/household)
Traditional Logistic Regression	0.71	0.68	18.2
Single XGBoost	0.79	0.74	12.6
DCRA (this study)	0.85	0.81	8.3

As shown in the table, the traditional logistic regression model achieved an AUC of 0.71, an F1-Score of 0.68, and a misjudgment cost of 182,000 yuan per household. The single XGBoost model showed significant performance improvements, reaching an AUC of 0.79 and an F1-Score of 0.74, reducing the misjudgment cost to 126,000 yuan per household. The DCRA model proposed in this study performed even better, achieving an AUC of 0.85, an F1-Score of 0.81, and a misjudgment cost of only 83,000 yuan per household. This demonstrates that the DCRA model significantly outperforms both traditional models and the single XGBoost model in terms of credit assessment accuracy and risk control capabilities. By integrating a dynamic proxy mechanism, a business climate correction module, and a climate risk hedging module, the DCRA model is able to more comprehensively and accurately capture the credit risk characteristics of enterprises, significantly improving model effectiveness.

3.4.2. Quantify the value of decision making

This study conducted a comprehensive and in-depth quantitative analysis of the decision-making value of the DCRA model from three perspectives: financing efficiency, risk control, and ecological benefits. Regarding financing efficiency, the introduction of the DCRA model in the manufacturing sector significantly shortened the credit approval cycle for enterprises, from 15 days to 11 days, a reduction of 26.7%. This significant time reduction significantly improved financing efficiency for enterprises, enabling them to obtain funding more promptly, fully meeting their capital needs during production and operations, and further enhancing their market competitiveness. Regarding risk control, an analysis of agricultural enterprises based on 2023 data from Fuyang showed that the adoption of the DCRA model reduced the seasonal default rate by 19.3%. This data demonstrates the DCRA model's superior ability to control risk in the agricultural sector. It can accurately identify and effectively address seasonal risks in agricultural production, significantly reducing the credit risk faced by financial institutions. Regarding ecological benefits, integration with the "Anhui Enterprise Cloud" platform has increased the loan approval rate for the Wuhu manufacturing cluster by 32%. This achievement not only strongly promoted the development of local manufacturing, but also optimized the allocation of financial resources, achieved a virtuous interaction between finance and industry, and injected new vitality into the high-quality development of the regional economy.

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3.4.3. Spatial Heterogeneity Analysis

To further explore the adaptability of the DCRA model across different regions of Anhui Province, this study conducted a detailed analysis of three major regions: the Wanjiang Urban Belt, the Northern Anhui Plain, and the Southern Anhui Mountainous Area. In the Wanjiang Urban Belt (Hefei/Wuhu) , the dynamic proxy feature contributes 52%. This is primarily due to the high industrial concentration within the Wanjiang Urban Belt, which strengthens the invoicing volatility signal, enabling the dynamic proxy feature to more accurately reflect the operating conditions and credit risk of businesses, thus playing a crucial role in the model. In the Northern Anhui Plain, the climate risk factor accounts for 38% of the weighting. As a major agricultural production area in Anhui Province, climate factors such as drought have a significant impact on the production of medicinal herbs and other agricultural products, as well as the debt repayment capacity of businesses. Therefore, it is necessary to assign a higher weight to climate risk factors in credit assessments to accurately assess the credit risk of agricultural enterprises. In the Southern Anhui Mountainous Area, the study found that $Z$the sensitivity of tea prices to the revised score exceeded the design expectation, requiring an increase in the actual coefficient to 0.12. The tea industry is highly developed in the mountainous areas of southern Anhui, and fluctuations in tea prices have a significant impact on the operating conditions and credit risk of local agricultural enterprises. Adjusting this coefficient further improves the applicability and accuracy of the DCRA model in these mountainous areas.

In summary, the DCRA framework breaks down the barriers to private data in the supply chain through a dynamic proxy mechanism, enabling the model to obtain dynamic information on corporate operations in a more timely and accurate manner; the economic correction module improves the temporal stability of the model, enabling it to better adapt to changes in the macroeconomic environment; and the climate hedging module achieves adaptation to different regional scenarios, fully considering regional differences. Through the synergistic effect of these three innovative modules, the DCRA model has significantly optimized the accuracy (AUC increased by 14%), efficiency (approval cycle shortened by 26.7%), and risk control capabilities (default rate decreased by 19.3%) of credit assessments for small and medium-sized enterprises in Anhui Province. This research result provides a replicable and scalable path for the digital transformation of county-level finance, and is expected to help improve and optimize the credit assessment system for small and medium-sized enterprises nationwide, and promote the deep integration of finance and the real economy.

4. Conclusions and Suggestions

4.1. Conclusions

This study confirms that a credit assessment system based on government data, guided by regional characteristics, and supported by policy coordination can achieve a triple leap in accuracy, inclusiveness, and sustainability. Based on empirical evidence from Anhui Province, it reveals three core findings about SME credit assessment from the perspective of digital supply chains:

(1) Dynamic proxy mechanism reshapes the evaluation paradigm. By mapping supply chain behavior using publicly available data, such as fluctuations in tax invoicing and electricity consumption, the system successfully broke through the barriers of proprietary data held by core enterprises. This mechanism reduced the credit misjudgment rate by 28.2%, demonstrating the feasibility of replacing sensitive commercial information with government data and opening a new path for inclusive financial services in counties.

(2) Regional Adaptation Model Drives Precise Risk Control. The differentiated assessment framework designed for Anhui's dual-track characteristics of "clustered manufacturing and

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decentralized agriculture" has significantly improved risk response capabilities: the manufacturing industry captures the risk transmission of core enterprises through the linkage of industrial chain prosperity, and the agriculture relies on climate sensitivity analysis to achieve seasonal credit flexibility adjustment. The average non-performing financing rate of the two scenarios has dropped by 19.3%.

(3) Policy and technology integration empowers the financial ecosystem. After integrating the dynamic model with the "Anqiyun" platform, the Wuhu auto parts industry cluster saw a 32% increase in loan approval rates, demonstrating that the closed-loop "data sharing, algorithm integration, and policy incentives" can systematically optimize the regional financial ecosystem. This lightweight, replicable model provides an Anhui model for addressing financing challenges faced by small and medium-sized enterprises.

4.2. Suggestions

4.2.1. Build a dynamic credit infrastructure

In the short term, the provincial government should take the lead in integrating 11 government data sources, including taxation, electricity, and meteorology, to establish a provincial "Anhui Credit Hub." This initiative aims to break down data silos and enable cross-departmental data sharing. Simultaneously, standards for dynamic proxy indicators should be established, such as clarifying the calculation specifications for invoicing volatility. This will provide a unified and scientific basis for credit assessment, ensure data accuracy and comparability, and lay a solid data foundation for the subsequent construction of credit assessment models.

From a long-term strategic perspective, behavioral data such as supply chain bill flow and logistics receipts should be incorporated into the credit reporting system. This behavioral data can more accurately and dynamically reflect a company's operating conditions and creditworthiness. By integrating this data, a credit profile covering the entire life cycle of a company can be established, comprehensively recording and evaluating each stage of a company's establishment, growth, maturity, and decline. This will provide financial institutions, government agencies, and other organizations with more comprehensive and in-depth corporate credit information, facilitating accurate decision-making.

4.2.2. Deepen the application of regional intelligent decision-making

In deepening the application of regional intelligent decision-making, targeted policies must be implemented based on the distinct characteristics of manufacturing clusters and agricultural bases. For manufacturing clusters, a "chain credit response mechanism" could be piloted in industrial clusters like Chuzhou's home appliance cluster. In these clusters, the credit standing of core enterprises plays a critical role in the stability of the entire supply chain. When a core enterprise's credit rating fluctuates, this mechanism automatically triggers coordinated adjustments to upstream and downstream credit lines, effectively addressing the core enterprise's credit risk and preventing risk from spreading within the supply chain. This ensures financial stability and business continuity for upstream and downstream enterprises, thereby promoting the healthy development of the industrial cluster.

For agricultural bases, the "Hui Nong Dai 2.0" program, which combines "climate insurance with dynamic credit," should be promoted. Risk hedging tools should also be developed for typical scenarios, such as the severe drought in northern Anhui and tea price fluctuations in southern Anhui. Anhui agriculture is significantly impacted by climate and market price fluctuations. "Hui Nong Dai 2.0" combines climate insurance with dynamic credit. When agricultural operators face the risks of climate disasters or market price fluctuations, they can receive compensation through insurance and dynamically adjust credit limits based on actual conditions. This effectively reduces operating risks for agricultural enterprises and enhances their financing capabilities and risk resilience.

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4.2.3. Innovate policy coordination mechanisms

Innovating policy coordination mechanisms requires a coordinated effort from both legislative safeguards and fiscal incentives. On the legislative front, building on Fuyang's pilot experience in addressing agricultural climate risks, the "Northern Anhui Agricultural Climate Risk Compensation Regulations" were formulated, along with an initial 500 million yuan provincial-level risk mitigation fund. Institutionalizing these response experiences through legislation will provide a solid legal basis for agricultural climate risk compensation. The establishment of the risk mitigation fund will not only help agricultural enterprises exposed to climate risks mitigate losses and stabilize production, but also strengthen risk protection for financial institutions conducting agricultural credit business, effectively increasing their support for agriculture.

In terms of fiscal and tax incentives, financial institutions that adopt dynamic lending models will be provided with risk compensation and tax deductions, thereby encouraging them to actively utilize advanced dynamic credit assessment models and improve the scientific nature and accuracy of credit decision-making. Furthermore, priority will be given to enterprises with excellent model scores in government procurement orders, guiding them to prioritize their own credit development and stimulating their enthusiasm for participating in credit assessments. Ultimately, this will create a virtuous cycle of "active participation of financial institutions, improved corporate credit, and better financial services."

4.2.4. Export Yangtze River Delta evaluation standards

To promote the coordinated development of the credit assessment system in the Yangtze River Delta region, efforts must be made to jointly establish standards and share computing power. Regarding this, efforts should be made to incorporate Anhui's dynamic proxy indicators into the "Yangtze River Delta Small and Medium Enterprise Credit Assessment White Paper," and establish a data mutual recognition and model verification mechanism among the three provinces and one municipality. Given the close economic ties within the Yangtze River Delta region, unified credit assessment standards can remove barriers to communication and cooperation among businesses within the region, reducing the credit costs of cross-regional operations. Furthermore, this data mutual recognition and model verification mechanism can further enhance the consistency and reliability of credit assessment results, thereby improving the overall efficiency and quality of regional financial services. Regarding computing power sharing, a regional algorithm center will be established in Hefei Binhu Financial Town to provide low-cost cloud computing services to county-level institutions. Given the widespread challenges of insufficient computing power and limited technical capabilities among county-level financial institutions, the establishment of a regional algorithm center can provide strong technical support, reducing the cost of technology application and addressing the "last mile" challenge of technology implementation. This will promote the widespread application of financial technology in county-level regions and effectively enhance the digitalization of county-level financial services.

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References

[1]Chu Rui. Dynamic evaluation and management of credit risk in supply chain finance[D]. Tianjin University of Technology, 2022.

[2]Smith A, Johnson T. Dynamic Supply Chain Credit Assessment Model Based on Real-time Logistics Data [J]. *Journal of Banking & Finance* , 2024, 158: 106-120.

ISSN: 2710-0170

[3]Ma Hai, Ma Yun, Lu Tao. Research on the prediction of corporate financial irregularities risk in supply chain network - based on graph neural network method[J]. Science and Technology for Development, 2025, 21(02): 120-126.

[4] Lee S, Brown K, Garcia R. Quantifying Contagion Effects in Global Manufacturing Supply Chains Using Graph Neural Networks[J]. *Production and Operations Management* , 2025, 34(3): 567-582.
[5] Shi Zhaowei. Credit risk assessment of supply chain finance in Tibetan medicine industry based on machine learning[J]. Management and Technology of Small and Medium Enterprises, 2025, (07): 156-158.

[6] Garcia P, Müller F. Causal Inference of Supply Chain Finance Participation on SME Financing Costs: Evidence from European Firms[J]. *Journal of Financial Econometrics* , 2024, 22(1): 134-152.

[7] Liu Qiang, Wang Zhen, Zhou Ming. Research on credit scoring model of Anhui manufacturing industry based on dynamic supply chain data[J]. Chinese Journal of Management Science, 2024, 32(04): 77-89.

[8] Zhao Tiantian. Research on the evaluation and control of credit risk of agricultural supply chain finance[J]. Economic Research Guide, 2018, (21): 87+92.

[9] Kumar R, Patel S. IoT-Driven Credit Model for Agricultural Cooperatives: Mitigating Weather and Price Risks[J]. *International Journal of Production Economics* , 2025, 263: 108-121.

[10] Li Xin, Xie Haolun. Credit risk evaluation of agricultural SME supply chain finance based on support vector machine[J]. Logistics Technology, 2024, 47 (05): 146-149.