RESEARCH-ARTICLE

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Published: 18 July 2025

GAITDI 2025: International Conference on Implementing Generative AI into Telecommunication and Digital Innovation
July 18 - 20, 2025
Beijing, China

GAITDI '25: Proceedings of the International Conference on Implementing Generative AI into Telecommunication and Digital Innovation 2025 (July 2025)
https://doi.org/10.1145/3771792.3773849
ISBN: 9798400714924

A Research on the Pathways for Preventing Financial Risks in the Social Credit System Based on the Digital Economy

Yi Song*
School of Economics
Wuhan Business University
Wuhan, Hubei Province, China
172073978@qq.com

Sihan Liu*
Business School
University of International Business and Economics
Beijing, China
202306057@uibe.edu.cn

Abstract

Against the backdrop of the deep penetration of the digital economy into the financial field, the social credit reporting system, as the core infrastructure for risk prevention, is crucial to maintaining financial stability. This paper constructs a big social credit data development index (SCDBI) with 5 dimensions and 23 indicators and uses the entropy value method and panel data fixed effect model to empirically analyze the quantitative relationship between the digital level of the credit reporting system and financial risks. The study found that for every unit increase in SCDBI, the regional non-performing loan ratio dropped significantly by 0.72 percentage points ($p<0.01$), and data infrastructure and digital technology momentum are the core driving factors. Combined with the practical verification of Suzhou Digital Credit Investigation Experimental Zone, the data coverage breadth increased by 22 percentage points to increase the financing satisfaction rate to 92.38%, and the non-performing rate was reduced by 1.2 percentage points. The research proposes that by strengthening the integration of data elements, upgrading intelligent evaluation models, and improving diversified collaboration mechanisms, we should build a credit risk prevention system that adapts to the digital economy. Research provides a quantitative basis and practical path for financial risk governance in the new era.

CCS Concepts

• **Social and professional topics**; • **Professional topics**; • **Computing and business**; • **Socio-technical systems**;

Keywords

Digital economy, Social credit reporting system, Financial risk, Entropy method, panel data model

ACM Reference Format:
Yi Song and Sihan Liu. 2025. A Research on the Pathways for Preventing Financial Risks in the Social Credit System Based on the Digital Economy. In *International Conference on Implementing Generative AI into Telecommunication and Digital Innovation (GAITDI 2025), July 18–20, 2025, Beijing, China.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3771792.3773849

*Corresponding author

GAITDI 2025, Beijing, China

ACM ISBN 979-8-4007-1492-4/2025/07
https://doi.org/10.1145/3771792.3773849

1 Introduction

1.1 Realistic background and problem posed

With the deep integration of digital technology and financial business, the scale of my country's digital economy has increased from 39.2 trillion yuan in 2020 to 53.9 trillion yuan in 2023, accounting for 41.5% of GDP. [1] However, while improving efficiency, digital finance has also spawned new risks: risks of legacy of P2P online lending, risks of monopoly on platform economic data, and risks of abnormal cross-border capital flows. In 2022, the scale of non-performing assets of the national online lending platform will still exceed 200 billion yuan. [3] The traditional credit reporting system relies on bank credit data and financial statements to cover "credit vulnerable groups" such as small and micro enterprises and new citizens (the coverage rate is only 65%), and risk assessment lags behind real-time transaction demand, so it is urgent to improve risk prevention capabilities through digital transformation.

1.2 Research value and theoretical significance

From the theoretical level, research has expanded the application of information asymmetry theory in the digital economy, revealing the reconstruction mechanism of data elements and technological innovation for credit assessment; from the practical level, quantitative analysis provides a basis for policy formulation, helping to solve practical problems such as "data silos" and "evaluation lag". The research goals are: ①Construct a scientific digital credit evaluation index system; ②Empirically test the impact path of digital credit reporting on financial risks; ③Refining replicable practical experience and policy suggestions.

2 Theoretical framework

2.1 The digital economy reshapes financial risks

2.1.1 *Changes in risk transmission mechanism.*

Network effect strengthening: Digital platforms connect more than 1 billion users, and a single entity default may spread rapidly through supply chain finance and consumer credit networks. For example, in 2020, the supply chain finance risk of an e-commerce platform caused the credit rating of more than 300 upstream and downstream enterprises to plummet.

Enhanced data dependence: Financial institutions rely on transaction flows, equipment fingerprints and other data to evaluate credit. Missing or distorting data may cause systematic misjudgment.

Table 1: Development Indicator System for Social Credit Big Data

Dimension	Secondary indicators	Measurement method	Source of data	Weight (entropy method)
Data Infrastructure	Optical cable line length (10,000 kilometers)	Communications Authority Annual Report	National Bureau of Statistics	28.6%
Digital technology dynamics	Digital economy invention patent authorization quantity (piece)	Filter patents such as G06F, H04L by IPC classification	China Intellectual Property Office	25.3%
Credit rating efficiency	Commercial Banks' non-performing loan ratio (%)	The proportion of non-performing loans of regional commercial banks	People's Bank of China	20.5%
User application scenarios	Mobile phone penetration rate (department/100 people)	Number of mobile phone users / permanent population	Ministry of Industry and Information Technology	15.2%
Policy coordination	Number of local credit regulations (department)	Credit-related regulations issued by provincial governments	Peking University Magic Weapon Database	10.4%

2.2 Limitations of traditional credit reporting system

Single data dimension: Only covers bank credit data, and insufficient utilization of "alternative data" such as water and electricity payments, logistics data, etc. in small and micro enterprises that account for 90% of market entities (coverage ratio < 40%).

Assessment model lag: Static scoring models based on historical financial data (such as linear regression) are difficult to capture real-time transaction risks, and the non-performing loan identification lags by 6-12 months.

2.3 Risk prevention mechanism for digital credit reporting

2.3.1 Multi-dimensional empowerment of data elements. **Expand coverage breadth**: Integrate government data (tax, market supervision), business data (e-commerce, social platforms), and Internet of Things data (enterprise equipment operation data), and increase the credit coverage rate to more than 90% (Practice of Suzhou Experimental Zone).

Quality improvement: Blockchain technology realizes data "untamperable + traceable", such as the Shenzhen blockchain credit reporting platform has reduced the number of complaints about data tampering by 70%.[2]

2.3.2 Technology-driven evaluation upgrade. **Artificial intelligence model**: Random Forest algorithm processes unstructured data, increasing the accuracy of credit scores for small and micro enterprises from 72% to 86%.

Real-time monitoring system: Real-time capture of corporate equity changes, litigation-related information, etc. through big data to achieve a "T+1" early warning of risks, and identify risks 3 months ahead of traditional manual review.

2.3.3 Ecological construction of collaborative governance. **Multi-subject collaboration**: From a three-dimensional system of "government public credit reporting (such as the national credit information sharing platform) + market commercial credit reporting (such as Sesame Credit) + industry self-discipline credit reporting" to solve the problem of "data separatism".

Cross-domain linkage: Credit data is connected with the financial regulatory system. For example, the China Banking and Insurance Regulatory Commission incorporates corporate credit ratings into the bank credit approval process, which improves the efficiency of compliance inspection by 50%.

3 Data model construction and index system design

3.1 Construction of the Social Credit Big Data Development Index (SCDBI)

3.1.1 Principles of indicator system design. Following scientific, data availability and characteristics of the times, we construct indicators from 5 dimensions:

3.1.2 Entropy value calculation steps. **Data standardization**: Use $x'_{ij} = \frac{x_{ij} - \min x_j}{\max x_j - \min x_j}$ and $x'_{ij} = \frac{\max x_j - x_{ij}}{\max x_j - \min x_j}$ are standardized-for positive indicators (such as the number of broadband ports) and negative indicators (such as the non-performing loan ratio) respectively.

Entropy value calculation: Calculate the specific gravity $p_{ij} = \frac{x'_{ij}}{\sum\limits_{i=1}^{n} x'_{ij}}$ of the i-th sample of the jth index; Entropy value $k(\sum_{i=1}^{n} p_{ij} \ln p_{ij})(k = 1/\ln n)$

Weight determination: Weight $(w_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)})$ Finally, the weights of each dimension are obtained.

Table 2: Describe the statistical results

Variable	Observation	Mean	Standard Deviation	Min	Maximum	Data Characteristics
FR	310	1.87%	0.65%	0.92%	3.54%	The average of eastern provinces is 1.52%, while the average of western provinces is 2.13%
SCDBI	310	0.0032	0.0026	0.0003	0.0166	Beijing and Shanghai are significantly higher than the central and western regions
PGDP	310	¥56800	¥23400	¥12300	¥156700	Regional difference coefficient 0.41 (2020)
FIN	310	8.48	0.85	3.40	10.67	Correlation coefficient with SCDBI 0.68**

Table 3: Regression results of fixed effect model

variable	coefficient	Standard error	tvalue	Pvalue	Economic significance explanation
SCDBI	-0.72***	0.15	-4.85	0.000	SCDBI 1 unit per liter, the failure rate decreases by 0.72%
PGDP	-0.35**	0.16	-2.31	0.022	The higher the economic level, the lower the risk
FIN	-0.28*	0.15	-1.89	0.061	Financial deepening reduces information asymmetry
R&D	-0.19	0.14	-1.32	0.187	The impact of innovation ability is not significant (p>0.1)
GOV	0.12	0.11	1.12	0.264	Government intervention has no significant impact on risk
Individual fixed effect	controlled				Reflect regional heterogeneity such as industrial structure
Time fixed effect controlled	controlled				Capture the impact of macro policies such as financial deleveraging
R^2	0.89				Strong model explanatory power

3.2 Measuring model setting

Build a two-way fixed effect model:

$$FR_{it} = \alpha_0 + \beta_1 SCDBI_{it} + \beta_2 X_{it} + \delta_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Interpreted variables: Regional non-performing loan ratio (FR), the non-performing loan ratio of RMB in each province is used to reflect the credit risk level.

Core explanatory variables: The Social Credit Big Data Development Index (SCDBI) is calculated by entropy method, and the value range is [0, 0.02]. The larger the value, the higher the level of credit digitization.

Control variables:

- Economic base (per capita GDP, PGDP): reflects regional economic risk resistance.
- Level of financial development (FIN): logarithms of total social financing, measuring the degree of financial deepening.
- Innovation capability (R&D): R&D funds account for GDP, reflecting technology-driven capabilities.
- Government intervention (GOV): The proportion of fiscal expenditure to GDP reflects the strength of policy support.

4 Empirical analysis: Data-driven risk prevention effects

4.1 Data description and sample selection

Data source. Panel data of 31 provinces (autonomous regions and municipalities) from 2011 to 2020, among which the SCDBI indicators come from the National Bureau of Statistics, the Ministry of Industry and Information Technology, the China Credit Information Center, etc.; financial risk data comes from the "China Regional Financial Operation Report"; control variables come from the CSMAR database.

4.2 Benchmark regression results

Core Discovery:

Table 4: Regression analysis results

Variable	Eastern Region	Central and Western Regions	Explanation of causes of differences
SCDBI	-0.65***	-0.81***	The data foundation in the central and western regions is weak, and there is a lot of room for improvement
PGDP	-0.22*	-0.45**	Resilience in the central and western economies is more sensitive to risks
FIN	-0.35**	-0.20	Eastern financial deepening has passed the peak of marginal benefits

Significant negative impact of SCDBI: After controlling other variables, the increase in credit digitization level is a key factor in reducing financial risks, and the verification hypothesis H1 is valid.

Auxiliary role of the economic foundation: Per capita GDP and financial development level have a inhibitory effect on risks, but are weaker than SCDBI, indicating that technology-driven is more efficient than scale expansion.

4.3 Analysis of Dimensional Effects and Heterogeneity

4.3.1 Decomposition of core dimensions. Through hierarchical regression, it was found that data infrastructure (β =-0.35***) and digital technology kinetic energy (β =-0.28***) contributed 63% of the total effect, while policy synergy (β =-0.08) had no significant impact. (picture)

4.3.2 Regional heterogeneity analysis. The samples were divided into eastern (11 provinces) and central and western (20 provinces), and the regression results showed:

4.3.3 Robustness and endogenous test. Instrumental Variable Method (2SLS):

- **Selection of instrument variables:** population density (highly correlated with SCDBI, ρ =0.72**, and does not directly affect financial risks).
- **Results:** The F value in the first stage = 28.6>10, excluding the problem of weak instrument variables; the coefficient in the second stage - 0.68***, consistent with the benchmark result, solving the endogenous problem.

Replace the interpreted variable: The "comprehensive financial risk index" (including credit, market, and liquidity risks, calculated by principal component analysis), the regression coefficient is - 0.65*** (p<0.01), and the model is good robust.

5 Typical Practice Verification: Model Mapping of Suzhou Digital Credit Investigation Experimental Zone

5.1 Practical background and data effectiveness

As the first digital credit investigation experimental zone for small and micro enterprises in the country, Suzhou has achieved the upgrade of the credit investigation system through the dual-wheel drive of "data + technology":

5.2 Breakthrough in data integration

Integrate more than 200 data such as taxation, customs, water and electricity. The enterprise credit coverage rate increased from 62% in 2019 to 84.52% in 2023, solving the problem of "data island".

5.2.1 Technology application innovation. Blockchain technology realizes data "available and invisible", and the willingness of enterprise data sharing has increased from 45% to 82%.

The AI risk control model introduces 100+ unstructured indicators such as transaction flows and equipment energy consumption and compresses the loan approval time for small and micro enterprises from 3 days to 2 hours.

5.2.2 Risk prevention effect. The financing satisfaction rate increased from 70.46% to 92.38%, 15 percentage points higher than the national average.

The non-performing loan ratio dropped from 2.8% to 1.6%, and the risk identification accuracy rate was 30% higher than that of the traditional model (Table 5).

5.3 Model matching analysis

The SCDBI value of Suzhou from 2019 to 2023 (up from 0.0042 to 0.0095) was substituted into the model, and the non-performing loan ratio decreased by 0.85 percentage points, which was the difference from the actual decline of 1.2 percentage points, mainly from the superposition effect of local policies (such as risk compensation funds bear 30% losses), and the verification model's explanatory power of core variables reached more than 70%.

6 Path optimization: from empirical results to policy design

6.1 Data element level: build a full-dimensional credit data source

6.1.1 National data platform integration project. Accelerate the connection between the national credit information sharing platform and financial regulatory data, and achieve 100% coverage of tax, social security and judicial data by 2025, and the coverage rate of enterprise industrial, commercial, water and electricity data exceeds 90%.[4]

Pilot the "data sandbox" mechanism, allowing financial institutions to call desensitized government data within the compliance framework. For example, Shenzhen Qianhai has opened 127 government data interfaces, benefiting 80,000 companies.

Table 5: The results of risk prevention effectiveness

index	2019	2023	Rate of change	Model simulation value	Explanation of actual difference
Credit coverage	62%	84.52%	+22.52%	+20.3%	Contribution to open government data 12%
Non-performing loan rate	2.8%	1.6%	-1.2%	-0.85%	Contribution to technical model optimization 0.35%
Financing Cost	6.8%	5.2%	-1.6%	-1.2%	Credit rating optimization reduces interest rate spreads

Table 6: Real time risk warning system

Warning level	**Trigger condition**	**Disposal measures**	**Response time**
Yellow warning	Tax overdue 1 period or underpayment rate > 10%	MS reminder + 50% quota freeze 50%	T+1
Orange warning	Related transactions account for > 30% or 1 lawsuit involving litigation	Manual review + Stop new credit grants	T+3
Red warning	Breach of trust is executed or abnormal capital flows	Full collection + Included in blacklist	T+24 hours

6.1.2 Alternative data development and standardization. Formulate the ”Non-Bank Credit Data Collection Standards” to clarify the legal collection boundaries of data such as e-commerce transactions, logistics trajectories, and enterprise electricity use, and solve the ”credit gap” problem of small and micro enterprises.

Promote the ”Xinyi Loan” model, such as Jiangsu ”Sufu Loan” based on 120 alternative data, increasing the proportion of unsecured credit loans to 45%.

6.2 Technical drive level: Upgrading the intelligent evaluation and monitoring system

6.2.1 National promotion of AI risk control model. Establish a national intelligent credit reporting model library, open up algorithm interfaces such as random forests and gradient enhancement trees, and support the rapid deployment of small and medium-sized banks, and aim to increase the accuracy of credit assessment for small and micro enterprises from 75% to more than 85%.

Case:Zhejiang Ant Commercial Bank’s ”Big Tit” model access 200 + unstructured indicators, making the loan non-performing rate of small and micro enterprises in the county stable at below 1.2%.

6.2.2 Construction of real-time risk warning system. Build a ”three-level early warning” system (Table 6), integrate indicators such as abnormal transaction flow (50% exceeding registered capital in a single day), negative public opinion (3 items per week), equity changes (3 times in the quarter), and risk ”early detection and early disposal”.[5]

Technology application: Shenzhen’s “Golden Eagle System” monitors 2 million market entities in real time, and the early warning signal is triggered 3 months in advance, and the risk disposal efficiency is improved by 40%.

6.3 Institutional coordination level: Improve diversified governance and policy guarantees

6.3.1 Construction of legal and regulatory system. Accelerate the issuance of the Social Credit Law to clarify data ownership, sharing rules and privacy protection. For example, it is stipulated that enterprise data collection requires the explicit consent of the subject, and the proportion of personal data desensitization processing shall not be less than 70%.

Pilot the ”credit repair” mechanism, such as Suzhou allows enterprises to repair their credit records within 6 months after completing rectification, with a repair pass rate of 65%.

6.3.2 Cultivation of market-oriented credit reporting institutions. Support cross-regional services of leading enterprises (such as Sesame Credit and Qianhai Credit Reporting), form a dual-track system with ”public credit reporting as the basis and commercial credit reporting as the supplement”, and aim to cultivate 3-5 credit reporting technology companies with a market value of over 100 billion yuan.

Establish a rating system for credit reporting agencies and include data quality and privacy protection levels in the assessment. In 2023, the first batch of 10 institutions received AAA ratings, accounting for 60% of the market share.

6.3.3 Regional and international collaboration. Regional level: Promote mutual credit recognition of the Yangtze River Delta and the Guangdong-Hong Kong-Macao Greater Bay Area. For example, the recognition of Shanghai’s corporate credit rating in Hangzhou and Shenzhen is 85%, and the efficiency of cross-regional loan approval is increased by 50%.[6]

International level: Participate in the cross-border credit investigation cooperation of the "Belt and Road", establish a China-Russia and the Middle ASEAN credit data sharing platform, pilot the "whitelist" system for cross-border trade, and reduce exchange rate fluctuations and default risks.

7 Conclusion and research prospects

7.1 Core Research Conclusion

The quantitative relationship is significant: for every 10% increase in the social credit big data development index, the non-performing loan ratio drops by 0.7 percentage points. Data infrastructure and digital technology are the core driving forces, verifying the effectiveness of technology empowering credit reporting.

The practice path is clear: through data fusion (improving coverage), technology upgrade (optimizing evaluation model), and system coordination (improving regulations), financial risks can be systematically reduced. The practice of Suzhou Experimental Zone has proved that this path can improve financing efficiency by 22 percentage points and the non-performing rate decreases by 1.2 percentage points.

The policy enlightenment is clear: it is necessary to break through data barriers, strengthen technology research and development, cultivate market entities, and build a new credit reporting system driven by the dual wheel "technology + system".

7.2 Research Outlook

Integration of cutting-edge technologies: Exploring the application of federated learning in data privacy protection and studying virtual credit evaluation models in meta-universe scenarios.

Macroeconomic impact. Analyze the regulatory effect of the economic cycle on the risk prevention effect of the credit reporting system, such as whether the risk inhibition effect of SCDBI is enhanced during recession periods.

Global rule construction. Participate in the formulation of cross-border data flow standards, study credit reporting coordination mechanisms in cross-border payments of digital RMB, and provide credit support for the internationalization of RMB.

Through this research, we hope to provide theoretical support and practical reference for my country to build a more resilient financial risk prevention system in the digital economy era, promote the upgrade of the social credit reporting system from "data collection" to "intelligent governance", and help achieve a dynamic balance between "effective market" and "prosperous government".

Acknowledgments

This work was supported by the project fund: Wuhan Business School Scientific Research Project "Research on the Path and Mechanism of Preventing Financial Risks in the Social Credit Reporting System" (No. 2023KY014).

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